SUPPORTING DECISION MAKING FOR THE PREVENTION OF CHILD MALTREATMENT IN NORTH CAROLINA

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ABSTRACT

Gracelyn Howell Cruden: SUPPORTING DECISION MAKING FOR THE PREVENTION OF CHILD MALTREATMENT IN NORTH CAROLINA
(Under the direction of Kristen Hassmiller Lich)

Child maltreatment is a distressingly prevalent problem in the United States, with over 674,000 children estimated to be witness to domestic violence or otherwise affected by abuse or neglect in federal fiscal year 2017. While evidence-based programs exist to prevent child maltreatment, only a small proportion of families receive such services. Tools are needed to support decision makers when they are assessing their local context and selecting discrete evidence-based programs to reduce child maltreatment.

This research addresses three aims in order to support such decision making in North Carolina (NC): 1) To understand how county-level indicators of child and family well-being co-vary using data from the U.S. Census and RWJF County Health Rankings; 2) To collaboratively develop a systems informed hypothesis of child maltreatment risk and protective factors using a Group Model Building (GMB) approach with NC stakeholders, and structure an early quantitative system dynamics simulation model to compare the potential effects of three evidence-based child maltreatment prevention programs, and 3) To develop and pilot test a multi-criteria decision analysis (MCDA) tool to assess whether interventions are differentially ranked with a manual ranking compared to ranks calculated with the tool.

In Aim 1, we find that latent profiles of North Carolina counties can be characterized by low, moderate, and high risk, but the moderate risk profile is also associated with the highest level of predicted drug overdose deaths and with highest mean of predicted child maltreatment

reports. In Aim 2, stakeholders emphasized the role of parental trauma and access to peer supports, and the simulation model offered preliminary insights into the importance of system shocks such as newborns. In Aim 3, over half of decision makers (55%) ranked the three interventions differently with their manual ranking compared to rankings calculated with the MCDA tool.

The results of this research suggest that stakeholders conceptualize of child maltreatment risk factors in a multi-level, interconnected manner, and that decision support tools such as the ones presented here can aid with facilitating, not replacing, community conversations around how best to address child maltreatment within the local context.

This work is dedicated to the children and families of North Carolina who are incredibly resilient, and to the inspiring, empathetic individuals, who work tirelessly to support them- especially those who were part of the Group Model Building team.

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LIST OF ABBREVIATIONS

ACS	American Community Survey
AIC	Akaike's Information Criteria
BIC	Bayesian Information Criteria
BLRT	Bootstrapped Likelihood Ratio
BLUEPRINTS	Blueprints for Healthy Youth Development
CEBC	California Evidence-Based Clearinghouse for Child Welfare
CHR	County Health Rankings
CLD	Causal Loop Diagram
CDC	Center for Disease Control and Prevention
CPS	Child Protective Services
CTC	Communities That Care
CVD	Cardiovascular Disease
DM	Decision Makers
EBP	Evidence-Based Prevention Program
FIML	Full Information Maximum Likelihood
GMB	Group Model Building
IRB	Institutional Review Board
IY	Incredible Years
LCA	Latent Class Analysis
LMR	Lo-Mendell Rubin Test
LPA	Latent Profile Analysis

MCDA	Multi-Criteria Decision Analysis
NC	North Carolina
NFP	Nurse Family Partnership
NNT	Number Needed to Treat
PCIT	Parent Child Interaction Therapy
PTSD	Post-Traumatic Stress Disorder
QALY	Quality-Adjusted Life Year
RPFs	Risk and Protective Factors
RWJF	Robert Wood Johnson Foundation
SC	SafeCare
TF-CBT	Trauma-Focused Cognitive Behavioral Therapy
US	United States
VA	Veteran's Affairs
WIC	Women, Infant, and Children
WSIPP	Washington State Institute for Public Policy

Chapter 1 : INTRODUCTION

Overview

Nearly 17,000 families in NC were recommended for services after substantiated reports of child maltreatment in 2016 and over 55,000 reported claims of child maltreatment.[1] Child maltreatment is known to have lifelong consequences, including developmental delays, increased risk of suicidal ideation, and chronic depression and anxiety. Most evidence-based programs to address child maltreatment in North Carolina are selected and implemented at the county level, making the county-level a natural unit of analysis. However, effectiveness trials of programs that aim to prevent maltreatment have rarely been conducted at the county level and rarely report factors at the local level that may affect outcomes and implementation. While guidelines and checklists exist, rigorous, evidence-based decision-making tools are needed to help decision makers choose the programs that are most likely to have significant population level health impact given a county's context.

Child Maltreatment Burden

Child maltreatment, including physical, sexual, and emotional abuse or neglect, is a highly traumatic experience that results in negative mental, emotional, and behavioral health outcomes across the life course.[2–5] Maltreatment is associated with increased behavioral difficulties and disorders, mental health distress, developmental delays, and lower academic performance during childhood.[2,6,7] Later in life, adolescents and adults who were maltreated as children may exhibit biological disturbances such as increased cortisol production, aggressive behavior and increased criminal activity, and have four to twelve times the risk for alcoholism, drug abuse, depression, and suicide attempts compared to those who were not abused as children.[8–14] Maltreated children are more likely to mistreat their own children, creating a reinforcing loop of adverse behavior and multi-generational behavioral health concerns.[15,16]

Key abbreviations:
EBP- Evidence-based Prevention Programs
RPFs- Risk and Protective Factors
GMB- Group Model Building

Preventive interventions help avoid adverse childhood experiences such as maltreatment and reduce the risk of developing behavioral health disorders due to maltreatment. To ensure the highest likelihood of impact, communities must choose evidence-based prevention programs (EBPs). Impact, however, can vary based on a population's risk and protective factors (RPFs), such as age,[17–19] racial and ethnic background,[20,21] economic status, history of abuse or behavioral health disorders,[22,23] or access to another preventive EBP. These interconnected factors and their determinants comprise the "local context."[24,2525,26] However, the field lacks best practices for quantifying this contextual heterogeneity and matching EBPs to local contexts to maximize impact. Reviews of available interventions to prevent child maltreatment and associated behavioral health disorders have concluded that the complexity of the underlying risk factors require us to think carefully and systemically when selecting policies and EBPs to prevent adverse outcomes.[23,27] Adding further complexity, the environments in which EBPs are tested for efficacy are often meaningfully different from those in which they will be implemented with respect to available resources and community-level factors such as parental employment opportunities.[9,10,28] Decision makers need innovative methodologies to estimate potential EBP impact within service delivery systems with limited resources that may appear to be or in practice be qualitatively different from the context in which the EBPs were originally tested. This decision making is particularly difficult when decision makers must choose between subpopulations, such as children or adolescents, and mechanistic targets such as parenting practices or health care provider training. Current evidence-based community prevention process efforts often lack support in helping communities simulate and directly compare the potential impact of alternatives given their local context, or use decision support tools unique to the given process.[29] More generalized tools are needed for communities that cannot access such structured models. Additionally, preventive interventions often have positive effects in both the short and long term, as preventive interventions aim to change behaviors across generations and behavior that take time to change. When arguing for the potential of one intervention compared to another, it is particularly helpful when decision makers can conceptualize the full potential impact of interventions across time and related limitations.[30]

Further, implementation research has found that the highly heterogeneous and complex local context plays an important role in shaping implementation effectiveness.[31–35] [31–35]Local context, such as population demographics, socioeconomic inequality, historical injustice, and environmental structures, can not only exacerbate physical, emotional, and behavioral diseases and affect the prevalence of adverse events such as maltreatment, but can also influence treatment availability and compliance.[30,36,37]

Without methodological support for aligning EBPs to local context, decision makers are less likely to choose the EBPs with the greatest potential impact given local context.[38–42] Thus, my goal is to assist decision makers during the *exploration* and *preparation* phases of implementation[24] when EBPs are selected based on local context, a goal that is directly responsive to NIMH Strategic Objective 4.4 to “develop new capacity for research that evaluates the public health impact of mental health services innovations.”[43] I will use an engaged systems science approach, Group Model Building, to create a system dynamics simulation model with and for North Carolina decision makers. The simulation model will be designed to increase decision makers' knowledge of the local context shaping children's behavioral health outcomes and the potential effectiveness of EBPs in reducing child maltreatment. While local capacity is also an important part of implementation planning and evidence-based program selection, it is outside of the scope of this dissertation. Local capacity includes factors such as organizational climate, budget, and workforce capacity. Further, local context and capacity may influence important implementation outcomes such as fidelity, which in turn can mediate the effectiveness of interventions, though implementation outcomes are also outside of the current proposal's scope.

Rationale

The driving hypothesis of this dissertation is as follows: Local context shapes underlying risk and protective factors targeted by EBPs and thus EBP outcomes. Thus, EBP selection and implementation efforts could be more efficient and effective with the aid of a decision support model to compare the potential EBP impact over time given local context and the complexity surrounding child maltreatment risk. Figure 1.1 depicts this driving hypothesis, showing that EBP implementation efforts can also be affected by local context at the organizational and community level, but will not be the focus of this proposal.

