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ABSTRACT

Human trafficking victimization is harmful to individuals, families, institutions, communities, and nations. It is commonly understood that human trafficking is a widespread problem, yet the variation in global estimates is extreme, ranging from 12.3 million to 20.9 million to 45.8 million people worldwide. The wide variation in estimates has led some to argue that claims about the scope of the problem are unsubstantiated. Calculating an estimate of human trafficking victims has proven to be complex; there is growing recognition that it is necessary to improve the methodologies used to generate such estimates. This article addresses the need for a better understanding of the methodologies used in human trafficking prevalence estimation studies. We conducted a comprehensive scoping review of prior human trafficking prevalence studies, including an analysis of the methodologies utilized and the context in which they were used, and offer a set of recommendations for future research on human trafficking prevalence. The goal of this effort is to provide guidance to researchers planning to undertake prevalence estimation studies and to help advance and improve human trafficking prevalence estimation research.

Introduction

Human trafficking casts a wide net of harm, negatively affecting individuals, families, public safety, the healthcare system, and the criminal justice system. Stakeholders, including policymakers, service providers, health care providers, law enforcement officers, and courtroom actors, involved in anti-trafficking efforts need data to inform their responses to human trafficking within their jurisdictions. Trafficking victims and those at risk for being trafficked need well-informed, targeted interventions and prevention efforts. They deserve a coordinated effort designed to ameliorate the deleterious effects of trafficking, which include increased rates of PTSD, depression, suicide, and physical harm from violence (Hopper & Gonzalez, 2018; Okech et al., 2018). A critical first step toward mobilizing efforts that best serve trafficking victims involves a better understanding of the scope and nature of the problem. However, calculating an estimate of human trafficking victims has proven to be a difficult and monumental task.

Despite the known challenges to estimating human trafficking prevalence, there continues to be great interest in generating meaningful estimates of the number of victims, on both micro and macro scales. However, there is growing recognition that it is necessary to improve the methodologies used to generate such estimates, a task that was even called for in a January 2020 Executive Order Combating Human Trafficking and Online Child Exploitation in the United States[1] (Executive Order 13,903,

2020). This article addresses the need for a better understanding of the methodologies used in human trafficking prevalence estimation studies. We conducted a comprehensive scoping review of prior human trafficking prevalence studies, including an analysis of the methodologies utilized and the context in which they were used, and offer a set of recommendations for future research on human trafficking prevalence.

Background

There is no systematic methodology for estimating human trafficking prevalence in its entirety (De Vries & Dettmeijer-Vermeulen, 2015). The U.S. government, labor rights groups, and many international organizations assert that human trafficking is a widespread problem, subjugating tens of millions of people around the world (International Labour Organization [ILO] & Walk Free Foundation, 2017). Yet, the variation in global estimates is extreme.

There are many reasons for the broad and inconsistent ranges of estimates in published human trafficking studies and reports. First, the populations involved in human trafficking – victims, survivors, exploiters, buyers – are largely hidden populations, meaning that the size of these groups is unknown and there is no known sampling frame from which to access them (Tyldum & Brunovskis, 2005). Second, despite the internationally agreed upon definition of trafficking in persons established in the Palermo Protocol (UN General Assembly, 2000), there continue to be differences in national and state definitions of what constitutes trafficking. Legal definitions of trafficking can impact the availability, nature, and scope of data that is collected that may capture human trafficking victimization (De Vries & Dettmeijer-Vermeulen, 2015). Beyond different legal definitions of trafficking, individual research studies often differ in how trafficking victimization is conceptualized, determined, and tallied that may not be aligned with established legal definitions.

An additional reason for the broad range in existing human trafficking estimates has to do with the different types of data used in calculating these estimates, such as administrative data from agencies providing services to victims in crisis, surveys of individuals in contact with other governmental and non-governmental agencies and organizations (e.g., social services, healthcare, and criminal justice), and interviews with representative samples of those at-risk for trafficking (National Academies of Sciences, 2020). While there are advantages to each of these strategies to understanding specific elements of the human trafficking problem, it is prudent to be honest about the limitations of each of them as well, especially as it relates to generalizability.

The variation in estimates has led some to argue that claims about the scope of the problem are questionable. Further casting doubt about the magnitude of the problem, there have been relatively few human trafficking arrests, charges, and convictions. For example, while there were 11,500 potential trafficking situations identified by the National Human Trafficking Hotline, only 1,830 suspected trafficking cases were opened by federal law enforcement agencies in 2019 (U.S DoS, 2020). Although some prosecutions occur at the state and local levels, this seems remarkably low given estimates about the size of the problem. While trafficking-related prosecution numbers are low, research indicates that traffickers are often charged with other offenses that are easier to prove (Farrell et al., 2012). In recognition that the complex nature of trafficking makes it difficult to collect data of sufficient quality needed to estimate scope of the problem, the U.S. Department of State stopped reporting prevalence estimates in their annual reports altogether by 2016 (p. 10).

In response to the issues surrounding prevalence estimates, Weitzer (2014) advocated for microlevel studies that are better equipped to provide more valid prevalence estimates, richer contextual information about those with lived experience, and more actionable information for the deployment of resources. However, based on our research, there has not been a comprehensive review of human trafficking prevalence studies to better understand the scale, scope, and methods used. Moreover, the anti-trafficking field is lacking a systematic approach for designing either small- or large-scale prevalence studies that are feasible within the target population and maintain the needed level of rigor. It is important to consider that trafficking occurs in diverse settings, and

Table 1. Search Terms.

