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Directed acyclic graphs: An under-utilized tool for child maltreatment research

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Abstract

BACKGROUND: Child maltreatment research involves modeling complex relationships between multiple interrelated variables. Directed acyclic graphs (DAGs) are one tool child maltreatment researchers can use to think through relationships among the variables operative in a causal research question and to make decisions about the optimal analytic strategy to minimize potential sources of bias.

OBJECTIVE: The purpose of this paper is to highlight the utility of DAGs for child maltreatment research and to provide a practical resource to facilitate and support the use of DAGs in child maltreatment research.

RESULTS: We first provide an overview of DAG terminology and concepts relevant to child maltreatment research. We describe DAG construction and define specific types of variables within the context of DAGs including confounders, mediators, and colliders, detailing the manner in which each type of variable can be used to inform study design and analysis. We then describe four specific scenarios in which DAGs may yield valuable insights for child maltreatment research: (1) identifying covariates to include in multivariable models to adjust for confounding; (2) identifying unintended effects of adjusting for a mediator; (3) identifying unintended effects of adjusting for multiple types of maltreatment; and (4) identifying potential selection bias in data specific to children involved in the child welfare system.

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CONCLUSIONS: Overall, DAGs have the potential to help strengthen and advance the child maltreatment research and practice agenda by increasing transparency about assumptions, illuminating potential sources of bias, and enhancing the interpretability of results for translation to evidence-based practice.

Keywords

directed acyclic graphs; causal diagrams; confounding; selection bias; colliders; methodology

Child maltreatment is a prevalent and complex social and public health issue. In 2016, child protective service (CPS) agencies in the United States received an estimated 4 million referrals, including approximately 7.2 million children, for alleged maltreatment (U.S. Department of Health and Human Services, 2017). Estimates based on retrospective self-report indicate that more than 40% of individuals experience maltreatment during childhood (Finkelhor, Turner, Shattuck, & Hamby, 2013; Hussey, Chang, & Kotch, 2006). The magnitude of child maltreatment underscores that evidence-based, interdisciplinary prevention and intervention strategies grounded in rigorous scientific research are critically needed. Of primary importance in the child maltreatment research and practice agenda is identifying causes and consequences of childhood abuse and neglect in order to inform prevention and intervention efforts. In working toward this goal, we are often confronted with the challenge of modeling multiple interrelated variables and complex causal pathways. To help address the challenges associated with child maltreatment research, we can leverage tools and methods commonly employed in a variety of disciplines. Foster and McCombs-Thornton previously described the utility of causal inference for child maltreatment research (Foster & McCombs-Thornton, 2013). In their article, Foster and McCombs-Thornton recommended the use of graphical tools called directed acyclic graphs (DAGs) to illustrate relationships among variables and to identify variables that should and should not be included as covariates in multivariable models (Foster & McCombs-Thornton, 2013). Here, we expand on this recommendation to provide a practical resource on the use and utility of DAGs for child maltreatment researchers.

DAGs are commonly used in modern epidemiologic practice (Fleischer & Roux, 2008; Hernández-Díaz, Schisterman, & Hernán, 2006; Merchant & Pitiphat, 2002; Richiardi, Barone-Adesi, Merletti, & Pearce, 2008; Wilcox, Weinberg, & Basso, 2011) to help researchers make decisions about the optimal analytic strategy for a given research question. Drawing a simple “back of the envelope” DAG is an efficient and effective way to think through a causal research question and the associated network of interrelated variables. DAGs can further aid researchers by illuminating potential sources of bias, helping us to avoid analytic mistakes that may lead to erroneous conclusions. The steps to construct and analyze a DAG are relatively simple and straightforward and do not require an extensive background in causal inference. As such, DAGs can serve as a useful tool for child maltreatment researchers to enhance the selection of analytic strategies and enhance the quality of maltreatment research. In this paper, we first review DAG terminology and concepts relevant to child maltreatment researchers. We then describe four specific scenarios in which DAGs may yield valuable insights for child maltreatment research: (1) identifying covariates to include in multivariable models to adjust for confounding; (2) identifying unintended effects of adjusting for a mediator; (3) identifying unintended effects of adjusting for multiple types of maltreatment; and (4) identifying potential selection bias in data specific to children involved in the child welfare system.

A brief overview of directed acyclic graphs: terminology and concepts

DAGs are graphical depictions of causal relationships among variables (Pearl, 1995). In constructing DAGs, we specify relationships among variables based on existing empirical evidence, theoretical knowledge, and our subject matter expertise (Greenland, Pearl, & Robins, 1999; Hernán, Hernández-Díaz, Werler, & Mitchell, 2002; Rothman, Greenland, & Lash, 2008; VanderWeele, Hernán, & Robins, 2008; VanderWeele & Robins, 2007a). As a research tool, DAGs are intended to compliment other tools we commonly use in child maltreatment research such as conceptual frameworks, theories of change, and logic models (Greenland et al., 1999). The primary advantage of DAGs for child maltreatment researchers is that these diagrams can be systematically analyzed by hand or through freely available software, such as the web application DAGitty (http://www.dagitty.net) or the R package “dagitty”, to inform the construction of multivariable models. Whereas other research tools such as conceptual frameworks can be used in a similar manner as DAGs to clarify assumptions regarding relationships among multiple variables, the added advantage of DAGS is that they can be used to easily detect potential sources of bias and to identify intended and unintended consequences of including specific variables in multivariable models.