This dissertation is further motivated by the hypothesis that child maltreatment is a wicked, complex problem and is thus the best course(s) of action to prevent it should be motivated by systems science**.** Complex problems are those that have dynamic short and long-term effects that are difficult to intuit, feedback processes such as reinforcing and balancing loops, and multiple levels of influence.[27,44–46] Complex problems are the product of complex systems that produce behavior that may be unexplained or surprising if only the individual components are observed.[47]

Complexity is manifest in terms of non-linear relationships, multi-level interactions, lag time between cause and effect, and feedback loops, all of which interact to generate non-intuitive, "emergent" behaviors.[45,48–50] Feedback loops are dynamic linkages between factors that, when changed, reverberate to either reinforce or undermine change over time, and are a powerful determinant of longitudinal outcomes and a key component of system dynamics models.[51,52] Explanations of a complex public health problem such as child maltreatment are not only incomplete but incorrect without appropriate acknowledgement of the various structures and processes that give rise to them. Systems science models offer an opportunity to explicitly model dynamic hypotheses of intervention effects that can be tested and iteratively re-tested without having to invest in full-scale implementation to observe intervention effects, which is costly and time-consuming.[45,53–55]

Systems thinking and methodology are ideally suited to take into account the complex systems affecting child well-being and behavioral health while selecting interventions to prevent adverse outcomes.[54,56–59] Intervention effectiveness trials with only brief follow-up outcomes are often unable to observe positive delayed effects that may be observed in adolescence or even early adulthood due to the complex nature of child development.[14,60] For example, the effects of child maltreatment may present as externalizing behavior during childhood, but shift to suicidal ideation or substance abuse during adolescence. System dynamics models allow us to anticipate and quantify these delayed effects by connecting evidence without waiting on costly longitudinal trials.[54,56,57]

For this dissertation, the system affecting child maltreatment and mental health is defined as "a set of interrelated components"[61] that interact to produce their own pattern of behavior over time.[50] The system to be modeled includes community, individual, and family-level risk and protective factors that affect the probability of maltreatment, as well as the services that deliver programs at the county level. The majority of current risk and evaluation models cannot account for co-varying effects of factors across time and are unable to adequately account for system complexity.[50,54,62,63] For example, parental stress is affected by external factors dictated by local context such as employment opportunities. A negative (reinforcing) feedback loop occurs when parents become more stressed, increasing the incidence of maltreatment, which in turn increases child behavioral health disorders that then further increases parent stress, in turn reinforcing maltreatment risk. This "vicious cycle" escalates over time.[60,64,65] Figure 1.2 depicts how system dynamics can help improve learning about complex problems so as to inform future research and improve population health outcomes.

The overall objective of this dissertation is to develop support tools for decision makers as they determine which factors should be targeted to prevent child maltreatment and which evidence-based interventions may impact those factors and be aligned with community resources and needs. Further, this proposal aims to increase decision makers' ability to understand local context and choose the interventions that will have the greatest impact in their communities given that context, with context defined as population characteristics and service system organization. I posit that systems science approaches can support a) increased understanding of the complex system shaping child maltreatment risk and b) planning efforts for child maltreatment prevention that will yield more nuanced and desirable results than approaches that rely on singular interventions or prevention plans that are not informed by systems science.

Over the long-term, I want to develop tools that support decision makers as they work to improve community resilience and prevent adverse health and social outcomes across the life course. Specifically, I hope to support the identification of high-impact leverage points and specific evidence-based interventions. I hypothesize that when decision makers select evidence-based programs for implementation in their communities using systems engaged approaches such as Group Model Building or use tools that account for complexity during the intervention selection and implementation planning processes, those decision makers will observe greater population health impact and more efficient resource allocation in their communities. Additionally, I hypothesize that the Group Model Building process can improve the accuracy of GMB team members' mental models about the systems and factor shaping child maltreatment and behavioral health.

Specific Aims

To support these objectives, this dissertation is designed to answer three aims.

Aim 1 will empirically derive latent county subgroups, or risk profiles, using *latent profile analyses,* linking observed factors from publicly available surveillance data that cluster around counties based on county-level risk of child maltreatment reports. Aim 1 is innovative in its use of a national level dataset with publicly available data that is not specific to families involved with or at risk for involvement with child protection services to understand how aggregate risk factors relate to one another and to predicted child maltreatment rates. In collaboration with child welfare and mental health services experts who are influential in selecting and delivering family-based programs for implementation in North Carolina,

Aim 2 will use a Group Model Building approach to co-develop a qualitative dynamic hypothesis that characterizes the complex structure of risk and protective factors affecting child well-being and maltreatment. We will then translate this hypothesis into a quantified system dynamics simulation model to estimate the potential effects of three GMB selected evidence-based prevention programs on maltreatment risk given baseline community and family factors.

This simulation model is meant to serve as a learning model that can help decision makers understand the types of leverage points targeted by evidence-based interventions as well as the types of leverage points that may not traditionally be targeted by traditional child maltreatment prevention interventions.

Aim 3 will explore the validity of a multi-criteria decision analysis (MCDA) tool that will be developed with the GMB stakeholders with a pilot sample of decision makers to characterize the criteria that decision makers consider when comparing and selecting EBPs for implementation and support evidence-informed decision making. We will also test how EBP ranks with the tool compare to rankings without the tool and after decision makers participate in a brief intervention to improve their understanding of child maltreatment risk complexity. Finally, we will explore the range of factors that decision makers consider when selecting interventions and challenges for implementing EBPs through semi-structured interviews.

Briefly, the expected outcomes of this project are threefold. First, I expect to empirically define latent county subgroups of risk that can be used for understanding how surveillance data at the county level can be monitored for assessing child maltreatment rate risk. Second, I will build a simulation learning model that can be improved and expanded upon in future studies. Third, I will gain preliminary insight into the utility of a multi-criteria decision analysis tool and what they consider when selecting interventions for implementation.

Significance

This project will provide a significant contribution to the field by a) operationalizing a simulation learning model for child maltreatment that can be improved in future research as the evidence of differential EBP effectiveness by local context grows and built upon for modeling implementation processes such as partnership building and resource allocation strategy alternatives and b) increasing our knowledge of what factors decision makers consider when selecting programs to prevent child maltreatment at the county level. Further, it will result in a dynamic hypothesis of child maltreatment that is co-developed with stakeholders who serve families in a variety of contexts (Aim 2). This qualitative hypothesis will be built upon to iteratively build a simulation learning model that will be the first of its kind to understand how risk and protective factors across the ecological model of child development relate to child maltreatment risk (Aim 2). Previous applications of systems thinking and methodologies to child maltreatment have primarily focused on case load simulation, i.e. entry and exit out of the child welfare and foster care system, and decision making with respect to claim substantiation.[59,66,67] While there have been several calls for researchers and practitioners to apply systems science thinking to help understand the 'wicked' problem of child maltreatment and associated solutions, examples of such applications are scarce. Thus, this study can help advance the field by taking a preliminary step towards understanding how, and the extent to which bringing systems thinking to decision makers can help elucidate the risk and protective factors for child maltreatment at the local level and inform selection of EBPs to optimally prevent child maltreatment. Finally, this dissertation will develop the first tool based in multi-criteria decision analysis that is developed to support the comparison of evidence-based prevention interventions across contexts, outcomes, and prevention planning processes (Aim 3).

Figure 1.1: Driving Hypothesis

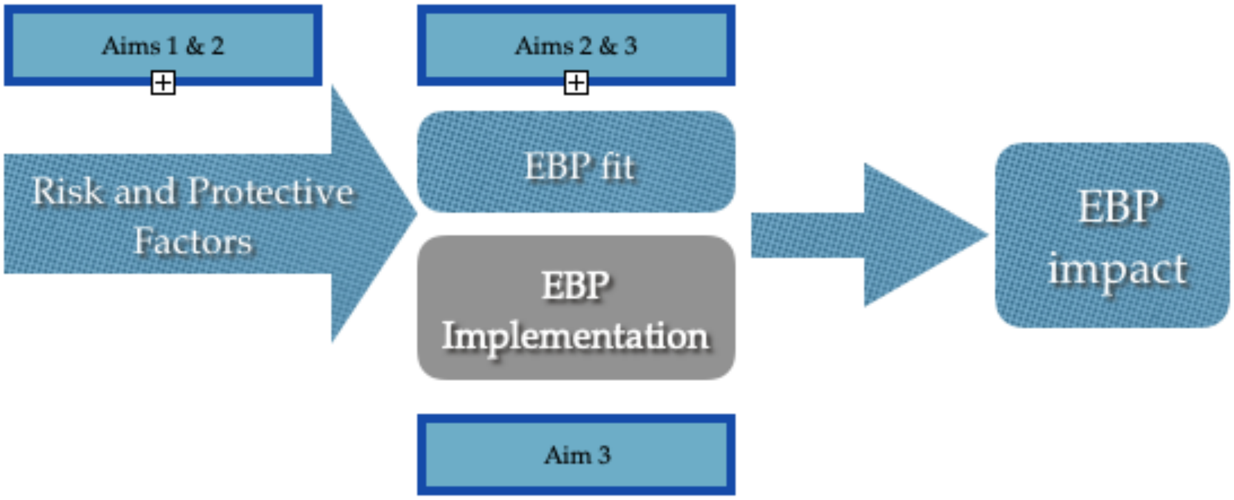
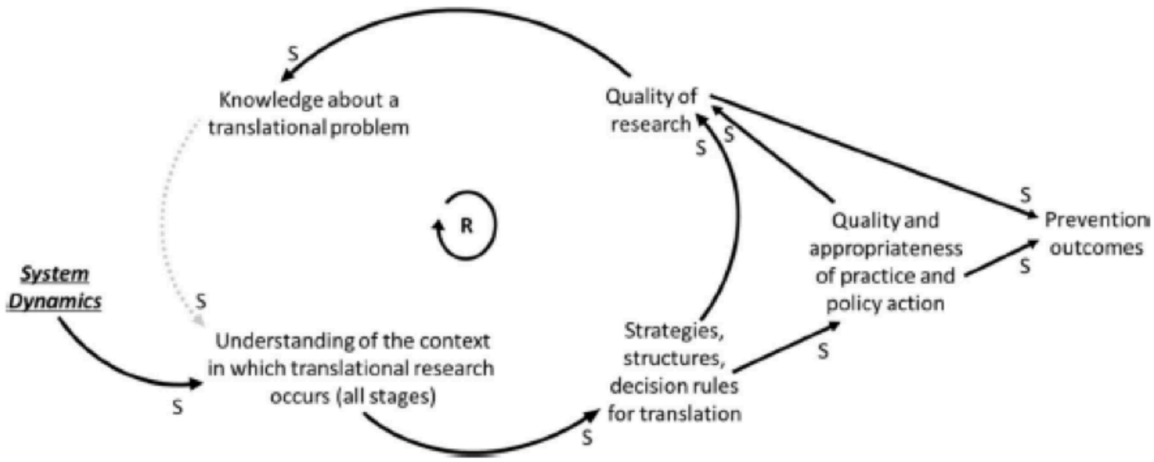


