Evaluation and Program Planning 80 (2020) 101792

Contents lists available at ScienceDirect

Evaluation and Program Planning

journal homepage: www.elsevier.com/locate/evalprogplan

Latent class analysis risk profiles: An effective method to predict a first re-report of maltreatment?[☆]

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ARTICLE INFO

Keywords:
Child maltreatment
Child maltreatment report
Risk profile
Latent class analysis

ABSTRACT

Recurrence of child maltreatment is a significant concern causing substantial individual, family and societal cost. Variable-based approaches to identifying targets for intervention may not reflect the reality that families may experience multiple co-occurring risks. An alternative approach was tested using baseline data from the National Survey of Child and Adolescent Well-being (NSCAW) I and II to develop Latent Class Analysis models of family risk classes using variables derived from prior studies of re-reporting. The samples were collected approximately 10 years apart offering a chance to test how the approach might be impacted by demographic or policy shifts. The association between baseline classes and later re-reports was tested using both samples. A two-class model of high versus low presence of baseline risk resulted that was strongly associated with later likelihood of re-report and results were relatively stable across the two studies. Person-centered approaches may hold promise in the early identification of families that require a more comprehensive array of supports to prevent re-reports of maltreatment.

1. Introduction

Annually, over 4 % of US children are reported to and investigated by child protective services (CPS) for various forms of child abuse or neglect (U.S. Department of Health & Human Services, Administration for Children & Families & Administration on Children, Youth & Families, Children's Bureau, 2020). A recent study estimates that 37.4 % of US children are the subject of a CPS report during childhood (Kim, Wildeman, Jonson-Reid, & Drake, 2017). While a primary goal of CPS involvement is to assure child safety (Jonson-Reid & Drake, 2018), repeat reports are not rare. Rates of re-reports vary across timeframes. Studies following cases for up to two years will often show about 20 % of cases are re-reported (Casanueva et al., 2015; Connell, Bergeron, Katz, Saunders, & Tebes, 2007; English, Marshall, Brummel, & Orme, 1999; Fluke, Shusterman, Hollinshead, & Yuan, 2008). While re-report rates slow over time, rates of 31 % to over 60 % in studies including three or more years of follow-up have been noted (Connell et al., 2007; Dakil, Sakia, Lin, & Flores, 2011; Drake, Jonson-Reid, & Sapokaite, 2006; Jonson-Reid, Drake, Chung, & Way, 2003).

The personal and economic burden of child maltreatment is high in the United States (Fang, Brown, Florence, & Mercy, 2012). Re-reporting is strongly associated with worse outcomes across a number of domains (Jaffee & Maikovich-Fong, 2011; Jonson-Reid, Kohl, & Drake, 2012). A repeat contact with CPS also raises the cost to the child welfare system and indicates a failure to achieve the goal of child safety. The need to understand which families are at highest risk of recurrent CPS contact has led to the development of a variety of risk assessment tools with varying degrees of accuracy (Fluke et al., 2008; Institute of Medicine/National Research Council, 2014; Schlonsky & Wagner, 2005). Unfortunately, despite efforts to reduce recurrence, recurrence rates appear similar across time when comparing studies with similar follow-up periods (e.g., Casanueva et al., 2015; English et al., 1999; Fluke et al., 2008). One potential barrier to understanding recurrence may be a reliance on traditional variable centered approaches to modelling risk that can lead to a narrowly targeted intervention (e.g., poor parenting skills would suggest parenting skills intervention). Families involved in

☆ This research was supported by funding through the Administration for Children and Families, US DHHS grant # 90CA1832 *Intervening in Child Neglect: A Microsimultion Evaluation Model of Usual Care*. Opinions expressed here do not necessarily reflect those of the funding agencies. Data are from the National Study of Child and Adolescent Well-being I & II and can be accessed with permission through the National Data Archive on Child Abuse and Neglect.

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https://doi.org/10.1016/j.evalprogplan.2020.101792
Received 5 March 2019; Received in revised form 31 January 2020; Accepted 5 February 2020
Available online 06 February 2020
0149-7189/

CPS may present with numerous risks that are simultaneously important to consider (Putnam-Hornstein & Needell, 2011; Thompson & Colvin, 2018). Further, few risk factors have received consistent exploration across multiple studies, making it difficult to draw conclusions about the strongest and more reliable predictors to target (Jonson-Reid et al., 2019). One of the more consistent predictors of future risk is a history of prior reports (Dakil et al., 2011; White, Hindley, & Jones, 2015), however, an indication of prior reports is not helpful for assessing risk of recurrence at the time of a family's first CPS contact.

Person-centered analytic approaches allow for the identification of groups of individuals with similar patterns of risk or protective factors and is becoming more common in child maltreatment research (Roesch, Villodas, & Villodas, 2010). This analytic approach is also known as clustering individuals or pattern focused and within the last ten years has seen increasing application in the attempt to predict later outcomes based on the class typology (Woo, Jebb, Tay, & Parrigon, 2018). This latter application, however, is still very rare in research on re-reporting. Only one known published study exists and this was limited to infants in a single state (Eastman, Mitchell, & Putnam-Hornstein, 2016). CPS populations may differ across regions and time due to economic, policy and demographic changes (Jonson-Reid et al., 2017). Because class typologies are created from the clustering of individuals with a pattern of attributes, it is not clear that any such typology would be stable enough to be useful in explaining child welfare outcomes like re-reporting. Thus, an approach to modelling risk must be re-assessed across locations and over time to look for changes in the number of classes as well as the importance of modifiable factors that are included in the process of classification. The present article presents results of an attempt to use a person-centered approach to identifying meaningful classes of families at the time of a first contact with CPS using a multi-state sample including children ages birth to 15. Using variables identified in prior recurrence research baseline classes were then tested to see if they predicted later re-reports. Because two iterations of this study exist with a ten- year gap and some differences in states included, this allowed for a comparison of the stability of this approach over time.

2. Background: risk factors and conceptual framework for child maltreatment re-reporting

Consistent with the common use of an ecological framework to guide recurrence research (White et al., 2015), the following brief review summarizes research on risk factors for maltreatment re-reporting at the child, family, and community levels.