DAGs consist of nodes, labeled as variables (measured or unmeasured), with single headed arrows connecting the nodes to indicate the direction of causal relationships between variables (Greenland et al., 1999). The causal relationships depicted on DAGs are qualitative and non-parametric, meaning that the arrowheads do not covey information about the form of the relationship between variables (Greenland et al., 1999). On a DAG, any pathway that can be traced through a sequence of single headed arrows pointing in the same direction is a causal pathway (Greenland et al., 1999). In Figure 1, we have drawn an arrow leading from childhood emotional neglect (i.e., exposure or independent variable) to depressive symptoms (i.e., outcome or dependent variable) to indicate a causal pathway in which childhood emotional neglect is hypothesized to cause depressive symptoms. Of note, these diagrams are acyclic meaning that there are no closed loops (VanderWeele & Robins, 2007a). If an exposure causes an outcome, the outcome cannot also cause the exposure (Rothman et al., 2008). Approaches to dealing with time-dependent confounding are described elsewhere (Daniel, Cousens, De Stavola, Kenward, & Sterne, 2013).

Below, we illustrate three additional types of variables important for DAG construction and analysis: confounders, mediators, and colliders. In Figure 2, parental mental health represents a confounder of the relationship between childhood emotional neglect and depressive symptoms. A confounder is a variable that is a common cause of both the exposure and the outcome (Rothman et al., 2008). We refer to the pathway from childhood emotional neglect to depressive symptoms through parental mental health as a confounding pathway. A confounding pathway will bias our estimate of the effect of the exposure on the outcome unless we condition on at least one variable along this pathway (Greenland et al., 1999). We can condition on a variable in either the design or analysis phase of a study through restriction, matching, stratification, or multivariable adjustment. In child maltreatment research, the most common approach to conditioning on a variable is to include it as a covariate in a multivariable model (i.e., multivariable adjustment). By conditioning on a variable along a confounding pathway, we close, or block, this previously open pathway (Hernán et al., 2002) and mitigate its associated bias. In Figure 2, if we condition on parental mental health, we block the open pathway from childhood emotional neglect to depressive symptoms through parental mental health and remove the confounding bias associated with this pathway. In describing and analyzing DAGs, we often refer to confounding pathways as "backdoor pathways" given that an arrowhead points to the exposure (Rothman et al., 2008), and we "back out" of the exposure onto the confounding pathway. Here, we want to emphasize that in constructing DAGs, we do not define confounding based on statistical associations found in our data, but rather on *a priori* empirical knowledge and subject matter expertise regarding the causal relationships operative among the variables of interest (Hermán et al., 2002).

In Figure 3, poor attachment representations is a mediator of the relationship between childhood emotional neglect and depressive symptoms. A mediator is a variable that is on the causal pathway from the exposure to the outcome (i.e., is affected by the exposure and affects the outcome) (Rothman et al., 2008). In some disciplines, we refer to mediators as intermediate variables (Rothman et al., 2008). When considering mediators, there are three different types of effects of potential interest: indirect, direct, and total effects. In Figure 3, the pathway from childhood emotional neglect to depressive symptoms through poor attachment representations is an indirect effect (Schisterman, Cole, & Platt, 2009). The direct effect of childhood emotional neglect on depressive symptoms is the effect that is not mediated by poor attachment representations or any other intermediate variable.(Rothman et al., 2008) The total effect of childhood emotional neglect on depressive symptoms is the effect through all causal pathways, including both direct and indirect pathways (Schisterman et al., 2009). Depending on our research question and aims, we may be primarily interested in the direct effect of childhood emotional neglect on depressive symptoms or the total effect of childhood emotional neglect on depressive symptoms. Our subsequent analysis strategy will differ depending on our interest in the direct versus total effect, as discussed in scenario 2 below.

In Figure 4, poor academic performance represents a collider between aggressive behaviors and low self-esteem. A collider is a variable that is a common effect of two other variables on the DAG (Rothman et al., 2008; VanderWeele & Robins, 2007a). We can identify a collider on a DAG as a variable where two arrowheads meet (Rothman et al., 2008; VanderWeele & Robins, 2007a). A pathway with a collider is closed or blocked at the collider such that no effect occurs through this pathway (Greenland et al., 1999). In Figure 4, the pathway from childhood emotional neglect to depressive symptoms through aggressive behaviors, poor academic achievement, and low self-esteem is blocked at poor academic achievement. Importantly, conditioning on a collider will induce an association between the "parents" of the collider. For example, adjusting for academic achievement in a multivariable model, stratifying by academic achievement in analyses, or recruiting only study participants with low academic achievement (all forms of conditioning on a collider) will create a previously nonexistent association between aggressive behaviors and low self-esteem. This will open a new pathway from childhood emotional neglect to depressive symptoms through aggressive behaviors and low self-esteem. Consider the case in which we have stratified by academic achievement in analyses. In examining only those individuals with poor academic achievement, if we know that an individual does not have low self-esteem, it is likely that this individual exhibits aggressive behaviors. Here, by conditioning on academic achievement, we have induced a previously nonexistent association between aggressive behaviors and low self-esteem because given that we know the value of one of these variables (e.g., low self-esteem), we can determine the value of the other variable (e.g., aggressive behaviors). For additional examples and information regarding colliders, we refer readers to an article by Cole and colleagues (Cole et al., 2009). We also want to highlight that being a collider is pathway specific (Rothman et al., 2008). A variable may function as a collider on one pathway, but as a confounder or mediator on another pathway, depending on the directionality of the arrows.