Figure 1.2: Systems Dynamics in the Knowledge Translation Cycle (Hassmiller Lich et al. 2016)



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Chapter 2 : **LITERATURE REVIEW**

Burden of Child Maltreatment

While considerable reductions in child maltreatment rates have been seen in the past twenty years, they remain high compared to the first National Incidence Survey of maltreatment in 1980.[1] Child maltreatment includes physical, emotional, and sexual abuse, as well as neglect and exposure to domestic violence.[2–4] In 2015, over 3.5 million children were referred to child welfare agencies, with over 2 million (58%) of referrals substantiated as cases of abuse or neglect.[5] An estimated 9.2 per every 1000 children in the United States are estimated to suffer from one of the five types of child maltreatment annually, with 2.3 of these being repeat victims.[5] In other words, over 683,000 children were known to be victims of maltreatment, though national surveys suggest that this figure may underestimate the burden of maltreatment by up to ten to twenty times for abuse and neglect, respectively.[6–9]

Surveys of adolescents and their caregivers suggest that the rates of victimization are actually much higher than those recorded by Child Protective Services (CPS).[7] Using data from the Add Health study, Hussey, Chang, and Kotch found that as much as 41.5% of adolescents reported at least one instance of supervision neglect, and almost half that (19.1%) were left unattended three or more times.[7] Another 11.8% reported physical neglect, and 28.4% reported physical assault, with half of those adolescents reporting physical abuse on three or more occasions. Contact sexual abuse was more similar to CPS reports but still higher in the Add Health dataset, with 4.5% of adolescents reporting at least once instance. Further, to properly account for and understand the burden of maltreatment on children, one must consider not only the prevalence, but also the frequency, severity, type, and chronicity that characterizes the abuse.[4]

Risk and Protective Factors

Bronfenbrenner's 1979 framework remains the most popular framework we utilize to discuss the risk and protective factors that shape child development and may associated with maltreatment. He was one of the first to emphasize that we need not only to pay attention to a variety of factors, but how multiple factors form an ecology that may vary in magnitude in influence on a child's well-being throughout child development. Bronfenbrenner goes on to say that the factors and settings, such as school, home, and child care, are often interconnected and influenced by multiple levels, including policy. Child development not only happens within, but is influenced by these multilevel, interconnected factors.

Thus, a complete understanding of the environments that support healthy child development requires a multi-level, systemic understanding. Due to the interconnectedness and complexity of child development and maltreatment, the prevalence of a risk factor does not mean that maltreatment will occur. Further, some risk factors have been found to be significantly associated with some types of maltreatment and not others, or the significance of a single factor may disappear once other factors are controlled for.[7] Thus, it is crucial to understand the important nuances of risk.

The current dissertation aims to classify counties based on prevalent risk and protective factors (RPFs) related to child maltreatment, and simulate which evidence-based programs may be most effective, given this context. A structured literature review was undertaken to develop a strong understanding of the relevant RPFs that should be included in the simulation model. The included RPFs are depicted in Figure 2.1 with respect to their associated ecological levels, and a more complete list can be seen in Table 2.1. Key government and non-profit reports, such as those distributed by the Center for Disease Control and Prevention and the National Academy of Medicine, as well as three recent meta-analyses from the peer-reviewed literature informed the current detailed framework of child maltreatment.[7,8,10–12] A brief description of the relevant factors, accompanied by a critique of the literature informing our understanding of the influence of each RPF follows below. The reader is referred to the report New Directions in Child Abuse Research for a more thorough discussion of the literature supporting each RPF.[8] Unfortunately, due to a lack of sufficient longitudinal studies, the ways in which these risk factors interact in a complex manner and influence the risk for maltreatment is still relatively unknown.[8]

Micro/Individual-Level (Child)

The primary risk factors at the individual level include physical or mental health disorders, young age, race/ethnicity, and lack of opportunities to have positive interactions with adults. Children with physical, emotional, or mental health challenges are estimated to have 1.7 times the risk of maltreatment compared to their able-bodied peers, likely due to increased caregiver burden, parental stress, and stigma.[8]

Hussey, Chang, and Kotch found that race/ethnicity, defined across six categories, was significantly associated with each of four types of maltreatment (supervision neglect, physical neglect, physical assault, contact sexual abuse), but the significance remained only for Native American and Multi-racial/Other Race children for supervision neglect and for Multi-racial/Other Race children for physical neglect and assault after adjustment for other sociodemographic factors.[7] It is particularly crucial to discuss the influence of race or ethnicity as a risk factor for child maltreatment, as significant disparities exist in the prevalence of children of color in the child welfare system.[13] However, there is concern that children of color are differentially assessed and more likely to be taken away for the maltreatment at the same level of severity as White children due to racism and institutional racism.[13–15] Drake, Lee, and Jonson-Lee found that differential reporting rates for Whites and Blacks is non-significant once they controlled for poverty, though they only explored substantiated claims in the state of Missouri.[16] Institutional and systemic racism likely contribute not only to the incidence of child maltreatment due to the systematic denial of mental health and social support services for families of color, but also due to differential rates of substantiation of maltreatment claims due to racism and associated biases within child welfare agencies.[14,17]

Thus, an exploration of the causes of child maltreatment and how to prevent it are incomplete without acknowledging additional complex issues such as racism. Based on critical race theory, a public health critical race praxis framework encourages public health researchers to not only acknowledge race, but to 1) explore how racism currently operates, such as how social hierarchies operate and are related to racial profiles 2) understand how racialization shapes the outcome or problem of interest and vice versa, 3) explicitly define racism and how it will be measured in a project, and 4) include anti-racist actions as part of the project's endeavors.[18] For the purposes of the current project, intentional effort will be made to include individuals with various race and ethnic backgrounds in the Group Model Building (GMB) team, and GMB model structuring sessions will include discussions on the influence of race and racism.

Protective factors at the micro level, such as opportunities for prosocial interaction with adults, are difficult to account for using surveillance data. Thus, protective factors at the micro level be assumed constant and equivalent across counties in the model unless explicitly targeted by the modeled EBPs and data is available to support the contrary. These factors include the child's levels of resilience as well as opportunities for contact with positive adults other than the primary caregiver(s) such as youth organization leaders, teachers, and health care providers. The factors that make some children more resilient that others are still not well-understood, but it is clear that this is a malleable trait that can be improved with individual therapy.[19–21] Opportunities for positive interaction with adults can allow children to feel nurtured, and that they are worthwhile, thus increasing their desire to be a part of the community, and practically can increase the likelihood that maltreatment events are discovered.[22–25]

Micro-Level (Family/Parent)

Risk factors at the family, or parent, level include single parenthood (particularly single mothers), parental stress, parental substance misuse and mental health disorders, financial burden/family income, high childcare burden, parental age, family transitions (such as divorce), parenting skills, non-marital partner cohabitation, parental history of physical or sexual abuse, and immigration status. These factors are often interconnected and have little influence alone, but the presence of more than one can have an additive (or multiplicative) adverse effect on child well-being.[26] Further, due to the sparsity of longitudinal studies, the temporal and causational relationship of these factors with child well-being is less established, but associations remain of varying strength across studies.[8] Debate often centers around whether the role of individual parenting factors such as parental history of abuse and mental health disorders is a sufficient or necessary condition, or whether socioeconomic factors such as poverty and lack of social support play more important roles.[26] Targeting parent mental health without acknowledging the external stressors that remain, such as poverty, may diminish their likelihood of recovery and increase the stigma around mental health by blaming parents for their mental health disorders as a cause of child maltreatment. Thus, approaches to child maltreatment prevention that are successful and equitable should not only consider the parents' skills and well-being, but the environments in which they operate and which shape their ability to be successful parents.[27–29]

Further, some studies have found that the risk factors for some types of abuse look qualitatively different compared to those for neglect, with little to no overlap.[8,26] For example, Chaffin, Kelleher, & Hollenberg found that maternal age was a significant predictor of neglect but not of physical abuse, that household size was significantly related to the risk of physical abuse and of neglect, and that the effect of depression on risk of physical abuse diminished to non-significant once substance abuse and social variables such as socio-economic status and marital status were controlled for.[26] Neglect is more often framed within the context of exo-level and macro level factors such as community violence and poverty as opposed to being framed in association with family level factors such as caregiver relationship structure or parenting skills.[30]

Exo-Level (Community)

Cross-sectional and longitudinal studies of community influences on child maltreatment have largely focused on the neighborhood level, examining risk factors such as community violence and collective efficacy or iterations of collective efficacy such as social cohesion.[31–35] Community violence is theorized to affect the likelihood of child maltreatment due by influencing social norms about the acceptability of violence overall.[8] Explorations of social cohesion as a protective factor against child maltreatment have been inspired by the sociological work describing the influence of collective efficacy on child and adolescent outcomes, including adolescent pregnancy and child maltreatment risk.[36,37] Collective efficacy is defined as "task-specific construct that relates to the shared expectations and mutual engagement by adults in the active support and social control of children", and is considered a mediating mechanism through which neighborhood disadvantage affects health.[33,36,38] Sampson, Morenoff, and Earls extended the concept of collective efficacy to include its impact on children by exploring how social capital is constructed, maintained, and felt at the neighborhood level through processes such as intergenerational closure, reciprocated exchange, and informal social control and mutual support of children.[36] In short, communities that have social capital in the form of individuals who have strong social networks and felt capacity to actively affect child outcomes have better child outcomes. Earlier work on the effect of neighborhoods on health in the 1980s focused on concentrated disadvantage, including concentrated poverty and associated effects on racism and social exclusion.[36] Edwards and Bromfield explored the effect of an iteration of collective efficacy, neighborhood belonging, on conduct disorders of a nationally representative sample of four to five-year-old Australian children.[39] They found that conduct disorders, which may stress parents and increase the likelihood of maltreatment, was significantly related to neighborhood socioeconomic status, neighborhood belonging, and neighborhood safety after controlling for family demographics.