Human Trafficking, Sex trafficking, Labor trafficking, Forced labor, Child labor, Child prostitution, Indentured servitude, Debt bondage, Domestic servitude, Labor exploitation, Sexual exploitation, Modern slavery, *OR* Forced Marriage	*AND*	Prevalence, Estimate, *OR* Scope

studies need to be tailored to the specific context. For example, trafficking occurs in both licit and illicit industries and formal and informal markets, including sex work, construction, beauty services, and traveling sales crews, among others. Moreover, it is not geographically constrained but rather may be found in urban, suburban, rural, and frontier communities. The methods utilized in a study designed to estimate the prevalence of sex trafficking among domestic minors in New York City (i.e., Curtis et al., 2008), for example, may not be appropriate for estimating the prevalence of labor trafficking among adult migrant farmworkers in rural North Carolina (i.e., Zhang et al., 2019a). Additional work is needed to develop best practices for designing prevalence estimation strategies under various conditions.

To fill this gap in the literature, we conducted a comprehensive scoping review of prior research on exploitation and trafficking for sex and labor. A scoping review is an increasingly popular method for synthesizing and mapping a body of research (Pham et al., 2014). In contrast to a systematic review or meta-analysis, which aim to collate and synthesize the results from different studies, scoping reviews aim to map the existing literature on a specific topic or research question (Arksey & O'Malley, 2005; Pham et al., 2014). The purpose of this scoping review is to map the strategies that have been used to estimate the prevalence of human trafficking across different industries, victim populations, and geographic scopes (e.g., worldwide, nation, state, city). We then consider the strengths and weaknesses of the various methodological approaches that have been used in prior research and consider how they may best be utilized under various conditions. The goal of this effort is to provide guidance for the selection of prevalence estimation strategies for future human trafficking prevalence studies to support advancement and improvement in this area of human trafficking research.

Methods

Data Sources and Search Strategy

The focus of this scoping review was primarily on the sampling and estimation strategies that have been used in prior research to estimate the extent of human trafficking in various populations, including within the U.S., in other geographically specific regions, and worldwide. The search terms were intentionally broad, including trafficking and other forms of sexual and labor exploitation, because the methods used to estimate the prevalence of these related abuses may also be relevant for estimating the prevalence of trafficking (see Table 1). These terms were searched in the following databases: PubMed, Web of Science, Embase, Criminal Justice Database (via ProQuest Central), PsychINFO, Sociological abstracts, National Criminal Justice Reference Service, and Google Scholar. Additional articles were then identified through reference lists of those picked up in the initial search. The search was limited to articles and reports published between 1999–2020.

Inclusion Criteria and Screening

Studies were eligible for inclusion if they included an original prevalence estimate that went beyond a simple descriptive estimate based on a convenience sample (e.g., clients of a single victim service provider). Articles that discussed prevalence estimation without providing an original estimate were excluded. Articles were also limited to those published in English. When duplicates were identified (i.e., the same data and estimate were reported in multiple publications), the article with the most comprehensive discussion of methods was used.

Titles and abstracts were first screened to exclude articles that were not related to the prevalence of human trafficking (e.g., articles focusing more generally on the phenomenon of sex trafficking). The search and initial screening yielded 138 potentially relevant articles. The full text was sought for each of these articles and they were further screened for inclusion. Of those, 94 articles were excluded because they did not include an original prevalence estimate. Forty-four studies sought to estimate the prevalence of sex and labor trafficking and/or exploitation. For each of the 44 relevant studies, information on data sources, geographic scope, type of trafficking/exploitation, population sampled, sample size, and sampling and prevalence estimation strategies was extracted and recorded in a spreadsheet.

Results

The general characteristics of prevalence studies included in this review are summarized in Table 2 and full details about each study are provided in Table 3. Human trafficking prevalence studies have focused on both large and small geographic areas. About nine percent of the studies undertook a global estimate and half (50%) focused on the national level, estimating results for one country. The remaining studies focused on even smaller geographies: 20% on states or regions and 20% on cities, counties, or metropolitan areas. Over three-quarters of the studies included estimates of labor trafficking and over half included estimates of sex trafficking; many studies examined both. Most of the studies that focused on labor trafficking focused broadly on any labor sector; six studies mentioned one or more specific industries (Datta & Bales, 2013; Zhang et al., 2014; Sommerfelt, 2015; Busch-Armendariz et al., 2016; Gilbert et al., 2018;; Zhang et al., 2019a). Only two studies produced estimates of forced marriage. Most studies included youth in their estimates (48% focusing on only youth and 46% focusing on both youth and adults), and only 7% of studies produced estimates or adults only.

There was also variation in the data sources and sampling strategies used to estimate the prevalence of human trafficking. Nearly half of the studies conducted primary data collection using surveys (46%), about one in three (32%) relied on administrative data, about one in four (23%) conducted a secondary

Table 2. Methodological Characteristics of Included Studies.

Methodological Characteristic	Number (n = 44)	Percentage (%)
Geographic scope		
Global	4	9.1
National	22	50.0
State or region	9	20.5
City, county, or metropolitan area	9	20.5
Trafficking type^		
Sex	25	56.8
Labor	34	77.3
Forced marriage	2	3.6
Victim age		
Youth only	21	47.7
Adults only	3	6.8
Youth and adults	20	45.5
Data sources^		
Survey (primary data collection)	20	45.5
Survey (secondary analysis)	10	22.7
Administrative	14	31.8
Census	2	3.6
Media reports	2	3.6
Sampling strategy^		
Probability	17	38.6
Mark-recapture or multiple systems estimation	14	31.8
Respondent-driven sampling or link tracing	7	15.9
Time location sampling	1	2.3
Other	6	13.6

^Percentages may not sum to 100% because some studies estimated multiple types of trafficking and used multiple data sources or sampling strategies

Table 3. Summary of Prevalence Study Methods.