2.1. Child characteristics

Certain child characteristics have been associated with a higher risk of CPS re-reports. One of the more consistent findings is that being younger at the time of initial report is related to increased risk (Bae, Solomon, Gelles, & White, 2010; Fuller & Nieto, 2014; Jedwab, Harrington, & Dubowitz, 2017; White et al., 2015). Findings regarding the association of race or ethnicity and re-reporting are mixed. Some studies report that under-represented minorities (usually Black or Hispanic) have lower rates of re-reporting compared to White children (Fuller & Zhang, 2017; White et al., 2015) while others have found no association (Cheng & Lo, 2015; White et al., 2015). Most studies have found no difference in re-reporting by gender (Cheng & Lo, 2015; Jedwab et al., 2017; White et al., 2015). Measurement of child level risk factors is inconsistent across studies. Some studies have found that indicators of developmental, emotional, physical, or behavioral problems are associated with higher risk of re-reporting (Kahn & Schwalbe, 2010; Kohl, Jonson-Reid, & Drake, 2009; Marshall & English, 1999; White et al., 2015), but others found no significant association (Cheng & Lo, 2015; White et al., 2015).

2.2. Family characteristics

There is substantial variation in how caregiver and family characteristics are measured and their association with recurrence. Larger family size has been associated with risk of re-reporting, but is measured in very few studies (Bae et al., 2010; White et al., 2015). In some studies, increased risk of re-reporting is associated with some measure of caregiver drug and/or alcohol abuse (White et al., 2015) and poor mental health (Casanueva et al., 2015; Kim & Drake, 2017). Other studies have found no association or lower risk (Helton, 2016; Kahn & Schwalbe, 2010; White et al., 2015). Despite the intuitive relationship between risk of recurrent maltreatment and indicators of poor parenting skills or prior generational maltreatment, these factors are not consistently predictive across studies (White et al., 2015). Similarly, there are mixed findings concerning the importance of caregiver education, poverty, low social support, criminal behavior and marital status (Casanueva et al., 2015; Eastman et al., 2016; White et al., 2015). While studies of first reports to CPS have been associated with material hardships relating to food, housing, utility, or other basic needs (Dworsky, Courtney, & Zinn, 2007; Slack, Lee, & Berger, 2007, 2011; Yang, 2015), these factors do not consistently predict re-reporting.

2.3. Community characteristics

Despite the noted relationship between community factors and maltreatment occurrence (Coulton, Crampton, Irwin, Spilsbury, & Korbin, 2007), relatively few studies of recurrence have attempted to control for community factors. Some studies have found that various measures of neighborhood poverty are associated with higher re-reporting, though these were done in the same state (Drake et al., 2006; Jonson-Reid, Drake, & Zhou, 2013; Jonson-Reid, Emery, Drake, & Stahlschmidt, 2010). Another study found that community demographic profile but not poverty *per se* was associated with re-reporting (Maguire-Jack & Font, 2014).

2.4. Index report characteristics

The initial report type and disposition are not modifiable once a CPS report is made and the research linking initial report type to re-reporting is mixed. When maltreatment type is measured, children reported for neglect often have higher risk of re-reporting (White et al., 2015). Across studies, case disposition (i.e., substantiation) has had no or a small association with re-reporting (Drake, Jonson-Reid, Way, & Chung, 2003; Kohl et al., 2009; White et al., 2015; Zhang, Fuller, & Nieto, 2013).

2.5. Person-centered analytic approaches

Given the variability in the number of factors tested consistently in the research, many gaps in our understanding of recurrence remain. We know even less about how combinations of factors within subgroups of CPS involved families may impact risk. In other words, it is possible that a given variable may not be predictive alone but may combine with others to form meaningful classifications of families (Putnam-Hornstein & Needell, 2011; Roesch et al., 2010). Although the use of interaction terms in variable centered models may improve our understanding of joint effects, testing of interaction terms in the published re-reporting literature is also rare. Only one known published study has applied a latent class approach to understand the risk of re-reporting. Using birth records linked to CPS records, Eastman et al. (2016) identified two low risk classes, a medium risk and a high-risk class among infants that were then tested to see if they predicted a subsequent report within five years. Their study included families with prior reports as well as screened out cases and was limited to a single state. Two of the classes were defined largely by non-modifiable factors (maternal age at birth, prior CPS history). There are two other studies of re-reporting that have used a partitioning approach that clustered subjects, but the clusters are based on individual variables that represent significant "splits" based on re-report status (Dakil et al., 2011; Sledjeski, Dierker, Brigham, & Breslin, 2008). These approaches tend to yield few variables of interest and do not produce classes of people per se.

2.6. Present study

The present study applies a latent class approach to attempt to identify meaningful classes of risk of recurrence based on caregiver and CPS worker report among families with children under that age of 15 and limited to first-time reports using the National Surveys of Child and Adolescent Well-being (NSCAW) I and II. The research aims are as follows:

1 To explore the utility of a latent class approach to identify meaningful subgroups of families with first time investigated reports of maltreatment based on modifiable risk factors derived from baseline data collection. This remains exploratory as only one prior study of re-reporting used a similar approach but was limited to risk present among infants and included families with prior CPS history in a single state (Eastman et al., 2016).
2 To explore whether risk classes at baseline were associated with later differences in the likelihood of re-reporting within 36 months. This aim is dependent on the success of Aim 1.
3 The final aim was to examine whether the class solution (number of classes and item response probabilities) remained stable over time. There is a nearly 10-year difference in baseline data collection for NSCAW-I and NSCAW-II with NSCAW-II collected just as the economic recession began.

3. Method

The present analysis used data from the two National Surveys of Child and Adolescent Well-Being—NSCAW-I and NSCAW-II (National Data Archive on Child Abuse & Neglect, 2020a; National Data Archive on Child Abuse & Neglect, 2020b) obtained by permission of one of the authors. The two NSCAW studies follow two different samples, each nationally representative of the child welfare population with investigated reports that are then followed across several waves. NSCAW-I sampled children ages birth to 15 and families after a closed investigation from October 1999 through December 2000 and NSCAW-II baseline sampling occurred from February 2008 through April 2009. The decision to conduct separate analyses using both studies was made to determine if both the class solution and any association with the likelihood of a re-report remained stable across the two time periods. Human subjects' approval was granted by the XXX [omitted for blind review] university human subjects committee for both the license to use NSCAW from the National Data Archive on Child Abuse and Neglect and the present analyses.

3.1. Sample

NSCAW studies used a two-stage cluster sampling design and select one child per family. NSCAW-I included 5,501 children sampled from 92 primary sampling units PSU: generally county CPS agencies, clustered in nine strata, eight individual large states and a final strata containing small samples from several states. About 10 years later, NSCAW-II included 5,251 children excluding 621 cases that were only included for a state's supplementary baseline study selected from 77 PSUs in eight strata. Some states participating in NSCAW-I did not participate in NSCAW-II.

