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Research using population-based administration data integrated with longitudinal data in child protection settings: A systematic review

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Abstract

Introduction

Over the past decade there has been a marked growth in the use of linked population administrative data for child protection research. This is the first systematic review of studies to report on research design and statistical methods used where population-based administrative data is integrated with longitudinal data in child protection settings.

Methods

The systematic review was conducted according to Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) statement. The electronic databases Medline (Ovid), PsycINFO, Embase, ERIC, and CINAHL were systematically searched in November 2019 to identify all the relevant studies. The protocol for this review was registered and published with Open Science Framework (Registration DOI: **10.17605/OSF.IO/96PX8**)

Results

The review identified 30 studies reporting on child maltreatment, mental health, drug and alcohol abuse and education. The quality of almost all studies was strong, however the studies rated poorly on the reporting of data linkage methods. The statistical analysis methods described failed to take into account mediating factors which may have an indirect effect on the outcomes of interest and there was lack of utilisation of multi-level analysis.

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Conclusion

We recommend reporting of data linkage processes through following recommended and standardised data linkage processes, which can be achieved through greater co-ordination among data providers and researchers.

Introduction

Population-based administrative data is routinely collected by organisations to deliver services and to monitor, evaluate and improve upon those same services [1]. Some examples of the types of data include administrative health data, disease registries, primary care databases, electronic health records, population registries and birth and death registries [2]. The data may be linked within a single service sector, such as health, or with surveys and across sectors such as education, child protection and corrective services [1, 3, 4]. Bringing together data from various administrative data sources provides a rich repository of data that can be used for research purposes. The linked data enables researchers to study risk and protective factors and to examine outcomes from various databases brought together [5, 6]. The trend of using administrative data for research purposes has increased exponentially [7–13]. To date, there has not been a systematic review that has focussed on methods of analysis of integrated population-based administrative data with longitudinal data in child protection settings.

Population-based administrative data is invaluable in research as it offers complete coverage of a given population which overcomes the imprecision associated with sampling errors [14]. It offers superior statistical power and precision to determine associations between rare exposures and outcomes, and using these samples as sampling frames for subsequent surveys [1, 15–18]. Administrative data is useful when studying causes of complex diseases and conditions as well as assessing outcomes of clinical or therapeutic interventions [17, 19–21]. Use of multiple linked administrative data allows researchers to explore comorbidity and variability in outcomes within target populations and compare these between specific clinical population groups and against outcomes in the general population [22–25]. As the purpose of this systematic review is related to child protection settings, it will be used as an example to elucidate the benefits and limitations of using population-based administrative integrated with longitudinal data in research.

Population-based administrative data allows the study of outcomes among cohorts of hard to reach or high-risk populations such as those in the juvenile justice system, and those involved with the child protection system [15, 26, 27]. For example, child protection administrative data allow longitudinal examination of population-level patterns and trends in child maltreatment and complex multi-level analysis, particularly where the data is linked to individuals who are related [27–31]. The data allow the determination of cumulative incidence of risk and protective factors among various population subgroups with different levels of child protection involvement [22, 32, 33]. Therefore the data allows researchers to trace various trajectories of specific cohorts from birth to adulthood [34].

Use of child protection administrative data in research reduces the burden on individuals to disclose sensitive or traumatic experiences and also reduces the risk of recall bias, social desirability and stigma, which may occur, for instance, in retrospective self-report of child maltreatment [4, 27]. Administrative data is less prone to selection bias since the data includes the entire population served by the Child Protection Agency. Such data is also used to evaluate the frequency of use, effectiveness and costs of services across populations and over time [35].

Further, using administrative data is more cost-effective and efficient in that data is readily available when needed [36] and one can avoid the cost and burden associated with face to face data collection.

Despite all the advantages of using population-based administrative date, there are some limitations to using and accessing administrative data. Key variables of interest to researchers are often not recorded since administrative data are primarily collected for the delivery of programs and services [14]. The data may be subjected to biases, such as under-reporting of the incidence of child maltreatment in child protection research or lack of availability of data for some respondents, particularly difficulty in reaching vulnerable groups [1]. In addition, the type of data being collected routinely may lack the depth of information required to answer important research questions [27]. Another important limitation of administrative data is that individual-level socio-economic status (SES) parameters are often not available [37].

Linked administrative data may be subject to linkage error when some records that should be matched or able to be linked were not linked (missed matches) or records were linked incorrectly (false matches), which could lead to biased estimates of association [7, 38]. There are also data access challenges, such as delays in getting approvals to link datasets, especially getting access to cross-jurisdictional linked datasets [26]. There may be restrictions placed by data custodians on who may access linked data, thereby limiting the ability of researchers to access all the data they may need [1]. Despite the above limitations of using population-based administrative data alone, there are advantages of linking population based administrative data to longitudinal data.

The benefits of conducting longitudinal research in child protection settings are well documented, as this type of research allows researchers to analyse trends, changes in early exposures, risks, behaviours and outcomes over a long period of time [18, 39]. Longitudinal studies are also powerful in that they overcome common issues around temporal associations and causal risk factors for outcomes of child abuse and neglect [5]. Longitudinal studies also allow researchers to update certain information about participants, such as socio-demographic characteristics, and also obtain in-depth information about certain topics and service involvement, which otherwise could not be collected from administrative data alone [18, 40].

Despite the notable benefits of conducting longitudinal studies, they are known to be notoriously expensive as they involve several waves of data collection, and could run for several years before the outcomes of a study are determined [37]. It may be difficult to obtain sufficient numbers of eligible participants, particularly when recruiting hard to reach populations and access to children in out-of-home care is generally tightly controlled, resulting in low response rates [41]. Longitudinal data are also subject to different biases such as under-reporting, recall errors and high attrition rates [18], resulting in reporting of biased estimates if the biases are not appropriately accounted for in the analysis. A systematic review conducted by Farzanfar, Abumuamar [42] highlighted the potential for bias and on the reporting of longitudinal studies. Another review by Karahalios, Baglietto [43], found that 56% of studies had a high risk of bias with regards to attrition. Longitudinal studies also place a high burden on respondents due to frequent contact.

Combining population-based administrative data with longitudinal data has several advantages. For example, linking child protection administrative data to longitudinal data allows use of retrospective administrative data on prenatal or early childhood experiences to determine a trajectory of long term adult outcomes which can be measured from longitudinal data [44–47]. Young people who have had child protection contact are known to have worse outcomes than young people in the general population [48, 49]. Thus, integrating longitudinal data and administrative data enables comparison of outcomes using population level data. Other benefits of linking longitudinal data with administrative data include the following: i) crossvalidation of self-reported information from longitudinal surveys with administrative data [26, 38, 50, 51]; ii) reducing data incompleteness and biases inherent in longitudinal data as reported earlier [40, 52, 53]; and iii) overcoming high attrition rates common in longitudinal data [52, 54, 55]. In summary, combining these two data sources increases the usability and possible applications of the data.

Using population-based administrative data integrated with longitudinal data has its own limitations. One of the challenges is the introduction of bias by linking data only where consent has been provided by respondents [1, 56]. Further, the linkage may be of poor quality and the data from administrative records may not exist or be incomplete for many longitudinal participants [1].

A wide variety of factors affect the accuracy of reported results in child protection settings. These include the reference population, data source, sampling strategy, sample size and analytical factors [41, 57]. While data integration offers unique advantages, it is important to consider various techniques and methods of analysis to report study outcomes and to correct for biases which may be introduced by bringing together data from various sources. When modelling outcomes using administrative data integrated with longitudinal data it is important to consider time between occurrences of events (survival analysis), all possible confounders, and mediating and moderating factors. These may include early childhood experiences, pre-natal and parental risk factors, socio-demographic and environmental factors [58]. Failure to account for these factors may lead to biased estimates and false inference. Sensitivity analysis may be conducted to investigate the extent to which some changes or modifications in the confounding variables may have an effect on reported outcomes. For example, multiple regression models may be constructed involving child maltreatment notifications as a risk factor compared to modelling substantiated maltreatment on outcomes [45, 59].

Some of the considerations that need to be taken into account when analysing these datasets involve methods of dealing with biases in the datasets. Missing data can lead to biased estimates of regression parameters when the probability of missingness is associated with outcomes. Different strategies are used to handle missing data in statistical analyses, such as: i) imputation of missing data, [60, 61]; ii) using maximum likelihood estimation methods to model data from subjects who drop out of the study compared to those who complete the longitudinal study; and iii) weighting the available data using non-response methods to account for missing data [62, 63]. Some concurrence or agreement tests may need to be conducted to determine validity of responses from either data sources [64–66].

Some studies have demonstrated that longitudinal data analysis should account for possible within-subject correlation and different covariance structures of episodes of various disease outcomes over time. Some of the analytical methods used for this include generalized estimating equations (GEE) and mixed-effects models [67–71].

Previous reviews have focused on measurement of the diagnosis of diseases or outcomes, including administrative data characteristics and strengths and limitations of the two data sources [17, 72–74]. A systematic review conducted by Tew, Dalziel [26] focussed on the use of linked hospital data for research in Australia, thereby limiting the generalisability of the findings. Young and Flack [13] conducted a review that reported on recent trends of using linked data. Even though this paper used systematic search strategy, it was not published as a systematic review. In addition, the study highlighted areas where linked data is commonly used, particularly in cross-sectorial linked data and areas where its use could be improved, however it did not mention use of longitudinal data to enhance reporting of outcomes. A systematic review conducted by Andrade, Elphinston [75], highlights the need for future research to focus on collecting better measures for outcomes data and linking data to multiple administrative databases. A systematic review conducted by da Silva, Coeli [76] examined the issue of consent for data linkage, which is one of the sources of bias in using linked data.

Selecting appropriate statistical analysis of administrative data integrated with longitudinal data can improve the reporting of risk and protective factors related to child protection outcomes. This can be achieved through careful selection of variables and optimal use of the data extracted from the administrative and longitudinal data. The over-arching aim of this review is to provide a synthesis of the different methods of analysis used when administrative data is integrated with longitudinal data and make recommendations about approaches to enhance research findings thereby minimising risk of bias and other limitations. Specifically, the following objectives will be investigated: i) to describe the study designs and methods used in reporting linked administrative data when combined with longitudinal data in child protection settings; and ii) to identify statistical methods, gaps and opportunities in the analysis of administrative data integrated with longitudinal data in child protection settings.

Although research on combining administrative data integrated with longitudinal data in child protection research is available, to the best of our knowledge, no systematic reviews have reported on the statistical methods used when the two data sources are combined. This systematic review is an essential step towards informing policy, practice and future research directions in methodological aspects of using administrative data integrated with longitudinal data in child protection settings.

Methods

The systematic review was conducted according to Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) statement [77] which outlines minimum standards for reporting systematic reviews and meta-analysis. A completed PRISMA checklist is provided in S1 Table. The protocol for this review was registered and published with Open Science Framework (Registration DOI: **10.17605/OSF.IO/96PX8**).

Eligibility criteria

To be included in this review, peer reviewed studies needed to have at least one administrative database integrated with a longitudinal data. Selected studies were limited to studies involving child protection settings and published in English only. Studies involving systematic reviews or meta-analysis were excluded. In addition, anecdotes, reviews, book chapters, letters to the editor, editorials and conference abstracts were excluded. Studies had to meet all eligibility criteria to be included in the review.

Information sources and search strategy

The electronic databases Medline (Ovid), PsycINFO, Embase, ERIC, and CINAHL were systematically searched in November 2019 to identify all the relevant studies. In line with the objective of this review, terms were identified in electronic databases that are related to the following three concepts: i) data source (administrative data or population based data); ii) study design (longitudinal study or cohort study or prospective study); and iii) setting (child protection). Searches were conducted using free-text in all databases because we had too few relevant subject headings for our purposes. In addition, websites that provide a publication repository for studies involving linked data, such as the Population Health Research Network, were searched. The reference list of included studies was manually searched to find additional relevant studies. A full search strategy for all databases is shown in S2 Table.