Year	Author	Geographic Scope	Trafficking Type	Victim Age	Sample Size	Data Sources	Population Sampled	Sampling Strategy
Greene et al., 1999	Greene, et al.	Country (U.S.)	Sex	Youth	640	Survey (primary)	Runaway homeless youth	Probability
Kruse & Mahoney, 2000	Kruse & Mahoney	Country (U.S.)	Labor	Youth	Varied by survey	Survey (secondary)	Youth aged 15+	Other
Belser et al., 2005	Belser, et al.	Global	Labor	Youth, Adult	3,164	Administrative, survey (secondary), media	Reported cases of forced labor	Mark-recapture
Edwards et al., 2006	Edwards, et al.	Country (U.S.)	Sex	Youth	13,570	Survey (secondary)	Students, grades 7–12	Probability
Levison et al., 2007	Levison, et al.	6 cities, Brazil	Labor	Youth	239,340	Survey (secondary)	Youth aged 10–16	Probability
Curtis, et al. 2008	Curtis, et al.	1 city, U.S.	Sex	Youth	329	Survey (primary)	Youth involved in commercial sex	RDS
Ball & Hampton, 2009	Ball & Hampton	Country (Ukraine)	Sex, Labor	Youth, Adult	Varied by survey	Surveys (Secondary, 2; primary, 1)	Key informants, households	Probability (2), purposive
Kazmirski et al., 2009	Kazmirski	Country (U.K.)	Forced Marriage	Youth	58	Surveys (primary)	Service Providers	Convenience
Levison & Langer, 2010	Levison & Langer	Countries (6)	Labor	Youth	Varied	Census	Youth aged 10–17	Probability
Williamson et al., 2010	Williamson, et al.	1 state, U.S.	Sex, Labor	Youth, Adult	None	Census, prior research	Foreign born persons and American youth	Other
Steinfatt & Baker, 2011	Steinfatt & Baker	Country (Cambodia)	Sex	Youth, Adult	558	Observational	Sex venues	Other
International Labour Organization, 2012	ILO	Global	Labor	Youth, Adult	7,519	Administrative, Media	Reported cases of forced labor	Mark-recapture
ICF International, 2012a	ICF	Country (Paraguay)	Labor	Youth	1,002 households & 1,135 children	Survey (primary)	Children in households	Probability
ICF Macro, Inc, 2012b	ICF	1 region, Rwanda	Labor	Youth	2,839 interviews	Survey (primary)	Households	Probability
ICF Macro, Inc, 2012c	ICF	Country, (Pakistan)	Labor	Youth	650 worksites, 3,484 household interviews	Survey (primary)	Households and worksites	Probability
Datta & Bales, 2013	Datta & Bales	Countries (5)	Sex, Labor	Youth, Adult	Varied	Survey (secondary)	Households	Probability
Zhang et al., 2014	Zhang, et al.	1 county, U.S.	Labor	Adults	826	Survey (primary)	Unauthorized adult migrant workers	RDS
Bales et al., 2015	Bales, et al.	Country (U.K.)	Sex, Labor	Youth, Adult	2,744	Administrative	Presumed victims	MSE
Sommerfelt, 2015	Sommerfelt	Country (Haiti)	Labor	Youth	2,078 households, 1,617 youth	Survey (primary)	Children in households	Probability
Van Dijk & van der Heijden, 2016	Van Dijk & van der Heijden	Country (Netherlands)	Sex, Labor	Youth, Adult	1,561	Administrative	Identified victims	MSE

(Continued)

Table 3. (Continued).