The present study was focused on improving understanding of a first re-report and excluded children with prior reports leaving 2,585 NSCAW-I and 2,626 NSCAW-II children. Second, 617 NSCAW-I children and 883 NSCAW-II children placed into foster care right after the first report were excluded because caregiver characteristics referred to foster parents not caregivers in the family of origin. Finally, 42 NSCAW-I and 108 NSCAW-II children aged over 14 years were excluded to assure the full sample was eligible did not turn 18 for a re-report in the 36-month follow-up period. This resulted in 2,257 NSCAW-I children and 1,634 NSCAW-II children available for analyses.

3.2. Data collection and measures

Risk indicators for the present study were derived from questions asked during baseline interviews with caregivers and CPS workers. NSCAW-I conducted baseline interviews with caregivers within 2–6 months after the close of the index report investigation and CPS workers within 12 months of the closure. NSCAW-II conducted CPS worker interviews closer to baseline but had a rolling period of baseline data collection and documentation is less specific about the interview timing. Both initial CPS and caregiver interviews asked about subjects to respond about baseline conditions.

3.2.1. Dependent variables

There are two outcomes of interest for the present study: the creation of risk classes (i.e., subgroups of families) based on latent class analyses and then, if successful, testing if classes predict a re-report up to 36 months later. Unweighted re-report rates were 19.9 % for NSCAW-I and 24.0 % for NSCAW-II, and weighted re-report rates were 18.5 % for both studies. NSCAW-I relied primarily on caseworker recall of re-reporting at follow-up interviews (Smith et al., n.d.). The administrative data linkage was better for NSCAW-II and researchers advise using both caseworker report and official records for this study (Casanueva et al., 2015).

3.2.2. Risk indicators

Based on the literature, we constructed eleven risk indicators (see below) from original study items (see Table 1) and used these "manifest" indicators to identify "latent" subgroups. The focus was on modifiable factors or stressors that could be buffered by services at various levels of the ecology. For simplicity given the exploratory nature of the application of the method, we dichotomized indicators. When there were both caregiver self-report and child welfare caseworker reports for the same baseline characteristic these were included as any "yes" for that indicator. Most items had no missing values or had very low rates (mostly < 10 %). We treated missing values as "no" to represent "identified" as compared to not identified risk factors, which more closely represents how information (either known or not known) is available to a child welfare worker in the field. While CPS worker interviews occurred after caregiver interviews, the caregiver questions typically asked for responses based on a situation or event within the past 12 months. In other words, both informants were responding in regard to the same time period.

1 *Childcare burden*: Some prior studies suggest that the risk of recurrent maltreatment is higher among families with a higher childcare burden, which may include having a younger child, more children, and/or a child with developmental or health problems. While not modifiable, there are respite, parenting and childcare services that could potentially reduce the strain. The combination of the factors was due to sample size.
2 *Low socio-economic status (SES)*: We measured a family's low SES by an indicator of poverty status and/or employment status.
3 *Material hardship*: Compared to prior studies using CPS risk/safety assessment (e.g., Sledjeski et al., 2008), we based the variable on observable measures of family's material hardship based on receipt or need of relief services (e.g., emergency shelter or food pantry).
4 *Domestic violence*: Caregiver's domestic violence exposure has receive less attention in the re-reporting literature, but is commonly comorbid with maltreatment and noted as requiring specialized

Table 1
Unweighted Descriptive Statistics for NSCAW I (N = 2,257) and NSCAW II (N = 1,634).

Variable	Measure	NSCAW I	NSCAW II
Latent class indicator		n (%)	n (%)
Care burden	Caregivers (CG) meeting any of the following conditions:	1409 (62.4)	1038 (63.5)
	(1) having a child aged 2 years or younger[3,4]	*936 (41.5)*	*851 (52.1)*
	(2) having more than 4 children[3,4]	*147 (6.5)*	*125 (7.7)*
	(3) having a child with developmental issues[3]	*457 (20.3)*	*216 (13.2)*
Low SES	CG meeting any of the following conditions:	1441 (63.9)	1123 (68.7)
	(1) no CG working regularly[3]	*633 (28.1)*	*727 (44.5)*
	(2) having income under Federal poverty line[3]	*1310 (58.0)*	*878 (53.7)*
Material hardship	CG meeting any of the following conditions:	308 (13.7)	490 (30.0)
	(1) received (past 12 m (months)) food from a community source[3]	*236 (10.5)*	*332 (20.3)*
	(2) received (ever) or needed (past 12 m) emergency shelter/housing[3]	*109 (4.8)*	*247 (15.1)*
Domestic violence	CG meeting any of the following conditions:	653 (28.9)	518 (31.7)
	(1) needed (past 12 m) domestic violence services[4]	*206 (9.1)*	*263 (16.1)*
	(2) active domestic violence at the time of CPS investigation[4]	*288 (12.8)*	*206 (12.6)*
	(3) self-reported (CTS2) severe violence by a partner (past 12 m)[3]	*378 (16.8)*	*358 (21.9)*
Substance abuse	CG meeting any of the following conditions:	429 (19.0)	435 (26.6)
	(1) needed (past 12 m) services for drug problems[4]	*172 (7.6)*	*231 (14.1)*
	(2) active drug abuse at the time of CPS investigation[4]	*301 (13.3)*	*289 (17.7)*
	(3) overnight admission/ER visit (past 12 m) for alcohol/drug issues[3]	*20 (0.9)*	*46 (2.8)*
	(4) required (past 12 m) by CPS to receive alcohol/drug services[3]	*36 (1.6)*	*130 (8.0)*
	(5) self-reported drug abuse (CIDI-SF DD[1] *≥ 3; DAST-20*[2] *≥ 3)*[3]	*89 (3.9)*	*188 (11.5)*
Mental health	CG meeting any of the following conditions:	775 (34.3)	534 (32.7)
	(1) needed (past 12 m) services for mental health (MH) problems[4]	*237 (10.5)*	*247 (15.1)*
	(2) serious MH problems at the time of CPS investigation[4]	*249 (11.0)*	*187 (11.4)*
	(3) overnight admission/ER visit/day Tx for MH (past 12 m)[3]	*43 (1.9)*	*69 (4.2)*
	(4) required (past 12 m) by CPS to receive MH services[3]	*41 (1.8)*	*64 (3.9)*
	(5) self-reported poor MH (SF-12: standardized MH score < 40)[3]	*512 (22.7)*	*287 (17.6)*
Low social support	CG meeting any of the following conditions:	1528 (67.7)	1259 (77.1)
	(1) no another CG in home at the time of CPS investigation[4]	*1238 (54.9)*	*873 (53.4)*
	(2) having low social support at the time of CPS investigation[4]	*557 (24.7)*	*303 (18.5)*
	(3) self-reported low social support (SSQ3[1] *< 3; FSSQ*[2] *≤ 4)*[3]	*273 (12.1)*	*773 (47.3)*
CA/N history	CG have history of child maltreatment as a child[4]	379 (16.8)	266 (16.3)
Criminal history	CG have ever arrested for any offense[3,4]	653 (28.9)	549 (33.6)
Parenting need	CG meeting any of the following conditions:	281 (12.5)	459 (28.1)
	(1) received (past 12 m) parenting skill/home management training[3]	*260 (11.5)*	*407 (24.9)*
	(2) required (past 12 m) by CPS to receive these services[3]	*119 (5.3)*	*273 (16.7)*
Community	CG has a negative view on their neighborhoods (PFMS mean ≥ 1)[3]	425 (18.8)	283 (17.3)
Group variables			
Child sex	Female	1101 (48.8)	783 (47.9)
Child race	Non-Hispanic Black	677 (30.0)	402 (24.6)
	Non-Hispanic White	974 (43.1)	590 (36.1)
	Hispanic	421 (18.7)	509 (31.2)
	Other race	185 (8.2)	133 (8.1)
CA/N type	Neglect only	896 (39.7)	702 (43.0)
	Physical abuse only	427 (18.9)	230 (14.1)
	Sexual abuse only	182 (8.1)	67 (4.1)
	Other type only	463 (20.5)	381 (23.3)
	Multiple types	289 (12.8)	254 (15.5)
Substantiation	Substantiated/indicated index CAN report	1211 (53.7)	670 (41.0)
Outcome	Re-report of child maltreatment by 36-month follow-up[4]	417 (18.5)	359 (22.0)