Study selection

Screening of titles and abstracts of the retrieved studies was conducted between December 2019 and March 2020. The first author screened all titles and abstracts while the second reviewer (LP) independently screened a random selection of 40% of studies to identify the candidate studies for the full text review. The reviewers graded each abstract as eligible, possibly eligible or not eligible (using the inclusion and exclusion criteria defined above). Both reviewers independently screened 100% of full-text studies. Any disagreements about eligibility of full-text studies were settled by discussing the differences in the assessment and reaching a consensus on which studies to include. Five studies were used to pilot the screening criteria, and data extraction process, which were modified after consultation between researchers. Inter-rater reliability using weighted Kappa between the two independent reviewers was established for the abstract selection and quality appraisal of included studies. The weighted Kappa measures the degree of disagreement between the two raters; the greater the disagreement the higher the weight.

Methodological quality

Since there is no standard criteria for assessing the quality of study designs involving integration of population-based administrative data and longitudinal data, a combination of three critical appraisal methods for assessing the methodological quality of studies was utilised. The critical appraisal methods were the "Qualsyst" critical appraisal tool by Kmet et al. [78] (henceforth referred to as kmet checklist), the Guidance for Information about Linking Data sets (GUILD) [7], which focus on the methodological process of linking data, and the Reporting of studies Conducted using Observational Routinely-collected health Data (RECORD) [79].

The Kmet checklist has 14 items that use a 3-point ordinal scale (0 = no, 1 = partial, 2 = yes) of which three items were not applicable to our study design. The checklist items assess the study design, description of participants' characteristics, appropriateness of sampling strategy and sample size, robustness of outcome and exposure variables, analytical methods, estimates of variance, control for confounding and whether conclusions drawn reflect results reported. A Qualsyst score of > 80% was interpreted as strong quality, 60–79% as good quality, 50–59% as adequate quality, and < 50% as poor methodological quality.

The GUILD statement has three broad domains with items within each domain that focus on the data source population and linkability of the dataset, data linkage process and quality of data linkage including accounting for linkage error. The RECORD statement, an extension from the STROBE guidelines, consists of a checklist of 13 items related to the title, abstract, introduction, methods, results, and discussion section of studies and other items relating to routinely collected health data [79]. Three items were selected from the RECORD checklist as they were the only items that did not overlap with the GUILD items; these items were combined with the GUILD statements. Due to the absence of a standard scoring system for the GUILD and RECORD statements, a similar scoring method to Kmet was used. Prior to conducting the quality appraisal, the two reviewers (FC and LP) met to discuss the scoring method for these guidelines.

The second reviewer conducted quality assessment (using Kmet, GUILD and RECORD statements) on a random selection of 40% of the included studies. Any differences in ratings from the two reviewers were settled by discussing the differences in the assessment and reaching a consensus on the final score for each of the quality appraisal methods. The differences for Kmet were defined as any difference in the rating from one category to the next (e.g., when a study was rated as good quality (60–79%) by one reviewer, while the same study is rated as poor quality (<50%) by the other reviewer). However, because most studies received poor

GUILD and RECORD ratings, discussions on agreement between scores were conducted for GUILD and RECORD ratings with more than 15% difference for each study.

Data collection process

Comprehensive data extraction forms were developed to extract relevant data from the included studies under the following four headings: study characteristics, administrative data, longitudinal data and statistical methods. The included studies were heterogeneous in terms of study design and quality, therefore a narrative synthesis of the findings of the included studies was conducted.

Results

Study selection

A total of 1,123 studies were retrieved from the electronic database search and eight from other sources. Out of these, a total of 698 studies remained after duplicates were removed. A total of 664 records did not meet the inclusion criteria, resulting in 34 full-text studies which were assessed for eligibility. The final number of studies that met the inclusion criteria and were included in data synthesis were 30 and of these 10 were identified by manually scrutinising the references of the eligible studies. Fig 1 below shows a flowchart of the search and selection process of the included studies.

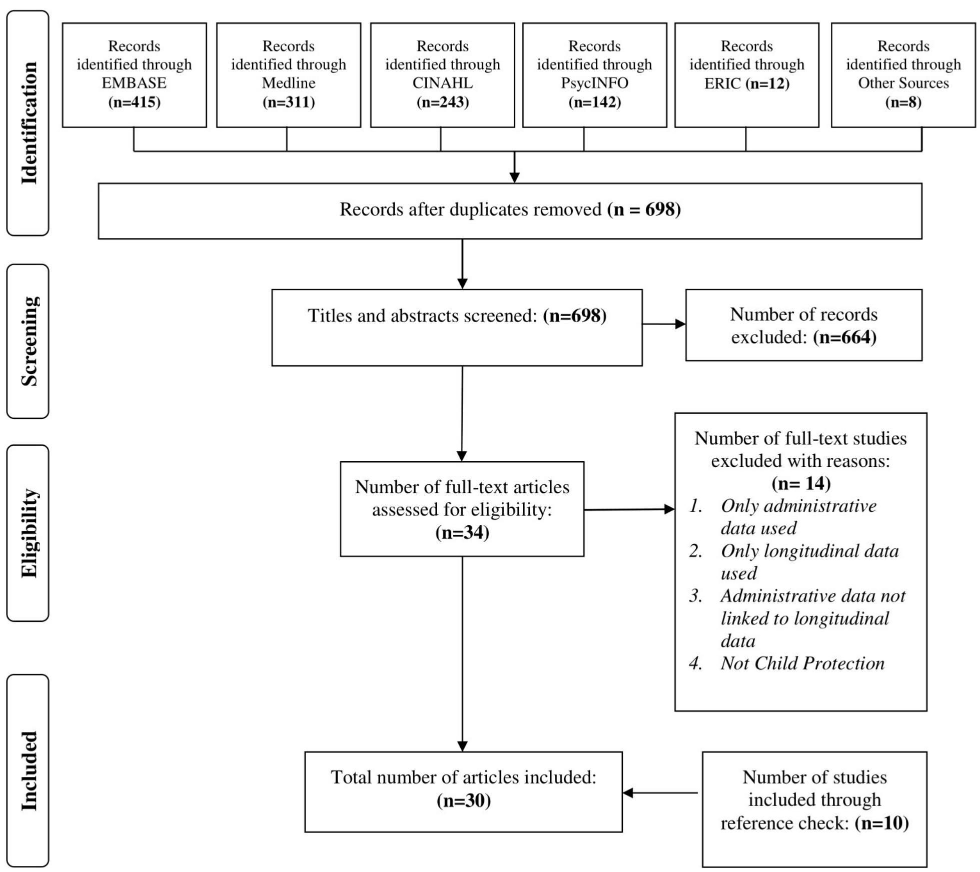

Fig 1. PRISMA flow diagram.

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Characteristics of included studies

The studies were conducted in a variety of countries with Australia having the highest number of publications (50%), followed by the USA (20%) and the United Kingdom (17%). While all studies were conducted in child protection settings, only a few were specific to out-of-home care settings (20%). The outcomes investigated were varied; the most common outcomes were child maltreatment (30%), mental health (20%), drugs and alcohol abuse (20%), education (17%), domestic violence (7%), and health insurance (7%). Table 1 below shows a summary of all included studies, and Table 2 has more detailed information for each study.

Almost all studies were birth cohorts and they each measured different variables at different points in time. In the majority of studies, baseline data consisted of prenatal or postnatal data as reported by the mothers, while outcome data were obtained during follow-up waves. Six major longitudinal studies were reported from the publications, the main one being the Mater-University Study of pregnancy (MUSP) which was conducted in Queensland, Australia from 1981–2004 [58, 80–82]. While these studies had multiple follow-up waves, the authors mostly reported on the baseline wave and one follow up wave. The duration of follow up from the baseline to the last wave ranged from 3 to 21 years. Each longitudinal study had multiple publications demonstrating that a range of exposures and outcomes can be investigated in linked child protection datasets. There was an almost equal number of males and females reported in 70% of studies, while the gender split was unknown in 9 studies.

Table 1. Characteristics of the study population.

Characteristic		N	%
Country	Australia	15	50%
	USA	6	20%
	UK	5	17%
	Denmark	2	7%
	Sweden	2	7%
Research Area	Child Protection	9	30%
	Drugs & Alcohol	6	20%
	Mental Health	6	20%
	Education	5	17%
	Domestic Violence	2	7%
	Health Insurance	2	7%
Population group	Child protection Contact	24	80%
	Out-of-home care	6	20%
Linkage Method	Deterministic	17	57%
	Probabilistic	2	7%
	Deterministic & Probabilistic	2	7%
	Not reported	9	30%
Admin datasets	1	25	83%
	>1	5	17%
Name of Longitudinal Study	The Mater-University Study of pregnancy (MUSP)	14	47%
	Alaska Pregnancy Risk Assessment Monitoring System (PRAMS)	5	17%
	The Avon Longitudinal Study of Parents and Children (ALSPAC)	5	17%
	Danish longitudinal survey of children (DALSC)	5	17%
	Swedish longitudinal Evaluation Through Follow-up (ETF) project	2	7%
	National Survey of Child and Adolescent Well-Being (NSCAW)	2	7%

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Table 2. Characteristics of included studies.

Author (Year)	Country	Aims/ Objectives	Research Area	Child Protection Contact (CPC) vs. OHC	Administrative Data Source	Number of administrative datasets (Deterministic/ Probabilistic Linkage)	Linkage Quality (Yes/ No)
Egulend et al. (2009)	Denmark	To identify problems among children in foster and residential care compared to in home care children, and to all non-welfare children of the same age, and to analyse factors associated with mental health problems in children in out-of-home care	Mental Health	OHC	1.National Health Register; 2.Psychiatric Research Register 3.Child Protection Register	2 (Deterministic)	No
Hansson et al. (2018)	Sweden	To describe and discuss differences between children placed in OHC and non-OHC children in the Swedish compulsory school, with respect to special needs education, school mobility and academic achievement.	Education	OHC	Statistics Sweden	1 (NR)	No
Kisely et al. (2019)	Australia	To examine whether notified and/or substantiated child maltreatment is associated with the prevalence and persistence of smoking in early adulthood	Drugs & Alcohol	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Kisely et al. (2018)	Australia	To examine, using a prospective record-linkage analysis, whether substantiated child maltreatment is associated with adverse psychological outcomes in early adulthood.	Mental Health	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Kisely et al. (2019)	Australia	To study the association of different types of child maltreatment with alcohol use disorders at 21 years of age	Drugs & Alcohol	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Olsen et al. (2018)	Denmark	To investigate the association for children in OHC and non-OHC peers between school change in lower secondary school and two educational outcomes: (1) self-perceived academic abilities at age 15 and (2) staying-on rates in upper secondary school at age 18	Education	OHC	Danish Register Data	1 (Deterministic)	No
Parrish et al. (2016)	USA	To determine the predictive relationship between a maternal pre-birth self-reported history of intimate partner violence (IPV) and any post-birth reported allegation to Child Protective Services (CPS) by age 2	Domestic violence	CPC	Alaska's Child Protective Services Agency Register	1 (Probabilistic)	No
Parrish et al. (2017)	USA	A description of the creation of the (ALCANLink) project and the benefit of the ALCANLink methodology by documenting the bias in incidence and hazard ratios that can arise in birth cohort linkage studies due to incomplete data linkages, non-linkage assumptions, and single source outcome ascertainment	Child protection	CPC	1. Vital records; 2. Child death review; 3. Alaska Permanent Fund Dividend (PFD) records	3 (Deterministic & Probabilistic)	Yes
Raghavan et al. (2017)	USA	To quantify the magnitude of non-ascertainment bias, develop a profile of children who are at greatest risk for non-ascertainment,	Health insurance	OHC	1.Medicaid Analytic eXtract (MAX) Research Data Assistance Centre; 2.Child Welfare Agency	1 (Deterministic)	Yes
Sidebotham et al. (2000)	UK	A study of patterns of child abuse and factors that may affect risk in a pre-school population	Child protection	CPC	Avon Social Services Child Protection Register	1 (NR)	No
Sidebotham et al. (2003)	UK	To determine characteristics of children that may predispose to maltreatment.	Child protection	CPC	Avon Social Services Child Protection Register	1 (NR)	No
Sidebotham et al. (2006)	UK	to analyse the multiple factors affecting risk of abuse in young children within a comprehensive theoretical framework	Child protection	CPC	Avon Social Services Child Protection Register	1 (NR)	No