Year	Author	Geographic Scope	Trafficking Type	Victim Age	Sample Size	Data Sources	Population Sampled	Sampling Strategy
Busch-Armendariz et al., 2016	Busch-Armendariz	1 state, U.S.	Sex, Labor	Youth, Adult	*Varied*	Administrative, Survey (primary)	Presumed and identified victims, social service agencies	Other
Phillips, 2017	Phillips	1 city, U.S.	Sex	Youth	403	Administrative	Persons arrested for CSE-related crimes (victims, buyers, facilitators)	Mark-recapture
Cruyff et al., 2017	Cruyff, et al.	Country (Netherlands)	Sex, Labor	Youth, Adult	8,234	Administrative	Presumed victims	MSE
International Labour Organization & Walk Free Foundation, 2017	ILO & Walk Free	Global	Sex, Labor	Youth, Adult	71,758	Survey (primary)	Households	Probability
Atteraya et al., 2018	Atteraya, et al.	Global	Labor	Youth	7,147	Survey (secondary)	Households	Probability
Gilbert et al., 2018	Gilbert, et al.	Country (Haiti)	Labor	Youth, Adult	2,916	Survey (primary)	Households	Probability
2018	Parks, et al.	1 state, India	Labor	Adult	4,306	Survey (primary)	Worksites	Mark-recapture
2018	Pinzon-Rondon, et al.	Country (Colombia)	Labor	Youth	50,000+	Survey (secondary)	Households	Probability
UNODC, 2018a	UNODC(a)	Country (Ireland)	Sex, Labor	Youth, Adult	311	Administrative	Known victims	MSE
UNODC, 2018b	UNODC(b)	Country (Romania)	Sex, Labor	Youth, Adult	4,622	Administrative	Known victims	MSE
UNODC, 2018c	UNODC(c)	Country (Serbia)	Sex, Labor	Youth, Adult	2,660	Administrative	Known victims	MSE
Anderson et al., 2019	Anderson, et al.	1 state, U.S.	Sex, Labor	Youth, Adult	1,032	Administrative	Known victims	Other
Dank et al., 2019	Dank et al.	1 city, Nepal	Sex	Youth	600	Survey (primary)	Adult entertainment workers	RDS
Zhang et al., 2019a	Zhang, et al.	1 state, U.S.	Labor	Adult	404	Survey (primary)	Migrant farmworkers	Probability
Zhang et al., 2019b	Zhang, et al.	1 state, India	Labor	Youth	562	Survey (primary)	Child laborers	Link tracing with TLS
Bales et al., 2019	Bales, et al.	1 city, U.S.	Sex, Labor	Youth, Adult	185	Administrative	Known victims	MSE
Farrell et al., 2019	Farrell et al.	2 cities, U.S.	Sex, Labor	Youth, Adult	635	Administrative	Known victims	MSE
Vincent et al., 2019	Vincent, et al.	1 city, India	Sex	Youth, Adult	317	Survey (primary)	Sex workers	Link tracing
Lyneham et al., 2019	Lyneham, et al.	Country (Australia)	Sex, Labor	Youth, Adult	414	Administrative	Known victims	MSE
Shabbir et al., 2020	Shabbir, et al.	1 region, Pakistan	Labor	Youth	*Unknown*	Survey (secondary)	Children	Probability
Jordan, et al., 2020	Jordan, et al.	Country (Nepal)	Sex	Youth	227	Survey (primary)	Children	RDS

Table 3. (Continued).

Year	Author	Geographic Scope	Trafficking Type	Victim Age	Sample Size	Data Sources	Population Sampled	Sampling Strategy
Bhatia et al., 2020	Bhatia, et al.	Country (Nepal)	Labor, Forced Marriage	Youth	9,346 households1,599 girls	Survey (secondary)	Children in households	Probability
Martin et al., 2020 University of Georgia, 2020	Martin et al. University of Georgia	1 state (U.S.) 1 metro area (U.S.)	Sex Sex and labor	Youth Youth	71,007 641	Survey (primary) Survey (primary)	9th and 11th graders Homeless youth	Probability Mark-recapture

analysis of existing survey data, and a few used other data (census data and media reports). These prevalence studies used a range of sampling and estimation strategies, including traditional probability samples (39%), variants of multiple systems estimation (MSE) and mark-recapture techniques (32%), respondent-driven sampling (RDS) and related link-tracing strategies (16%), time-location sampling (2%), and other novel approaches (14%). In the next section, we summarize the types of studies for which each of these methods were used and describe their potential applicability for estimating human trafficking prevalence in the U.S.

Traditional Probability Samples

Studies using a traditional probability sample rely on an existing sampling frame of the population of interest to select a representative sample. While different sampling designs are used across probability methodologies, these techniques use random selection and are appropriate when the total population size from which you are sampling is known. In trafficking research, probability samples have been utilized when survey research (for example, a household survey) may be able to capture potential trafficking or exploitation.

Traditional probability samples were used in 17 studies. Most of these estimated the prevalence of child labor outside of the U.S. (Levison et al., 2007; Levison & Langer, 2010; ICF International, 2012a; ICF Macro, Inc, 2012b, 2012c; Sommerfelt, 2015; Atteraya et al., 2018; Gilbert et al., 2018; Pinzon-Rondon et al., 2018; Shabbir et al., 2020; Bhatia et al., 2020). For the most part, these studies were able to conduct a secondary analysis of household survey data that had been collected for other purposes. For example, Pinzon-Rondon et al. (2018) analyzed data from the Colombian Demographic and Health Survey to estimate the number of children between the ages of six and 17 who worked during the week prior to the survey. This is a nationally representative survey that covered numerous topics and was administered to more than 50,000 households in Colombia. Use of an existing survey is a rigorous method for estimating the prevalence of child labor if coverage and responses are high and the questions are sufficiently detailed. In terms of applicability to estimating human trafficking prevalence in the United States, unfortunately there are no existing household-based surveys that could be re-analyzed to estimate the prevalence of human trafficking.

Two studies used household surveys to generate an estimate of "slavery in Europe" (Datta & Bales, 2013) and a "global estimate of modern slavery" (International Labour Organization & Walk Free Foundation, 2017). Both studies used data collected through representative household surveys from a sample of countries and extrapolated the findings to other countries. For example, International Labour Organization & Walk Free Foundation (2017) developed a survey to estimate the prevalence of human trafficking and administered it to a representative sample of households in 48 countries. The researchers added a few questions to an existing survey to capture information on trafficking experiences in several countries.

Ball and Hampton (2009) conducted three separate studies to arrive at an estimate of human trafficking from Ukraine. Two of the studies involved inserting questions into existing probability-based household surveys and the third relied on key informant interviews. They then looked across the findings from all three studies to arrive at an estimate.

