Social Determinants of Severe Injury Among Pediatric Patients During the COVID-19 Pandemic: An Exploratory Study

Rebeccah L. Sokol, PhD, Usha Sethuraman, MD,
Katherine Oag, MSN, RN, ACCNS-P, CCRN, Lisa Vitale, BSN, RN, CPN,
Lydia Donoghue, MD, & Nirupama Kannikeswaran, MD

Introduction: This study sought to identify social determinants of health (SDH) patterns associated with severe pediatric injuries.
Method: We used cross-sectional data from children (≤18 years) admitted to a pediatric trauma center between March and November 2021 (n = 360). We used association rule mining (ARM) to explore SDH patterns associated with severe injury. We then used ARM-identified SDH patterns in multivariable logistic regressions of severe injury, controlling for patient and caregiver demographics. Finally, we compared results to naive hierarchical logistic regressions that considered SDH types as primary exposures rather than SDH patterns.
Results: We identified three SDH patterns associated with severe injury: (1) having child care needs in combination with neighborhood violence, (2) caregiver lacking health insurance, and (3) caregiver lacking social support. In the ARM-informed logistic regression models, the presence of a child care need in combination with neighborhood violence was associated with an increased odds of severe injury (aOR, 2.77; 95% CI, 1.01−7.62), as was caregiver lacking health insurance (aOR, 2.29; 95% CI, 1.02−5.16). In the naive hierarchical logistic regressions, no SDH type in isolation was associated with severe injury.
Discussion: Our exploratory analyses suggest that considering the co-occurrence of negative SDH that families experience rather than isolated SDH may provide greater insights into prevention strategies for severe pediatric injury. J Pediatr Health Care. (2022) *36*, 549−559

KEY WORDS

Association rule mining, social determinants of health, pediatric injury

School of Social Work, University of Michigan, Ann Arbor, MI

Division of Emergency Medicine, Department of Pediatrics, Children's Hospital of Michigan, Central Michigan University, Detroit, MI

Division of Surgery, Department of Pediatrics, Children's Hospital of Michigan, Central Michigan University, Detroit, MI

Conflicts of interest: None to report.

Correspondence: Rebeccah L. Sokol, PhD, School of Social Work, University of Michigan, 1080 S. University Ave., Ann Arbor, MI 48109; e-mail: rlsokol@umich.edu.

J Pediatr Health Care. (2022) *36*, 549-559

0891-5245/$36.00

Published online June 1, 2022.

https://doi.org/10.1016/j.pedhc.2022.05.021

INTRODUCTION

Injuries are the leading cause of mortality among children aged 0−18 years in the United States (Centers for Disease Control and Prevention, 2018). Several social and material factors are associated with pediatric injuries, known as social determinants of health (SDH). The risk of injury progressively increases from the most advantaged to the least advantaged individuals in society (Marmot, 2010; Viner et al., 2012). Researchers have identified associations between pediatric injury and specific negative SDH—including financial insecurity, unsafe housing, and neighborhood disadvantage (Gielen et al., 2012; Newgard et al., 2011; Shai, 2006). However, identifying isolated negative SDH risk factors for severe injury does not account for the reality that multiple negative SDH often coexist within families

(Harlem, 2020; Pourmotabbed et al., 2020; Whittle et al., 2020). Thus, although isolated negative SDH may increase the risk of injury, studying patterns of SDH better reflects families' lived experienced. Machine learning techniques provide methods for identifying such patterns. The present exploratory study aimed to identify which negative SDH interrelate to increase risk for severe pediatric injury.

The influence of an ongoing pandemic and its resultant social isolation on injury risk is a new area of research (Barboza, Schiamberg, & Pachl, 2021; Yamaoka et al., 2021). Because of the COVID-19 pandemic, families experienced heightened levels of multiple different types of childhood injury risk factors, such as caregiver depression, caregiver unemployment, and lack of child care (Kalluri, Kelly, & Garg, 2021; Lee, Ward, Chang, & Downing, 2021b; Russell, Tambling, Horton, Hutchison, & Tomkunas, 2021). However, no studies have evaluated associations between families' constellations of negative SDH and childhood injuries during the pandemic. Thus, the present study sought to identify which SDH patterns were associated with severe pediatric injuries during the second year of the COVID-19 pandemic.

An issue in traditional regression modeling entails how to represent co-occurring negative SDH. One strategy is to ignore the structure of co-occurrence and focus on a single SDH while controlling for other SDH. In this approach, a specific negative SDH may be dismissed as not contributing to increased risk for severe injury if it is not a sufficient cause for the severe injury itself—even if its combination with another negative SDH increases injury risk. Another option is to include interaction terms between SDH. However, the number of interaction terms grows exponentially with SDH. Thus, the researcher must establish a priori which interactions to include. Another common approach is creating a count of the total number of SDH. This approach assumes the impact of a given SDH is fungible (i.e., it can be replaced by a different SDH) and additive (i.e., the influence of any given SDH is equal to other SDH).

Association rule mining (ARM) is a rule-based machine learning method for identifying observed relations between variables (i.e., SDH and severe injury) that can overcome the limitations of traditional regression approaches (Hornik, Grün, & Hahsler, 2005). In contrast to ignoring co-occurrence and focusing on a single SDH, deciding a priori which SDH co-occurrences to focus on, or reducing SDH to frequency counts, ARM allows the identification of patterns as they exist in the data. Each generated pattern—referred to as a rule in ARM terminology—contains an antecedent and a consequent. Antecedents and consequents can be interpreted as if-then statements. For example, consider the following rule: food insecurity and unemployment lead to severe injury. In this rule, food insecurity and unemployment are antecedents to severe injury, and severe injury is the consequent. The rule implies that if food insecurity and unemployment are present, then severe injury is present.

The present study used ARM on cross-sectional, observational data from children aged 0−18 years admitted to a level 1 urban pediatric trauma center between March 26, 2021 and November 14, 2021. We first used ARM to identify SDH patterns associated with severe injury. We then used these identified patterns as the primary exposure variables in multivariable logistic regressions of severe injury, comparing results to a naive hierarchical logistic regression. The overall goal of this exploratory study was to identify patterns of SDH associated with severe pediatric traumatic injuries.