(*Continued*)

Table 2. (Continued)

Author (Year)	Country	Aims/ Objectives	Research Area	Child Protection Contact (CPC) vs. OHC	Administrative Data Source	Number of administrative datasets (Deterministic/ Probabilistic Linkage)	Linkage Quality (Yes/ No)
Sidebotham et al. (2002)	UK	To determine risk factors for child maltreatment within the socio-economic environment of a contemporary UK child population	Child protection	CPC	Avon Social Services Child Protection Register	1 (NR)	No
Teyhan et al. (2019)	UK	To use record linkage of birth cohort and administrative data to study educational outcomes of children who are looked-after (in public care) and in need (social services involvement), and examine the role of early life factors.	Education	OHC	1. Children Looked-After (CLA) Data Return; 2. Children in Need (CIN) Census; 3. National Pupil Database	3 (NR)	No
Austin et al. (2019)	USA	Identify longitudinal trajectory classes of CPS contact among Alaska Native (AN/AI) and non-Native (NN) children and examine preconception and prenatal risk factors associated with identified classes	Child protection	CPC	1. Alaska Office of Children's Services (OCS); 2. Alaska Child Death Review; 3. Death certificate files; 4. Alaska Dept. of Revenue	4 (NR)	No
Austin et al. (2018)	USA	To use multiple novel data sources and time-to event analysis to examine preconception and prenatal predictors of time to first contact with CPS among a representative sample of Alaska children.	Child protection	CPC	1. Alaska Office of Children's Services (OCS); 2. Alaska Child Death Review; 3. Death certificate files; 4. Alaska Dept. of Revenue 5. Geographic census classification data 6. Alaska Birth Defects Registry	6 (NR)	No
Hansson et al. (2020)	Sweden	To investigate the effects of school mobility on academic achievements for OHC-children as well as for NOHC-children.	Education	OHC	Statistics Sweden: Child Welfare Register	1 (NR)	No
Abajobir et al. (2017)	Australia	Examine the association between different types of substantiated child maltreatment and self-reported psychotic experiences as measured by the Young Adult Self-Report (YASR) items and the Peter's Delusions Inventory (PDI) using data from a large population-based birth cohort study.	Mental Health	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Abajobir et al. (2017)	Australia	Examine the effect on QoL of multiple forms of substantiated child maltreatment controlling for selected potential confounders and/ covariates, and concurrent depressive symptoms.	Mental Health	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Abajobir et al. (2016)	Australia	This study examines whether distinct types of childhood maltreatment differentially predict different forms of intimate partner violence	Domestic violence	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Abajobir et al. (2016)	Australia	This study investigates the association between exposure to prospectively-substantiated childhood maltreatment between 0 to 14 years of age and lifetime cannabis use, abuse and dependence reported at 21 years	Drugs & alcohol	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Abajobir et al. (2017)	Australia	Determine the association between substantiated childhood maltreatment and injecting drug use	Drugs & Alcohol	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Strathean et al. (2009)	Australia	Explored whether breastfeeding may protect against maternally-perpetrated child maltreatment.	Child protection	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No

(*Continued*)

Table 2. (Continued)

Author (Year)	Country	Aims/ Objectives	Research Area	Child Protection Contact (CPC) vs. OHC	Administrative Data Source	Number of administrative datasets (Deterministic/ Probabilistic Linkage)	Linkage Quality (Yes/ No)
Mills et al. (2013)	Australia	To examine whether notified child maltreatment is associated with adverse psychological outcomes in adolescence, and whether differing patterns of psychological outcome are seen depending on the type of maltreatment.	Mental Health	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Mills et al. (2016)	Australia	Investigate the incidence of CSA in the same birth cohort using both retrospective self-report and prospective government agency notification, and examine the psychological outcomes in young adulthood.	Mental Health	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Mills et al. (2014)	Australia	This study examines whether child maltreatment experience predicts adolescent tobacco and alcohol use. The secondary question was whether specific patterns of types of maltreatment were associated with alcohol and/or tobacco use.	Drugs & alcohol	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Mills et al. (2019)	Australia	to investigate whether child maltreatment is associated with adverse outcomes in cognitive function, high school completion and employment by the age of 21	Education	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Mills et al. (2017)	Australia	To investigate whether: (1) child maltreatment is associated with life-time cannabis use, early-onset cannabis use, daily cannabis use and DSM-IV cannabis abuse in young adulthood; and (2) behaviour problems, tobacco use and alcohol use at age 14 are associated with cannabis use.	Drugs & Alcohol	CPC	Queensland Department of Families, Youth and Community Care (DFYCC)	1 (Deterministic)	No
Parrish et al. (2011)	Australia	To assess the utility of combining PRAMS data with child protective services (CPS) records to identify risk factors associated with Protective Services Reports (PSR) suggestive of child maltreatment	Child protection	CPC	Alaska's Child Protective Services Agency Register	1 (Probabilistic)	Yes
Raghavan et al. (2012)	USA	To estimate the amount of Medicaid expenditures incurred from the purchase of psychotropic drugs–the primary drivers of mental health expenditures among children in the child welfare system	Health insurance	CPC	1.Medicaid Analytic eXtract (MAX) Research Data Assistance Centre; 2.Child Welfare Agency	1 (Deterministic & Probabilistic)	Yes

Author (Year)	Name of Longitudinal Study	Study Period	Sampling Method	Study Population				Waves in the study: (Age: sample size)	Wave reported: (Age: Sample Size)
				Age at Baseline	Year of birth	Gender-Males (%)	Cohort size at Baseline		
Egulend et al. (2009)	Danish longitudinal survey of children (DALSC)	1995–2007	NR	Birth	1995	NR	1. Non-CPC (6,000); 2. OHC (1,072); 3. In-home care (1,457)	Wave 1, Baseline: (4 months, n = 6,622); Wave 2: (3.5 years, n = 6,622); Wave 3: (7 years, n = 7,198); Wave 4: (11 years, n = 8,225); Wave 5: (15 years, n = 7,132)	Wave 4: (11 years, Non-welfare children n = 5,242; OHC: n = 433; In-home care: n = 95)

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Table 2. (Continued)

Author (Year)	Country	Aims/ Objectives	Research Area	Child Protection Contact (CPC) vs. OHC	Administrative Data Source		Number of administrative datasets (Deterministic/ Probabilistic Linkage)		Linkage Quality (Yes/ No)
Hansson et al. (2018)	Swedish longitudinal Evaluation Through Follow-up (ETF) project	1971–2001	Stratified systematic sampling	9 years	1972; 1977; 1982; 1987; 1992	NR	(4,500–12,000)* 5 Cohorts	1948 Cohort: (12 years, n = 12,000); 1953 Cohort: (12 years, n = 9,000); 1967 Cohort: (12 years, n = 9,000); 1972 Cohort: (9 & 12 years, n = 9,000); 1977 Cohort: (9 & 12 years, n = 4,500); 1982 Cohort: (12 years, n = 9,000); 1987 Cohort: (15 years, n = 9,000); 1992 Cohort: (9 years, n = 9,000)	Wave 1, Baseline (7 years; n = N/A); Wave 2: (9 years; Pooled Data from 5 Cohorts (non-OHC: n = 40,107; OHC: n = 1,482)
Kisely et al. (2019)	The Mater-University Study of Pregnancy (MUSP)	1981–2004	NR	Birth	1981–1983	47%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth, n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth, n = 7,223); Wave 4 (14 years: n = NR); Wave 5 (21 years: n = 3,758 & subset n = 2,548)
Kisely et al. (2018)	The Mater-University Study of Pregnancy (MUSP)	1981–2004	NR	Birth	1981–1983	53%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth, n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 5 (21 years: n = 3,778)
Kisely et al. (2019)	The Mater-University Study of Pregnancy (MUSP)	1981–2004	NR	Birth	1981–1983	47%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 5 (21 years: n = 3,762)
Olsen et al. (2018)	Danish longitudinal survey of children (DALSC)	1995–2011	NR	Birth	1995	53%	907 OHC; 5,900 non-OHC	Wave 1, Baseline: (4 months, n = 6,622); Wave 2: (3.5 years: n = 6,622); Wave 3: (7 years: n = 7,198); Wave 4: (11 years: n = 8,225); Wave 5: (15 years: n = 7,132); Wave 6: (18 years: n = 5,139)	Wave 1, Baseline: (Birth, OHC: n = 907, non-OHC: n = 5,900); Wave 5: (15 years: OHC: n = 169, non-OHC: n = 4,568); Wave 6: (18 years: OHC: n = 817, non-OHC: n = 4,322)

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Table 2. (Continued)

Author (Year)	Country	Aims/ Objectives	Research Area	Child Protection Contact (CPC) vs. OHC	Administrative Data Source		Number of administrative datasets (Deterministic/ Probabilistic Linkage)		Linkage Quality (Yes/ No)
Parrish et al. (2016)	Alaska Pregnancy Risk Assessment Monitoring System (PRAMS)	2009–2014	Stratified systematic sampling	Birth	2009–2010	NR	2,389	1990–2016 Cohorts: (Annual sample sizes per state range from about 1000 to 3000 women)	Wave 1: (Birth-2 years: n = 2,389)
Parrish et al. (2017)	Alaska Pregnancy Risk Assessment Monitoring System (PRAMS)	2009–2014	Stratified systematic sampling	Birth	2009–2011	NR	1,235	1990–2016 Cohorts: (Annual sample sizes per state range from about 1000 to 3000 women)	Wave 1: (Birth: n = 1,235)
Raghavan et al. (2017)	National Survey of Child and Adolescent Well-Being (NSCAW)	1999–2003	NR	NR	NR	NR	Child Protection Contact (CPC) (5,501); Long term foster care placement (LTFC) (727)	Wave 1: (Birth: n = 6,228); Wave 2: (9 years: n = 5,873); Wave 3: (14 years: n = NR)	Pooled (Wave 1-wave 3) sample: (CPS: n = 2,309, LTFC: n = 423)
Sidebotham et al. (2000)	The Avon Longitudinal Study of Parents and Children (ALSPAC)	1991–1998	NR	Pre-birth	1991–1992	NR	14,451	Wave 1: (Pre-birth: n = 14,893); Wave 2: (1 month: n = 14,256); Wave 3: (6–8 months: n = 11,194, Partner = 6,861); Wave 4: (18 months: n = 10,750); Wave 5: (21 months: n = 10,323); Wave 6: (30 months: n = 10,289); Wave 7: (33 months: n = 9,635)	Wave 3: (8 months, n = 11,194, Partner: n = 6,861); Wave 4: (18 months, n = 10,750); Wave 5: (21 months, n = 10,323); Wave 6: (30 months, n = 10,289); Wave 7: (33 months, n = 9,635)
Sidebotham et al. (2003)	The Avon Longitudinal Study of Parents and Children (ALSPAC)	1991–1998	NR	1 month	1991–1992	(56% registered & 52% non-registered)	14,256	Wave 1: (Pre-birth: n = 14,893); Wave 2: (1 month: n = 14,256); Wave 3: (6–8 months: n = 11,194, Partner = 6,861); Wave 4: (18 months: n = 10,750); Wave 5: (21 months: n = 10,323); Wave 6: (30 months: n = 10,289); Wave 7: (33 months: n = 9,635)	Wave 2: (1 month, n = 14,256); Wave 6: (30 months, n = 115 registered vs n = 14,105 non-registered children)
Sidebotham et al. (2006)	The Avon Longitudinal Study of Parents and Children (ALSPAC)	1991–1998	NR	Pre-birth	1991–1992	NR	14,256	Wave 1: (Pre-birth: n = 14,893); Wave 2: (1 month: n = 14,256); Wave 3: (6–8 months: n = 11,194, Partner = 6,861); Wave 4: (18 months: n = 10,750); Wave 5: (21 months: n = 10,323); Wave 6: (30 months: n = 10,289); Wave 7: (33 months: n = 9,635)	Wave 2: (One month: n = 14,256); Wave 7: (36 months: n = NR)