Variables to include on a directed acyclic graph

In constructing a DAG, we include the exposure and outcome of interest as well as additional variables hypothesized to be related to the exposure, outcome, or other variables on the DAG. Key additional variables to include are those that are a common cause of at least two other variables on the DAG (Glymour, 2006) and variables that are potential mediators of the exposure-outcome relationship. As previously stated, we identify additional variables to include on the DAG and determine the directionality of arrows connecting variables based on the existing scientific literature, theoretical expectations, and our own subject matter expertise. We do not base decisions on statistical associations observed in our data. In addition, we do not limit variables included on the DAG to those measured in our data. We include all relevant variables, both those measured and unmeasured (or poorly measured) in our data. This is a central aspect of DAG construction as it helps to highlight potential confounding (i.e., backdoor) pathways that we cannot block in the analysis phase of the study. We can represent unknown or unmeasured common causes on the DAG by labeling a node with the letter “U” and drawing arrows to the affected variables (Glymour, 2006). For example, Figure 4, the node “U” represents an unknown common cause of both childhood neglect and depressive symptoms. Last, it is important to note that in constructing a DAG, the lack of an arrowhead between two variables represents the assumption that there is no causal relationship between these variables (Greenland et al., 1999). For example, the absence of an arrowhead from childhood emotional neglect to depressive symptoms in Figure 1 would indicate that we assume there is no effect of childhood emotional neglect on depressive symptoms.

Directed acyclic graphs in child maltreatment research

Below we describe four scenarios in which DAGs may be particularly useful for child maltreatment research: (1) identifying covariates to include in multivariable models to adjust for confounding; (2) identifying unintended effects of adjusting for a mediator; (3) identifying unintended effects of adjusting for multiple types of maltreatment; and (4) identifying potential selection bias in data specific to children involved in the child welfare system. These examples are hypothetical scenarios intended to illustrate the utility of DAGs for child maltreatment research and do not necessarily indicate the presence of empirical or theoretical support for the DAGs presented. Because DAGs are a visual representation of a researchers' assumptions about causal relationships among variables based on existing knowledge (Rothman et al., 2008), it is important to keep in mind that no DAG is the "right" DAG. In fact, a researcher may draw multiple DAGs with varying assumptions for the same research question. Researchers may disagree on the assumptions made in a particular DAG. However, use and publication of these diagrams makes such assumptions explicit to both those conducting and consuming the research.

Scenario 1: Using directed acyclic graphs to identify covariates to include in multivariable models to adjust for confounding

Suppose we are interested in the effect of childhood physical abuse on the subsequent development of opioid dependence. In examining the effect of childhood physical abuse on opioid dependence, it is important for us to consider potential confounders that may bias our estimate of effect. In Figure 5 we constructed a DAG to address this research question, including the exposure and outcome, as well as additional variables hypothesized to mediate the exposure-outcome relationship or to be a common cause of at least two other variables on the DAG.

We can now use a set of relatively simple steps to analyze the DAG to identify covariates to include in a multivariable model to adjust for confounding (Greenland et al., 1999). The steps are as follows:

1. Remove all arrows originating from the exposure.

   Confounders are variables that are a common cause of both the exposure and the outcome (Rothman et al., 2008). Removing arrows originating from the exposure removes pathways in which the exposure is a cause of another variable. In Figure 2, we would remove the arrows extending from childhood physical abuse to neurobiological changes, emotional distress, opioid dependence, and chronic pain.

2. Identify any open (i.e., unblocked) confounding (i.e., backdoor) pathways from the exposure to the outcome.

   In Figure 5, there are 21 open backdoor pathways from childhood physical abuse to opioid dependence (see Table 1 for complete list). To close an open backdoor pathway, we need to condition on at least one variable along the pathway. For example, an open pathway in Figure 2 is childhood physical abuse ← childhood poverty ← parental substance abuse→ opioid dependence. To close this backdoor pathway, we can condition on parental substance abuse or childhood poverty.

3. Identify all minimally sufficient adjustment sets (i.e., sets of variables that are minimally sufficient to adjust for confounding).

   A set of variables is sufficient to adjust for confounding if adjustment for this set of variables closes or blocks all remaining open backdoor pathways (Greenland et al., 1999; Rothman et al., 2008). A set of variables is minimally sufficient if no subset of these variables is also sufficient (Greenland et al., 1999; Rothman et al., 2008).

Based on a review of Table 1, we conclude that the minimally sufficient adjustment set for Figure 5 includes the following three variables: childhood poverty, parental mental health, and parental substance abuse. According to the analysis of our DAG, conditioning on these variables would be sufficient to remove bias due to confounding in our estimate of the effect of childhood physical abuse on opioid dependence.

Importantly, if any of the variables in our minimally sufficient adjustment set functions as a collider on another pathway on the DAG, conditioning on this variable may open up new backdoor pathways. If this is the case, we may choose not to condition on this variable to avoid opening a new pathway, or we may choose to condition on additional variable(s) to close or block the newly opened pathways (Greenland et al., 1999). For example, in Figure 5, childhood poverty is a collider between parental mental health and parental substance abuse. Because parental mental health and parental substance abuse are part of our minimally sufficient adjustment set, we are already conditioning on these variables in our analysis, which will block the new pathway opened by conditioning on childhood poverty. If parental mental health and parental substance abuse had not been part of our minimally sufficient adjustment set, we may have considered conditioning on one of these variables in our analysis in order to block the new pathway opened by conditioning on childhood poverty.