METHODS

Study Design and Setting

This was a cross-sectional, observational study of 360 children aged ≤ 18 years admitted to an urban level 1 pediatric trauma center between March 26, 2021 and November 14, 2021 (Figure 1). Data came from patient electronic medical records and caregiver questionnaires. Information extracted from patient records included: patient demographics, patient insurance status, injury severity score (ISS), total burn surface area (TBSA), interventions performed, and outcomes. Research assistants, blinded to injury severity, approached caregivers (i.e., the parent or legal guardian) and invited them to complete a 10-min SDH questionnaire on an electronic device before child discharge (Supplementary Table). The questionnaire included questions on the SDH of children and caregivers. The caregiver provided consent before completing the questionnaire. Wayne State University Institutional Review Board approved all study protocols.

Measures

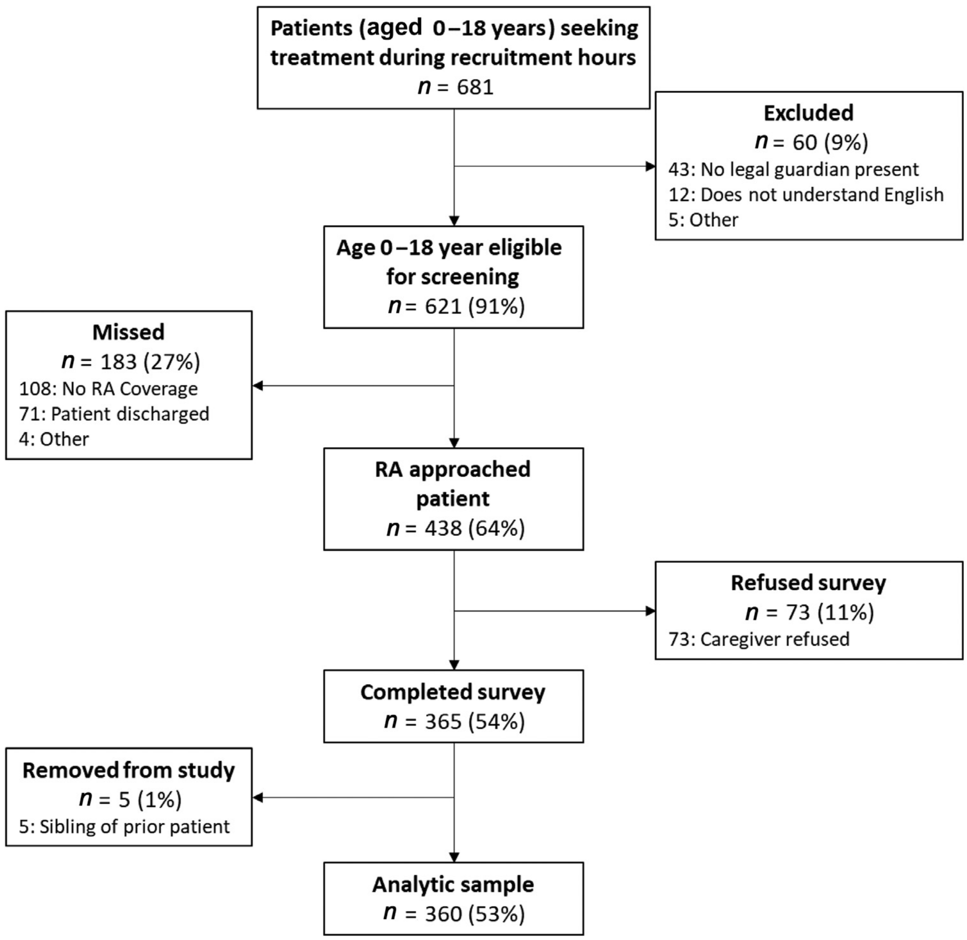
Severe injury

We defined severe injury as the following: ISS ≥ 16, TBSA ≥ 15, pediatric intensive care unit admission, blood product transfusion, operative intervention, or death secondary to the injury. The ISS is the most well-known scoring system for injury severity, and it attempts to standardize the severity of injuries sustained during a trauma (Baker, O'Neill, Haddon, & Long, 1974), with ISS ≥ 16 traditionally used to define severe injury (Sasser et al., 2012). Given the well-documented limitations of ISS (Sasser et al., 2012), we also used pediatric intensive care unit admission, blood product transfusion, operative intervention, and death secondary to the injury to classify injuries as severe versus mild or moderate. In burn victims, ISS is not calculated, and so a TBSA indicates the burn severity, with TBSA ≥ 15 indicating severe burns in children.

Social determinants of health

The SDH questionnaire included validated items to assess negative SDH, including food insecurity (Hager et al., 2010) and financial instability (Brcic, Eberdt, & Kaczorowski, 2011), and previously developed items to assess employment needs (from the Panel Study of Income Dynamics), lack of caregiver health insurance (from the Behavioral Risk Factors Surveillance System), health care access issues (from the Behavioral Risk Factors Surveillance System), child care needs, poor mental health of caregiver or patient

FIGURE 1. Study participant flow chart. RA, research assistant.



(Gottlieb, Hessler, Long, Amaya, & Adler, 2014), transportation needs (Park et al., 2010), neighborhood violence (Goldman-Mellor, Margerison-Zilko, Allen, & Cerda, 2016), housing instability (Bottino, Fleegler, Cox, & Rhodes, 2019), unsafe housing conditions (Bottino et al., 2019), and lack of social support (Uwemedimo & May, 2018). The team also extracted child insurance status (i.e., insured or uninsured) from the patient medical record. The study team dichotomized each negative SDH to indicate the presence versus absence.

Demographic characteristics

We extracted patient demographic data from the medical record, including child age (in years), race (White, Black, American Indian or Alaska Native, Asian, Pacific Islander, multiracial, or not documented [nonmutually exclusive]), ethnicity (Hispanic or non-Hispanic), and gender (male, female, or other). From the caregiver questionnaire, we obtained information on caregiver age (in years), relationship to child (parent, grandparent, aunt/uncle, other legal guardians), the highest level of education completed (less than high school, high school graduate, or General Educational Development [GED], some college, 2-year college degree, 4-year college degree, graduate education), race (White, Black, American Indian or Alaska Native, Asian, Pacific Islander, or another race [nonmutually exclusive]), and ethnicity (Hispanic or non-Hispanic). We categorized patient and caregiver race into mutually exclusive categories: (1) White, (2) Black, (3) multiracial, or (4) another race. We categorized caregiver education into (1) less than high school, high school graduate, or General Educational Development; (2) Some college or 2-year college degree; or (3) 4-year college degree or graduate education. We dichotomized the caregiver relationship to the child into parent versus another guardian.