Measure abbreviations: CIDI-SF DD: Composite International Diagnostic Interview-short form drug dependence. DAST-20: drug abuse screening test score. SSQ3: social support questionnaire μ score. FSSQ: functional social support μ score. CTS2: revised conflict tactics scale. SF-12: short-form health survey. PFMS: Philadelphia family management study.
[1]NSCAW I [2] NSCAW II [3] Caregiver interviews [4] Caseworker interviews.

screening and services (Hamby, Finkelhor, Turner, & Ormrod, 2010; Kohl & Macy, 2008; Sledjeski et al., 2008).

5 *Substance abuse*: Any mention of caregiver's drug or alcohol abuse was combined to establish this indicator.
6 *Mental health*: This variable included any indicator of mental health disorder as reported by the CPS worker or as noted in the caregiver interview.
7 *Low social support*: This indicator included caregiver's direct report of low social support and/or single-parent status. Lower social support particularly in the context of single parenting may exacerbate childcare burden (Harknett & Hartnett, 2011).
8 *CA/N history*: This is an indicator of caregiver's own child abuse and neglect victimization history, which may be a risk factor requiring attention to the particular trauma, emotional regulation or social connection issues resulting from that experience (Berlin, Appleyard, & Dodge, 2011).
9 *Criminal history*: The caregiver had a noted criminal history. Such a history may require additional attention to barriers to employment as well as possible history of separations from the child(ren) in the past (Phillips, Dettlaff, & Baldwin, 2010).
10 *Parenting need*: We measured parenting need by receipt of, or request for, parenting skill or home management training.
11 *Community*: NSCAW studies have no small area-level data. We therefore used caregiver's perception of their neighborhood, a recommended approach for understanding maltreatment incidence (Coulton et al., 2007).

3.2.3. Grouping variables

The goal of the analysis was to develop risk profiles based on modifiable factors. It cannot be assumed that demographic or index report characteristics lack influence, nor is it clear how much influence such factors exert once significant factors are controlled. For example, there is great concern regarding racial disparity in maltreatment reporting, particularly between Blacks and Whites, but this typically disappears or even reverses after controlling for risk factors like socioeconomic status (Drake, Lee, & Jonson-Reid, 2009; Kim & Drake, 2018; Maloney, Jiang, Putnam-Hornstein, Dalton, & Vaithianathan, 2017; Putnam-Hornstein, Needell, King, & Johnson-Motoyama, 2013). While child neglect typically recurs more frequently in the literature, Eastman et al. (2016) found that neglect loaded across all risk groups. Four demographic and maltreatment report variables were included in posthoc tests of invariance: child sex, racial/ethnic group, index maltreatment type, and index report disposition. Child race/ethnicity was categorized into non-Hispanic White, non-Hispanic Black, Hispanic, and others. Index report maltreatment types was measured as neglect only, physical abuse only, sexual abuse only, other type only, and multiple types. Substantiation was coded as “substantiated” for substantiated or indicated index reports or “unsubstantiated”.

3.3. Analysis

We used latent class analysis (LCA) to attempt to identify subgroups of families based on modifiable risk factors at the time of baseline interviews. LCA is used to classify individuals/cases into distinctive groups (i.e., latent classes) based on their responses/outcomes across a set of observed variables (Clogg, 1995; McCutcheon, 1987). Latent classes are defined based on the probabilities of risk indicators (item response probabilities or IRP) conditional on latent class membership. Put simply, families are grouped into classes based on combinations of risk indicators and then these combinations are used to label the risk profile. Within latent classes, it is assumed that there are no significant associations between the manifest indicators that make up those classes (Asparouhov & Muthén, 2015). We followed Asparouhov and Muthén (2015) procedure to address this assumption. Conditional dependence is identified by the Pearson test statistic. When this statistic exceeded 10, corresponding residual associations between pairs of items within the LCA were further assessed by including these associations in an LCA model, known as an LCA model with uniform associations (Asparouhov & Muthén, 2015). The decision to include a residual association in the LCA model was based on the *T* test of the modeled association and its contribution to the overall model fit as suggested by Asparouhov and Muthén (2015).