For a given DAG, we will identify more than one minimally sufficient adjustment set (Glymour, 2006; Greenland et al., 1999). When selecting a final adjustment set from multiple options, preferable sets are those that exclude colliders, unmeasured (or poorly measured) variables, and variable with large amounts of missing data.

While commonly used by epidemiologists and other researchers to analyze DAGs, the above steps represent only one method available for DAG analysis. For an alternative set of relatively intuitive steps, we refer researchers to an article by Shrier and Platt (Shrier & Platt, 2008).

As you might imagine, drawing a DAG and identifying open backdoor pathways and minimally sufficient adjustment sets can quickly become cumbersome as our DAG becomes more complex. Moreover, we may choose to explore multiple DAGs that represent competing but reasonable assumptions about the interrelation of variables relevant to our research question. Fortunately, there is existing, freely available software that we can use to identify all minimally sufficient adjustment sets for a given DAG. DAGitty (http://www.dagitty.net) is a web application for drawing and analyzing DAGs that is relatively user-friendly for novice and experienced DAG users alike (Textor, Hardt, & Knüppel, 2011). Users can create DAGs directly with DAGitty's graphical interface or by preparing model code. After creating a DAG in DAGitty, users are provided with lists of all minimally sufficient adjustment sets for estimating total and direct effects, and mathematical assumptions embedded in the DAG are clearly illustrated through color coding of various types of pathways and variables (e.g., causal vs. biasing pathways) and a list of conditional independences implied by the DAG (Textor, Hardt, & Knüppel, 2011). In addition, there is an R package, ‘dagitty’, available through the comprehensive R archive network (CRAN) that provides the same functions as DAGitty (Textor, van der Zander, Gilthorpe, Liśkiewicz, & Ellison, 2016). We used the DAGitty (Textor et al., 2011) web application and provide the model code for replicating the DAG presented in Figure 5 (supplemental Table 1). This text can be inserted in the model code section of the DAGitty interface to reproduce and analyze Figure 5 as a learning exercise. Whether manually or through use of software, formal analysis of a DAG can facilitate identification and selection of an appropriate covariate set to adjust for bias due to confounding.

Scenario 2: Using directed acyclic graphs to identify unintended effects of adjusting for a mediator

In child maltreatment research, we are often interested in estimates of the direct, rather than the total, effect of abuse or neglect on an outcome in order to identify targets for prevention and interventions strategies. A common strategy for estimating direct effects is to adjust for mediators in addition to confounders in multivariable models. For example, in Figure 5, neurobiological changes, emotional distress, and chronic pain represent mediators on the pathway from childhood physical abuse to opioid dependence. To estimate the direct effect of childhood physical abuse on opioid dependence, we might adjust for these variables in our multivariable model. However, consider Figure 6, which presents a portion of the DAG from Figure 2. Adjusting for chronic pain (represented on the DAG by the box around the node for chronic pain) may introduce a new source of bias in our estimate of the direct effect of childhood physical abuse on opioid dependence. When adjusting for mediators, bias can occur when there is confounding of the relationship between the mediator and the outcome (Glymour, 2006; Rothman et al., 2008). In Figure 6, unintentional injury is a confounder of the association between chronic pain and opioid dependence. Note that chronic pain is also a collider between childhood physical abuse and unintentional injury. Thus, by adjusting for chronic pain, we induce an association that previously did not exist between the “parents” of the collider, childhood physical abuse and unintentional injury (represented by the dashed line) (Glymour, 2006; Rothman et al., 2008). An intuitive explanation of this induced association is that because childhood physical abuse and unintentional injury both cause chronic pain, if we know an individual has chronic pain, but has not had an unintentional injury, it is likely that this individual experienced childhood physical abuse. In other words, by adjusting for chronic pain, we create an association between unintentional injury and childhood physical abuse within strata of chronic pain (Glymour, 2006).

Importantly, the induced association between childhood physical abuse and unintentional injury opens up a new backdoor pathway from childhood physical abuse to opioid dependence that will bias our estimate of effect (Glymour, 2006; Rothman et al., 2008). We often refer to this bias as collider stratification bias or collider bias (Greenland, 2003). If unintentional injury is measured our data, we can adjust for unintentional injury to close or block the newly opened backdoor pathway. However, if unintentional injury is unmeasured in our data, we will not be able to address this new source of bias, and we may subsequently decide that estimating the total, rather than the direct, effect is more appropriate given the constraints of our data. By constructing a DAG, we can quickly identify scenarios under which adjusting for a confounded mediator will introduce bias into our estimate of effect (Rothman et al., 2008). A detailed overview of mediation analysis and confounding assumptions in the estimation of direct and indirect effects is provided by VanderWeele (VanderWeele, 2016).

Scenario 3: Using directed acyclic graphs to identify unintended effects of adjusting for multiple types of maltreatment

A frequent aim in child maltreatment research is to estimate the effect of a specific type of abuse or neglect on an outcome, isolated from the effect of other types of co-occurring maltreatment. As with the estimation of direct effects, a common strategy for estimating the effect of a specific type of abuse or neglect is to adjust for other types of maltreatment in addition to confounders in multivariable models. Consider the simplified DAG presented in Figure 7. In estimating the effect of childhood physical abuse on opioid dependence, we might think to adjust for childhood sexual abuse in an effort to isolate the effect of childhood physical abuse from the effects of childhood sexual abuse. However, if childhood sexual abuse shares common causes with both childhood physical abuse and opioid dependence, collider bias will be introduced by adjusting for childhood sexual abuse. In Figure 7, social norms are a cause of both childhood physical abuse and childhood sexual abuse. Child sex is a cause of both childhood sexual abuse and opioid dependence. Thus, by adjusting for childhood sexual abuse (represented by the box drawn around the node for childhood sexual abuse), we induce an association between social norms and child sex (represented in Figure 7 by the dashed line) and open up a new backdoor pathway from childhood physical abuse to opioid dependence. Here, use of a DAG allows us to easily recognize the bias that would be introduced by adjusting for childhood sexual abuse, and we can revise our analysis plan accordingly. If social norms are measured in our data, we can adjust for social norms to close or block the newly opened backdoor pathway. If social norms are unmeasured in our data, we may choose to forgo adjusting for childhood sexual abuse in order to avoid introducing this new source of bias.