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Table 2. (Continued)

Author (Year)	Country	Aims/ Objectives	Research Area	Child Protection Contact (CPC) vs. OHC	Administrative Data Source		Number of administrative datasets (Deterministic/ Probabilistic Linkage)		Linkage Quality (Yes/ No)
Sidebotham et al. (2002)	The Avon Longitudinal Study of Parents and Children (ALSPAC)	1991–1998	NR	Pre-birth	1991–1992	52%	14,256	Wave 1: (Pre-birth: n = 14,893); Wave 2: (1 month: n = 14,256); Wave 3: (6–8 months: n = 11,194, Partner = 6,861); Wave 4: (18 months: n = 10,750); Wave 5: (21 months: n = 10,323); Wave 6: (30 months: n = 10,289); Wave 7: (33 months: n = 9,635)	Wave 2: (One month: n = 14,256); Wave 3: (8 months: n = 11,194); Wave 5: (21 months: n = 10,323); Wave 7: (33 months: n = 9,635)
Teyhan et al. (2019)	The Avon Longitudinal Study of Parents and Children (ALSPAC)	1991–2009	NR	Pre-birth	1991–1992	(50% (No CLA/CIN); 48% CIN; 51% CLA)	14,868	Wave 1: (Pre-birth: n = 14,893); Wave 2: (1 month: n = 14,256); Wave 3: (6–8 months: n = 11,194, Partner = 6,861); Wave 4: (18 months: n = 10,750); Wave 5: (21 months: n = 10,323); Wave 6: (30 months: n = 10,289); Wave 7: (33 months: n = 9,635)	Wave 3: (1 year: n = 13,988); Wave 8: (7–18 years, Booster: n = 718); Wave 9: (>18 years, Booster: n = 183)
Austin et al. (2019)	Alaska Longitudinal Child Abuse and Neglect Linkage (ALCANLink) project & PRAMS	2009–2014	Stratified systematic sampling	Birth	2009–2011	(53% AN & 49% NN)	AN (1,257); NN (2,102)	1990–2016 Cohorts: (Birth, n = 1,000–3,000)	Wave 1: (Birth -5/6 years)
Austin et al. (2018)	Alaska Longitudinal Child Abuse and Neglect Linkage (ALCANLink) project & PRAMS	2009–2015	Stratified systematic sampling	Birth	2009–2011	51%	3,549	1990–2016 Cohorts: (Birth, n = 1,000–3,000)	Wave 1 (Birth -5/6 years)
Hansson et al. (2020)	Swedish longitudinal Evaluation Through Follow-up (ETF) project	NR	Stratified systematic sampling	9 years	1972; 1977; 1982; 1987; 1992	NR	(4,500–12,000)* 5 Cohorts	1948 Cohort: (12 years, n = 12,000); 1953 Cohort: (12 years, n = 9,000); 1967 Cohort: (12 years, n = 9,000); 1972 Cohort: (9 & 12 years, n = 9,000); 1977 Cohort: (9 & 12 years, n = 4,500); 1982 Cohort: (12 years, n = 9,000); 1987 Cohort: (15 years, n = 9,000); 1992 Cohort: (9 years, n = 9,000)	Wave 2: (9 years, n = NR); Wave 3: (12 years, n = NR)
Abajobir et al. (2017)	The Mater-University Study of Pregnancy (MUSP)	1981–2004	NR	Birth	1981–1983	47%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth, n = 7,223); Wave 3: 5 years; Wave 4 (14 years: n = NR); Wave 5 (21 years: n = 3,752)

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Table 2. (Continued)

Author (Year)	Country	Aims/ Objectives	Research Area	Child Protection Contact (CPC) vs. OHC	Administrative Data Source		Number of administrative datasets (Deterministic/ Probabilistic Linkage)		Linkage Quality (Yes/ No)
Abajobir et al. (2017)	The Mater-University Study of Pregnancy (MUSP)	1981–2004	NR	Birth	1981–1983	50%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth, n = 7,223); Wave 3: (5 years: n = NR); Wave 4 (14 years: n = NR); Wave 5 (21 years: n = 3,730)
Abajobir et al. (2016)	The Mater-University Study of Pregnancy (MUSP)	1981–2004	NR	Birth	1981–1983	45%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 4 (14 years: n = NR); Wave 5 (21 years: n = 3,322)
Abajobir et al. (2016)	The Mater-University Study of Pregnancy (MUSP)	1981–2004	NR	Birth	1981–1983	48%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 4 (14 years: n = NR); Wave 5 (21 years: n = 2,526)
Abajobir et al. (2017)	The Mater-University Study of Pregnancy (MUSP)	1981–2004	NR	Birth	1981–1983	47%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth, n = 7,223); Wave 5: (21 years: n = 3,750)
Strathean et al. (2009)	The Mater-University Study of Pregnancy (MUSP)	1981–2000	NR	Birth	1981–1983	52%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth, n = 7,223); Wave 2: (6 months: n = 6,621); Wave 4: (15 years: n = 5,890)

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Table 2. (Continued)

Author (Year)	Country	Aims/ Objectives	Research Area	Child Protection Contact (CPC) vs. OHC	Administrative Data Source		Number of administrative datasets (Deterministic/ Probabilistic Linkage)		Linkage Quality (Yes/ No)
Mills et al. (2013)	The Mater-University Study of Pregnancy (MUSP)	1981–2000	NR	Birth	1981–1983	52%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth, n = 7,223); Wave 4: (14 years: n = 5,172)
Mills et al. (2016)	The Mater-University Study of Pregnancy (MUSP)	1981–2004	NR	Birth	1981–1983	52%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth, n = 7,223); Wave 5: (21 years: n = 3,739)
Mills et al. (2014)	The Mater-University Study of Pregnancy (MUSP)	1981–2000	NR	Birth	1981–1983	52%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 4: (14 years: n = 5,200)
Mills et al. (2019)	The Mater-University Study of Pregnancy (MUSP)	1981–2004	NR	Birth	1981–1983	NR	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 5: (21 years: n = 3,778)
Mills et al. (2017)	The Mater-University Study of Pregnancy (MUSP)	1981–2004	NR	Birth	1981–1983	47%	7,223 Mother & Child pairs	Wave 1, Baseline: (Mother and child dyads at birth: n = 7,223); Wave 2: (6 months: n = 6,720); Wave 3: (5 years: n = 5,308); Wave 4: (14 years: n = 5,216); Wave 5: (21 years: n = 3,805); Wave 6: (30 years: n = 2,904)	Wave 1, Baseline (Mother and child dyads at birth: n = 7,223); Wave 4: (14 years: n = NR); Wave 5: (21 years: n = 3,778)

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Table 2. (Continued)

Author (Year)	Country	Aims/ Objectives	Research Area	Child Protection Contact (CPC) vs. OHC	Administrative Data Source		Number of administrative datasets (Deterministic/ Probabilistic Linkage)		Linkage Quality (Yes/ No)	
Parrish et al. (2011)	Alaska Pregnancy Risk Assessment Monitoring System (PRAMS)	1997–2004	Stratified systematic sampling	Birth	1997–1999	48%	5, 421	1990–2016 Cohorts: (Annual sample sizes per state range from about 1000 to 3000 women)	Wave 1, Baseline (Birth: n = 5,421); Wave 2: (48 months: n = 4,217)	
Raghavan et al. (2012)	National Survey of Child and Adolescent Well-Being (NSCAW)	1999–2003	NR	2 years	NR	48%	NSCAW (2,831); Matched child observations (2,821)	Wave 1: (Birth: n = 6,228); Wave 2: (9 years: n = 5,873); Wave 3: (14 years: n = NR)	Pooled (Wave 1-wave 4): n = 5,652	
Author (Year)	**Timeframe between reported waves (months)**	**Outcome Measures**		**Missing data (Yes/ No)**	**Attrition rate**	**Described attrition (Yes/No)**	**Corrected attrition (Yes/ No)**	**Attrition analysis (Yes/No)**	**Selection bias (Yes/ No)**	**Sensitivity analysis Yes/No)**
		Standardized	**Non-standardized**							
Egulend et al. (2009)	36 months	1. Strengths and Difficulties screening (SDQ) for mental health 2. ICD-10 Psychiatric diagnosis	1. School performance and satisfaction; 2. Leisure activities	Yes	NR	Yes	Yes	No	No	No
Hansson et al. (2018)	Waves 1–2 = 24 months	Cognitive Test Scores	Academic achievement	Yes	NR	No	Yes	No	Yes	No
Kisely et al. (2019)	(Waves 1–4 = 168 months); Waves 4–5 = 84 months)	1. WHO (CIDI-DSM-IV) scale) for Nicotine use, dependence & withdrawal; 2. Depression (CES-D) scale	1. Prevalence of smoking; 2. Persistent smoking	Yes	48%	Yes	Yes	Yes	No	Yes
Kisely et al. (2018)	(Waves 1–5 = 252 months)	1. Centre for Epidemiological Studies-Depression scales (CES-D) 2. Achenbach Youth Self-Report (YASR) scale; 3. WHO (CIDI-DSM-IV) scale	None	Yes	48%	Yes	Yes	Yes	No	Yes
Kisely et al. (2019)	(Waves 1–5 = 252 months)	WHO (CIDI-DSM-IV) scale for alcohol use and dependence	Alcohol use in the last month	Yes	48%	Yes	Yes	Yes	No	No
Olsen et al. (2018)	(Waves 1–2 = 180 months); Waves 2–3 = 36 months)	None	1. Self-perceived academic ability (SAA) 2. Staying-on rates	Yes	NR	Yes	No	Yes	No	No
Parrish et al. (2016)	N/A	None	Maltreatment report to Child Protective Services	Yes	N/A	No	No	No	No	Yes
Parrish et al. (2017)	N/A	None	Child maltreatment	Yes	NR	Yes	Yes	Yes	Yes	No
Raghavan et al. (2017)	Wave 1- Wave 3 = 36 months	None	Ascertainment of foster care status	Yes	NR	No	No	No	Yes	No
Sidebotham et al. (2000)	(Waves 3–4 = 10 months); (Waves 4–5 = 3 months); (Waves 5–6 = 9 months); (Waves 6–7 = 3 months)	None	Child abuse investigations and registrations	No	NR	No	No	No	No	No
Sidebotham et al. (2003)	(Waves 2–6 = 29 months)	None	Child protection registration	Yes	NR	Yes	No	No	Yes	No
Sidebotham et al. (2006)	Wave 2–7: 35 months	None	1. Investigation for suspected maltreatment; 2. Registration on the child protection register	Yes	NR	Yes	No	No	Yes	No
Sidebotham et al. (2002)	(Waves 2–3 = 7 months); (Waves 3–5 = 13 months); (Waves 5–7 = 12 months)	None	Child abuse registration	Yes	NR	No	No	No	Yes	No

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Table 2. (Continued)