Analysis

We used R programming version 4.0.2 for data management and analyses. We first calculated the prevalence of each negative SDH among patients in the study and the average number of negative SDH per patient (as reported by caregivers). For any given negative SDH, we calculated the percentage of cases in which the given negative SDH was the only one present and identified the average number of co-occurring negative SDH per negative SDH.

Association rule mining

We used ARM to explore and identify SDH patterns in children with severe injuries. We conducted ARM using the arules R-package version 1.6.8 (Hahsler et al., 2022) to define these patterns. ARM is a rule-based machine learning method for identifying observed patterns between variables (i.e., SDH and injury severity; Hornik et al., 2005). Association rules use confidence, support, and lift metrics to indicate the certainty, prevalence, and associational strength of a specific rule. Confidence refers to how often a given rule is true, and this equates to the ratio of the frequency of the antecedent over the frequency of the antecedent and consequent occurring together (e.g., what is the probability that severe injury occurs if food insecurity and unemployment occur). Support refers to the probability that two or more specific determinants exist within the same family, or how often the antecedent and consequent appear together (e.g., the prevalence of severe injury and food insecurity and unemployment)? Finally, lift is the ratio of the observed support to that expected if the antecedent and consequent were independent. A lift of 1 means that the probability of occurrence of the antecedent and that of the consequent are independent of each other. Hence, a higher lift indicates a higher chance of co-occurrence of the consequent with the antecedent.

For the ARM analyses, we restricted the sample to patients whose caregivers reported at least one SDH (n = 248). We restricted extracted rules to those in which severe injury was the consequent, as the goal of the ARM analysis was to determine what patterns of SDH were associated with severe injury. We also determined minimum support (2%), confidence (20%), and lift (> 1.00) thresholds for rules to ensure that: (1) the patterns were common enough in the full sample of 360 patients to allow for statistical testing ($n \geq 20$); (2) rules were true at least one-fifth of the time; (3) rules were more common than chance alone would predict.

ARM-informed multivariable logistic regression

After identifying the SDH patterns, we conducted multivariable logistic regression models informed by the ARM algorithm. Specifically, rather than entering multiple negative SDH of the same type simultaneously into the model as in a hierarchical regression, we entered SDH patterns associated with injury severity in the ARM analysis into separate models. All models controlled for demographic variables, including patient age and gender, caregiver age, race, ethnicity, relationship to the child, and level of education. We omitted patient race and ethnicity from these models, given their high correlation and collinearity with caregiver race and ethnicity (r = 0.94−0.96).

Naive hierarchical multivariable logistic regression

Using multivariable linear logistic regression models generated hierarchically, we evaluated the associations between SDH and severe injury (vs. mild/moderate injury). The baseline model included only demographic variables, including patient age and gender, caregiver age, race, ethnicity, relationship to the child, and level of education. As with the ARM-informed regression, we omitted patient race and ethnicity from models, given their high correlations and collinearity with caregiver race and ethnicity (r = 0.94−0.96). Model 2 added financial determinants (i.e., financial instability, employment needs, and food insecurity) to the baseline model. Model 3 added housing determinants (i.e., housing instability, unsafe housing), Model 4 added community-level determinants (i.e., transportation needs, child care needs, lack of social support, neighborhood violence), Model 5 added health care determinants (i.e., caregiver uninsured, child uninsured health care access issues), and Model 6 added mental health determinants (caregiver poor mental health and child poor mental health). We conducted a likelihood-ratio test between each model iteration to identify if the inclusion of additional negative SDH improved model fit. We retained only those variable sets that significantly improved model fit at each step.

For ARM-informed and naive multivariable logistic regression models, given missing data on key variables for 48 patients, we conducted multivariate imputation by chained equations using the mice R-package version 3.14 (Van Buuren & Groothuis-Oudshoorn, 2011). We imputed 20 datasets and pooled results over the analyses of these 20 datasets.

RESULTS

Table 1 provides descriptive characteristics for the 360 patients and their caregivers in this study, stratified by injury severity. The average age of patients was 7.4 years (standard deviation = 5.3). Most patients were male (61%), White (43%), and non-Hispanic (92%). The average age of caregivers was 35.5 years (standard deviation = 12.6). Caregivers were predominately the patient's parent (94%), White (42%), non-Hispanic (90%), and attained less than high school or a high school education (43%). Severely injured patients were more likely to identify as Black or multiracial than mild or moderately injured patients (χ^2[3, n = 360]= 10.6; p = .01), and caregivers of severely injured patients were less likely to attain a 4-year college degree or graduate education than caregivers of mild or moderately injured patients (χ^2[2, n = 355] = 7.43; p = .02).

Sixty-nine percent of caregivers identified at least one SDH. Financial instability was the most prevalent negative SDH (34% of patients), followed by child care needs (33%) and food insecurity (29%; Figure 2A; Table 1). Severely injured patients were more likely to be uninsured than mild or moderately injured patients (χ^2[1, n = 352] = 6.24; p = .01), but no other individual negative SDH differed between families of severely and mild or moderately injured patients (Table 1). Negative SDH co-occurrence was common, with 49% of families having two or more negative SDH (Figure 2B). Caregivers being uninsured was the most common negative SDH to occur in isolation: 27% of caregivers who reported being uninsured reported no other negative SDH (Figure 2C). Unsafe housing, health care access

TABLE 1. Characteristics of pediatric patients admitted to an urban level 1 pediatric trauma center between March 26, 2021 and November 14, 2021 and their caregivers