Scenario 4: Using directed acyclic graphs to identify potential selection bias in data specific to children involved with the child welfare system

In child maltreatment research, many of our data sources are specific to children involved with the child welfare system. It is widely recognized within the field that results from these data sources are not generalizable to all children who have experienced maltreatment as many cases of abuse and neglect are not officially reported to child welfare service agencies (Everson et al., 2008). Less well recongized is that under certain circumstances, use of this selective sample may affect the internal validity of our results and produce spurious statistical associations (Foster & McCombs-Thornton, 2013; Glymour, 2006; Hernán et al., 2002). In Figure 8, we illustrate the potential for this selection bias. Suppose we are interested in examining the effect of accumulating childhood adversities on the development of externalizing behaviors. In Figure 8, we have drawn a box around the node for child welfare involvement to indicate that our data pertains only to children involved with the child welfare system (i.e., that we have conditioned on child welfare involvement in the design phase of the study). Importantly, selection bias may occur if the likelihood of child welfare involvement depends on both the exposure and outcome of interest (Glymour, 2006). Here, our primary concern is whether the exposure and outcome reflect processes that were operative prior to the child entering the child welfare system (Foster & McCombs-Thornton, 2013). For example, if both the adverse events and the child exhibiting externalizing behaviors played a role in the child coming to the attention of the child welfare system, estimating the effect of childhood adversities on externalizing behaviors only among child welfare-involved children may produce spurious results. This is because, in using data specific to children involved with the child welfare system (ie, by conditioning on child welfare involvement), we restrict our sample based on a common effect of the exposure and outcome (i.e., a collider). Such restriction will induce an association between the exposure and the outcome (represented in Figure 8 by the dashed line), or the "parents" of the collider. In this scenario, even if there were no true effect of accumulating adversities on externalizing behaviors, we would see an association in our data because we have conditioned on a collider. Here, DAGs force us to carefully consider the assumptions we make regarding the timing of the exposure and outcome relative to child welfare system involvement. DAGs help us to clearly depict scenarios in which using data specific to children involved with the child welfare system may introduce bias. In studies with data specific to child welfare-involved children, we should include a node indicating child welfare involvement on our DAG (as in Figure 8) to help illuminate such sources of bias. This scenario also illustrates that is important to assess for collider stratification bias with respect to both the study design or data source (e.g., restriction, matching) and our analytic approach (e.g., matching, stratification, multivariable adjustment) that may contribute to such bias.

Limitations of directed acyclic graphs

DAGs are a research tool, and like any research tool, they have limits to their utility. First, because DAGs are non-parametric, DAGs do not provide any information regarding the functional form or strength of hypothesized causal relationships (Glymour, 2006). Second, while DAGs readily convey open confounding pathways that may lead to biased results, DAGs do not indicate the magnitude of this bias (Glymour, 2006). Third, DAGs cannot be used to detect, reduce, or elimitate measurement error, which, like confounding and selection bias, is an important threat to the validity of the results of a study (Greenland et al., 1999). Last, there is currently no systematic or intutive way to depict effect measure modification (i.e., interaction) on DAGs, though there is some theoretical work in this area (Weinberg, 2007; VanderWeele & Robins, 2007).

We might reasonably question the value of DAGs given that there is uncertainty regarding the true underlying causal structure (for any causal question), and that we may construct the "wrong" DAG. In practice, we might construct multiple seemingly plausible DAGs for a research question, a reality which may cause discomfort for some researchers. If after reviewing the existing theoretical and empirical evidence, we do not have enough information to justify the selection of one DAG over another, or there is disagreement within the research team as to the "right" DAG (hint: there is no "right" DAG), one reasonable solution is to repeat analyses and compare results under the different sets of assumptions encoded in the competing DAGs (Shrier & Platt, 2008). DAGs have also drawn criticism from some researchers for being overly simplistic (Krieger & Davey Smith, 2016; Vandenbroucke, Broadbent, & Pearce 2016). Arguably, any graphical method or diagrammatic framework likely represents an oversimpliciation of a more complex reality that as researchers we are charged with disentangling. However, in our opinion, renouncing DAGs for their simplicity discounts the value that they offer for specifying assumptions, revealing sources of confounding, and mitigating bias – all critical elements of research design, analysis, and interpretation and elements that can help us in child maltreatment research to carefully construct causal models in order to identify appropriate risk and protective factors to target in prevention and intervention efforts.