Author (Year)	Country	Aims/ Objectives	Research Area	Child Protection Contact (CPC) vs. OHC	Administrative Data Source		Number of administrative datasets (Deterministic/ Probabilistic Linkage)		Linkage Quality (Yes/ No)	
Teyhan et al. (2019)	(Waves 3–8 = 84 months); (Waves 8–9 = 132 months)	None	1. Educational attainment; 2. Persistent absence from school; 3. Special educational needs (SEN) status; 4. School Mobility	Yes	NR	No	No	No	No	Yes
Austin et al. (2019)	Wave 1 (5/6 years)	None	Child Protective Service Contact	Yes	NR	No	No	No	No	No
Austin et al. (2018)	Wave 1 (5/6 years)	None	Age at first CP contact	Yes	NR	No	No	No	No	Yes
Hansson et al. (2020)	Waves 2–3 = 36 months	None	Cognitive ability	Yes	NR	No	No	No	No	No
Abajobir et al. (2017)	(Waves 1–2 = 6 months); (Waves 2–3 = 54 months); (Waves 3–4 = 108 months); (Waves 4–5 = 84 months)	1. Achenbach's YASR Behaviour Checklist (Auditory & Visual Hallucinations); 2. Peter's Delusional Inventory (PDI); 3. WHO (CIDI-DSM-IV) scale for diagnoses of psychosis	None	Yes	48%	Yes	Yes	Yes	Yes	Yes
Abajobir et al. (2017)	(Waves 1–2 = 6 months); (Waves 2–3 = 54 months); (Waves 3–4 = 108 months); (Waves 4–5 = 84 months)	1. Achenbach's Young Adult Self-Report (YASR) Behaviour Checklist (4 items); 2. Centre for Epidemiological Studies Depression Scale (CES-D)	QoL Self Report (Happy/ Satisfaction scales)	Yes	48%	Yes	Yes	Yes	No	No
Abajobir et al. (2016)	(Waves 1–2 = 6 months); (Waves 2–3 = 54 months); (Waves 3–4 = 108 months); (Waves 4–5 = 84 months)	1. Composed abuse scale (CAS) 2. Child Behaviour Checklist (CBCL) 3. Life events scale; 4. Conflict tactics scale	None	Yes	54%	Yes	Yes	Yes	No	Yes
Abajobir et al. (2016)	(Waves 1–2 = 6 months); (Waves 2–3 = 54 months); (Waves 3–4 = 108 months); (Waves 4–5 = 84 months)	WHO (CIDI-DSM-IV) scale for Lifetime cannabis abuse and dependence	Early age of onset of cannabis abuse	Yes	65%	Yes	Yes	Yes	Yes	No
Abajobir et al. (2017)	(Waves 1–5 = 252 months)	Depression: Delusions-Symptoms-States Inventory scale (DSSI)	Ever injected illicit drugs	Yes	48%	Yes	Yes	Yes	Yes	Yes
Strathean et al. (2009)	(Waves 1–3 = 6 months); Waves 3–4 = 174 months)	Depression: Delusions-Symptoms-States Inventory scale (DSSI)	Child maltreatment	Yes	18%	Yes	Yes	Yes	Yes	Yes
Mills et al. (2013)	(Waves 1–4 = 168 months)	Achenbach Youth Self-Report (YSR) questionnaires	None	Yes	28%	Yes	No	Yes	No	Yes
Mills et al. (2016)	(Waves 1–5 = 252 months)	WHO (CIDI-DSM-IV) scale for psychological outcomes at age 21	None	Yes	48%	Yes	Yes	Yes	No	Yes
Mills et al. (2014)	(Waves 1–4 = 168 months)	None	1. Smoking status; 2. Alcohol use	Yes	28%	Yes	No	Yes	No	Yes
Mills et al. (2019)	(Waves 1–5 = 252 months)	Peabody Picture Vocabulary Test (PPVT)	1. Failure to complete high school; 2. Failure to be employed or education at 21 years	No	48%	Yes	No	No	No	No

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Table 2. (Continued)

Author (Year)	Country	Aims/ Objectives	Research Area	Child Protection Contact (CPC) vs. OHC	Administrative Data Source		Number of administrative datasets (Deterministic/ Probabilistic Linkage)		Linkage Quality (Yes/ No)	
Mills et al. (2017)	(Waves 1–5 = 252 months)	1. WHO (CIDI-DSM-IV) scale for Cannabis use/ dependence; 2. Achenbach Child Behaviour Checklist (CBCL); 3. Delusions–Symptoms–States Inventory (DSSI)	Self-report	Yes	48%	Yes	No	No	No	No
Parrish et al. (2011)	(Waves 1–2 = 48 months)	None	Protective service report	No	22%	No	No	No	No	No
Raghavan et al. (2012)	Wave 1- Wave 4 = 48 months	Internalizing or externalizing scales of the CBCL	1. Non-zero Medicaid expenditures in a calendar year; 2. Mean total annual Medicaid expenditure per child	No	NR	No	No	No	No	Yes

Notes

CIDI Composite International Diagnostic Interview

CPC Child Protection Contact

CPS Child Protective Services

CSA Child Sexual Abuse

DSM-IV Diagnostic and Statistical Manual of Mental Disorders, 4^{th} edition

DVSA Domestic violence and sexual assault

IPV Intimate Partner Violence

LTFC Long Term Foster Care

N/A Not Applicable

NR Not Reported

OHC Out-of-home care

SDQ Strength and Difficulties Questionnaire

WHO World Health Organisation

YASR Young Adult Self Report

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The cohort sizes ranged from 1,200 children to approximately 14, 000 children. Most studies (83%) reported only one administrative database that was integrated with the longitudinal data, while 17% had multiple datasets linked and these ranged from census data, psychiatric registers, educational databases, medical aid data, child birth and death reviews. Almost all (97%) of the studies reported a state-wide child protection dataset integrated with the longitudinal data. About 23% of studies from two longitudinal studies reported systematic random sampling method. These studies were the Alaska Pregnancy Risk Assessment Monitoring System (PRAMS) and the Evaluation through Follow-up (ETF) studies.

GUILD [7] recommend reporting on the following three aspects when reporting on studies using linked datasets: i) description of the population included in the data set i.e. how the data were generated, processed and quality controlled, ii) data linkage processes, and; iii) quality of data linkage including accounting for linkage error. Most studies only reported on one of the steps which is the data linkage method used. Fifty seven percent reported using a deterministic linkage method which mainly involved using a unique personal identification number to link datasets. This linkage method is well established in Scandinavian countries [24, 83], and is increasingly becoming common in other countries. Only two studies reported using probabilistic matching, which involves using a set of non-unique identifiers to link data [84]. Two studies [55, 85] reported using a combination of probabilistic and deterministic methods and nine studies did not report on any linkage methods.

Only four studies reported on the linkage quality. Parrish, Young [86] reported on the proportion of successful matches, manual review of suspected matches that met a certain probability score threshold, [55] while two studies from Raghavan, Brown [85] and reported on the number of records that were linked and unlinked from the source file including statistical differences in linked and unlinked data on key variables.

Biases reported

There are several biases which commonly occur in longitudinal studies [47]. However, for the purposes of this review we report on three of the most common occurring biases, attrition, missing data and selection bias.

Missing data. Incomplete data is common in longitudinal research, as reflected in this review where missing data were reported in 87% of the studies (Table 3). In the past, three traditional mechanisms of missing data were reported [87]. When missingness is unrelated to the data, this is termed missing completely at random (MCAR), while if the probability of missing data on a variable is unrelated to the value of that variable itself but may be related to the values of other variables in the dataset this is referred to as missing at random (MAR). A mechanism which should not be ignored in longitudinal analysis is termed missing not at random (MNAR) [87, 88]. This refers to missingness that is contingent on the unobserved data, as reported in studies where there was an over-representation of children exposed to child protection agencies with missing data resulting in over-estimation of outcomes in this group compared to the general population [89, 90] and also missing data due to attrition.

Studies in this review reported missing data on certain covariates (MCAR) such as child maltreatment, parental race, paternal income and education and breastfeeding status [47, 52, 81, 91–96]. Missing data were also reported on outcome variables such as those from the Strengths and Difficulties Questionnaire [24]. There are a range of simple to more sophisticated analytical methods of handling missing data that can be applied to reduce bias in reported outcomes. The simplest method reported was listwise deletion [4, 21, 59, 97, 98] and including missing data as a separate category for each covariate in regression analysis (Missing Indicator Method) [47, 81, 93–96]. Sophisticated methods included multiple imputation using Markov chain iterative regression methods (MCMC) [94], multiple imputation using chained equations (MICE) [45], and multiple imputation using the fully conditional specification (FCS) method [99] (S3 Table).

Missing data due to attrition. Attrition) is a type of missingness that can occur in longitudinal studies, which typically occurs due to loss to follow up, death, emigration or non-return of a survey and withdrawal from the study [100]. Attrition rates were reported for 53%

Table 3. Biases reported.

Type of Bias	N (Number of studies)	%
Missing data	26	87%
Attrition rate	-	18–65%
Described attrition	19	63%
Corrected attrition	12	40%
Analysis of attrition	14	47%
Selection bias	10	33%
Sensitivity Analysis	13	43%

https://doi.org/10.1371/journal.pone.0249088.t003 of the studies and the rates ranged from 18% to 65% (Table 3). Even though the attrition rate was not mentioned in almost half of the studies, attrition was described for 63% of all studies. The review identified attrition as occurring due to loss of follow-up or differential attrition occurring among families with reported cases of substantiated maltreatment, those from higher socio-economic disadvantaged backgrounds and among males and indigenous people (particularly among MUSP studies) [4, 21, 46, 82, 97, 98, 101, 102]. Other attrition reported was death or early infant loss [47, 55, 93, 96], non-response [47] and emigration [47, 55].

Forty seven percent (47%) of all studies mentioned that they conducted some attrition analysis, while 40% reported some methods of correcting attrition loss. While these methods were described in the studies, the analysis output was not shown for all studies. Attrition analysis was conducted to determine if there would be any significant differences in outcomes among participants lost to follow up and those remaining in the study. The main methods of correcting for attrition were inverse probability weighting [46, 58, 59, 81, 101, 103, 104] and propensity score analysis [21, 97, 98], while no specific method was described in some studies [24]. Inverse probability weighting was conducted to the analysis of subjects remaining in the cohort to adjust for loss to follow up to the included subjects to restore the representation of subjects. Propensity score analysis was conducted to determine the impact of differential attrition by inclusion of a weighted variable which takes account of baseline covariates.

Selection bias. Selection bias occurs when there is a systematic difference between those who participate in the study and those who do not (affecting generalisability) [105, 106]. Selection bias was reported for 33% of the studies (Table 3). Selection bias may result in over-estimation of outcomes among young people exposed to child protection compared with young people in the general population [89]. Restricting the study to certain population groups which may not be representative of the entire population of interest may lead to selection bias [55, 85]. In addition, selection bias also occurs if a population of interest possesses certain unique characteristics giving them a higher chance of recruitment to a study compared to the population without those characteristics [93, 95, 96]. Some authors reported conducting weighted analysis in order to account for potential selection bias [46, 103, 104].

Sensitivity analysis. Sensitivity analysis is conducted to determine if small changes in exposure or confounding variables alter the significance of reported outcomes in situations where there could be potential measurement errors [107]. Sensitivity analysis was reported for 43% of the studies, but only eight out of the thirteen studies reported the actual method of analysis conducted. Sensitivity analysis was conducted through modifying some covariates, such as child maltreatment, by expanding the definition to include or exclude notified or suspect cases of maltreatment and through measuring multiple forms versus a single form of abuse [21, 52, 58, 59, 81, 104].

Other authors also reported restricting the analysis to groups of people with certain characteristics [45] or adding [94] or removing [81] one or more covariates to the analysis in order to reduce bias. Addition of covariates at subsequent waves resulted in either strengthening, weakening or no change to the effect sizes in some studies [99]. The main sensitivity analysis methods presented in the eight studies were logistic regression [21, 45, 58, 59, 81, 98, 102] and multiple regression analysis [52] controlling for known confounders and effect modifiers (S3 Table).

Statistical methods

There were two groups of statistical methods identified in the study. These included data preparation methods and the main statistical analysis method reported.

Data preparation methods. Most authors conducted some preliminary data preparation, descriptive or bivariate analysis to address missing data and identify significant covariates to include as confounders in final in multivariate models. Multiple data preparation methods were described and ranged from descriptive statistics to bivariate and simple regression analysis (S3 Table). In addition, multiple imputation, data weighting and propensity analysis procedures were applied to correct for missing data. Some authors did not provide full details of the analytical methods used to correct for missing data. Common descriptive parameters were frequencies, percentages, means, incidence rates and population attributable risk. Chi-square tests (53%) were also commonly reported as a method to determine association of confounders and outcome variables. Other methods included two-sample *t*-tests (13%), correlation analysis (7%) and to a lesser extent, concordance analysis (3%), logistic regression (3%), and cumulative risk factor analysis (3%).