	All patients (n = 360)		Severe injury (n = 55)		Mild/moderate injury (n = 305)		
Characteristics	***n***	**%**	***n***	**%**	***n***	**%**	**χ^2 or t test**
Demographic variables							
Patient age, years (mean ± standard deviation)	7.4 ± 5.3		8.5 ± 5.8		7.2 ± 5.2		$t(70.1) = -1.57$
Patient gender							
Female	140	39	23	42	117	38	$\chi^2(1) = 0.23$
Male	220	61	32	58	188	62	
Transgender, nonbinary, or other	–	–	–	–	–	–	
Patient race							
White	151	43	15	27	136	45	$\chi^2(3) = 10.6$[*]
Black	145	40	30	55	115	38	
Multiracial	48	13	5	9	43	14	
Other race[a]	16	4	5	9	11	4	
Patient ethnicity							
Hispanic	30	8	–	–	–	–	$\chi^2(1) = 0.10$
Non-Hispanic	330	92	–	–	–	–	
Caregiver age, years (mean ± standard deviation)	35.5 ± 12.6		34.9 ± 9.8		35.6 ± 13.0		$t(93.7) = 0.45$
Caregiver relationship to child							
Parent	339	94	–	–	–	–	$\chi^2(1) = 0.02$
Other caregiver[b]	18	5	–	–	–	–	
Caregiver race							
White	150	42	15	27	135	44	$\chi^2(3) = 6.92$
Black	151	42	30	55	121	40	
Multiracial	13	4	–	–	–	–	
Other race[a]	46	13	–	–	–	–	
Caregiver ethnicity							
Hispanic	27	8	–	–	–	–	$\chi^2(1) = 0.002$
Non-Hispanic	324	90	–	–	–	–	
Caregiver education							
Less than high school or high school	156	43	29	53	127	42	$\chi^2(2) = 7.43$[*]
Some college or 2-year college	116	32	21	38	95	32	
4-year college or graduate school	83	23	5	9	78	26	
Financial determinants							
Financial instability	122	34	16	30	106	36	$\chi^2(1) = 0.65$
Employment needs	52	14	8	15	44	14	$\chi^2(1) < 0.01$
Food insecurity	104	29	14	26	90	30	$\chi^2(1) = 0.30$
Housing determinants							
Housing instability	70	19	11	20	59	20	$\chi^2(1) = 0.02$
Unsafe housing	17	5	5	10	12	4	$\chi^2(1) = 2.66$
Community-level determinants							
Transportation needs	36	10	6	11	30	10	$\chi^2(1) = 0.03$
Child care needs	117	33	21	38	96	32	$\chi^2(1) = 0.69$
Lack of social support	40	11	9	16	31	10	$\chi^2(1) = 1.71$
Neighborhood violence	44	12	9	16	35	12	$\chi^2(1) = 0.98$
Health care determinants							
Uninsured, caregiver	37	10	11	20	26	9	$\chi^2(1) = 6.24$[*]
Uninsured, child	10	3	–	–	–	–	–
Health care access issues	13	4	–	–	–	–	–

(continued on next page)

TABLE 1. *(Continued)*

Characteristics	All patients (n = 360)		Severe injury (n = 55)		Mild/moderate injury (n = 305)		χ^2 or t test
	n	%	n	%	n	%	
Mental health determinants							
Poor mental health, caregiver	65	18	12	22	53	18	$\chi^2(1) = 0.45$
Poor mental health, child	63	18	10	19	53	18	$\chi^2(1) = 0.88$
Social determinants of health patterns[c]							
Child care need + neighborhood violence	20	6	7	13	13	4	$\chi^2(1) = 6.24$*
Uninsured, caregiver	37	10	11	20	26	9	$\chi^2(1) = 6.24$*
Lack of social support	40	11	9	16	31	10	$\chi^2(1) = 1.71$

Note. *Cell sizes < 5 suppressed. Differences between severely versus mild/moderately injured patients were assessed using χ^2 (for categorical characteristics) or t test (for continuous characteristics).*
[a]*Other includes Asian, American Indian or Alaska Native, Pacific Islander, and unknown.*
[b]*Other includes grandparents, aunts, uncles, or other legal guardians.*
[c]*Social determinants of health patterns identified using association rule mining.*
*$p < .05$.

needs, and uninsured children never occurred in isolation (Figure 2C). The average number of co-occurring negative SDH associated with each negative SDH varied between three and five (Figure 2D).

Association rule mining

Table 2 provides the association rules that define the patterns of SDH associated with severe injury among pediatric patients with at least one reported negative SDH (n = 248). Overall, we extracted three unique SDH patterns associated with severe injury: (1) having child care needs in combination with neighborhood violence, (2) caregiver lacking health insurance, and (3) caregiver lacking social support. The rule with the highest confidence was that between having child care needs in combination with neighborhood violence and severe injury: 35% of patients whose caregivers reported both a child care need and neighborhood violence had a severe injury. The pattern of having child care needs in combination with neighborhood violence was more common among severely injured as compared with mild/moderately injured patients (χ^2[1, n = 357] = 6.24; p = .01), as was lacking health insurance (χ^2[1, n = 352] = 6.24; p = .01; Table 1). The other two patterns—(1) having food and housing insecurity in combination with poor mental health and (2) caregivers lacking social support—were equally common among severely injured as compared with mild/moderately injured patients (Table 1).