Conclusions

In this paper we demonstrate that DAGs are an accessible research tool with the potential to strengthen and advance the child maltreatment research and practice agenda by helping researchers to identify bias stemming from data sources and analytic strategies. DAGs can be applied to a variety of research questions within the child maltreatment field and can complement other tools like theoretical models to clearly communicate complex research questions and assumptions among variables. Disentangling complex relationships among multiple variables is a common challenge in child maltreatment research that is critical to identifying targets for evidence-based prevention and intervention, and DAGs represent one tool child maltreatment researchers can use to help achieve this goal.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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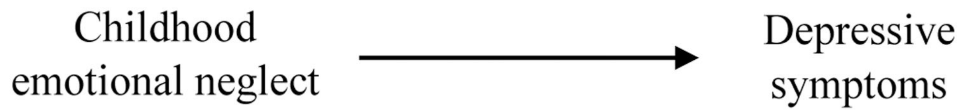

Figure 1.
Example of an exposure-outcome relationship on a directed acyclic graph

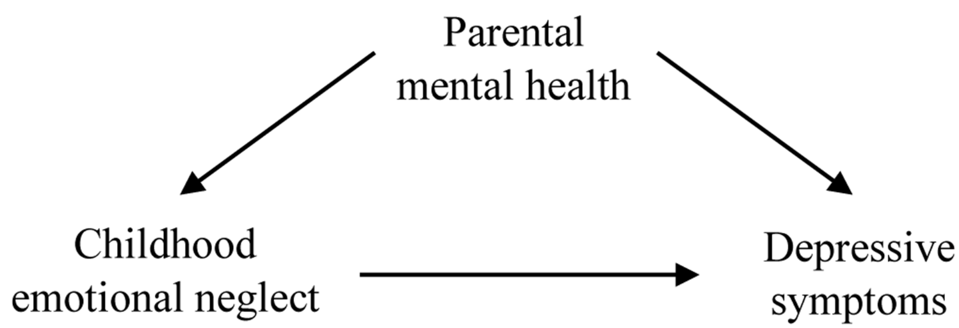

Figure 2.
Example of a confounder on a directed acyclic graph

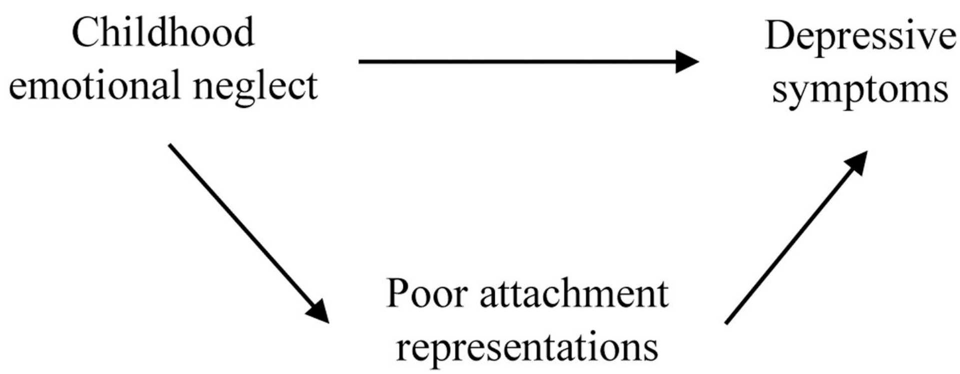

Figure 3.
Example of a mediator on a directed acyclic graph

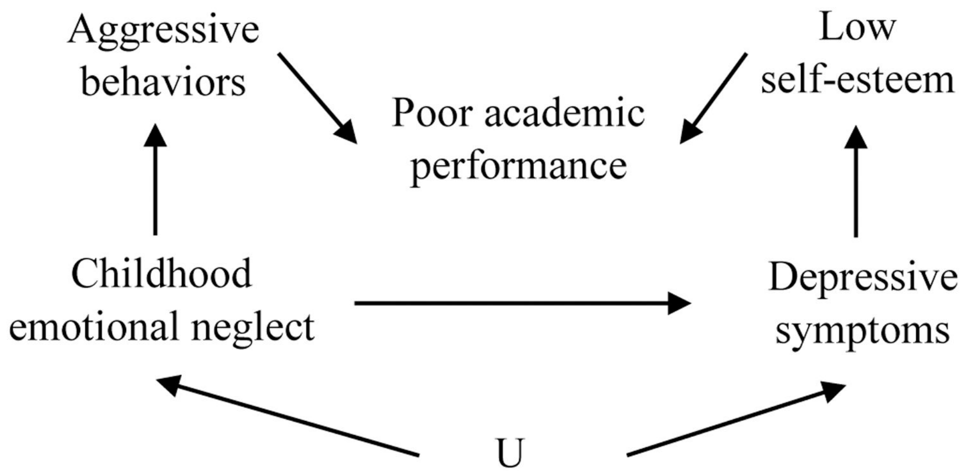

Figure 4.
Example of a collider on a directed acyclic graph

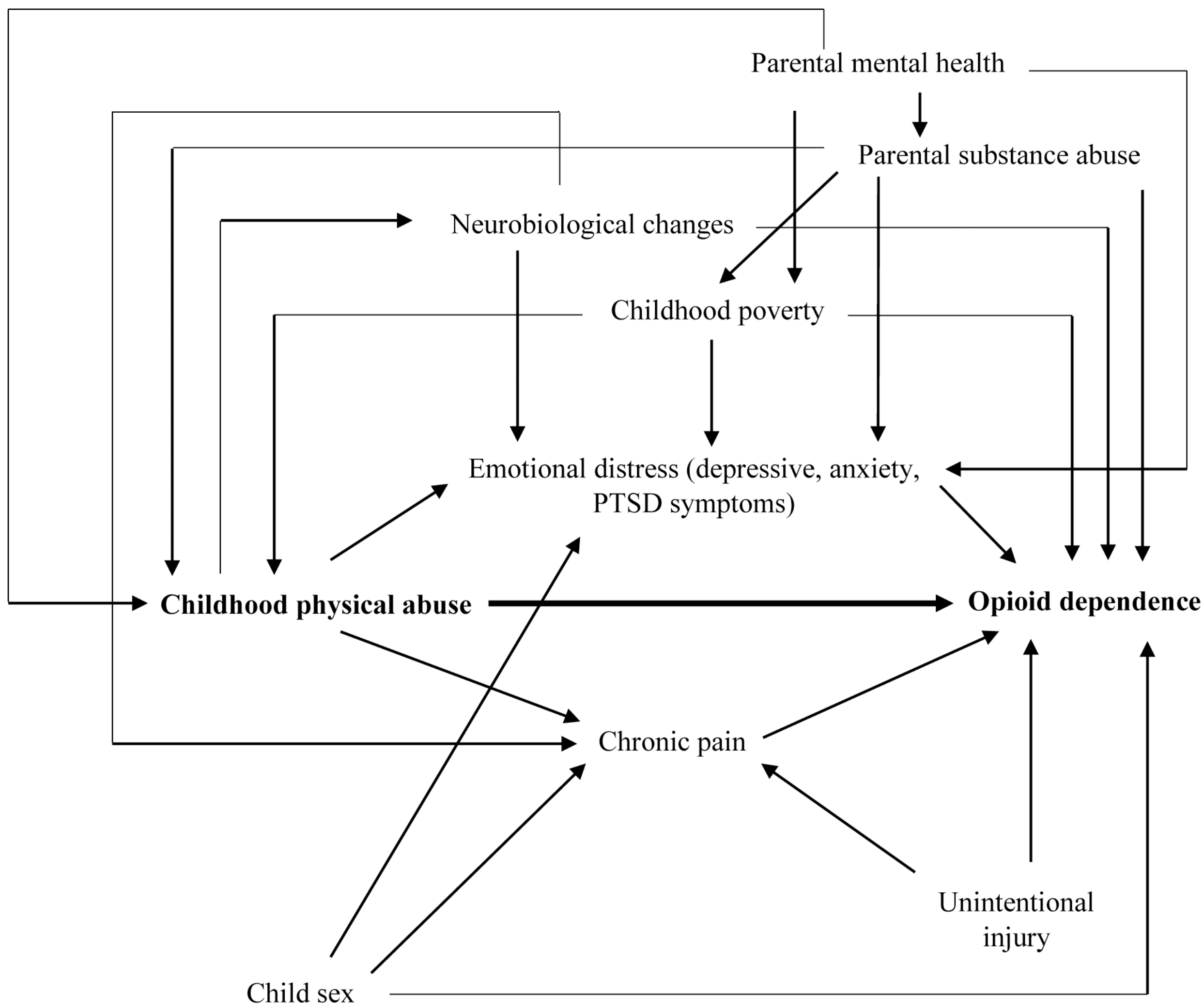

Figure 5.
Directed acyclic graph of variables operative in the effect of childhood physical abuse on opioid dependence

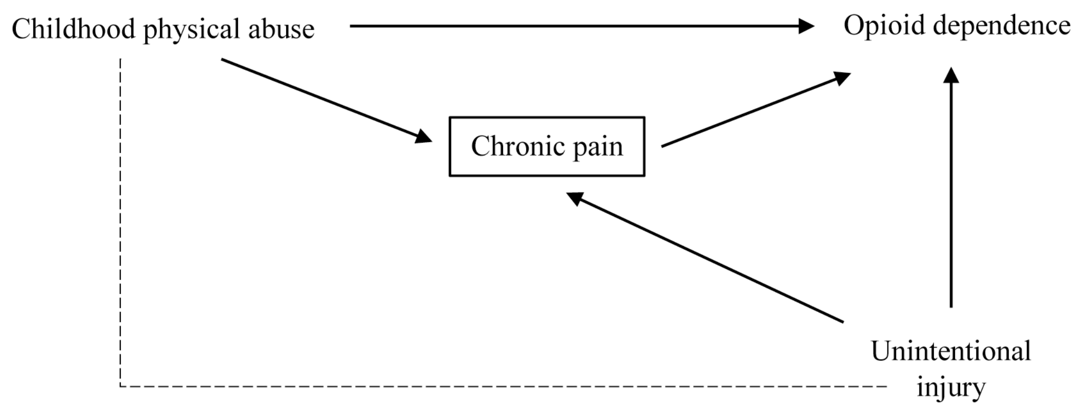

Figure 6.
Directed acyclic graph illustrating a confounded mediator

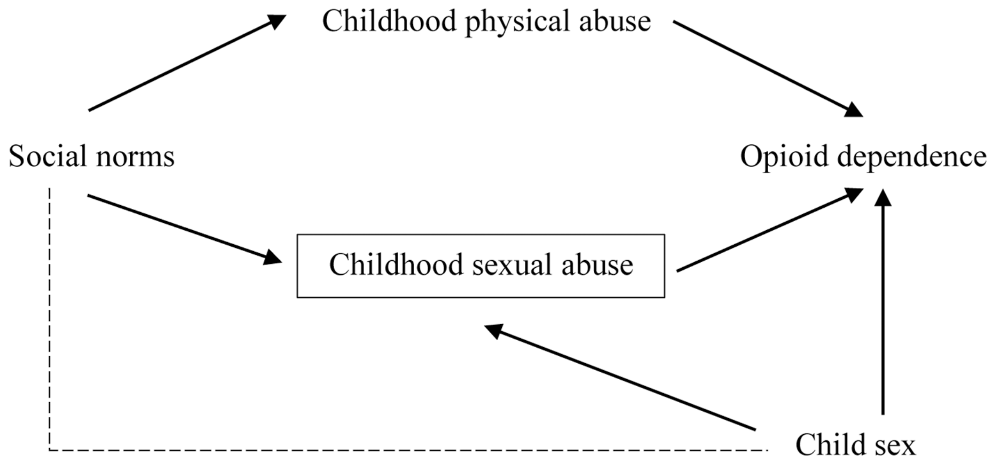

Figure 7.
Directed acyclic graph illustrating unintended effects of adjusting for multiple types of maltreatment