Main analytical method. The main method of analysis for each study was identified. These are shown in Table 4. The main analytical method reported by most studies was logistic regression (63%) followed by multiple regression methods (10%). Logistic regression methods were used for analysing risk factors and associated outcomes, attrition analysis and sensitivity analysis. Advanced analytical methods included generalised linear models (GLM) [108], multinomial logistic regression using Vermunt's three step Latent Class Analysis approach and Growth Mixture Modelling [92], and survival analysis using Kaplan-Meier, Cox (proportional hazards) regression and Nelson-Aalen Estimation methods [55, 99]. A few studies used a combination of methods, where in most cases logistic regression was included as one of the main methods [45, 47, 55, 82]. Only one study reported descriptive statistics as their main method of analysis [109].

The main outcomes evaluated in the studies were standardised and self-reported measures from the main research areas reported in Table 5. There were some notable similarities of reported confounding variables across all studies and most of them (93%) used individual and family characteristics as confounders. These included early childhood experiences, socio-demographic variables, pre-natal exposure and parental (mostly maternal) risk factors. Five studies reported on potential mediating variables, these included school mobility [47, 89], parenting age, education, psychiatric history and poverty [93], gender [46], *y*oung people's income, education, marital status, neighbourhood characteristics [21], smoking and alcohol use [97, 102], receipt of social welfare, education and marital status [104], race and receipt of public aid [86]. One study [94] found that parenting and social stress did not moderate the relationship between intimate partner violence and maltreatment. One study reported [98] the following as potential mediating variables: receipt of social welfare, the young person's educational achievement, and the young person's marital status. Only three studies [47, 90, 92] reported some a*ssumptions* of *statistical tests such as tests for normality and homogeneity in variances before conducting data analysis.*

Quality assessment

The Kmet, GUILD and RECORD checklists were used to rate the methodological quality of included studies. The results of the quality assessment are shown in Table 6. Based on the "QualSyst" Standard Quality assessment for evaluating primary research papers by Kmet, Cook [78], the final quality scores ranged from 55% (adequate quality) to 100% (Strong quality) with a median score of 91%, indicating high quality across all studies reviewed. The final quality scores for the GUILD and RECORD checklist ranged from 10% to 79% and only three studies had scores greater than 50%. The median score was 23%, indicating poor quality across all studies reviewed. The inter-rater reliability test was 81% (95%CI: 75%; 88%) for the Kmet scores and 77% (95%CI: 70%; 85%) for the GUILD and RECORD scores.

Table 4. Main statistical method.

Author	Domain & Analysis Procedure	Statistical parameters	Assumption test	Independent Variables	Mediation and Moderating Variables
Egulend et al, (2009)	Regression Analysis Logistic Regression	Odds ratios, 5% significance level	NR	Individual, family	NR
Hansson et al. (2018)	Regression Analysis Multiple Regression Analysis	Beta, standard errors, t-statistic, significance level	NR	Individual, family	Mediating: School change
Kisely et al. (2019)	Regression Analysis Logistic Regression	Odds ratios, 95% CIs, p-values	NR	Individual, family	Mediating: Alcohol use and depression
Kisely et al. (2018)	Regression Analysis Logistic Regression	Odds ratios, 95% CIs, p-values	NR	Individual, family, community	Mediating: Income, education, Marital status, Characteristics of neighbourhood
Kisely et al. (2019)	Regression Analysis Logistic Regression	Odds ratios, 95% CIs, p-values	NR	Individual, family, community	NR
Olsen et al. (2018)	Regression Analysis Multiple Regression Analysis & Linear Probability Model	Unstandardized beta, P-values, adjusted R-squared, standard errors, Significance testing p values (95%, 99%, and 90%)	NR	Individual, family	Mediating: School change
Parrish et al. (2016)	Regression Analysis Logistic Regression	Frequencies, percentages, odds rations, 95% CI	NR	Individual, family	Moderating: Parenting and social stress
Parrish et al. (2017)	1. Regression Analysis Logistic Regression 2. Survival Analysis Nelson-Aalen Estimation	1. Odds ratios, confidence intervals, p-values; 2. Weighted Aalen hazard-based estimation, incidence proportion, frequency counts, weighted proportions, Hazard ratios, 95% CI, p-values	NR	Individual, family	NR
Raghavan et al. (2017)	Regression Analysis Logistic Regression	Odds ratios, standard errors, p-vales	NR	Individual	NR
Sidebotham et al. (2000)	Descriptive Analysis	Frequencies, Percentages, Incidence rate/ 10,000 children	N/A	Individual, family	N/A
Sidebotham et al. (2003)	Regression Analysis Logistic Regression	Odds ratios, standard errors, p-vales	NR	Individual, family	NR
Sidebotham et al. (2006)	Regression Analysis Logistic Regression	Odds ratios, 95% CIs, p-values	NR	Individual, family, community	Mediating: Age at parenting, education, psychiatric history, poverty
Sidebotham et al. (2002)	Regression Analysis Logistic Regression	Odds ratios, 95% CIs	NR	Individual, family	NR
Teyhan et al. (2019)	Regression Analysis Multilevel regression analysis (Linear and logistic regression models)	Odds ratios, 95% CIs, p-values	NR	Individual, family, community	NR
Austin et al. (2019)	Advanced Regression Analysis 1. Multinomial logistic regression 2. Growth Mixture Modelling	1. Trajectory class probabilities 2. Lo-Mendell-Rubin Adjusted Likelihood Ratio test, P-value	Yes	Individual, family	NR
Austin et al. (2019)	Survival Analysis 1. Kaplan-Meier method 2. Cox (proportional hazards) regression.	1. Cumulative incidence proportion 2. 95% CI, Hazard ratios, p-values	NR	Individual, family	NR
Hansson et al. (2020)	Regression Analysis Multiple Regression Analysis	Standard errors, t-statistic, p-values, 95% CI	Yes	Individual, family	NR
Abajobir et al. (2017)	Regression Analysis Logistic Regression	Prevalence, Odds ratios, p-values, 95% CI	NR	Individual, family	NR

(*Continued*)

Table 4. (Continued)

Author	Domain & Analysis Procedure	Statistical parameters	Assumption test	Independent Variables	Mediation and Moderating Variables
Abajobir et al. (2017)	Regression Analysis Logistic Regression	Prevalence, Odds ratios, p-values, 95% CI.	NR	Individual, family	NR
Abajobir et al. (2017)	Regression Analysis Logistic Regression	Prevalence, Odds ratios, p-values, 95% CI.	NR	Individual, family, community	NR
Abajobir et al. (2017)	Regression Analysis Logistic Regression	Prevalence, Odds ratios, p-values, 95% CI.	NR	Individual, family	Mediating: Gender
Abajobir et al. (2017)	Regression Analysis Logistic Regression	Prevalence, Odds ratios, p-values, 95% CI.	NR	Individual, family	Mediating: Gender
Strathean et al. (2009)	Regression Analysis Logistic Regression	Prevalence, Odds ratios, p-values, 95% CI.	NR	Individual, family	NR
Mills et al. (2013)	Regression Analysis Multiple Regression Analysis	Mean differences in internalizing and externalizing scores, regression coefficients, 95% CI	NR	Individual, family	NR
Mills et al. (2016)	Regression Analysis Logistic Regression	Odds ratios, 95% CI, p-values	NR	Individual, family	NR
Mills et al. (2014)	Regression Analysis Logistic Regression	Odds ratios, 95% CI, p-values	NR	Individual, family	Mediating: Smoking & alcohol use at 14 year follow-up
Mills et al. (2019)	Regression Analysis 1. Multiple Regression Analysis 2. Logistic Regression	1. Frequencies, percentages, mean scores, standard deviation, Population Attributable Risk (PAR%), Unstandardised regression coefficients, 95% CI, p-values; 2. Odds ratio, 95% CI, p-values	NR	Individual, family	NR
Mills et al. (2017)	Regression Analysis Logistic Regression	Odds ratio, 95% CI, p-values	NR	Individual, family	NR
Parrish et al. (2011)	Regression Analysis Logistic Regression	Beta coefficient, standard errors, Wald F statistic, p-values, 95% CI, Odds ratio	NR	Individual, family	Mediating Public aid, race
Raghavan et al. (2012)	Regression Analysis 1. Logistic Regression 2. Generalized linear model (GLM)	1. Odds ratios, 95% CI, p-value; 2. GLM coefficients, 95% CI, p-value	NR	Individual	NR

Notes
CPS Child Protective Services
CI Confidence Interval
LTFC Long Term Foster care
DVSA Domestic violence and sexual assault
N/A Not Applicable
NR Not Reported
PPVT Peabody Picture Vocabulary Test

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Discussion

This systematic review sought to describe the study designs and statistical methods used when administrative data is integrated with longitudinal data in child protection settings and make recommendations about approaches to improve the quality of reporting of research findings, thereby minimising risk of bias and other limitations. There has been a steady growth in the number of studies which use administrative data integrated with longitudinal data in child protection settings since 2000. A total of 30 studies were identified that integrated these data to determine outcomes in the areas of child maltreatment, mental health, drug and alcohol abuse

Table 5. Study description.

Author	Sample Size	Confounders	Outcome
Egulend et al, (2009)	OHC (1,072); In-home care (1,457); Non- Child Protection Contacts (71,321)	All Children, Children in out-of-home care, In-home care children, non-welfare children, number of siblings, Danish born children, Mother's age, teenage mothers, single mothers, mother's education, mother's employment status, mother/ father died, mother/ father with a psychiatric illness, mother/ father substance abuse problem, mother/ father previously convicted, mother/ father in care as children	Clinical diagnosis of psychiatric illnesses
Hansson et al. (2018)	Non-OHC (40,107); OHC (1,482)	Gender, migration, parents' education, OHC vs Non-OHC, relocations	1. Cognitive Ability Test Level; 2. Special Needs Education
Kisely et al. (2019)	Smoking status (3,758); Nicotine use dependence (2,548); Propensity Analysis (7,223)	Gender of the child, parental race, maternal age, mother's relationship status, family income at study entry (first prenatal visit), maternal smoking, and maternal education at study entry, childhood maltreatment	1. Cigarette smoking; 2. Any cigarette use; 3. Long-term cigarette use; 4: CIDI-Auto (12-month Nicotine use disorder)
Kisely et al. (2018)	1. YASR(3,725); 2. CIDI-Auto (2,508); 3. CES-D (3,778)	Gender of the child; parental ethnicity; maternal age; mother's relationship status; family income at the time of study entry (first prenatal visit) and maternal education status at study entry, overall child maltreatment, emotional, physical, sexual abuse, neglect.	1. YASR (Internalising & Externalising); 2. CIDI, DSM-IV (Depression, Anxiety, PTSD) 3. CES-D
Kisely et al. (2019)	1. Alcohol use in the last month (3,762); 2. Alcohol use disorder (2,531)	First prenatal visit (Race, maternal age, mother's education, marital status and family income) and at 21-year follow up (employment, marital status, educational level and residence in a problem area), childhood maltreatment	1. Alcohol use in the last month; 2. CIDI DSM-IV Alcohol use disorder
Olsen et al. (2018)	1. OHC (107); 2. Non-OHC (3,805)	Gender, birth weight, ethnicity, citizenship, psychiatric diagnosis, bullying, family type, mother's educational level, father's educational level, mother's disposable income, father's disposable income.	1. Self perceived academic ability at age 15 years; 2. School change in lower secondary school
Parrish et al. (2016)	Total (2,389)	Self-reported IPV, race, maternal education, maternal smoking, maternal alcohol use, poverty, parents marital status, prenatal care, maternal age	Maltreatment report to Child Protective Services
Parrish et al. (2017)	Total (1,235)	Birth paid by Tricare (military families), sex of the child, maternal education at child's birth, marital status at birth, maternal alcohol use during pregnancy, maternal smoking during pregnancy, maternal race, birth defect, mother or child on Medicaid at birth, fathers name listed on birth certificate, maternal age at birth, multi-agency maltreatment report, mother reported being divorced/separated 12 months before pregnancy, mother reported moving 12 months before pregnancy, mother reported losing a job 12 months before pregnancy, mother reported partner/ husband losing a job 12 months before pregnancy	Censorship; Multi-source report of maltreatment
Raghavan et al. (2017)	LTFC (1,569); CPS (8,917)	Age, gender, race/ethnicity, Insurance type, primary care case management, urban/rural location, health condition, health care access	Ascertainment of foster care status
Sidebotham et al. (2000)	1.Registered children (139); 2. Children investigated but not registered (190); 3. Children neither investigated nor registered (13, 927)	1. Time period (8, 18, 21, 30 33 months); 2. Registered children; children investigated but not registered; children neither investigated nor registered	1. Rates of child protection registrations; 2. Proportion of child abuse investigations and registrations; 3. Parental reporting of child abuse
Sidebotham et al. (2003)	1. Registered children (115) 2. Non-registered children (14,105)	Low birthweight, unintended pregnancy, hospital admissions, developmental concerns, reported positive attributes, feeding difficulties, temper tantrums, parental concerns about the child's development, and not seeing the child in a positive light.	Child protection registration prior to 6 years of age
Sidebotham et al. (2006)	Registered children (115); Investigated children (178); Neither registered nor investigated (13, 963)	Parental ontogenic background (Young parent, low educational achievement, psychiatric history, history of childhood abuse (any); Exosystem (socio-demographic) variables (Any indicator of poverty, Mother employed, Poor social network. Microsystem (family) variables (high parity, single mother, reported domestic violence, reordered family); Child variables (Unintended pregnancy, Low birthweight, Few positive attributes reported	1. Children registered for maltreatment; 2. Children investigated for maltreatment
Sidebotham et al. (2002)	Registered children (85); Non-registered children (13, 089)	Maternal employment, mobility (house moves), social network score.	1. Child Abuse registrations 2. Child maltreatment