Children can be faced with both school and neighborhood level violence in addition to family level violence. While family level violence is considered a type of maltreatment, school and neighborhood violence are moderating factors on maltreatment risk. Youngblade et al found that neighborhood violence was significantly associated with child externalizing disorders, while school violence was associated not only with externalizing disorders but with internalizing disorders and academic performance, as well.[25] Child reports of violence have been associated with child well-being and maltreatment rates as well.[8,40–42]

Several cross-sectional studies have focused on the county level instead of the neighborhood, however. Maguire-Jack found that a higher level of spending on preventive services was significantly associated with lower individual child maltreatment risk.[32] An older but still important study by Spearly and Lauderdale found that Texas counties with more families with a median income below $15,000, single mothers, and working mothers had higher rates of county maltreatment, suggesting that community level factors can be indicative of maltreatment risk.[43] Similar to other studies, they found that the community level factors related to maltreatment risk varied by race and ethnicity.[43] Using the American Community Survey 5-year estimates, which will also be used in the current proposal, Eckenrode et al found that counties with greater income inequality and percentage of children in poverty were more likely to have child maltreatment rates.[44] A notable exception to the cross-sectional literature on county level risk indicators is a longitudinal analysis of economic indicators in Pennsylvania counties by Frioux et al. They found that county-level unemployment levels and foreclosure rates in the preceding year were positively, significantly associated with maltreatment claims and substantiated cases.[45]

Macro-Level (Social and Political)

One of the most influential risk factors at the macro level is the stigma against the use of violence on children and perception of what constitutes as maltreatment. While it has largely been socially unacceptable to commit sexual abuse, physical or emotional abuse can be considered disciplinary and even encouraged.[8] Emotional abuse can be especially hard to detect and is likely vastly underreported, as the signs are often not easily visible (e.g. corporeal). Furthermore, children may not even realize that the abuse they are suffering is excessive and instead think of it as “normal.” As child maltreatment prevention efforts have increased over the past twenty years, advocates have explicitly aimed to increase the unacceptability (stigma) of physical abuse, and the relative decline in physical abuse seems to support the benefit of these efforts.[8] However, as the prevalence of neglect remains mostly stable, more work needs to be done to educate parents about the associated harms of neglect.

State and federal policies can also influence the likelihood of maltreatment and its detection. For example, due to efforts promoted by groups such as the North Carolina Child Fatality Task Force, there have been increases in universal, selective, and indicated prevention programs in North Carolina since 2005.[46]

Due to the relatively small geographic size of the focus of this proposal, these macro-level factors will not be explicitly built into the simulation model unless the EBPs modeled directly target them. It will be assumed that the level of stigma or policy influence is constant across counties and populations unless otherwise noted.

Decision Making Challenges in Child Maltreatment Prevention Policy and Public Health Efforts

Decision makers at the county level, including public health department officials, non-profit organizations, and legislators, face particularly important decisions that affect the potential for preventing child maltreatment in North Carolina (NC), as NC is one of nine states in which counties are responsible for managing the child welfare system and delivering maltreatment prevention programs.[47] The primary exception is regional health alliances in which multiple county health departments work together, particularly in rural, small population, low-resourced areas. Thus, most evidence-based programs (EBPs) for preventing child maltreatment that are currently implemented in North Carolina, such as Nurse Family Partnership and Triple P, are implemented at the county level.[48,49] Some counties are beginning to collaborate with Managed Care Organizations in order to pool resources and reach more patients across North Carolina.

States and counties have taken a variety of approaches to address child maltreatment risk, from enhanced primary care services to detect and treat family psychosocial issues to implementing home visiting programs at the regional or state level.[50] Some states implemented recommendations or supportive policies and financial incentives to influence upstream risk factors such as parental education and financial distress by aiming to reduce high school dropout, offering housing vouchers, and increasing child support payments.[50] Community based funding for child maltreatment programs often comes from Medicaid, Social Service block grants, or block grants such as the Community Based Grants for the Prevention of Child Abuse and Neglect through the 1974 Child Abuse Prevention and Treatment Act.[50]

The North Carolina Institute of Medicine convened a task force to assess child maltreatment in North Carolina and develop priorities for action in 2005. Progress on the 37 recommended actions was discussed in an updated report in 2007. The priorities were strongly centered on prevention, including developing a public-private leadership group for child maltreatment prevention, changing social norms, increasing the use of evidence-based and promising practice, and increasing funding for prevention.[51] To increase the use of EBPs, the task force noted the importance of being aware of the prevention research, identifying strategies to disseminate information, and identifying was to support EBP implementation. Crucially, an evidence-based working group helped funders realize that they shared common goals and strategies for achieving these goals. Funders included Family Resource Centers, the Duke Endowment, Kate B. Reynolds Charitable Trust, and the NC Division of Public Health. These funders helped launch the NC Nurse Family Partnership Initiative starting in 2008, and continue to expand the program throughout the state. Additional funding sources being explored include the Division of Social Services and Children's Trust Fund.[51]

Broadly speaking, decision making is difficult and complex at any level. People typically hold inaccurate mental models to explain reality given their limited and biased perspectives, fail to account for long term consequences, and do not anticipate some effects due to interconnected factors and indirect effects such as feedback loops.[52,53] For example, Braverman and Blumenthal-Barby found that in a simulated scenario, providers altered their treatment decisions based on previous courses of action.[54] Likewise, it is a well-known phenomenon that the severity of sentencing in the courtroom can be influenced by the preceding cases. Cognitive biases, such as hindsight bias and affirmation bias, can also affect what information decision makers retain, such as the outcomes of a given decision.[55] In particular, people tend to recall details that are in line with preconceived beliefs and outcomes more accurately and in greater volume than information to the contrary, and stop exploring solutions when a satisfactory (not necessarily perfect) solution is found due to limited abilities to process input, a phenomenon known as bounded rationality.[55]

Given that child maltreatment is a complex problem, decision makers must select EBPs in the face of this complexity and consider multiple influences on child maltreatment, as well as their decision-making process. The decision-making ecology framework, for example, has been applied to child welfare agency processes to explore how decision makers consider the individual case, agency level factors such as the organizational attitude and previous experiences, and the outer context such as laws and initiatives.[30] Using this framework, Maguire-Jack and Font found that county levels factors, particularly the population size and percentage of the county that was Black or Hispanic, was more significantly predictive of new maltreatment reports than agency or casework characteristics such as the level of professional degree and length of time at the current organization of caseworkers, though child and family level factors such as age, race/ethnicity, and previous out of home child placement were the most important.[30] Likewise, decision support tools, such as the one proposed here, should take into account not only the directly causes of the outcome of interest, but those that are indirect, as they may be of near equivalence in impact and provide additional points for intervention and prevention.

When selecting an evidence-based intervention for implementation, decision makers are left to consult the literature or registries such as the California Evidence-Based Clearinghouse for Child Welfare or Blueprints for Healthy Youth Development. Unfortunately, literature reviews can be daunting in the absence of protected time and practiced skills for evaluating the literature, and evidence-based registries rarely include information on the environmental context that decision makers desire.[56] In the absence of this environmental information, decision makers rely on experience[55,57] or their intuition.[58–60] Intuition can be misleading and lead to poor decision making, however, as it is often applied inconsistently, is dependent on the decision maker's ability to understand cues and feedback in the environment, can be influenced by anchors in the environment or decision making process, and feedback to the contrary of intuition is often explained away or ignored.[53,60] Sosnowy et al found that decision makers in local health departments were more likely to use evidence-based decision making processes when information about local context and programs that fit local needs were available.[61]

Multi-level contextual effects on decision-making for EBP selection

Context: Physical and Cultural Environment

Further complicating decision making around EBP selection, most interventions have not been tested in the context in which it will eventually be implemented.[62] Concerns about the external validity of EBPs has been gaining attention in Implementation Science for child maltreatment in recent years, though most investigations have focused on the child welfare setting and organizational factors, not community and physical environment factors.[63–65] For example, rural health leaders often lament that they have a limited selection of EBPs to choose from, as most programs have been tested in well-resourced, demographically and geographically different urban areas. Communities want to know that the program will address their needs and goals while also utilizing their unique strengths and available resources. Scaling out an intervention to a new delivery setting, location, or population requires an understanding of the context in which an EBP was originally tested, and the key components that may vary in the new environment, the latter of which requires data that may or may not be available.[62] Simulation models can help researchers and decision makers quantitatively estimate the influence of environmental factors, as well as particular EBP components without costly randomized controlled trials.

Kegler, Rigler, and Honeycutt found that environmental characteristics such as rurality, the percentage of English speakers, the presence of particularly high or low-income subgroups, fear of immigration services, racial tension, economic distress, and geographic location of a community can affect decision making and relative priority setting.[67] Similar to many factors, rurality can be both a positive and potentially negative factor, as rurality could mean limited resources available for program implementation and social isolation, but can also be associated with service co-location due to limited resources and thus easier, more streamlined opportunities for collaboration between sectors as the same people wear multiple hats so to speak, whereas in urban areas there may be more difficulty in breaking through silos. Rural communities can have more transportation challenges due to limited public transit options and great distance between housing and services, but can also be associated with a central downtown or location where families can easily access services as they commute.[67] Further, it is crucial to not only be aware of the racial and ethnic composition of a community, but of the historical and current racial tensions that exist, and any disparities between the racial/ethnic composition of decision makers and the population being served. Kadushin et al are quite clear about the consequences of ignoring such environmental factors, stating that "an approach that ignores social class division and ethnic mistrust is unlikely to be successful."[68] Unfortunately, it is uncommon for an analysis of the organizational leadership's racial and socioeconomic background to accompany that of the community at large, a potentially grave misstep in community intervention planning.