To select an optimal model for the LCA, we chose the BIC (Bayesian Information Criterion). A simulation study found the BIC to be the best indicator among information criterion indicators (i.e., AIC, BIC, CAIC, and adjusted BIC) (Nylund, Asparouhov, & Muthén, 2007). While the same study found that the bootstrap likelihood ratio test (BLRT) was a more consistent indicator, the BLRT cannot be used while modeling residual associations. A model with a lower BIC value is favored as a balance between parsimony and model fit. We used BIC to guide decisions about the inclusion of residual associations, the optimal number of latent classes, and measurement equivalence (i.e., invariance) tests. Final decisions were also based on model interpretability according to the following three criteria: (1) whether every class is sufficient in size; (2) whether each class is distinguishable with regard to risk factors; and, (3) whether we can meaningfully define each latent class (Wang & Wang, 2012). Regarding classification quality, we considered the entropy value (ranging from 0 to 1): - 0.8 is considered high, 0.6 medium, and 0.4 as low quality (Wang & Wang, 2012). We also examined the average posterior class probability, where a value over 0.7 indicates acceptable classification quality (Masyn, 2013). We examined IRP conditional on latent classes to create the definition.

3.3.1. Measurement invariance

Last, we examined whether the risk profile was consistent across possible non-modifiable grouping variables (i.e., child sex, race/ethnicity, maltreatment type, and substantiation status). This approach avoids potential misclassification of covariate effects in deciding the number of classes (see Nylund-Gibson & Masyn, 2016). This was done by conducting multiple group analyses and compared a model fixing the item response probabilities as equal across the categories of a grouping variable (i.e., a measurement equivalence model) and a model allowing the item response probabilities to differ by a grouping variable (i.e., a measurement non-equivalence model) (see Kankaraš & Moors, 2009). In other words, we checked to see if the risk profile (defined by IRP) for each latent class differed by these grouping variables. When similar tests of invariance indicate significant variation, various options exist such as including them as co-variates in the prediction of later outcomes (e.g., Ayer et al., 2011).

3.3.2. Re-report probability

The second aim of the study was to see if the baseline classes predicted a later outcome (similar to Ayer et al., 2011; Eastman et al., 2016). Due to NSCAW’s multi-stage, clustered sampling design, researchers are warned not to exclude unwanted cases in order to avoid obtaining incorrectly weighted estimates (Dowd et al., 2013). The use of domain analysis is recommended to obtain weighted estimates separately for each group. A limitation of the application of domain analysis to LCA is that the unwanted domains (e.g., children with prior reports) influence overall model fit, which is used to determine the optimal number of latent classes. To prevent unwanted cases from shaping latent classes, we physically subsetted unwanted cases and conducted LCA in Mplus without weighting. Then, to facilitate inference back to the study population, we weighted the prevalence of the identified latent classes among retained cases by using domain analysis including both retained and excluded cases. NSCAW I and II provide the weighting, cluster, and strata variables to weight the stratified, clustered data with unequal selection probabilities to the US population (Dolan, Smith, Casanueva, & Ringeisen, 2011). Attrition is treated in the original data by giving a “0” weight (15.91 % of NSCAW I and 16.46 % of NSCAW II). Because exact dates were unreliably collected, re-report was simply a nominal variable (coded as “yes” or “no”). Due to weighting, PROC SURVEYFREQ in SAS 9.4 was used to test the association of the predicted risk classes with re-reporting.

4. Results

Table 1 presents the unweighted descriptive statistics for the study families. The majority of both NSCAW-I and NSCAW-II families had low socioeconomic status (63.9 % and 68.7 %, respectively). There proportion of risk factor endorsement of selected items was similar across the two studies, though the endorsement of material hardship, substance abuse and parenting needs was slightly higher among NSCAW-II families. Consistent with changing demographics in sampled states, there was a higher proportion of Hispanics among NSCAW-II families (31.2 %) compared to NSCAW-I families (18.7 %). The proportion of sexual abuse cases was higher in NSCAW-I (8.1 %) than in NSCAW-II (4.1 %) as NSCAW-I oversampled sexual abuse cases while NSCAW-II did not. After weighting and adjusting for attrition, the re-report probabilities were 18.5 % for both NSCAW-I and II (which is recognized as low for reasons explained in the methods section).

4.1. Comparison of competing latent class models

Competing models were examined to determine the optimal number of classes. Table 2 presents the values for log-likelihood, BIC, and entropy (a classification quality indicator) along with the number of pairs of items with Pearson test statistics > 10 (an indicator for residual associations) and the number of parameters in the LCA. Associations

Table 2
Latent Class Analysis Models.

Model	Log-likelihood	BIC	Entropy	No. of item pairs with Pearson > 10	No. of parameters
NSCAW I					
1-class LCA	−13516.3	27117.6	1.00	33	11
2-class LCA	−13215.6	26608.8	0.47	6	23
2-class LCA-UA	−13129.8	**26483.6**	0.44	0	29
3-class LCA	−13172.3	26614.9	0.48	3	35
3-class LCA-UA	−13121.3	26536.1	0.45	0	38
4-class LCA	−13129.3	26621.5	0.52	1	47
4-class LCA-UA	−13110.1	26590.8	0.53	0	48
5-class LCA	−13102.1	26659.8	0.52	0	59
6-class LCA	−13080.6	26709.4	0.49	1	71
6-class LCA-UA	−13070.5	26696.9	0.48	0	72
7-class LCA	−13060.6	26762.2	0.55	0	83
8-class LCA	−13045.2	26824.0	0.56	0	95
9-class LCA	−13031.2	26888.7	0.59	0	107
NSCAW II					
1-class LCA	−10457.7	20996.8	1.00	32	11
2-class LCA	−10148.3	20466.8	0.54	8	23
2-class LCA-UA	−10035.0	**20306.8**	0.51	0	32
3-class LCA	−10089.0	20437.0	0.57	4	35
3-class LCA-UA	−10000.8	20312.3	0.52	0	42
4-class LCA	−10048.6	20445.0	0.56	2	47
4-class LCA-UA	−10029.8	20414.8	0.52	0	48
5-class LCA	−10005.9	20448.4	0.53	1	59
5-class LCA-UA	−9995.7	20435.3	0.53	0	60
6-class LCA	−9986.7	20498.8	0.58	0	71
7-class LCA	−9966.8	20547.8	0.61	0	83
8-class LCA	−9950.0	20602.8	0.65	0	95
9-class LCA	−9937.8	20667.2	0.66	0	107

LL = log-likelihood. BIC = Bayesian information criterion. Pearson = Pearson test statistic for a residual association. LCA = Latent class analysis. LCA-UA = Latent class analysis with uniform associations.