(*Continued*)

Table 5. (Continued)

Author	Sample Size	Confounders	Outcome
Teyhan et al. (2019)	No CLA or CIN (9,432); CIN(64); CLA (49)	Social care status, Age, sex, socio-economic position, maternal age, highest educational qualification; financial difficulties; housing tenure; partner status; smoking; alcohol intake; social support; and depressive symptoms	1. Educational attainment; 2. Persistent absence from school; 3. Special educational needs (SEN) status; 4. School Mobility
Austin et al. (2019)	AN(1,253); NN (2,094)	Maternal age and education at childbirth, preconception and prenatal substance use, and experiences of emotional, traumatic, partner, and financial stress in the 12 months prior to childbirth	Longitudinal trajectory classes of CPS contact
Austin et al. (2019)	Total (3,549)	Maternal race, maternal age, maternal education, maternal marital status, residence at childbirth, number of living children, maternal history of pregnancy terminations, pregnancy intendedness, timing of prenatal care, number of stressful live events, maternal experience of intimate partner violence (IPV), maternal alcohol use, maternal smoking during pregnancy, maternal marijuana use, socioeconomic status, infant sex, infant birth defects	Age at first CP contact
Hansson et al. (2020)	OHC (1,099); Non OHC(30, 936)	Gender, migration, parents' education, school relocations, Cognsum	Academic achievement
Abajobir et al. (2017)	Total (3,752)	Youth gender, ADHD at 5 year, alcohol use, smoking, aggressive behaviour (at 14 years), receiving benefits, educational levels, marital status, residential problem area at 21 years, familial income over the first 5 years, chronic stress over first 6 months, and maternal reports of violence in homes at 14 years, any abuse, sexual abuse, physical abuse, emotional abuse, neglect	1. Auditory hallucinations 2. Visual hallucinations 3. Peter's Delusional Inventory (PDI) 4. DSM-IV Psychosis
Abajobir et al. (2017)	Total (3,730)	Child maltreatment, maternal age at first clinic visit, family income at first clinic visit, gender at birth, educational status, receipt of social security benefits and depressive symptoms at 21-year follow-up	Quality of Life Index Score
Abajobir et al. (2017)	Total (3,322)	Substantiated child maltreatment, sex at birth, receipt of social security benefits, educational level, marital status and residential problem area at 21-year, aggressive child behaviour, maternal poverty level, maternal marital stability, maternal stress, maternal negative life events, family violence	Intimate partner violence victimization
Abajobir et al. (2017)	Total (2,526)	Any maltreatment, sexual abuse, physical abuse, neglect, emotional abuse, age at substantiation, frequency of substantiation, maternal age at pregnancy, maternal prenatal and postnatal cigarette smoking, family poverty, educational level, marital status, gender at birth	Cannabis abuse, dependence, early age of onset of cannabis abuse and dependence
Abajobir et al. (2017)	Total (3,750)	Any maltreatment, sexual abuse, physical abuse, neglect, emotional abuse, receiving social security benefits, educational level, marital status at 21 years and paternal or maternal race at pregnancy, maternal alcohol use at 3–6 months and chronic depressive symptoms	Injecting drug use
Strathean et al. (2009)	Total (5,890)	Maternal prenatal demographic factors (age, marital status, education, race, employment); prenatal behaviours/attitudes (cigarette consumption and binge drinking during pregnancy, anxiety and pregnancy ambivalence); infant factors (birth weight and gender), and 6 month postpartum maternal behaviours and attitudes (mother-infant separation, employment, maternal stimulation/teaching of baby, maternal attitude of caregiving and postpartum depression). Models: 1. Breastfeeding duration, 2. Single vs. multiple episodes of maltreatment, 3. Exclude previously enrolled children, 4. Only children in Queensland at 14 years of age	Substantiated maternal child maltreatment
Mills et al. (2013)	Total (5,098)	Notified and substantiated maltreatment, type of maltreatment (exclusive; hierarchical scheme), gender, race, During pregnancy (maternal age, marital status, maternal education) family income prior to birth	Internalizing and externalizing scales of the Youth Self Report (YSR)
Mills et al. (2016)	Major depressive disorder (2, 304); Anxiety disorder (2,298); PTSD(2,292)	Self-reported CSA, Agency-notified CSA, Agency-substantiated CSA, gender, parental race, maternal age, maternal relationship status, family income, and maternal education	Major depressive disorder; Anxiety disorder; PTSD

(*Continued*)

Table 5. (Continued)

Author	Sample Size	Confounders	Outcome
Mills et al. (2014)	Any alcohol use (5,153); Any smoking (5,154)	Maltreatment notification, type of maltreatment, Family income, maternal alcohol use and maternal smoking (14y follow-up); maternal education and marital status (prenatal); and race, age, and gender.	Alcohol use; smoking
Mills et al. (2019)	1. Peabody Vocabulary Test (2,150); 2. Failure to complete high school (3,750); 3. Failure to be employed or in education (3,739)	Notified maltreatment, substantiated maltreatment, age, sex, race, family income, maternal education, birthweight *z* score, neonatal intensive care admission, maternal tobacco and alcohol use in pregnancy, breast feeding	1. Peabody picture vocabulary test 2. Failure to complete high school 3. Failure to be employed or education at 21 years
Mills et al. (2017)	Total (3,778)	Age, gender, race, family income, and maternal age, education, marital status, alcohol use, smoking, anxiety and depression, maltreatment type, additional adjustment for youth smoking and alcohol use at 14-year follow-up, youth internalizing and externalizing scale	Cannabis use/ dependence
Parrish et al. (2011)	Total Population (28,592); PSR (3,271)	Maternal age and education, DVSA (maternal physical abuse and forced sexual activities), Maternal tobacco use, Maternal marital status, Substance abuse, living children, medically vulnerable, public aid, risk group category	PSR to child protective services
Raghavan et al. (2012)	Total (5,652)	Child age, gender, race/ ethnicity, rural/urban location, insurance type, placement status, health status, CBCL score, maltreatment type	1. Annual probability of having any medication expenditures 2. Expenditures per child per year

Notes

AN Alaska Native

CI Confidence Interval

CIDI Composite International Diagnostic Interview

CES-D Centre for Epidemiological Studies–Depression Scale

CLA Children Looked After

CIN Children In Need

CP Child Protection

CPS Child Protective Services

DSM-IV Diagnostic and Statistical Manual of Mental Disorders, 4th edition

DVSA Domestic violence and sexual assault

IPV Intimate Partner Violence

LTFC Long Term Foster Care

N/A Not Applicable

NR Not Reported

NN Non-Native

OHC Out-of-home care

PPVT Peabody Picture Vocabulary Test

PSR Protective Services Report

PTSD Post-Traumatic Stress Disorder

SDQ Strength and Difficulties Questionnaire

YASR Young Adult Self Report

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and education. Since the focus of the review was on studies in child protection settings, the main administrative data reported was child protection data.

While most studies had multiple data collection points, the median number of waves reported for the longitudinal studies was two. The findings from this review can be grouped under three themes: i) quality of reporting on data linkage procedures; ii) biases reported; and iii) statistical methods used. Though some systematic reviews have been conducted on administrative data alone or longitudinal data alone in child protection or other settings [26, 110,

Table 6. Quality appraisal of included studies.

Study	Qualsyst (KMET)		GUILD and RECORD	
	Score (%)	Methodology Quality	Score (%)	Methodology Quality
Egulend et al. (2009)	50%	Adequate	24%	Poor
Hansson et al. (2018)	68%	Good	10%	Poor
Kisely et al. (2019)	91%	Strong	26%	Poor
Kisely et al. (2018)	91%	Strong	22%	Poor
Kisely et al. (2019)	91%	Strong	22%	Poor
Olsen et al. (2018)	86%	Strong	21%	Poor
Parrish et al. (2016)	82%	Strong	33%	Poor
Parrish et al. (2017)	86%	Strong	79%	Good
Raghavan et al. (2017)	86%	Strong	33%	Poor
Sidebotham et al. (2000)	60%	Good	10%	Poor
Sidebotham et al. (2003)	80%	Strong	16%	Poor
Sidebotham et al. (2006)	91%	Strong	29%	Poor
Sidebotham et al. (2002)	91%	Strong	16%	Poor
Teyhan et al. (2019)	91%	Strong	28%	Poor
Austin et al. (2019)	86%	Strong	72%	Good
Austin et al. (2018)	95%	Strong	71%	Good
Hansson et al. (2020)	73%	Good	9%	Poor
Abajobir et al. (2017)	95%	Strong	22%	Poor
Abajobir et al. (2017)	95%	Strong	26%	Poor
Abajobir et al. (2016)	95%	Strong	26%	Poor
Abajobir et al. (2016)	95%	Strong	26%	Poor
Abajobir et al. (2017)	91%	Strong	29%	Poor
Strathean et al. (2009)	95%	Strong	47%	Poor
Mills et al. (2013)	95%	Strong	22%	Poor
Mills et al. (2016)	95%	Strong	21%	Poor
Mills et al. (2014)	95%	Strong	21%	Poor
Mills et al. (2019)	91%	Strong	16%	Poor
Mills et al. (2017)	100%	Strong	16%	Poor
Parrish et al. (2011)	95%	Strong	19%	Poor
Raghavan et al. (2012)	100%	Strong	45%	Poor
Median	**91%**	Strong	**23%**	Poor

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111], this is the first systematic review of studies utilising administrative data integrated with longitudinal data in child protection settings.

Quality of reporting on data linkage procedures

Overall, the quality of all studies was strong (Qualsyst median score = 93%), but most of the studies rated poorly on the reporting of data linkage methods (GUILD and RECORD median score = 23%). Only three of the 30 studies [55, 92, 99] described the data linkage procedures in sufficient detail. This is of concern, as a small amount of data linkage errors may lead to significant bias and inconsistencies in estimating parameters of a statistical model. As described in the GUILD [7], researchers utilising linked data should take account of biases inherent in the data linkage process and account for such biases in the analysis. The GUILD guidelines recommend following three key steps when reporting analyses using linked data: i) describing the population included in the data set (i.e., how the data were generated, processed and quality controlled); ii) describing the data linkage processes; and iii) describing the quality of data linkage, including accounting for linkage error. Similar reporting items are recommended in the RECORD statement [79].