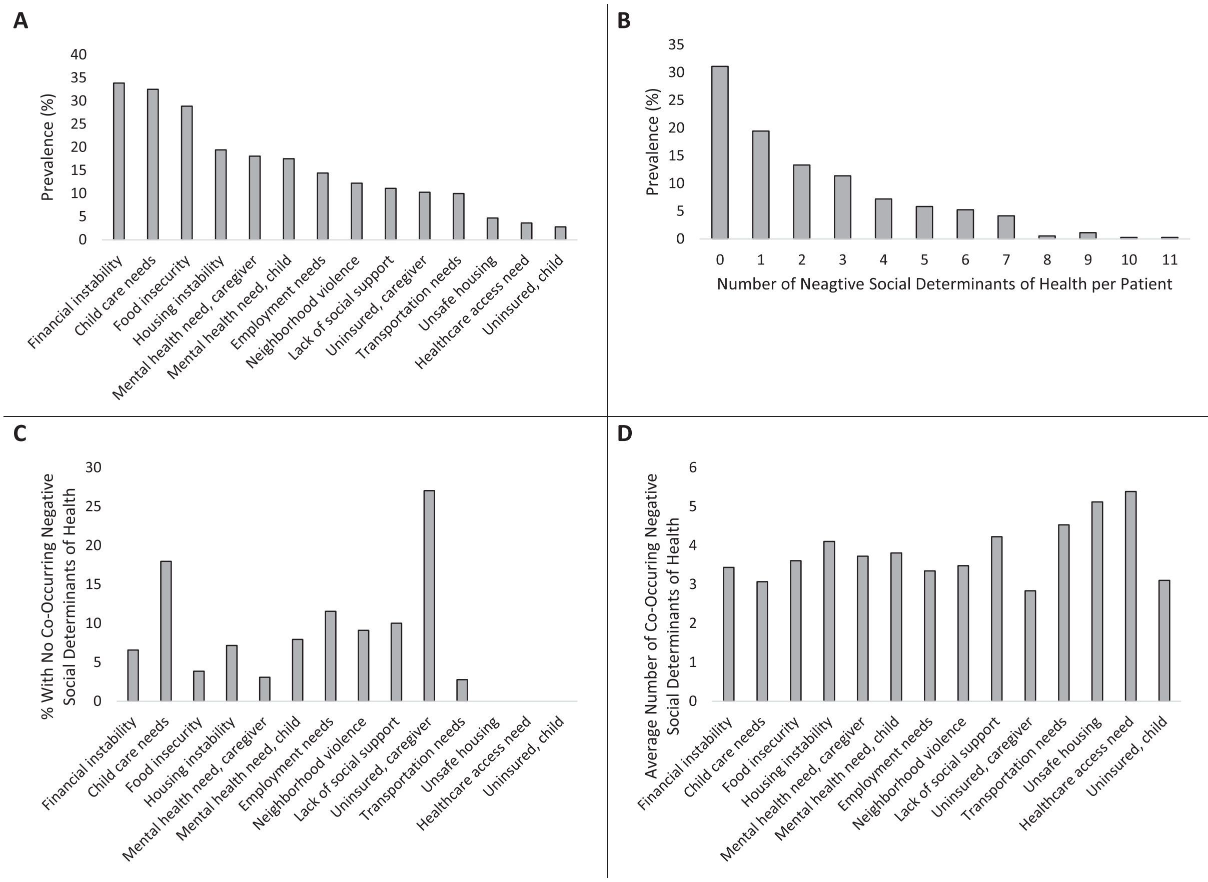
ARM-Informed Multivariable Logistic Regression

In the ARM-informed multivariate logistic regression models, two of the three identified SDH patterns were associated with severe injury. After controlling for demographic characteristics, the presence of a child care need in combination with neighborhood violence was associated with an increased odds of severe injury (adjusted odds ratios [aOR], 2.77; 95% confidence interval [CI], 1.01−7.62), as was the caregiver lacking health insurance (aOR, 2.29; 95% CI, 1.02−5.16; Table 3). The other pattern identified in the ARM analysis—caregiver lacking social support—was not associated with severe injury after controlling for demographic characteristics (aOR, 1.53; 95% CI, 0.66−3.57; Table 3).

Naive Hierarchical Multivariable Logistic Regression

In our hierarchical multivariable logistic regressions, no SDH sets (i.e., financial determinants, housing determinants, community-level determinants, health care determinants, or mental health determinants) improved model fit above the baseline demographic model (Table 4). In all hierarchical multivariable logistic regression models, caregiver education was significantly associated with severe injury, such that patients whose caregivers had less than a high school/high school education or some college/2-year college degree were more likely to have severe injuries compared with patients whose caregivers had a 4-year college degree and above (aOR, 2.94−3.58; 95% CI, from 1.04−8.60 to 1.23−10.5).

FIGURE 2. The prevalence of specific negative social determinants of health (SDH) among caregivers (A), the prevalence of the number of negative SDH per caregiver (B), the prevalence of each negative SDH in isolation given the presence of the negative SDH (C), and the average number of co-occurring negative SDH associated with each specific SDH (D)



DISCUSSION

Considering the co-occurrence of negative SDH that families experience may provide greater insight into severe pediatric injury prevention strategies than focusing on isolated SDH. As with prior research (Harlem, 2020; Pourmotabbed et al., 2020; Whittle et al., 2020), negative SDH often coexisted within families; nearly half of families in the study experienced two or more negative SDH. Two SDH patterns identified by ARM analyses—(1) child care needs in combination with neighborhood violence and (2) caregivers lacking health insurance—were associated with severe pediatric injury during the second year of the COVID-19 pandemic in our sample. Lack of caregiver health insurance was the only SDH associated with injury severity in bivariate associations, and no negative SDH type was associated with injury severity in the hierarchical models. Overall, this study suggests that ARM may be a useful exploratory analysis tool for identifying SDH patterns among families that are associated with various child health outcomes, including injury severity.

The first SDH pattern associated with severe injury in our sample was a caregiver having child care needs in combination with neighborhood violence. Prior geospatial injury studies have suggested that the locations in which injuries occur are not random and that environmental (e.g., the density of alcohol outlets) and socioeconomic (e.g., poverty) factors are associated with higher injury and crime rates (Bell, Schuurman, & Hameed, 2008; Newgard et al., 2011). Similarly, residents may feel unsafe in these areas with higher rates of injury and crime, so feeling unsafe in one's neighborhood may be a proxy for the environmental and socioeconomic conditions associated with injury. However, in our analyses, neighborhood violence was not a sufficient risk factor for severe pediatric injury; rather, it had to be combined with child care needs to increase the risk for severe injury.