Three studies used probability-based samples to estimate the prevalence of survival sex and commercial sexual involvement among youth in the U.S. (Edwards et al., 2006; Greene et al., 1999; Martin et al., 2020). Greene et al. (1999) developed a multistage sample of shelters in metropolitan and nonmetropolitan areas included in the National Household Survey on Drug Abuse to survey runaway and homeless youth about their experiences engaging in survival sex. In a secondary analysis of the National Longitudinal Study of Adolescent Health (Add Health), Edwards et al. (2006) estimated the prevalence of exchanging sex for money or drugs among 7–12th graders. Martin et al. (2020) developed a population-based prevalence estimate of the sexual exploitation of youth in Minnesota by adding a question to the Minnesota Student Survey, a tri-annual census of students in Minnesota schools. There is potential that this strategy could help establish a targeted estimate of human trafficking

prevalence in the United States. For example, if questions could be added to Add Health or other existing state-based school surveys, they would be a powerful data collection mechanism for understanding various forms of trafficking among adolescents.

One study used a multistage sample to estimate the prevalence of labor trafficking among migrant farmworkers in North Carolina (Zhang et al., 2019a). The researchers created segments from census blocks, assigned each segment to one of three strata, and then sampled them using probability proportional to size based on land area for crops that require manual labor, and oversampled segments with the highest proportion of land area for high labor crops.

The field team then drove through each selected segment and photographed dwellings that appeared to house migrant farmworkers. Field interviewers went back to all the identified dwellings and randomly selected individuals to participate in interviews. This type of multistage sampling could potentially be applied to other industries in the United States in which labor takes place in plain view, such as construction sites, landscaping, and carnivals if a sampling frame is not available.

Multiple Systems Estimation and Mark-Recapture

Multiple Systems Estimation (MSE) and mark-recapture assess the frequency that individuals are repeatedly identified through two or more data sources. They are different in that MSE uses secondary data on known victims of trafficking from multiple sources to estimate the total number of victims, while mark-recapture involves the actual identification of people through primary data collection efforts. In broad terms, these methods rely upon the comparison of two or more different samples of trafficking victims, examining the extent to which individuals are captured in more than one list (MSE) or identified more than once in a primary data collection effort (mark-recapture). MSE typically relies on multiple data sources whereas mark-recapture uses multiple time points from one data source. Statistical modeling, taking into account the sizes of the two (or more) samples as well as the extent of multiple captures of these individuals, can produce an estimate range of the total population size (Bird & King, 2018). It is worth noting that MSE may result in sparse overlap which can result in unstable estimation procedures (Chan et al., 2020)

Variants of MSE and mark-recapture were used in 14 studies (12 used MSE and 2 used mark-recapture). Thirteen of the studies were focused broadly on sex and labor trafficking and did not focus on specific industries. The geographic areas covered ranged from cities to the globe. Two early studies combined numerous data sources (e.g., ILO reports and studies, other international organizations, government statistics and reports, academic papers, and media reports) on the number of forced labor cases to estimate the prevalence of forced labor throughout the world (Belser et al., 2005; International Labour Organization, 2012). Due to the lack of direct measurement, the results from these studies were based on pooling results across a variety of data sources. More recent research has focused on smaller geographic areas – countries and cities. These studies collected data from governmental and non-governmental agencies that work with trafficking victims in some capacity in the selected geographic areas. Seven studies used administrative data on presumed or identified victims of sex and labor trafficking to estimate the number of victims in the U.K. (Bales et al., 2015), the Netherlands (Cruyff et al., 2017; Van Dijk & van der Heijden, 2016), Ireland (UNODC, 2018a), Romania (UNODC, 2018b), Serbia (UNODC, 2018c), and Australia (Lyneham et al., 2019). Three studies focused on cities within the U.S., including Kansas City (Phillips, 2017), New Orleans (Bales et al., 2019), and two unnamed communities (Farrell et al., 2019). For example, Bales et al. (2019) collected lists of confirmed trafficking victims from eight nonprofits and law enforcement agencies in New Orleans, created an anonymized table that summarized the number of cases observed on only one list, two lists, and three lists. A Poisson log-linear model was fitted to the data. Because MSE relies on existing data on trafficking victims, this method is only feasible if adequate data already exists on the population of interest.

Two studies used mark-recapture that involves "capturing" someone more than once during sampling in the field. The University of Georgia (2020) conducted three ten-day field activities in which they conducted interviews with homeless youth in places they were known to live and spend

time. The research team allowed the youth to participate in the survey more than once and identified duplicate respondents. In a study of bonded labor in India, Parks, Zhang et al. (2019) conducted data collection over three sampling periods at 17 purposively selected marketplaces where bonded laborers (or families) were known to visit. A team of enumerators invited every third person they passed to participate in an interview. Their mark-recapture procedure used worksites as the unit of the population, rather than individuals. A worksite was "captured" during a sampling period if at least one interviewee was a laborer there.

An important limitation of MSE is the utilization to estimate human trafficking prevalence only makes sense when there is adequate existing data (e.g., administrative data or records) for estimation purposes. For many populations of interest for human trafficking prevalence studies, there are no known existing data sources to use for estimation. Mark-recapture techniques, which were developed for counting wildlife (by actually marking them and observing whether they reappeared in a search effort) makes sense when target populations are easily accessible and/or visible, but are less effective for identifying hidden and hard to reach populations such as trafficking victims.

Respondent-Driven Sampling and Link Tracing

Respondent-driven sampling (RDS) and other link tracing methods are used when a sampling frame is not available. RDS and link tracing methodologies involve chain referrals among participants. Similar to traditional snowball sampling, both of these methods involve initial study recruits, "seeds," who fit the profile for study participation, who then refer additional people, who then also refer others, and so on. While RDS and link tracing use a snowball-type design, they assume selection from sample networks is carried out at random (Salganik & Heckathorn, 2004; Vincent & Thompson, 2017). Typically, RDS involves a small number of initial seed participants and multiple waves of recruitment initiated from each seed, while link tracing starts with a larger, representative sample of seeds and requires fewer (typically 2–3) recruitment waves.