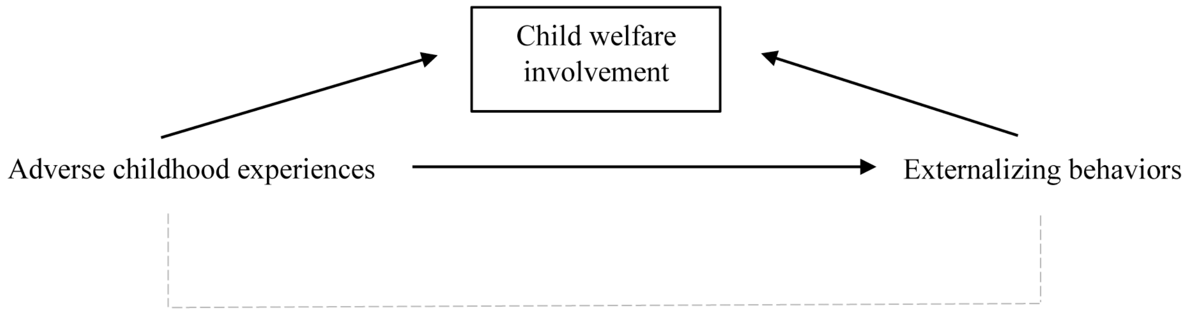

Figure 8.
Directed acyclic graph illustrating selection bias in data specific to child-welfare involved children

Table 1.

Open confounding pathways in Figure 5

Open confounding pathway	Variables to condition on to close confounding pathway[a]
1. Childhood physical abuse ← childhood poverty → opioid dependence	Childhood poverty
2. Childhood physical abuse ← childhood poverty → emotional distress → opioid dependence	Childhood poverty
3. Childhood physical abuse ← childhood poverty ← parental substance abuse → opioid dependence	Parental substance abuse; Childhood poverty
4. Childhood physical abuse ← childhood poverty ← parental substance abuse → emotional distress → opioid dependence	Parental substance abuse; Childhood poverty; Emotional distress
5. Childhood physical abuse ← childhood poverty ← parental substance abuse ← parental mental health → emotional distress → opioid dependence	Parental substance abuse; Childhood poverty; Emotional distress; Parental mental health
6. Childhood physical abuse ← childhood poverty ← parental mental health → parental substance abuse → opioid dependence	Parental mental health; Childhood poverty; Parental substance use
7. Childhood physical abuse ← childhood poverty ← parental mental health → emotional distress → opioid dependence	Parental mental health; Childhood poverty; Emotional distress
8. Childhood physical abuse ← parental substance abuse → opioid dependence	Parental substance abuse
9. Childhood physical abuse ← parental substance abuse ← parental mental health → childhood poverty → opioid dependence	Parental mental health; Parental substance abuse; Childhood poverty
10. Childhood physical abuse ← parental substance abuse ← parental mental health → childhood poverty → emotional distress → opioid dependence	Parental mental health; Parental substance abuse; Childhood poverty; Emotional distress
11. Childhood physical abuse ← parental substance abuse ← parental mental health → emotional distress → opioid dependence	Parental mental health; Parental substance abuse; Emotional distress
12. Childhood physical abuse ← parental substance abuse → emotional distress → opioid dependence	Parental substance abuse; Emotional distress
13. Childhood physical abuse ← parental substance abuse → childhood poverty → opioid dependence	Parental substance abuse; Childhood poverty
14. Childhood physical abuse ← parental substance abuse → childhood poverty → emotional distress → opioid dependence	Parental substance abuse; Childhood poverty; Emotional distress
15. Childhood physical abuse ← parental mental health → emotional distress → opioid dependence	Parental mental health; Emotional distress
16. Childhood physical abuse ← parental mental health → parental substance abuse → opioid dependence	Parental mental health; Parental substance abuse
17. Childhood physical abuse ← parental mental health → parental substance abuse → emotional distress → opioid dependence	Parental mental health; Parental substance abuse; Emotional distress
18. Childhood physical abuse ← parental mental health → parental substance abuse → childhood poverty → emotional distress → opioid dependence	Parental mental health; Parental substance abuse; Childhood poverty; Emotional distress
19. Childhood physical abuse ← parental mental health → parental substance abuse → childhood poverty → emotional distress → opioid dependence	Parental mental health; Parental substance abuse; Childhood poverty; Emotional distress
20. Childhood physical abuse ← parental mental health → childhood poverty → opioid dependence	Parental mental health; Childhood poverty

Open confounding pathway	Variables to condition on to close confounding pathway[a]
21. Childhood physical abuse ← parental mental health → childhood poverty → emotional distress → opioid dependence	Parental mental health; Childhood poverty; Emotional distress

[a]Conditioning on at least one variable on an open confounding pathway is sufficient to close or block the pathway.