Beyond community coalition functioning and decision making, researchers have also drawn attention to the relative effectiveness of interventions given the implementation context. Hobfoll, Walter, and Horsey point out that the theory of ecological congruency (see Figure 2.2) calls for an assessment and consideration of the ecological context such as community values, history, and resources prior to decide how, when, and how often to intervene in response to community trauma.[69] For example, if a community does not perceive a particular event or behavior to be traumatic, there may be less acceptance of an intervention to prevent or treat the supposedly traumatic event or behavior. Thus, interventions need to meet communities where they are. This is not to say that communities who do not believe that physical harm is a type of child maltreatment will be unreceptive to child maltreatment preventive interventions, for example, but that any intervention must also include education on the consequences of physical harm. Relatedly, Kadushin et al found that the economic class and racial/ethnic composition of a community affected who was hired to deliver interventions and that the worker demographic did not always match the population being served, a factor that has been shown to be important with respect to program effectiveness.[70,71]

Unfortunately, little information on environmental factors databases relevant to EBP effectiveness and implementation is provided by databases or clearinghouses that rank the quality of evidence behind various programs.[56] Decision makers are often pointed to these databases by technical assistance groups and prevention programs or systems such as Communities that Care,[72] thus this dearth of information on contextual relevance is a crucial gap in the type of information available to and desired by decision makers.[61] Bronfenbrenner reminds us that "Most families are doing the best they can under difficult circumstances; what we need to do is change the circumstances, not the families."[27] Bearing this statement's intent at heart, one purpose of this proposal is to understand which environmental factors at the county level are most influential on family and thus child well-being in terms of child maltreatment risk. Understanding which factors are most influential may help narrow the list of interventions that may be aligned with community needs by including programs that explicitly target those factors. Alternatively, understanding how factors relate to one another may help show that EBPs that target the same risk and protective factors may be nearly equivalent in effect, and thus decision makers can choose the EBP based on characteristics other than targeted factors such as resources required or qualitative preference. Table 2.2 provides a simple overview of how targeted RPFs may overlap between interventions.

Context: Prevalence of low-response and high attrition subgroups for EBPs of interest

Context does not only mean the delivery system or environment in which an EBP is selected, but can also mean the prevalence of subgroups that have been shown to have high rates of attrition or low rates of response during EBP trials. For example, mothers who smoked and had lower levels of education were found to drop out more frequently from the Nurse Family Partnership (NFP), a home visiting program to prevent child maltreatment.[73] McGuigan et al found that older mothers and Hispanic mothers were more likely to remain in the Ohio Healthy Start home visiting program. Families residing in areas with high levels of community violence were more likely to drop out, supporting previous findings by Garbarino and Sherman that showed women were less likely to seek supportive services when they lived in a high-risk community.[74] Lanier et al found that parents who had lower income and levels of functioning were more likely to drop out of parent-child interaction therapy in a community setting using a quasi-experimental design.[75] Such findings do not mean that these programs could not be effective in communities with high smoking prevalence among low-income mothers or high levels of community violence, but that additional resources would have to be accounted for during decision making and budgeting so as to increase retention. Thus, we must aim to understand who we are attempting to assist when considering the intervention responses and timing of implementation in order to improve population health.[76]

Trials for Triple P have largely found that the program is effective across countries and multiple delivery settings, with most of the variation in effect attributed to variation in intervention delivery and dosage.[77,78] However, few trials have acknowledged or directly assessed the influence of implementation locations other than country. Indeed, even the population trial of Triple P only acknowledge that counties were matched on characteristics such as population size, poverty rate, and child abuse rate, prior to stratified randomization, but did not analyze variation by county.[79] The population trial did note that parents with higher levels of housing instability, financial stress, and overall stress reported that it was harder to attend the program and maintain attendance.[79] Thus, such factors should be considered for Triple P and likely any program that requires regular, in-person, frequent attendance. Thus, understanding context for decision making requires an understanding of not only *what* is present, but *who.*

Context: Financial, Human, and Organizational Resources

While not a focus of the current proposal, it would be incomplete to have a discussion of community context without acknowledging resource availability. Resources included factors such as workforce for delivering an intervention, the health care and child welfare system infrastructures, community coalitions for implementation, funding available for program implementation, and less tangible factors such as leadership knowledge about and commitment to implementation. Maguire-Jack found that the level of funding spent on preventive services at the county level was significantly associated with lower odds of child maltreatment at the individual level.[32] Several evaluations of EBP implementation, such as Communities that Care (CTC) and Project STEP, have found that community coalition functioning is related to the successful implementation at the community level, suggesting that attention should be given to fostering relationships between groups responsible for selecting and implementing community wide interventions.[80–82] Relatedly, Kegler, Rigler, and Honeycutt found in a qualitative analyses of the functioning of eight community implementation sites that community decision making can also be influenced by not only current coalition functioning and collaboration but historical collaborative experiences and decision making, as well as macro community factors such as community level politics, history, and norms.[66] Finally, it is logical that decision makers should care about such practicalities as funding availability for implementation and sustainment as well, thus future iterations of simulation models to support implementation planning, such as the one proposed here, should include cost-effectiveness analyses and budget restrictions.[61]

The importance of resource availability may vary by intensiveness of the EBP. Trauma Focused Cognitive Behavioral Therapy (TF-CBT) and Parent Child Interaction Therapy (PCIT) have a more individual and family-based approach to treatment than the relatively population-based approaches of NFP and Triple P. Therefore, most research around these programs focus on the qualifications and resources of providers and organizations implementing the organizations than the communities in which they are implemented. These programs require moderately to highly qualified clinicians, as well as discrete settings such as community agencies in which to implement them. Further, clinicians must undergo at least 40 hours of training for PCIT, indicating that sufficient funds and policies must be in place to allow for such training.[83] With respect to population characteristics, TF-CBT is indicated for children up to age 18, and PCIT is indicated for children up to age 11, leading counties with a wider age range of children in need of services to possibly consider programs such as TF-CBT more heavily.

To close the discussion of the influence of context, it is worth noting that context is important if decision makers think it matters even if evidentiary support is deficient. That is, despite evidence that some programs can be successfully scaled out to new populations or delivery systems, the *absence* of evidence that a particular EBP in consideration will be effective in a given context allows decision makers to question whether the EBP will be effective for *their* community. This skepticism is a common human psychological reaction to new experiences in that decision makers may have seen previous programs fail in their community and assume that it is because of their community's unique circumstance or composition.[53] Further complicating the quality of EBP selection, decision maker's *perception* that their community is different, regardless of any statistically meaningful difference, will shape the way that decision making is undertaken, from problem formation and definition to EBP selection and implementation.[53] Thus, quantitative methods such as the latent profile analysis within this proposal can provide a useful tool for helping decision makers understand the relevant differences and similarities of their community and can (and should) be adapted to suit the preferences of decision makers in future iterations.[83]

Potential of Systems Science

System dynamics and systems thinking have long been applied in other disciplines, but the application of systems science to public health issues is relatively more recent.[84–92] The first applications of system dynamics to child maltreatment issues were in the 1980s, and there has been a recent increase in calls to apply systems science methods and thinking to public health issues.[93–97] These calls have proposed that systems science methods and thinking have the potential to provide a more comprehensive, multi-faceted approach to public health problem solving and move beyond the typical linear thinking and relatively short-sighted solutions produced by prevailing methods. Systems science methods and thinking are uniquely situated among available frameworks for addressing local context and addressing complex, wicked problems such as child maltreatment.[8,98,99]

Wicked problems are those that require multi-sectoral, multi-pronged solutions due to their complexity.[100] Child welfare is said to be a wicked problem because governments shift between blaming individual parents to the systems and environments in which parents operate, have difficulty selecting which measures to use to indicate success, and even shift between which child well-being outcomes to focus upon.[8] Systems science methods and thinking acknowledges the complexity and "wickedness" of many problems that society faces due to the complex linkages between factors that determine behavior, and, crucially, how the system itself produces emergent behaviors that are often difficult to predict precisely due to the complexity of interaction that create collective and emergent behaviors that are more than the sum of the collective parts of the system.[52,85,94]

While system dynamics was developed for supporting operational research and decision making in business by Forrester in the 1950s, there have been increasing calls for the use of methods such as system dynamics that can handle the complexity of population health and epidemiology, as well as the implementation efforts to address adverse population health outcomes.[88,101,102] Traditional statistical models often do not fully account for time lags, or delays, in intervention effects, feedback loops, and, crucially, *how* factors interrelate to produce health outcomes.[52,86,94,103] Instead, many statistical causal inference models simply control for or remove the influence of multiple factors to theoretically isolate the direct or indirect effect of a risk factor, such as race, when in reality race is a complex phenomenon whose impact on health is shaped by a myriad of other factors such as income, immigration status, social cohesion, community norms and history, and racism, to name a few, and a policy that aims to target only one of these will fall short of anticipated effects due to failure to account for all of the necessary and sufficient conditions that produce it. Notably, however, the decision about whether to use systems thinking and/or models does not have to exist in direction opposition to statistical uncertainty analyses such as Monte Carlo analyses and causal inference models.[103] Limitations exist with every model, and appropriate assumptions must be made about population exchangeability or external validity, data reliability, model external and internal validity, and model uncertainty.