Respondent-driven sampling or related forms of link tracing were used in seven studies. Most were focused on either sex or labor trafficking and had a limited geographic scope. Four of the studies used traditional RDS to estimate the prevalence of the commercial sexual exploitation of children in New York City (Curtis et al., 2008), Kathmandu (Dank et al., 2019), and Nepal (Jordan et al., 2020) and the prevalence of labor trafficking among unauthorized workers in San Diego County (Zhang et al., 2014). Two recent studies used link-tracing to estimate the prevalence of child labor in Bihar, India (Zhang et al., 2019b) and of sex trafficking in Muzaffapur, India (Vincent et al., 2019).

Miscellaneous Approaches

The remaining six studies used less traditional strategies to arrive at rough prevalence estimates. One study (Kruse & Mahoney, 2000) used secondary data from multiple sources to estimate the prevalence of illegal child labor in the U.S. However, the paper does not describe the methods in adequate detail to replicate. Kazmirski et al. (2009) collected data from local and national organizations on cases of forced marriage in England to estimate the prevalence of reported cases but did not extend the estimate to include unreported victims. Williamson et al. (2010) quantified potential pull factors for trafficking in Ohio among foreign born individuals (e.g., demand for foreign born workers, presence of trafficking in neighboring states) to estimate the number of individuals at-risk for trafficking based on Census population data. Then, they quantified the demand for sex and labor and used those ratings to estimate how many at-risk had been trafficked. A similar method was used for domestic minors involved in sex trafficking. Steinfatt and Baker (2011) used a geographic-based sampling approach to identify and sample sex venues in Cambodia. They then observed workers in the selected venues and counted the number of workers who appeared to be underage or unable to leave. Although the field team spoke with management at some of the venues, they did not interview or survey the workers. They used this observational data to estimate the prevalence of sex trafficking. Busch-Armendariz et al. (2016)

combined administrative data on individuals identified as known or likely trafficking victims and surveys with social service providers to estimate the prevalence of the sex trafficking and labor trafficking in high-risk populations. They developed victimization rates from the agency survey and then applied those percentages to high-risk populations. Anderson et al. (2019) de-duplicated lists of known sex and labor trafficking victims to identify the number of known victims and then incorporated those numbers with aggregate data to arrive at a prevalence estimate. While some of these novel approaches could be replicated, the methods are not as established or rigorous as the others that have been used.

Approaches Under Review

We also identified other methods that seem relevant but have never or only rarely been used in published human trafficking prevalence studies. These include time-location sampling (TLS) and network scale-up (NSUM).

TLS is based on the sampling of location-based populations by approaching the target population at specific locations (venues) and times where they congregate. TLS begins by establishing an understanding of where and when the target population tends to congregate. Then, it is possible to develop a sampling frame of venues-days-times where the target population congregates and to randomly select a set of those venues-days-times to sample. Once on site, a systematic process is used to select a representative sample of the population (e.g., every fifth person). TLS was pioneered by the Centers for Disease Control and Prevention in 1994 to conduct surveys with men who have sex with men (MSM) (MacKellar et al., 2007). Zhang et al. (2019b) applied TLS in city centers and major transportation hubs to recruit youths for their study on the prevalence of child labor in India. They worked with community agencies and service providers to identify public locations where child laborers frequent and used a random number table to approach every Nth child to request participation in an interview. They supplemented this approach with link-tracing in one city.

NSUM is unique in that it does not require sampling or surveying the target population. This method relies on a probability sample of the general population and survey questions ask about how many people the respondent knows who are in the target population(s) (e.g., how many direct care workers do you know who [indicators of trafficking]). NSUM has been used for more than twenty years in the study of MSM, heroin use, HIV, and other hidden populations (Ezoe et al., 2012; Kadushin et al., 2006; Killworth et al., 1998). Because NSUM has not been used to estimate the prevalence of human trafficking victimization, it is unclear how it will perform. There are, however, concerns over the reliability of this method in estimating prevalence; in studies of drug users it tends to significantly inflate the numbers due to inaccurate recalls from respondents (Salganik et al., 2011). It may also underestimate trafficking victimization because people may not openly share trafficking experiences with their friends or family.

Both TLS and NSUM have been used to estimate the prevalence of hidden populations but have rarely or never been applied to human trafficking. Both methods are currently being tested in studies funded by the State Department's Prevalence Reduction Innovation Forum in international contexts. The results of those studies will be useful in assessing the application of these methods to human trafficking.

Strengths and Weaknesses of Prevalence Estimation Strategies

After identifying the types of sampling and estimation techniques that are being tested or have been used in exploitation and trafficking prevalence studies, we considered the potential strengths and weaknesses of each method. Table 4 presents potential strengths and weaknesses of each method (probability sampling, MSE, RDS, TLS, and NSUM) in estimating the prevalence of human trafficking.