Since the beginning of the COVID-19 pandemic, there has been an ongoing child care crisis, with child care centers closing temporarily or permanently across the United States (Kalluri et al., 2021; Lee & Parolin, 2021a). In addition, many grandparents—a key source of child care among many families—died of COVID-19 within the first two years of the pandemic (Hillis et al., 2021). Combining low availability with the high cost of child care for the

TABLE 2. Association rules depicting patterns of social determinants of health associated with severe injury among pediatric patients with at least one reported social determinant of health (n = 248) admitted to an urban level 1 pediatric trauma center between March 26, 2021 and November 14, 2021

Pattern	Support	Confidence	Lift
Child care need + neighborhood violence	0.03	0.35	1.67
Uninsured, caregiver	0.04	0.30	1.42
Lack of social support	0.03	0.23	1.07

Notes. *Rules restricted to those with severe injury as the consequent, support ≥ 0.02, confidence ≥ 0.20, and lift > 1.00.*

average family, affordable access to quality child care has been limited across the United States, particularly within low-income urban communities similar to the one presently investigated (Moran, 2021). When caregivers cannot access needed child care, they often adjust to supervising or providing at-home education, which may lead to inadequate supervision (Lee et al., 2021b). Inadequate child supervision may increase injury risk among children when hazards to child safety are present (Morrongiello & Schell, 2010; Petrass, Finch, & Blitvich, 2009). Turning to the present analyses, a caregiver indicating child care needs may reflect a situation of suboptimal child supervision. In addition, indicating neighborhood safety concerns may reflect a context in which the number and types of hazards and risks are heightened. An interpretation of the present findings is that this dual condition of suboptimal child supervision co-

TABLE 3. Association rule mining informed multivariable logistic regression results presenting adjusted odds ratios and 95% confidence intervals for the associations between social determinants of health patterns and severe injury (vs. mild/moderate injury) among pediatric patients admitted to an urban level 1 pediatric trauma center between March 26, 2021 and November 14, 2021

Characteristics	Child care need + neighborhood violence model	Uninsured model	Lack of social support model
Patient age	1.06 (0.99−1.13)	1.06 (0.99−1.13)	1.06 (0.99−1.13)
Patient gender			
Female (reference)	–	–	–
Male	0.89 (0.48−1.66)	0.93 (0.50−1.75)	0.87 (0.47−1.63)
Caregiver race			
White (reference)	–	–	–
Black	1.52 (0.73−3.17)	1.61 (0.76−3.36)	1.62 (0.78−3.35)
Multiracial	0.51 (0.06−4.46)	0.62 (0.07−5.37)	0.55 (0.06−4.71)
Other[a]	2.10 (0.76−5.80)	2.02 (0.73−5.57)	2.00 (0.72−5.54)
Caregiver ethnicity			
Hispanic	0.66 (0.18−2.44)	0.59 (0.16−2.20)	0.70 (0.19−2.60)
Non-Hispanic (reference)	–	–	–
Caregiver age	0.99 (0.96−1.02)	0.99 (0.96−1.03)	0.99 (0.96−1.02)
Caregiver relationship to child			
Parent	1.17 (0.30−4.48)	1.14 (0.30−4.36)	1.22 (0.32−4.64)
Other[b] (reference)	–	–	–
Caregiver education			
Less than high school/high school	3.18 (1.11−9.10)*	3.13 (1.09−8.97)*	3.11 (1.09−8.88)*
Some college/2-year college	3.11 (1.08−8.97)*	3.12 (1.08−8.98)*	3.04 (1.06−8.73)*
4-year college/graduate school (reference)	–	–	–
Social determinants of health pattern			
Child care need + neighborhood violence	2.77 (1.01−7.62)*	–	–
Uninsured	–	2.29 (1.02−5.16)*	–
Lack of social support	–	–	1.53 (0.66−3.57)

Notes. *Displayed values are adjusted odds ratios (95% confidence interval). Results are pooled > 20 imputed datasets using multiple imputations with chained equations.*
[a]*Other includes Asian, American Indian or Alaska Native, Pacific Islander, and unknown.*
[b]*Other includes grandparents, aunts, uncles, or other legal guardians.*
*$p < .05$.

TABLE 4. Hierarchical multivariable logistic regression results present adjusted odds ratios and 95% confidence intervals for associations between types of social determinants of health and severe injury (vs. mild/moderate injury) among pediatric patients admitted to an urban level 1 pediatric trauma center between March 26, 2021 and November 14, 2021

Characteristics	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Patient age	1.06 (0.99–1.13)	1.06 (1.00–1.13)	1.06 (0.99–1.13)	1.06 (1.00–1.14)	1.06 (0.99–1.13)	1.06 (0.99–1.14)
Patient gender						
Female (reference)	–	–	–	–	–	–
Male	0.88 (0.48–1.64)	0.84 (0.45–1.56)	0.88 (0.47–1.63)	0.87 (0.46–1.62)	0.90 (0.48–1.70)	0.89 (0.48–1.66)
Patient race						
White (reference)	–	–	–	–	–	–
Black	1.67 (0.81–3.45)	1.64 (0.80–3.40)	1.64 (0.79–3.40)	1.65 (0.79–3.46)	1.55 (0.75–3.23)	1.77 (0.85–3.69)
Multiracial	0.55 (0.06–4.73)	0.55 (0.06–4.76)	0.55 (0.06–4.79)	0.56 (0.06–4.84)	0.64 (0.07–5.55)	0.58 (0.07–5.06)
Other[a]	2.13 (0.77–5.85)	2.13 (0.78–5.85)	2.14 (0.78–5.90)	2.05 (0.73–5.75)	1.99 (0.71–5.54)	2.23 (0.79–6.32)
Patient ethnicity						
Hispanic	0.67 (0.18–2.46)	0.65 (0.17–2.46)	0.70 (0.19–2.59)	0.68 (0.18–2.56)	0.54 (0.14–2.09)	0.65 (0.17–2.44)
Non-Hispanic (reference)	–	–	–	–	–	–
Caregiver age	0.99 (0.96–1.02)	0.99 (0.96–1.03)	0.99 (0.95–1.02)	0.99 (0.96–1.02)	0.99 (0.95–1.03)	0.99 (0.96–1.03)
Caregiver relationship to child						
Parent	1.20 (0.32–4.55)	1.22 (0.31–4.74)	1.27 (0.33–4.92)	1.20 (0.31–4.62)	1.10 (0.28–4.29)	1.21 (0.32–4.64)
Other[b] (reference)	–	–	–	–	–	–
Caregiver education						
Less than high school/high school	3.16 (1.11–9.01)*	3.58 (1.23–10.5)*	3.07 (1.07–8.82)*	3.09 (1.08–8.83)*	3.10 (1.08–8.93)*	3.18 (1.11–9.08)*
Some college/2-year college	3.06 (1.07–8.77)*	3.30 (1.13–9.59)*	3.10 (1.08–8.91)*	2.99 (1.04–8.60)*	2.94 (1.02–8.57)*	3.05 (1.06–8.78)*
4-year college/graduate school (reference)	–	–	–	–	–	–
Financial determinants						
Financial instability	–	0.69 (0.31–1.53)	–	–	–	–
Employment needs	–	0.99 (0.41–2.37)	–	–	–	–
Food insecurity	–	0.73 (0.32–1.69)	–	–	–	–
Housing determinants						
Housing instability	–	–	0.90 (0.41–1.98)	–	–	–
Unsafe housing	–	–	2.30 (0.70–7.60)	–	–	–
Community-level determinants						
Transportation needs	–	–	–	0.82 (0.31–2.22)	–	–
Child care needs	–	–	–	1.30 (0.67–2.50)	–	–
Lack of social support	–	–	–	1.43 (0.58–3.56)	–	–
Neighborhood violence	–	–	–	0.99 (0.42–2.37)	–	–
Health care determinants						
Uninsured, caregiver	–	–	–	–	2.19 (0.94–5.13)	–
Uninsured, child	–	–	–	–	2.70 (0.59–12.3)	–
Health care access issues	–	–	–	–	0.26 (0.03–2.53)	–
Mental health determinants						
Poor mental health, caregiver	–	–	–	–	–	1.64 (0.27–1.95)
Poor mental health, child	–	–	–	–	–	0.72 (0.27–1.95)
Likelihood-ratio test	–	$\chi^2(3) = 1.05$	$\chi^2(2) = 0.85$	$\chi^2(4) = 0.41$	$\chi^2(3) = 2.22$	$\chi^2(2) = 0.54$