between items were largely explained by latent classes. For example, the number of item pairs with Pearson statistics > 10 decreased from 33 to six (NSCAW I) and from 32 to eight (NSCAW II) as the number of latent classes increased from one to two (Table 2). Several pairs of items still showed substantial residual associations in the LCA, leading to their addition into the LCA model. In LCA models with uniform associations (LCA-UA), no pairs of items had a Pearson statistic > 10 (Table 2), indicating no severe misfit due to residual associations. The parameters column changes with the 11 item responses, the number of classes, and whether residual associations are added. For example, the single class LCA for NSCAW I had 11 parameters that estimated the 11 item-response probabilities (IRPs). The 2-class LCA had 23 parameters that estimated the 22 IRPs of the 11 items conditional on the "two" latent classes and the membership probability of Class 1 (the membership probability of Class 2 is not subject to estimation as it is decided by 1 – "the Class 1 probability"). The final 2-class LCA-UA model had 29 parameters: 23 parameters of two-class LCA + 6 residual associations (for the 6 item pairs with Pearson > 10 in the 2-class LCA). As shown in Appendix Table S1, the average posterior class probabilities were well above the acceptable .7 cutoff for both the two class LCA and LCA-UA models. The list of residual associations added in LCA-UA models is available in the Appendix (Table S2).

The BIC, as well as the interpretability criteria, supported the 2-class LCA-UA model in both NSCAW I and II. The 2-class LCA-UA had a substantially lower BIC value than the 2-class LCA: 26483.6 versus 26608.8 in NSCAW I and 26306.8 versus 20466.8 in NSCAW II. This indicated that that adding residual associations in a model substantially increased model fit. No higher-class LCA and LCA-UA models had a lower BIC value than the 2-class LCA-UA, suggesting that higher complexity (i.e., adding more parameters) did not increase model fit at a meaningful degree.To assess classification quality, we examined entropy and average posterior class probabilities. These indicators are not used for deciding the number of latent classes, but values near zero suggest a high degree of error in classifying subjects into latent classes (Masyn, 2013). The final models (i.e., 2-class LCA-UA models) showed low to medium entropy values (0.44 for NSCAW I and 0.51 for NSCAW II). No clear cutoff exists. While entropy indicates overall classification quality, the average posterior class probability indicates classification quality for each of the latent classes (Masyn, 2013). As shown in Appendix Table S1, average posterior class probabilities were over 0.7 for both NSCAW I (0.84 for Class 1 and 0.80 for Class 2) and NSCAW II (0.84 for Class 1 and 0.86 for Class 2), suggesting that each class was adequately separated and assignment accuracy acceptable (Masyn, 2013, p. 570). We examined item response probabilities (IRP) (i.e., probabilities of risk indicators conditional on latent classes) to define the two latent classes. IRP are depicted in Fig. 1 and are also available in Table S3 in the Appendix. For both NSCAW I and II, Class 1 IRP were higher than in Class 2 IRP, and we labeled Class 1 as the *high-risk* class and Class 2 as the *low-risk* class. Specific probabilities were, however, different across risk indicators, latent classes, and NSCAW-I and II. For both NSCAW-I and II, Class 1 included low social support, low SES, and high child care burden (IRP > 0.7). Class 1 in NSCAW I also showed moderate risk for mental health, domestic violence, and criminal history (0.7 > IRP > 0.3), while Class 1 in NSCAW II also included moderate risk for criminal history, substance abuse, parenting need, and material hardship. Generally, endorsement of needs regarding substance abuse, parenting, and material hardship showed a noticeable increase between the two NSCAW studies. The second study period coincides with onset of increasing opioid concerns as well as the 2008/2009 recession. Class 2 had lower risk of low social support, low SES, and care burden in NSCAW I but the risk of low social support in this class increased substantially in NSCAW II (the IRP of low social support became greater than 0.7). A large difference in IRP between Class 1 and 2 indicates a high degree of class separation (i.e., odds ratio of Class 1 IRP to Class 2 IRP > 5 or < 0.2) (Masyn, 2013). Mental health, substance abuse, and CA/N history showed a high degree of class separation in NSCAW I. In addition to these indicators, care burden and parenting need also showed a high degree of class separation in NSCAW

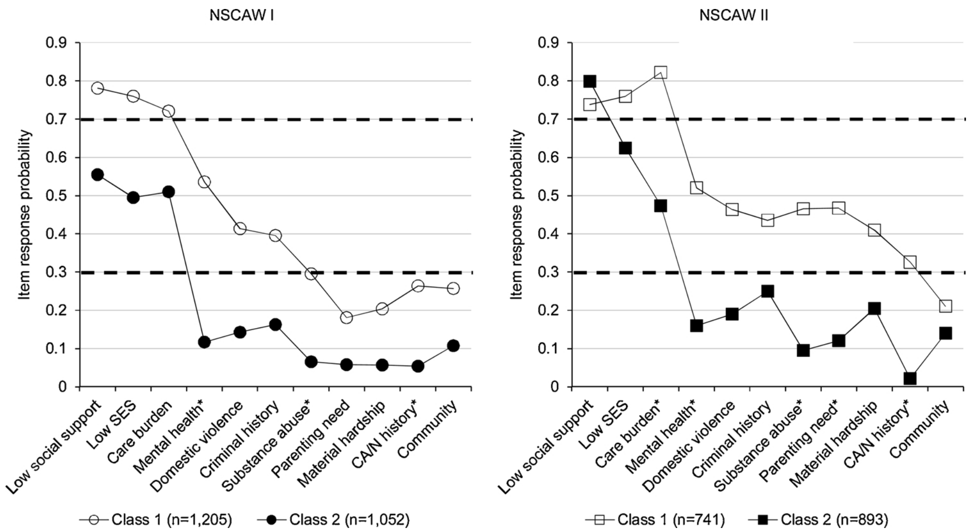

Fig. 1. Item response probabilities for the final latent class analysis model.
For both NSCAW I and II, the 2-class LCA-UA model is the final model (Table 2). Item response probabilities (IRP) > 0.7 or < 0.3 indicates a high degree of class homogeneity. *Odds ratios of class-1 IRP to class-2 IRP > 5 or < 0.2, indicating a high degree of class separation.

II.

4.1.1. *Measurement invariance*

As illustrated in Table 3, for all grouping variables in both NSCAW I and II, measurement equivalence models showed a lower BIC value than a measurement non-equivalence model, indicating that class-specific IRP (i.e., probabilities of risk indicators) were not meaningfully different between categories of a grouping variables. These findings suggested that we could move forward with the overall classes of *high/low* risk without adjusting for the non-modifiable factors in later analyses of re-report.