Discussion

Stakeholders involved in anti-trafficking efforts need data to inform their responses to human trafficking within their jurisdictions, a first step of which is a better understanding of the scope and nature of the problem. Over the past 20 years, efforts have been made to estimate the prevalence of human trafficking; however, given the complex nature of trafficking there is no single methodology that fits all contexts. Yet the imperative to improve the methodologies used to generate such estimates is widely understood and was even recognized in a 2020 Executive Order to Combat Human Trafficking and Online Child Exploitation in the United States (Executive Order 13,903, 2020). To this end, to help move the field of prevalence estimation forward, we conducted a scoping review and mapped strategies that have been used in prior research to estimate the prevalence of human trafficking. This included conducting an analysis of the strengths and weaknesses of the various approaches used and the contexts in which they may be most appropriate.

In summary, we identified four promising primary estimation strategies that prior research has used: probability samples, mark-recapture or multiple systems estimation techniques, respondent-driven sampling or related forms of link tracing, and time-location sampling. We also identified a number of studies that relied on other novel, but less rigorous, approaches, which we do not recommend for future prevalence studies.

Of the four promising estimation strategies that we identified, each method has a particular set of strengths and weaknesses for estimating the prevalence of human trafficking (see Table 4). Although some methods may have broader application than others, there is not a single method that could accommodate studying human trafficking in all its varied contexts. It is also important to note that no method can overcome the challenge of accessing a population that is completely confined. Further, all prevalence research, regardless of method chosen, can benefit from a pilot study. Formative research and a pilot study will help the research team assess whether the chosen method will work in their specific context and make technical decisions within the methods selected (e.g., household vs. establishment-based probability sample or RDS vs. link-tracing network referral sample). A minimum requirement to conduct a prevalence study is that the population of interest has some freedom of movement and communication. Our scoping review also identified three other factors that may be important to consider in selecting the most effective prevalence estimate strategy: characteristics of the industry and work environment of interest, characteristics of the worker population, and the geographic scope. Table 5 provides an overview of the interplay between these characteristics and different methodological approaches.

Probability samples are often considered the gold standard because they yield representative samples of the population of interest and offer easy to understand estimates of population quantities and model parameters. However, they may not always be feasible or appropriate for studying human trafficking in many contexts. Although a probability sample of the general population, such as a household- or school-based sample, does not have any constraints regarding geographic scope, industry, or worker population, it is unlikely to be successful because trafficking victims are a rare and hard-to-reach population which is difficult to capture in the general population.

A multi-stage probability sample with the establishment or employer as the primary sampling unit may be feasible in some industries. However, its reach would be limited to establishments that are legal and registered with some government authority (i.e., there is a sampling frame) and would potentially exclude the most vulnerable workers who have less formal work arrangements (e.g., paid in cash under the table). This type of sampling could not be used to study sex trafficking, for example, where prostitution is illegal and unregulated. Moreover, establishment-based surveys require cooperation from the employer and researchers may be denied access to employees altogether or only granted access to a limited or biased sample.

A geography-based probability sample (such as that used by Zhang et al., 2019a), may be feasible for studies in industries where worksites are outside and visible to the public (e.g., construction, landscaping, agriculture) or, potentially, where worksites are indoors with public access (e.g., restaurants,

Table 4. Summary of Methodological Strengths and Weaknesses for Estimating Trafficking Prevalence.

Method	Strengths	Weaknesses
Probability sample (e.g., multistage, stratified, cluster)	Traditional social science sampling method that yields representative samples of the population of interest; offers easy to understand parametric estimates for prevalence/baseline as well as intervention purposes Used in prior human trafficking prevalence studies Can sample firms or persons	All probability-based sampling requires a sampling frame, but trafficking victims are a rare and hard-to-reach population, which is difficult to capture in a survey Capturing a rare occurrence (i.e. trafficking victimization) among a general population necessitates a large sample size and extensive field work, which can be costly Multistage samples relying on employers as the primary sampling unit may be: (1) denied access to employees or (2) given access to a limited or biased sample of employees (e.g., legally authorized workers)
Multiple systems estimation (MSE)	Utilizes existing administrative data sources and does not require primary data collection Minimizes burden on participants – victims are not approached or asked about their trafficking experiences Time and cost efficient Used in prior human trafficking prevalence studies	Gross underestimation of prevalence because existing data only includes officially recognized victims – definitional inconsistencies can create many estimation difficulties. Okay for advocacy purposes and even for victim service/rescue operations, but not suited for estimations intended for interventions and least useful for impact assessment. Requires data on known victims from at least 2 independent data sources Requires personally identifiable data to link individuals across data sources MSE may result in sparse overlap between sources, which can lead to unstable estimating procedures Data sources may not use the same definition or screening tool to determine whether an individual is a victim Self-selection into lists may bias estimates (e.g., victim chooses to receive services) based on limited available lists (e.g., from service providers)
Respondent-Driven Sampling (RDS) and link tracing	Does not require an existing sampling frame Yields diverse samples of the target population that may approach probability samples if assumptions are met Used in prior human trafficking prevalence studies	Requires social connections and may exclude individuals who are socially isolated Reliance on initial "seeds" and subsequent participants to recruit new participants and penetrate the full universe. Difficult to balance uneven recruitment activities, with some having few waves of referrals and others appearing rather excessive. Because the research team does not have control over recruitment, it may yield smaller than desired sample sizes, longer than desired recruitment periods, and nonrepresentative samples Geographically constrained. Works only in small geographical locales; not useful when large communities or locations are included in a study. May require a large sample size, which can be costly

(Continued)

Table 4. (Continued).