Notes. *Displayed values are adjusted odds ratios (95% confidence interval). Results pooled > 20 imputed datasets using multiple imputations with chained equations. Likelihood-ratio test assesses improvement in model fit between Model 1 (baseline demographic model) and subsequent models.*

[a]*Other includes Asian, American Indian or Alaska Native, Pacific Islander, and unknown.*

[b]*Other includes grandparents, aunts, uncles, or other legal guardians.*

*$p < .05$.

occurring in a context with increased environmental hazards may increase children's risk of severe injury by providing an opportunity (i.e., decreased supervision) and means (i.e., hazards available within the child's setting) for injury.

The second SDH pattern associated with severe injury in our ARM-informed regression models was a caregiver lacking health insurance; however, caregiver insurance status was not associated with injury severity in the hierarchical multivariable logistic regression. This inconsistency is the product of other health care determinants (i.e., child insurance status and health care access issues) being included in the hierarchical regression model that explains the same portion of the variance in injury severity as caregiver insurance status, thus rendering the association between caregiver insurance status and injury severity nonsignificant. This discrepancy demonstrates that regression models are sensitive to the inclusion or exclusion of co-occurring negative SDH. Negative SDH often co-occur with each other and may be related to outcomes through similar mechanisms. Researchers must critically assess which negative SDH are appropriate to include in different statistical models. Using an ARM algorithm can guide the focal negative SDH to include in a regression model, and the researcher can then identify potential confounders of the association between the focal negative SDH and the outcome to include in such a model.

Considering the ARM-informed logistic regression results, researchers have repeatedly found that both adults and children lacking health insurance are less likely to seek medical care than insured individuals (Newton, Keirns, Cunningham, Hayward, & Stanley, 2008; Zhou, Baicker, Taubman, & Finkelstein, 2017). Regardless of child insurance status, children of caregivers who lack health insurance are less likely to obtain regular medical care than children of caregivers who have health insurance (Davidoff, Dubay, Kenney, & Yemane, 2003). Thus, it may be that caregivers who lack health insurance are less likely to seek medical care for their children following a mild or moderate injury compared with insured individuals. It also may be that caregiver insurance status is a surrogate for other factors that affect child injury severity, for example, financial strain and poverty.

Limitations

The present study has several limitations. As a convenience hospital-based sample, we were limited in comparing mild/moderate injury to severe injury, and we could not compare injury to no injury. Furthermore, findings may only generalize to those who ultimately seek medical care rather than the broader community. As observational, cross-sectional data, we are unable to infer causation. In addition, we did not include data for some patients with confirmed child maltreatment, as the legal guardians in most of these cases were not available to complete the SDH questionnaire. Finally, our use of machine learning techniques is exploratory. Identified SDH patterns associated with severe injury may be unique to the present sample. We attempted to overcome this limitation by controlling for several key demographic variables when assessing the association between SDH patterns and severe injury, but future work should evaluate if the presently identified SDH patterns are associated with severe injury in other populations.

Conclusions

Two SDH patterns identified using exploratory ARM—(1) child care needs in combination with neighborhood violence and (2) lack of caregiver health insurance—were associated with pediatric severe injury during the second year of the COVID-19 pandemic. Considering patterns of SDH that families experience rather than isolated SDH may provide greater insights into prevention strategies for severe pediatric injury.

SUPPLEMENTARY MATERIALS

Supplementary material associated with this article can be found in the online version at https://doi.org/10.1016/j.pedhc.2022.05.021.

REFERENCES

Baker, S. P., O'Neill, B., Haddon, W., Jr., & Long, W. B (1974). The injury severity score: A method for describing patients with multiple injuries and evaluating emergency care. *Journal of Trauma*, *14*, 187–196.

Barboza, G. E., Schiamberg, L. B., & Pachl, L. (2021). A spatiotemporal analysis of the impact of COVID-19 on child abuse and neglect in the city of Los Angeles, California. *Child Abuse and Neglect*, *116*, 104740.

Bell, N., Schuurman, N., & Hameed, S. M. (2008). Are injuries spatially related? Join−count spatial autocorrelation for small-area injury analysis. *Injury Prevention*, *14*, 346–353.

Bottino, C. J., Fleegler, E. W., Cox, J. E., & Rhodes, E. T. (2019). The relationship between housing instability and poor diet quality among urban families. *Academic Pediatrics*, *19*, 891–898.

Brcic, V., Eberdt, C., & Kaczorowski, J. (2011). Development of a tool to identify poverty in a family practice setting: A pilot study. *International Journal of Family Medicine*, *2011*, 812182.

Centers for Disease Control and Prevention. (2018). Ten leading causes of death by age group. Retrieved from https://www.cdc.gov/injury/wisqars/leadingcauses_images.html

Davidoff, A., Dubay, L., Kenney, G., & Yemane, A. (2003). The effect of parents' insurance coverage on access to care for low-income children. *Inquiry*, *40*, 254–268.