Similar to Table 2, the parameters column changes according to the number of item response probabilities, classes and response levels of grouping variables. Additionally, the number of parameters are impacted by whether the model is based on measurement equivalence or non-equivalence.

4.2. *Prevalence of latent classes and Re-report probabilities*

Table 4 presents the prevalence of latent classes at baseline and re-report probabilities within the 36-month follow-up period. The unweighted values indicated that 53.4 % of the NSCAW-I sample and 45.3 % of the NSCAW-II sample were classified into the *high-risk* class. When we weighted the values to infer the NSCAW target population with a first-time CPS contact for a subject child under age 15 and not placed in foster care, 44.0 % (95 % CI = 39.5–48.4) of NSCAW-I and 23.7 % (20.3–27.1) of NSCAW-II families were classified as *high-risk*.

The *high-risk* families had substantially higher probabilities of maltreatment re-reports by 3 years than the *low-risk* families. Before weighting, the re-report probabilities were 25.5 % for the *high-risk* families versus 13.1 % the *low-risk* families in the NSCAW-I sample and 30.2 % versus 18.5 % in the NSCAW-II sample. After weighting, the re-report probabilities of the *high-risk* families versus the *low-risk* families were 28.2 % (19.7–36.7) versus 11.1 % (7.0–15.3) for NSCAW-I families and 26.7 % (20.5–32.8) versus 15.8 % (11.1–20.4) for NSCAW-II families (Fig. 2). NSCAW I showed slightly better specificity than analyses based on NSCAW II (i.e., 11.1 % versus 15.8 %), though this difference was not statistically significant at the population level due to the large confidence intervals after weighting. The sensitivity of latent classes (i.e., having re-reports among the high risk class) was practically the same and not significant between NSCAW I and II.

5. Discussion

CPS has continued to struggle with the best means of assessing risk among clients to prevent recurrence, with few studies limited to families at the time of a first report. By using a person-centered approach we identified two subgroups of families (*high* and *low-risk),* that took into account the presence of multiple modifiable stressors and appeared to have predictive utility in regard to later re-report. While the proportion of families with endorsement of specific risk indicators did change between the two samples, the groupings remained similarly predictive across NSCAW I and II samples.

The utility of latent classes at one point in time in predicting recurrence is consistent with Eastman et al. (2016), however there were more classes identified in the prior study. There are multiple reasons

Table 3
Multiple-Group Analysis of the Final Latent Class Analysis Model.

	Measurement equivalence				Measurement non-equivalence			
	LL	BIC	Entropy	No. of param.	LL	BIC	Entropy	No. of param.
NSCAW I								
Child sex	−14693.5	**29626.4**	0.72	31	−14669.8	29748.8	0.73	53
Race/ethnicity	−15919.5	**32109.4**	0.82	35	−15793.8	32367.5	0.83	101
Maltreatment type	−16430.2	**33146.2**	0.84	37	−16216.4	33398.0	0.84	125
Substantiation	−14635.7	**29510.7**	0.75	31	−14599.1	29607.5	0.72	53
NSCAW II								
Child sex	−11166.2	**22583.9**	0.76	34	−11147.5	22709.4	0.76	56
Race/ethnicity	−12121.3	**24523.8**	0.84	38	−12028.0	24825.6	0.85	104
Maltreatment type	−12299.7	**24895.4**	0.86	40	−12189.4	25325.8	0.88	128
Substantiation	−11068.9	**22389.4**	0.78	34	−11020.9	22456.2	0.74	56

LL = log-likelihood. BIC = Bayesian information criterion. param. = parameters. For both NSACW I and II, the 2-class LCA-UA model is the final model (Table 2).

Table 4
Prevalence of Class and Re-Report by the Final Latent Class Analysis Model.

	NSCAW I				NSCAW II			
	Unweighted		Weighted		Unweighted		Weighted	
	n	%	n	% (95 % CI)	n	%	n	% (95 % CI)
Baseline								
Class 1	1,205	53.4	500,730	44.0 (39.5–48.4)	741	45.3	235,607	23.7 (20.3–27.1)
Class 2	1,052	46.6	638,319	56.0 (51.6–60.5)	893	54.7	760,134	76.3 (72.9–79.7)
36-month								
Total								
Re-report	377	19.9	204,781	18.5 (13.9–23.2)	328	24.0	184,858	18.5 (14.2–22.7)
No	1,521	80.1	899,951	81.5 (76.8–86.1)	1,037	76.0	816,127	81.5 (77.3–85.8)
Class 1								
Re-report	264	25.5	134,995	28.2 (19.7–36.7)	194	30.2	66154	26.7 (20.5–32.8)
No	771	74.5	343,448	71.8 (63.3–80.3)	448	69.8	181694	73.3 (67.2–79.5)
Class 2								
Re-report	113	13.1	69,785	11.1 (7.0–15.3)	134	18.5	118,704	15.8 (11.1–20.4)
No	750	86.9	556,503	89.0 (84.7–93.0)	589	81.5	634,433	84.2 (79.6–88.9)

For both NSACW I and II, the 2-class LCA-UA model is the final model (Table 2).

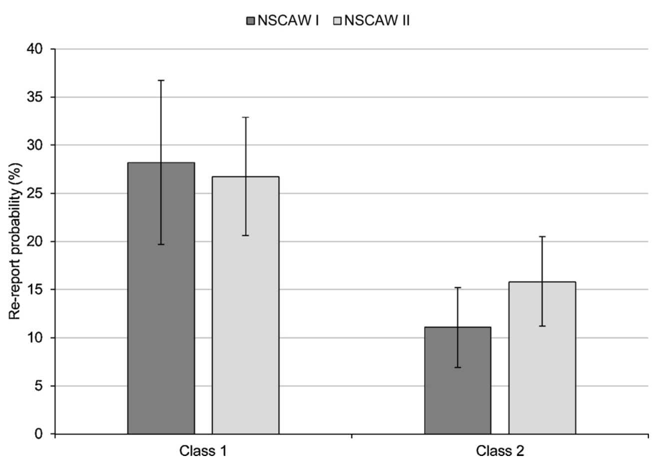

Fig. 2. Weighted child maltreatment re-report probabilities until 36-month follow up by latent class.

this may have occurred given the significant differences in the data used and sampling frames. Eastman et al. (2016) focused on re-reports within five years based on classes developed among infants using birth record information and limited CPS data in a single state. They also included families that had prior CPS contact (albeit not necessarily in regard to the same child). NSCAW studies include ages birth to 15 years, across urban areas from multiple states, and are limited to data taken from subject interviews and child welfare records (Dolan et al., 2011). Very young children have the highest rate of reported maltreatment (U.S. Department of Health & Human Services, Administration for Children & Families & Administration on Children, Youth & Families, Children's Bureau, 2020) and risk at birth (including variables derived from birth characteristics) may be more predictive of recurrence in young children. For example, although Palusci (2011) grouped infants with children ages 2–4, there were distinct risk factor differences between children ages birth to 4 and children over 5 in risk of recurrence. In the present study, we also attempted to limit the data to families at their first report. The constellation of factors important to families early in their CPS careers may be different than those who have had prior reports. Before discussing findings in more depth, we review the study's primary strengths and limitations.