Method	Strengths	Weaknesses
Network scale-up (NSUM)	Does not require identifying and surveying victims Question can be embedded in general population surveys Ability to estimate multiple hidden populations simultaneously (i.e., could ask about multiple industries) Minimizes harm to respondents – does not access the target population directly but rather a random sample of the general population reports about members of the target population Might reduce underreporting	Trafficking victimization is a rare and hidden event. It may require a prohibitively large sample to capture individuals who have trafficking victims in their social network. Measurement error recalling characteristics about people who are known is not perfect Barrier effects – there are different probabilities of knowing someone in the hidden population among members of the general population and inaccurate estimation of an individual's network size can affect the population size estimate Transmission error – would a person know that someone in their network was being trafficked. Data based on hearsay (potentially including personal stories, gossip, or even rumors) are highly unreliable because trafficking victimizations are not something people openly share with their friends or even families. ILO published official guidelines that specifically discourages collecting data gathering from third persons. Has not been applied to human trafficking prevalence yet (currently being tested in all PRIF-funded studies including Morocco, Pakistan, Costa Rica, Tunisia, and Brazil)
Time-location sampling (TLS)	Does not require an existing sampling frame Does not rely on "seeds" or other participants for recruitment Can yield a large, diverse sample of the target population and to generalize findings to that population	Target population needs to attend public venues (e.g., bars, businesses, parks) and be visually identifiable Excludes individuals who do not visit the selected venues, which limits generalizability Has limited application to human trafficking prevalence (currently being tested in the PRIF-funded Brazil, Morocco, and Tunisia studies)

Table 5. Considerations for Methods Selection.

Sampling Strategy	Geographic Considerations	Industry/Work Environment Considerations	Worker Population Considerations	Other Considerations
Probability sample-general population (e.g., household or school)	No constraints	No constraints	No constraints	Trafficking victims are a rare and hard-to-reach population, which is difficult to capture in general population samples
Probability sample-establishment	No constraints	Establishments are legal and registered	Formal employment is the norm	Requires cooperation from the employer. May be denied access to employees or given access to a limited or biased sample of employees
Probability sample-geographic	Narrow geographic scope	Worksites are outside and visible to the public or indoor with public access	No constraints	Requires approaching workers at their place of employment. If employers are present, they may deny access to employees or give access to a limited or biased sample of employees.
RDS/link tracing	Narrow geographic scope	No constraints	Workers are socially networked with and able to contact others in the industry	
TLS	Narrow geographic scope	No constraints	Workers in the industry are likely to frequent or congregate at the same venue for work, errands, socialization, etc.	Excludes individuals who do not visit the selected venues
MSE	No constraints	No constraints	Workers are likely to be in contact with agencies or organizations that may be aware of their trafficking status	Industry-specific databases are unlikely to exist
NSUM	No constraints	No constraints	No constraints	Data based on hearsay (potentially including personal stories, gossip, or even rumors) are highly unreliable because trafficking victimizations are not something people openly share with their friends or even families

beauty services). Because workers would be approached at their place of employment, employers may present the same obstacles to access as an establishment-based survey. Moreover, given the time and cost associated with developing the sampling frame, the geographic scope needs to be relatively narrow.

Moving away from traditional probability samples, RDS and related forms of link tracing are appropriate for estimating the prevalence of both sex and labor trafficking. Because the sampling procedure relies on chain recruitment, it is only feasible when workers are socially connected and able to contact others in the industry and when the geographic area of interest is relatively narrow. This approach would not be appropriate for industries where workers are physically and socially isolated (e.g., domestic workers or rural migrant farmworkers). RDS also traditionally assumes a narrow geographic scope and would not be appropriate for state- or national-level estimates, although technology may increasingly enable the connection – and peer referral – of more dispersed populations.

Because TLS and RDS most often rely upon respondents networked locally or congregating in particular locations, more entry points (in the case of RDS) and more sampling venues-days-times (in the case of TLS) would be necessary for studies attempting to cover more than a small geographic area. TLS also assumes that the workers are likely to frequent or congregate at the same venue for work, errands, socialization, or some other activity. This assumption is unlikely to be met for many industries. Even if the assumption is met, TLS excludes individuals who do not visit the sampled venues.

Unlike the approaches covered so far, MSE does not involve sampling and then surveying individuals. There are no geographic or industry-specific constraints to using this approach. However, because it relies on datasets of known victims, it assumes that workers are likely to be in contact with agencies or organizations that are aware of, and systematically maintain, their status as a trafficking victim. Known victims that come to the attention of official or community agencies likely represent a small fraction of total victims. Agencies also have different record keeping practices, which may not be compatible for list matching. All of these factors may lead to very narrow overlap between lists, necessitating further statistical assumptions (see, for example, Chan et al., 2020).

NSUM is also different from the other approaches in that it is not a sampling strategy but rather a way of asking questions. NSUM does not have any constraints regarding geographic scope, industry, or worker characteristics. It could potentially be used to estimate the prevalence of multiple forms of trafficking in one survey. However, due to its reliance on third-party information (i.e., the respondent reports on trafficking experiences of others in their network) the data may not be reliable because trafficking victimization is not something that people openly share.

The results of this scoping review support Weitzer's (2014) call for micro-level studies of human trafficking prevalence. By and large, studies that were focused on specific populations of interest benefitted from the use of specially targeted recruitment strategies that were appropriate to access that population. In particular, our analysis indicates that consideration of a target industry, characteristics of workers, and a clearly defined geographic region are helpful in determining the most appropriate sampling strategy to conduct prevalence assessments. There is an encouraging emerging body of evidence supporting the use of four major methods to accomplish these assessments, depending on those factors: traditional probability sampling, RDS or other variants of link tracing, TLS, and MSE.

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