Harron, Dibben [38] supports the notion of accounting for linkage errors as recommended by GUILD and RECORD, but states that it may be difficult for researchers to determine the quality of linked data since researchers may not have access to identifiable data. The authors therefore recommend conducting the following three methods to evaluate data linkage quality and identify potential sources of bias: i) post-linkage validation, ii) sensitivity analyses, and iii) comparison of characteristics of linked and unlinked records.

Most authors did not report sufficiently on the population included in the data set and how the data were generated and quality controlled. Most authors provided descriptions of the population in the source data and how the data were collected, but no information was reported on how the data were updated, processed and quality controls. Only a few authors explained how data were cleaned, including standardisation of missing data and treatment of special characters [55, 92, 99], and how manual linkages were conducted by reporting on data mismatches and duplicate cases [86].

The second GUILD step, which focusses on data linkage processes, was described in sufficient detail by the same authors [55, 92, 99] by reporting on how linkage rates were calculated and how probability match scores were used for weighting. Benchimol, Smeeth [79] state that the methods of linkage and methods of linkage quality evaluation should be reported by authors, though this information may not be provided by the data linkage unit. Furthermore, information on disclosure controls to reduce the re-identification of individuals from linked data was not reported in any of the studies. However, the majority (80%) of studies reported the method of data linkage (deterministic or probabilistic, or both), including reporting the unique ID that was used as the variable for deterministic linkage.

The last GUILD step involves analysis of linked data which takes linkage error into account. While the quality of data linkage can be determined prior and during data linkage, this step allows researchers to report on linkage error post data linkage. The analysts who conduct data linkage should provide researchers with reports of the data linkage process, including estimates of false and missed matches, so that there is transparency. If there are linkage errors, analysts can determine methods or procedures to correct for this before conducting any analysis, while acknowledging this may not always be possible [7]. Analysts could identify linkage errors by analysing differences or similarities between linked and unlinked data [112], though this method may introduce additional bias caused by missing records [10]. A simulation exercise developed by Parrish, Shanahan [55] enables post-estimation of linkage errors. The inclusion of linkage errors into research analyses is an evolving and relatively new area of methodological research. Some methods that have been developed by researchers model simple linkage errors derived from one-to-one matches rather than the more complex many-to-many or many-to-spine match scenarios that exist in modern day production linkage systems. [112, 113]

Biases reported

In longitudinal studies there is commonly missing data for various reasons, such as non-availability of data from specific variables or missing data due to participant attrition. Missing data may result in loss of statistical power, bias in estimation of parameters, and diminish the representativeness of samples in a study [114]. Almost all studies described missing data and a few conducted some analysis to correct for missing data. Biases may occur due to certain population groups being over-represented, for instance Aboriginal children are over-represented in child-protection or out-of-home care systems compared with other young people in Australia. Systematic bias may occur as a result of Aboriginal young people being more often reported and therefore at increased contact with child protection services. Some studies reported over-representation of children in OHC among those with missing school grades and this was corrected by replacing the missing grades with estimated grades (MAR) [89, 90]. If the missing data were not accounted for in the analysis this could have resulted in over or under-estimation of outcomes among the OHC group.

This review shows some variability in the reporting and analysis of missing data. A review conducted by Karahalios, Baglietto [43] highlighted that there is generally inconsistent reporting of missing data in cohort studies and methods employed to handle missing data in some studies may be inappropriate. While weighting was described as one technique to account for missing data, this method has limitations. For example, standard errors of estimates, such as means and proportions, are larger than they would be if the data were not weighted [115].

Listwise deletion as a method of handling missing data also has limitations as it requires data to be MCAR [116]. While some studies in this review applied this method it may not be appropriate, particularly if the missing values occur among populations with certain characteristics, such as those lost to follow up who were mostly disadvantaged or are hard to reach. In addition, listwise deletion results in a reduced sample size (and ultimately loss of statistical power), which is a concern particularly among young people with child protection contact where smaller sample sizes are reported compared to comparison groups in the general population.

Statistical methods

Most studies reported using logistic regression as a method of analysing the factors associated with reported outcomes. While this method was appropriate to determine the impact of reported outcomes with a binary scale, controlling for multiple confounders, more sophisticated methods of analysis were expected, particularly where mediating or moderating effects of some variables were required. One of the limitations in the reporting of logistic regression analysis was lack of descriptions on why this method was chosen in relation to fulfilling the assumption that there is a linear relationship between the logit of the outcome and each predictor variables. Likewise, with multiple regression methods the assumption of linearity has to be satisfied; this was not often described where linear regression methods were used.

Survival analysis methods were well described and utilised where there were more than two pre-specified time points and these included the Nelson-Aalen Estimation method [55], the Kaplan-Meier method, and the Cox regression method [99]. Three studies described more advanced methods of analysis which are Multinomial logistic regression model using Vermunt's three step Latent Class Analysis Approach, Growth mixture modelling and Generalised Linear Model [92, 108]. Sensitivity analysis was conducted particularly when definitions of child maltreatment were altered to either include substantiated maltreatment or reported allegations. Conducting sensitivity analysis prior to data modelling may not be necessary since sensitivity analysis is usually done after a statistical model has been estimated and the results interpreted [117].

The statistical methods applied to most of the included studies lack the sophistication expected of longitudinal studies with certain covariance structures. The methods used fail to take into account random or systematic error which may be inherent to the measurable observed variables [118]. Failure to account for such errors in the analysis may lead to under or over estimation of the true values of the measured outcomes. This limitation can only be overcome by using techniques such as structural equation modelling (SEM) that estimates latent variables which are not directly observed and which provide a closer estimation to measurement error for each observed variable [119]. Only one study used multi-level modelling; an analytical approach with similar benefits to SEM [45]. These methods were not explored in other studies as a technique for analysing longitudinal data where outcomes are studied over time (i.e., involving multiple data collection points) or accounting for the correlation of individual responses over time. This is surprising given the usefulness of these methods when analysing participants with varying lengths of follow-up due to death and MAR outcomes [120].

SEM also allows the estimation of the indirect effect of mediating variables on outcomes of interest [121, 122]. Seven studies [21, 47, 58, 89, 93, 97, 102] reported the role of mediating variables, without reporting on the indirect effects that these variables have on outcomes. Most authors reported several logistic regression models per study, whereas SEM is able to model multiple regression equations simultaneously, and hence provides a flexible framework for testing a range of possible relationships between the variables in the model, including mediating effects and possible latent confounding variables [123, 124].

Logistic regression analysis and multiple linear regression analysis assume a direct pathway analysis and, therefore, fail to take into account mediating factors which may have an indirect effect on the outcomes of interest [123]. More recently, Bayesian methods have been proposed as important complementary approaches for testing for mediation and computing the value of the mediation effect (often referred to as Bayesian Mediation Analysis) [125, 126]. Literature has determined that Bayesian methods of analysis are better suited to analyse data with small sample sizes as compared to frequentist methods, though it is important that the prior distribution is correctly specified to avoid obtaining less accurate estimates [117, 127].

Strengths and limitations

This review has several strengths. The systematic search used a comprehensive range of databases including directed search strategies from linked child protection data and longitudinal study websites and manual scrutiny of reference lists were conducted. The integrity of the review process was maintained through quality control procedures including independent assessment of the included and excluded studies. However, the review was limited to peer reviewed studies published in English only, thus limiting the ability to review unpublished studies and studies from non-English speaking countries. Future reviews should consider targeted searches that may uncover literature from other geographic regions such as Asia, Africa and South and Central America.

Recommendations for future research

Overall, the quality of studies was good but the reporting of data linkage procedures was poor. It is important that in future, researchers should conduct adequate data preparation consisting of checking for errors and missing data and ways to address these. Additionally, the generalisability of the findings on the reported studies may be questionable as the reporting omitted important aspects of mediation analysis and ways to overcome bias due to small sample sizes.

The review has shown that it is important that researchers follow the guidelines recommended by the GUILD and RECORD statements to report the quality of data linkage so that there is transparency in the reporting process. While some data linkage communities have recognised the need to improve on their reporting of linkage quality to researchers it remains apparent that there should be improved communication and engagement between researchers and the data linkage units so that the reporting of linkage quality can be provided more routinely and consistently [128]. The poor or lack of transparency in reporting data linkage processes, such as reports on linkage errors, may under or overestimate the quality of studies reported, particularly among the hard to reach populations as exemplified in these studies. The more vulnerable or hard to reach populations are often missed or miss matches, resulting in reduced sample size and loss of statistical power [10, 129].

In addition, our review has also shown that there was lack of reporting or referencing of validated data quality assessments conducted for administrative data. In the context of transparency, accuracy, and reliability of measurement from administrative data sources, it is important to reference validated appraisal tools. Additionally, due to variability in quality criteria for child protection administrative data sets, we recommend that future researchers implement a data quality framework [130, 131]. With the growing use of administrative data it is necessary that data quality indicators are operationalised and reported in studies. For example, leaders in the use of linked administrative data at the Manitoba Centre of Health Policy have identified 5 dimensions of data quality: accuracy, internal validity, external validity, timeliness, and interoperability.

These dimensions of data quality can serve as an important starting point for future reporting of administrative data. However, determining if these dimensions are comprehensive, what exact criteria should be used for each dimension, and the operationalisation of those dimensions into measurable data quality criteria remains elusive. As such, there is need to conduct a Delphi Study [132, 133] among leading experts in the field of administrative data, to establish consensus on the use of these data quality indicators to either be integrated into tools such as the GUILD [7] and RECORD [79] guidelines, or to develop a new comprehensive data quality appraisal tool.

Reporting of missing data may be done by following some recommended guidelines such as the STROBE [134] and RECORD [79] guidelines. According to these guidelines, the number of individuals used for analysis at each stage of the study should be reported followed by reasons for non-participation or non-response. When it comes to handling missing data, simple to more complex analytical methods should be applied and the method used should take into account the mechanism for missingness [114]. If a wrong technique is applied, this may lead to biased inferences [135].

If data is MCAR, listwise deletion can be conducted because the reason for missing data is unrelated to the data itself. Pairwise deletion can be used as an alternative to listwise deletion since it preserves more information than listwise deletion [114]. While if data is MAR, analysis of complete records only may be invalid and thus techniques such as multiple imputation and likelihood based methods should be applied, though if not carried out appropriately, this could lead to biased estimates. If the reason for missing data depends on the missing values (NMAR), it is important to account for this by modelling the missing data and thus avoid getting parameters with biased estimates.

Basic regression methods of analysis were reported in most studies. More advanced statistical techniques, such as SEM and Bayesian, should be incorporated in analysis of cohort studies, particularly where small sample sizes are involved and where there are multiple data collection time points and multiple covariates. Multilevel structural equation modelling (ML-SEM) combines the advantages of multi-level modelling and structural equation modelling and further enables researchers to scrutinize complex relationships between latent variables at different levels [136].

Conclusions

Studies utilising administrative data integrated with longitudinal data in child protection settings were homogenous in nature. Most were birth cohort studies that were integrated with child protection data. There was poor reporting of data linkage processes, whereby only three studies (10%) reported the data linkage process in sufficient detail. A few techniques to account for missing data were reported, but generally lacked sufficient analytical details. The main statistical method of analysis reported in most studies were regression analysis which fail to take into account mediating factors which may have an indirect effect on the outcomes of interest. Furthermore, there was lack of utilisation of multi-level analysis as would have been expected in longitudinal studies reported where an individual's responses over time are correlated with each other. While a few studies (10%) reported advanced statistical analysis methods, there is an opportunity to implement other advanced techniques in future studies where small samples are involved. Additionally, the methods should account for measurement and linkage errors and missing data due to attrition. The review emphasises the need for more effort to be channelled towards improvements in reporting of data linkage processes through following recommended and standardised data linkage processes, which can be achieved through greater co-ordination among data providers and researchers.

Supporting information

S1 Table. PRISMA checklist.
(DOCX)

S2 Table. Search strategy from all databases.
(DOCX)

S3 Table. Data preparation methods.
(DOCX)

S1 File.
(PDF)

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