5.1. Strengths and limitations

Strengths of the present study include the use of data from national probability samples, the ability to test the similarities of classes across two time periods, and the application of an analytic approach that is relatively rare in child welfare research (Eastman et al., 2016; Roesch et al., 2010). Another strength is that this study attempts to address multiple assumptions and recommendations regarding the development and selection of classes (Asparouhov & Muthén, 2015; Wang & Wang, 2012). Another strength is the potential to use risk indicators with a large gap in IRP between classes (i.e., the low and high-risk class) as targets for intervention that are also potentially available to child welfare workers during an assessment.

However, there were also significant limitations. The sampling design of NSCAW largely omits rural populations and is not representative of all policy contexts due to the focus on large child welfare serving states. The observed classes might change with the inclusion of rural families or greater representation of states with unique screening protocols or definitions of maltreatment. Also, the risk indicators selected were limited by the data available in the study. Future studies should explore risk profiles based on additional risk indicators and across different regions. As stated earlier, there may be important gains to identifying risk profiles using multiple data sources which may also vary by age of the child. Another limitation was that for simplicity, we dichotomized risk indicators. Future studies should assess consistency between classes identified by binary items and classes estimated by more nuanced approaches, such as measuring multiple ordered categories for risk indicators or using latent profile analysis for continuous indicators. On the other hand, the fact that the simple classification resulted in classes that had practical utility in predicting recurrence within samples of families at the time of a first report is promising. It was also not possible to follow the original NSCAW weighting strategy for the creation of the classes because of the need to focus on children with a first report and not immediately placed into foster care. Although the final classes were weighted for prevalence and probabilities of re-reporting, this process may have resulted in some unmeasured variability. On the other hand, the difference in predicted re-reporting was quite large and seemingly robust to small amounts of error.

5.2. Lessons learned

One advantage of our approach is that it makes no assumption of linear relationships and allows for complex combinations of variables to define a group of persons. The item responses that led to the class typologies triangulate well with the types of risk factors identified in prior variable-oriented findings (e.g., White et al., 2015). On the other hand, there is significant heterogeneity in findings from prior variable-based approaches (Jonson-Reid et al., 2019). Typologies may be more useful in regard to how various factors within a family and their context combine to increase or decrease risk. While having a single high-risk class endorsing multiple needs is not ideal from the standpoint of parsimony in analyses or guiding of targeted interventions, the constellation of risk is consistent with research on families involved with child welfare at high risk of recidivism (Jonson-Reid et al., 2010; Millett, Ben-David, Jonson-Reid, Echele, & Moussette, 2016; Thompson & Colvin, 2018). This is also consistent with the idea that cumulative risk may be more important that the presence or absence of a specific factor (Putnam-Hornstein & Needell, 2011). Using some form of a person-centered approach to assessment and case planning may hold promise for child welfare organizations trying to target scarce resources to the highest need families.

While the overall class structure remained stable across the two samples from different time periods, there was an indication that family risk profiles may be sensitive to broader trends like the "great recession." The probability of material need within the high risk class more than doubled in the approximately10 year gap. Some research indicates promise in reducing re-reporting through the provision of concrete support (Rostad, Rogers, & Chaffin, 2017). Such approaches may yield higher benefits in periods when rates of material needs are the highest. It is less clear why the parenting need indicator was more prevalent in the second NSCAW study. It is possible that this was related to changes in measurement, or changes in sampling more families that received services in NSCAW II, or other study artifacts.

Any approach to risk assessment must be feasible as well as effective. LCA may be more difficult to apply in the field compared to traditional risk and safety assessment tools. LCA does better, however, in accounting for measurement error than a traditional approach and it is possible to translate classes into profiles useful in field assessment. Several of the 11 factors we used are relatively easy to assess in the field based solely on data available from the report or immediate assessment (number of children, age of children, material needs and poverty, neighborhood conditions). Other items can be asked using very short instruments such as the AAS, a five item screener for domestic violence (Rabin, Jennings, Campbell, & Bair-Merritt, 2009), or the 5 item CAGE AID for substance abuse (SAMSHA, 2017). While these require scoring, this could automated on a cell phone app or tablet as part of the initial assessment and before service provision decisions are made. As advances in linked data systems are made (e.g., Jonson-Reid et al., 2010; Putnam-Hornstein & Needell, 2011; Putnam-Hornstein, King, & Rhodes, 2013), additional data may also be readily available, such as criminal history and treatment for mental health disorders. An algorithm could be easily programmed into a handheld application that could provide a high or low risk profile based on the data elements.

There are of course other emerging technologies promising to improve assessment of risk or even case finding that go beyond traditional variable based models. For example, machine learning approaches like predictive risk modeling (PRM) rely on finding patterns among variables present in existing data systems (Vaithianathan, Maloney, Putnam-Hornstein, & Jiang, 2013; Vaithianathan, Putnam-Hornstein, Jiang, Nand, & Maloney, 2017). It is unclear what the relative gain might be between methods using variables derived by prior research or theory or approaches based on statistical associations across variables found in complex computing algorithms. One possible strength of an LCA approach is that risk classes can be based on indicators with no information from the outcome while PRM relies on both to decide risk levels. Machine learning methods may also lend themselves more to providing a risk indicator than guiding the development of interventions given the fact that LCA still lends itself to model based inclusion of covariates that are distinctly modifiable. Ideally future research will include tests across regions that use differing models for assessing risk to gauge the relative gain against actuarial, LCA, PRM and other approaches.

Author statement

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.evalprogplan.2020.101792.

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