Previous Systems Science Based Studies in Child Maltreatment

A structured literature review was undertaken to identify previous studies that utilized systems science thinking and related simulation models to address questions related to the prevention of child maltreatment. PubMed, Scopus, and PsycInfo, two leading databases for health research and proceedings, were searched using a combination of search terms related to child maltreatment or abuse and systems science terms ("systems science," "complex systems," "systems theory"), systems based models (e.g. "decision tool," "agent based model," "decision trees") and goals of the study (e.g. "relative impact," "simulating impact," "selecting interventions). The full search strategy is included in Appendix B. Included studies were those that used systems thinking and/or methodologies to understand child maltreatment, its risk factors, or follow up actions to substantiated cases such as placement. Excluded studies included non-primary articles such as commentaries or meta-analyses, those trying to predict adult outcomes or for parents who had been abused, studies that limited a discussion of the system to family systems, or studies that did not use a systems science methodology.

After duplicates were removed (n=2), a total of 720 studies were reviewed by title and abstract, with 85 reviewed by full-text. A total of 41 studies were included; 28 represented a theoretical use of systems science thinking (primarily *Systems Theory* or Bronfenbrenner's *Ecological Approach*) to design an intervention, propose a new framework, or conduct a qualitative analysis or case study, and the remaining 13 used a systems-based model (four multi-level statistical decision models, two decision trees, two system dynamics, one conference proceeding with an agent-based model, and four agent-based model articles reporting the same two models). Most of the included theoretical studies are older, from the late 1990's and early 2000's, while the recent uptick in methodological studies is primarily due to the dissemination of two agent-based models. About half of the systems-based models utilized multi-level modeling such as hierarchical linear modeling and decision tress. These two methods are arguably systems based, as they do not explicitly utilize systems science methodology, but the systems thinking motivation behind the structure and specification of these models led them to be included for the purposes of this review. Only two studies used an agent-based model for simulating factors related to child maltreatment rates.[99,104] Two studies used a system dynamics model to understand risk factors around child maltreatment, with the first being in 1981 and the second in

2013.[105,106] Full text was not available for the first model, and the goal of the 2013 article was not to target modeling child maltreatment, but instead to model social determinants of population health using multiple health that did not include child maltreatment.[106] The other system dynamics models related to child maltreatment that have been developed, to the author's knowledge, have focused on case load dynamics and foster care placement, and have not focused on the risk and protective factors across the ecological system such as the model in the current proposal.[107] Most of these are in the grey literature such as reports from private organizations and thus did not show up in the described review.[107,108]

Previous System Dynamics Models for Health Care Intervention Decision Making

Several system dynamics models similar to the one proposed here have been utilized for exploring the potential effect of interventions for population health outcomes in partnership with decision makers. Five are particularly worth exploring due to their relevance to the current proposal. Mahamoud and colleagues developed a system dynamics model with secondary data that aimed to simulated dynamic changes in population characteristics and social determinants of health so that the effect of various interventions and the timeframe over which they will be efficacious on morbidity and mortality due to several health conditions could be observed.[106] They note that system dynamics models are aptly situated to model social determinants of health due to their structural nature, especially since the complex ways in which determinants interact and mediate health outcomes are still largely unclear. While they did not employ a GMB approach, they did involve stakeholders and noted the advantage of including stakeholders to develop consensus on potential policy actions and to identify the types of issues that are of highest priority. Across a range of interventions, both health and economic based such as housing or job creation, household income and social cohesion were consistently strong predictors of health outcomes in the simulated scenarios.

The PRISM model, developed by researchers at the Center for Disease Control and Prevention (CDC), modeled the effect of fifty interventions on cardiovascular disease and risk factors.[109] Interventions included policy-level interventions such as clinical services, air policies such as air pollution reduction, and lifestyle interventions such as nutrition. Interventions were considered ready to be modeled if more than 50% of published documents by agencies such as the American Psychiatric Association and U.S. Preventative Services Task Force recommended it. Notably, the model included population dynamics such as birth, death, and migration, as well as costs associated with each cluster of interventions. Health care policy interventions and established health care interventions had the largest effects on health outcomes, with air and lifestyle interventions having a modest effect. This model was later used for health care planning in Austin, TX, and interaction with model garnered enthusiasm among decision makers about the shared directions for action that they selected and increased their communication with one another about the local environment.[110] Hirsch and colleagues worked in partnership with the Cancer, Cardiovascular, and Pulmonary Disease Project of the El Paso County Department of Public Health and Environment to build a system dynamics model to simulate population level trajectories of cardiovascular disease (CVD) risk and various strategies to reduce CVD on the county level.[111] The model and theoretical framework that they utilized built upon previous CDC models that focused on obesity and diabetes prevalence, trajectories, and associated interventions, including the PRISM model. The El Paso model went beyond health impact to also simulate the costs associated with health outcomes and related risk factors. This model included potential interventions to two broad categories of "lifestyle and environment," such as smoking bans or housing support, and “medical and mental health outcomes” such as improving mental health service access, though no particular EBPs were modeled.

Zimmerman and colleagues conducted a participatory system dynamics modeling approach within the Veterans Affairs (VA) to help understand veterans’ outcomes after implementing a new process for treating mental health disorders such as post-traumatic stress disorder (PTSD), depression, and anxiety within the VA.[112] They used the system dynamics model to understand how systemic complexity and dynamic complexity was inhibiting implementation and quality improvement practices to improve mental health services in the VA, and included frontline staff as well as leadership to learn together about the complexity.[113] Similar to GMB, participatory system dynamics modeling helps by adding not only a structured process, but a tangible tool to the decision making process. The system dynamics model helped stakeholders understand how to improve reach of EBPs, shorten service delays, and when to time implementation of new interventions. Similar to the proposed model for this dissertation, the modeling team aimed to look at EBP alignment with the system. In contrast to the goals of the current proposal, Zimmerman et al. specified implementation reach as their primary outcome instead of symptom or diagnostic improvement. Such implementation outcomes are outside of the scope of the current proposed decision support simulation model.

Hassmiller Lich and colleagues also developed a system dynamics model for health care planning in the VA in collaboration with VA workers. Specifically, they compared the potential effectiveness of 15 stroke interventions.[114,115] This model accounted for population heterogeneity by 11 mutually exclusive patient stocks differentiated by patient risk factors, and then segmented post-stroke and post-transient ischemic attack patients by level of disability and timeline since diagnosis, respectively. Simulated interventions were all clinically based, and separated into prevention levels (primary, secondary, tertiary/acute care). Requisite resources for each intervention were assumed equal, and this model was unique among those discussed by using Quality Adjusted Life Years (QALYs) as an outcome. This allowed for the model to simulate a common public health measure, number needed to treat (NNT), across each intervention. The model suggested that primary preventive interventions were helpful on the population level, but not always efficient in terms of NNT. Interventions that were both effective and efficient were selected for potential implementation by the VA.

Finally, it is worth mentioning that qualitative system dynamics models can provide opportunities for team learning and intervention planning in the absence of a full quantitative model. Best et al used system dynamics mapping (concept mapping and causal loop diagramming) to improve leadership collaboration, communication between leaders and front line staff, and to understand not only the barriers and facilitators to implementing new interventions in the health care system, but *how* these barriers and facilitators are perceived to interact.[102] They then used the qualitative data to identify specific, action-oriented strategies to improve implementation for specific initiatives and more general guidelines that can support clinical system changes.

Current Mental Model

Donella Meadows, a leading thinker in systems science thinking, suggests that researchers explicitly map their internal mental models prior to gathering input on the system structure from external sources such as the literature or system stakeholders.[52] Thus, a preliminary mental model for the system can be found in Figure 2.3.

Group Model Building

Group Model Building (GMB) is an engagement approach for facilitating community learning around complex problems and improving stakeholder engagement with system dynamics models.[55,116,117] GMB involves stakeholders while defining the problem to be examined or solved, building a qualitative or quantitative system dynamics model, and reviewing the model predictions and simulation of various potential policy interventions.[55] GMB processes have been used for addressing community violence,[118] obesity,[119] health system planning,[55] and military reorganization.[55] The exact structure of each GMB session can vary by the project and team, as can the length of the project, though the shared goals across each GMB project are to gather stakeholders' mental models, to develop a systems science model, and to improve decision maker capacity.[53] Richardson and Anderson are credited with first structuring the roles for the GMB process and developing scripts, the latter of which have been further developed by groups such as the Social System Design lab at Washington University in St. Louis under the direction of Peter Hovmand.[53,117,120] GMB can be used for theory building, although it is relatively new to the fields of social work and child maltreatment prevention.