Gielen, A. C., Shields, W., McDonald, E., Frattaroli, S., Bishai, D., & Ma, X. (2012). Home safety and low-income urban housing quality. *Pediatrics*, *130*, 1053–1059.

Goldman-Mellor, S., Margerison-Zilko, C., Allen, K., & Cerda, M. (2016). Perceived and objectively-measured neighborhood violence and adolescent psychological distress. *Journal of Urban Health*, *93*, 758–769.

Gottlieb, L., Hessler, D., Long, D., Amaya, A., & Adler, N. (2014). A randomized trial on screening for social determinants of health: The iScreen study. *Pediatrics*, *134*, e1611–e1618.

Hager, E. R., Quigg, A. M., Black, M. M., Coleman, S. M., Heeren, T., Rose-Jacobs, R., . . . Frank, D. A. (2010). Development and validity of a 2-item screen to identify families at risk for food insecurity. *Pediatrics*, *126*, e26–e32.

Hahsler, M., Buchta, C., Gruen, B., Hornik, K., Johnson, I., Borgelt, C., & Ledmi, M. (2022). Package 'arules'. Retrieved from https://cran.uib.no/web/packages/arules/arules.pdf

Harlem, G. (2020). Descriptive analysis of social determinant factors in urban communities affected by COVID-19. *Journal of Public Health*, *42*, 466–469.

Hillis, S. D., Blenkinsop, A., Villaveces, A., Annor, F. B., Liburd, L., Massetti, G. M., . . . Unwin, H. J. T. (2021). COVID-19–associated orphanhood and caregiver death in the United States. *Pediatrics*, *148*, e2021053760.

Hornik, K., Grün, B., & Hahsler, M. (2005). Arules-A computational environment for mining association rules and frequent item sets. *Journal of Statistical Software*, *14*, 1–25.

Kalluri, N., Kelly, C., & Garg, A. (2021). Child care during the COVID-19 pandemic: A bad situation made worse. *Pediatrics*, *147*, e2020041525.

Lee, E. K., & Parolin, Z. (2021a). The care burden during COVID-19: A national database of child care closures in the United States. *Socius*, *7*, 1–10.

Lee, S. J., Ward, K. P., Chang, O. D., & Downing, K. M. (2021b). Parenting activities and the transition to home-based education during the COVID-19 pandemic. *Children and Youth Services Review*, *122*, 105585.

Marmot, M. (2010). Injury prevention: Addressing the social determinants. *Injury Prevention*, *16*(Suppl. 1), A277.

Moran, K. K. (2021). Perspectives on the child care search process in low-income, urban neighbourhoods in the United States. *Early Child Development and Care*, *191*, 655–669.

Morrongiello, B. A., & Schell, S. L. (2010). Child injury: The role of supervision in prevention. *American Journal of Lifestyle Medicine*, *4*, 65–74.

Newgard, C. D., Schmicker, R. H., Sopko, G., Andrusiek, D., Bialkowski, W., Minei, J. P., , & Resuscitation Outcomes Consortium Investigators. (2011). Trauma in the neighborhood: A geospatial analysis and assessment of social determinants of major injury in North America. *American Journal of Public Health*, *101*, 669–677.

Newton, M. F., Keirns, C. C., Cunningham, R., Hayward, R. A., & Stanley, R. (2008). Uninsured adults presenting to US emergency departments: Assumptions vs data. *JAMA*, *300*, 1914–1924.

Park, N. S., Roff, L. L., Sun, F., Parker, M. W., Klemmack, D. L., Sawyer, P., & Allman, R. M. (2010). Transportation difficulty of black and white rural older adults. *Journal of Applied Gerontology*, *29*, 70–88.

Petrass, L. A., Finch, C. F., & Blitvich, J. D. (2009). Methodological approaches used to assess the relationship between parental supervision and child injury risk. *Injury Prevention*, *15*, 132–138.

Pourmotabbed, A., Moradi, S., Babaei, A., Ghavami, A., Mohammadi, H., Jalili, C., & Miraghajani, M. (2020). Food insecurity and mental health: A systematic review and meta-analysis. *Public Health Nutrition*, *23*, 1778–1790.

Russell, B. S., Tambling, R. R., Horton, A. L., Hutchison, M., & Tomkunas, A. J. (2021). Clinically significant depression among parents during the COVID-19 pandemic: Examining the protective role of family relationships. *Couple and Family Psychology: Research and Practice*, *10*, 190–201.

Sasser, S. M., Hunt, R. C., Faul, M., Sugerman, D., Pearson, W. S., Dulski, T., & Lerner, E. B. (2012). Guidelines for field triage of injured patients: Recommendations of the National Expert Panel on Field Triage, 2011. *Morbidity and Mortality Weekly Report. Recommendations and Reports*, *61*, 1–20.

Shai, D. (2006). Income, housing, and fire injuries: A census tract analysis. *Public Health Reports*, *121*, 149–154.

Uwemedimo, O. T., & May, H. (2018). Disparities in utilization of social determinants of health referrals among children in immigrant families. *Frontiers in Pediatrics*, *6*, 207.

Van Buuren, S., & Groothuis-Oudshoorn, K. (2011). Mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software*, *45*, 1–67.

Viner, R. M., Ozer, E. M., Denny, S., Marmot, M., Resnick, M., Fatusi, A., & Currie, C. (2012). Adolescence and the social determinants of health. *Lancet*, *379*, 1641–1652.

Whittle, H. J., Leddy, A. M., Shieh, J., Tien, P. C., Ofotokun, I., Adimora, A. A., & Weiser, S. D. (2020). Precarity and health: Theorizing the intersection of multiple material-need insecurities, stigma, and illness among women in the United States. *Social Science and Medicine*, *245*, 112683.

Yamaoka, Y., Hosozawa, M., Sampei, M., Sawada, N., Okubo, Y., Tanaka, K., & Morisaki, N. (2021). Abusive and positive parenting behavior in Japan during the COVID-19 pandemic under the state of emergency. *Child Abuse and Neglect*, *120*, 105212.

Zhou, R. A., Baicker, K., Taubman, S., & Finkelstein, A. N. (2017). The uninsured do not use the emergency department more—They use other care less. *Health Affairs*, *36*, 2115–2122.