Table 2.1: Risk and Protective Factors by Socio-Ecological Level

Risk Factor	***Protective Factor***
Micro **Individual level**	
	Resilient Personality
	Opportunities for positive interaction with non-parent adult caregivers
Race	
Age	
Sex (Female)	
Physical/Mental Disability	
Parent/Family Level	
	Supportive Social Network
Parent Mental Health Disorders	
Parent Education Status	
Total Family Income	
Immigration Status	
Geographic Residence	
Parental Substance Misuse	
Young Mother	
Non-marital Cohabitation of Caregivers	
Parent Mental Health Disorders	
Deficient Parenting Skills	
Antisocial Personality Disorder	
History of Physical/Emotional/Sexual Abuse	
History or Current Domestic Violence	
Family disorganization	
Non-biological, transient caregivers	
Numerous dependents	
Single Parent	
Exo **Community Level**	
	Availability of Preventive Services
	Social Cohesion
Neighborhood Disadvantage	
Violence	
Social acceptability of violence against children and related norms	
Local Policy	

Table 2.2: Targeted Outcomes by Exemplar Evidence Based Programs

EBP	**Child maltreatment**	**Poor family management**	**Family conflict/violence**	**Parental attachment**	**Parent stress, mental health**
NFP					
Triple P					
Parent Child Interaction Therapy					
Trauma-focused CBT					

Figure 2.1: Ecological Model of Child Maltreatment

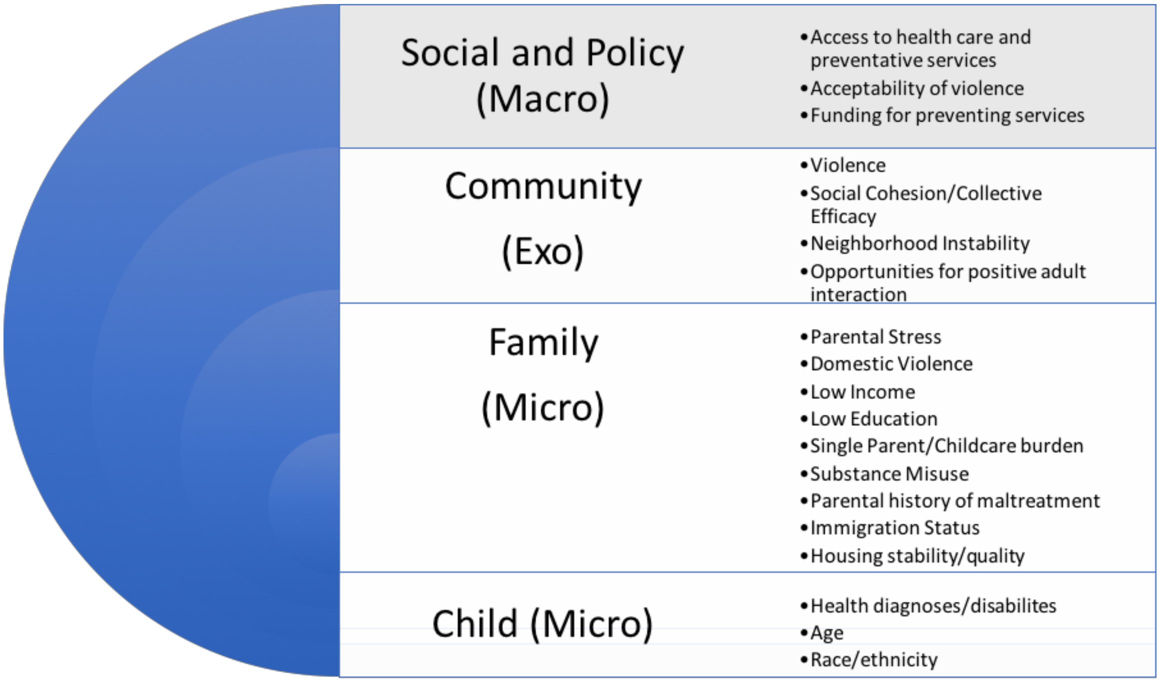


Figure 2.2: Model of Ecological Congruence (Hobfall, Walter, and Horsey 2008)

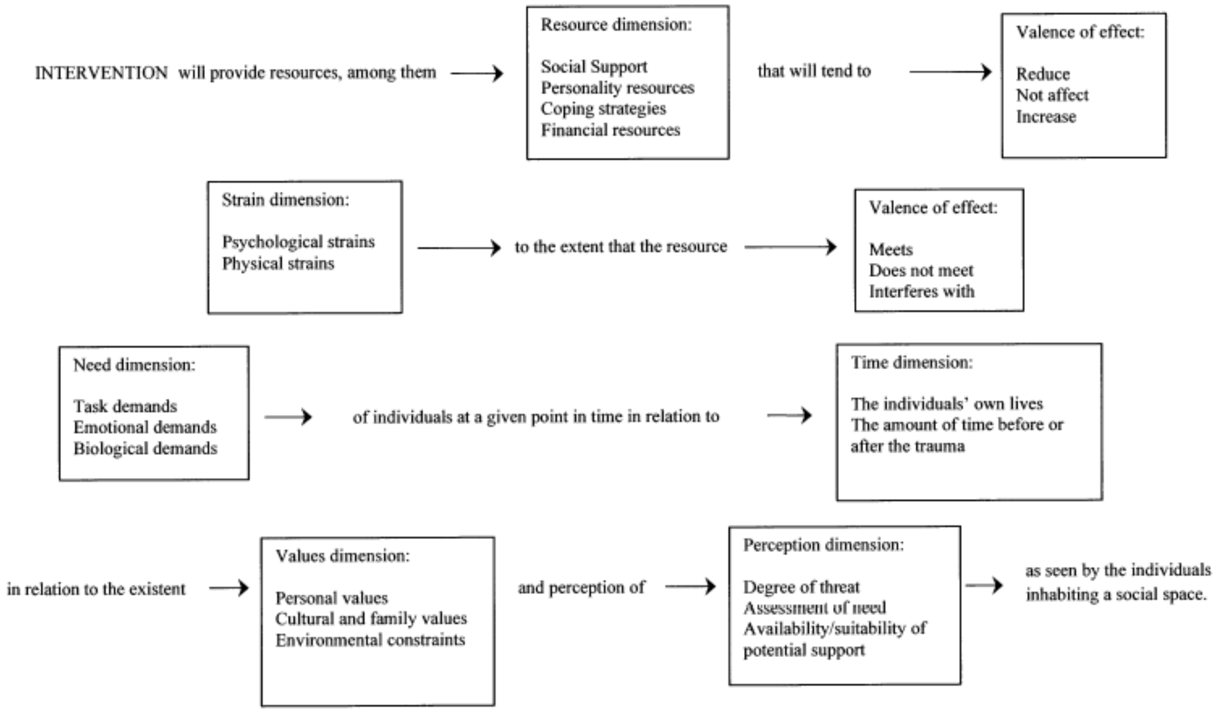
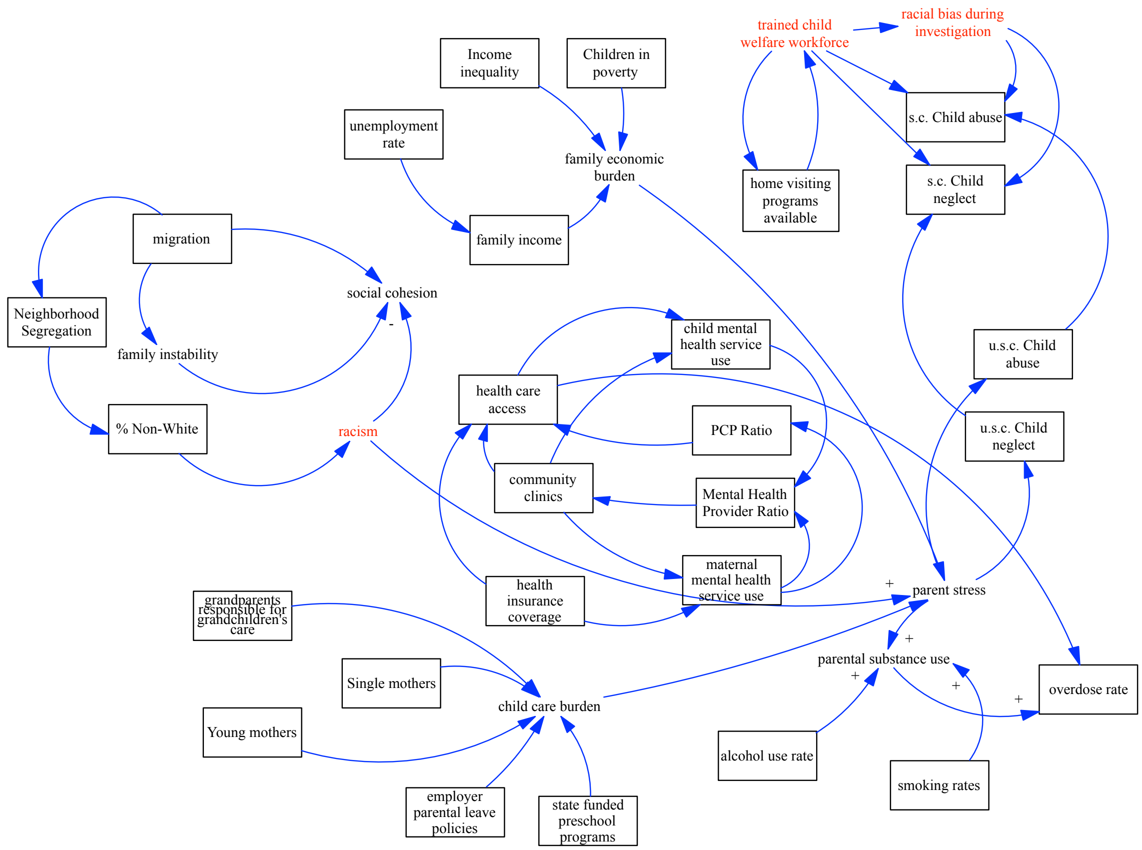


Figure 2.3: Preliminary Mental Model of Complex System Affecting Child Maltreatment and Behavioral Health Risk



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[1]Factors in red do not have directly measurable data; Variables not in boxes ("stocks") will be determined through confirmatory factor analysis; s.c. = substantiated claims for child maltreatment; u.s.c = unsubstantiated claims for child maltreatment

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Chapter 3 : **SPECIFYING LATENT COUNTY RISK PROFILES FOR CHILD MALTREATMENT RISK IN NORTH CAROLINA**

Introduction

In the 2015 federal fiscal year, over nine out of every 1,000 children in the United States (US) were found to be victims of child maltreatment.[1] While the US has made significant strides in reducing child abuse, far too many children still experience this trauma and associated life-long consequences.[2] Child maltreatment is associated with adverse outcomes in adolescence and adulthood, including increased substance abuse, lower educational performance, increased rates of mental health diagnoses such as PTSD and depression, and increased likelihood of further victimization such as domestic violence.[3–6] Clearly, there is urgent work to be done to prevent such adverse experiences.

County-Level Decision Making

Local health and social service departments are often on the front line of initiatives to prevent and detect child maltreatment cases. Nine states fund and plan initiatives at the county level and another three states have hybrid authority between states and counties to select and implement interventions aimed at preventing or treating child maltreatment.[7] When selecting interventions, decision makers must consider their local context, such as community demographics and resources. They must use their 'best guess,' in the absence of information from intervention trials to distinguish factors in their community that may affect outcomes after intervention implementation. Increasing our knowledge about local context may help improve implementation planning efforts as decision makers select which interventions are best suited to address the risk in their communities.[8]

Previous Work: County and Neighborhood Risk and Protective Factors

Previous studies to understand the influence risk and protective factors at the county or neighborhood level often utilize variable-centered approaches that aim to quantify the relationship between individual factors and outcomes.[9–11] However, Bronfenbrenner's ecological theory of child development posits that understanding child development and maltreatment should take a holistic viewpoint, acknowledging micro-level or individual factors, such as those related to parent and child characteristics, as well as exo, or community-level factors that interrelate over time.[12,13] This framework motivates the current study.

Micro-level, child-focused factors include those such as child demographics, school attendance, and physical or mental health diagnoses.[2] For example, children who irregularly attend preschool are more likely to have child maltreatment reports,[14] as are children who reside in areas with a lower proportion of children attending pre-school.[15,16,17]

Parent mental health is also important for understanding child maltreatment risk. There is mixed evidence around the magnitude of the effect of parental depression on child maltreatment.[18–21] Slack et al found that depressed mothers had 1.2 times the odds of child protective service investigations for neglect (*se* .11).[18] A similar increase in odds was observed for heavy drinking (OR 1.23, *se* .49) and drug use (1.09, *se* .74), but these increases were not statistically significant. In a meta-analysis of risk factors for child neglect, parent mental or physical health disorders were positively predictive of child neglect, but substance abuse was not significantly related.[19] Another meta-analysis found weak but statistically significant relationships between alcohol use and child maltreatment as well as consistently significant and strong effects for parent depression.[21]

Family structure is also crucial to understanding child maltreatment risk. Coulton found that increases in single parent, female-headed households at the neighborhood level over a twenty-year panel study was strongly associated with increased child maltreatment rates, a finding that aligned with previous research identifying single-mothers as a high-risk subgroup.[14,22,23] Lanier et al and Fong found that racial disparities in child maltreatment between Hispanic and Black families compared to White families were associated with poverty levels, as well as the prevalence of teen and unmarried mothers.[24,25] One pathway through which single-parenthood is hypothesized to lead to increased child maltreatment risk is through reduced social connetedness.[26–28] For example, Li et al found that families with higher social support had .29 the odds of child maltreatment reports compared to families with low levels of social support (95% CI .11-.80).[14]

Social processes at the exo level, such as the county or neighborhood, have also been shown to impact child maltreatment risk. Maguire-Jack and Showalter found that neighborhood social cohesion was a potential protective factor against child neglect, but not against abuse or other risk factors such as parental substance misuse and mental health disorders.[29] Maternal participation in community activities has been shown to be significantly associated with an increase in internal control, which was in turn significantly associated with decreased child neglect and physical abuse.[30] Conversely, as maternal perceptions of negative neighborhood experiences such as social cohesion increased, so did child neglect, abuse, and psychological aggression.

Parents need both economic and social support through social services and other forms of public assistance. A higher prevalence of prevention services at the county level is positively associated with decreased levels of child maltreatment.[31] Negash and Maguire-Jack found that in neighborhoods where parents had a higher level of perceived social support services, such as domestic violence shelters, food pantries, child and parenting support, and housing, there was a decreased risk of child maltreatment.[28]

Economic distress, such as poverty, housing insecurity and food insecurity are strong micro and exo-level predictors of child maltreatment. Maguire-Jack et al found that increasing disparities in poverty rates by race and ethnicity were associated with increased disparities in child maltreatment by race and ethnicity. Poverty disparities were highest in urban, population dense areas, and metro areas had higher levels of maltreatment compared to non-metro areas. These results point to the potential of individually measured child maltreatment risk factors to be shaped by aggregate community factors. Fong found that the risk of involvement with child protective services (CPS) increased as the proportion of families living in poverty in neighborhoods increased. Relatedly, Coulton et al found that the association between neighborhood poverty levels and child maltreatment rates was statistically significant at all three time points in a panel study (1990, 2000, 2010).[32] Unemployment rates and the percentage of families on public assistance were significantly associated with child maltreatment at the latter two timepoints.

Importantly, income translates to material resources that provide basic physical needs such as housing. For example, Gubits et al found that families who received long-term rent subsidies were significantly less likely to have at least one child removed from the home by CPS at 20 and 37-month follow-ups. Slack et al found additional support for the importance of housing stability among mothers who receive benefits from the federal Special Supplemental Nutrition Assistance Program for Women, Infants, and Children (WIC).[20] Families were significantly more likely to have CPS involvement compared to families not reporting housing instability, estimating two times the odds of involvement. In a study utilizing multivariate logistic regressions to estimate the relationship between a multitude of child neglect risk factors among probabilistic samples of low-income mothers in a national sample, New York, and Illinois, WIC receipt was not significantly associated with child neglect risk as defined by CPS involvement or parental self-report. According to family financial stress theory, material resource deprivation may not only be directly related to child maltreatment risk due to the inability of parents to provide for the basic physical and safety needs of children, but the stress of financial insecurity can affect parental well-being and the ability of parents to positively interact with their children.[33]

Research Questions and Hypotheses

Person-centered analytic approaches that take into account the interconnections between factors, such as latent class analyses, are needed to understand how these factors work together to shape health outcomes and child maltreatment risk. These factors are not independently distributed,[34–37] and as such efforts directed at a single factor without consideration of the broader profile are not likely to be as impactful as interventions targeted at prevalent risk and protective factor (RPF) profiles.[38–40] In order to support more impactful state and local policy planning, we must further our understanding of the relationships between local RPFs and population health outcomes such as child maltreatment. This study aims to develop a holistic understanding of child maltreatment due to micro and exo level factors that are observable at the county level by 1) generating empirically derived county composites defined by RPFs for child maltreatment using latent profile analysis and 2) estimating the differential association between child maltreatment reports based on these latent profiles. We hypothesized that 1) there are unique, unobservable, or latent, profiles across U.S. counties that can be defined by unique combinations of our nine domains of risk and protective factors for child maltreatment across the ecological levels affecting child development, and 2) these latent profiles will be differentially associated with reported rates of child maltreatment and maltreatment rates by the child victim's race/ethnicity.

Theoretical Framework for Current Analyses

We conducted a structured literature review of key meta-analyses, federal reports and trials reported in peer-reviewed publications to compile a comprehensive list of RPFs.[2,19,21,41,42] We then compared this list with variables available in two national and publicly available datasets including county-level specificity to identify the most parsimonious set of profile indicators for the current analyses. Figure 3.1 presents the RPFs that we include in the current analyses by ecological level and key domains within each level. Within the micro-level, we focused on the domains of child and parent education, child health care access, parent health, economic distress, material resources deprivation, financial support, and family structure. Our key domain at the exo, or community, level was social cohesion as measured by organizational memberships.

Contributions of the Current Study

As local decision makers are confronted with limited resources to reduce risk across a range of risk factors and seek to have a deeper understanding of their community's risk level beyond simplified generalizations such as low, medium, and high risk, a critical gap exists in our understanding of how to characterize the local context across a set of risk and protective factors.

We selected a latent profile approach because of the intuitive nature of such profiles for communicating how factors may interrelate.[10] Increasing our understanding of how factors co-vary in "profiles" across counties may improve decision-makers' ability to select locally-impactful interventions aligned with their community context. To make the profiles more accessible to county decision makers, we used surveillance data that is currently used in county health assessments and is thus familiar to county decision makers.

Methods

Data: Item-Response Indicators

We used publicly available, county-level surveillance data from 2016, the most recent year for which data was available from all sources. County risk and protective factors, or item-response indicators, were drawn from the Robert Wood Johnson Foundation County Health Rankings[43] and the American Community Survey (ACS) 5-year estimates. The ACS includes 1, 3, and 5-year estimates based on the most recent U.S. Census (2010) and the American Community Survey. These estimates offer tradeoffs between precision and recency, as the one-year estimates are the most recent, while the five-year estimates are the most reliable.[44] Five-year estimates include areas of all population size, while one-year estimates are only for populations greater than 65,000. Thus, the five-year estimates were utilized so as to include the smallest counties, representing approximately 42% of counties. While the ACS 5-year estimates are complete across all observations due to imputation by the U.S. Census Bureau, some factors in the RWJF CHR were missing, particularly in counties with fewer resources. To address missing data across six missing data patterns, we utilized the FIML approach in Mplus version 8.1.[45] Table 3.1 depicts the ten latent profile indicators by domain as well as the corresponding definitions and sources for each.

Data: Distal Child Maltreatment Outcomes

While we estimated the latent profiles with the full set of U.S. counties for which data was available (n=3141), we estimated the relationship between latent profiles membership and child maltreatment rates only for the state of North Carolina (NC), for which we had complete data across counties. Due to the suppression of data for counties with low base rates of maltreatment reports in our national outcomes dataset, we would have had proportionally significantly lower observations available to explore outcomes at the national level.[46] North Carolina alone had nearly 65,000 reported cases of maltreatment in the 2016 fiscal year, of which approximately 27,000 received or were recommended to services for treatment.[47] The final set of latent profile item-response indicators was determined by referencing our theoretical framework and reviewing the shape and variance of potential indicators. Several item-response indicators had particularly low variance, such as the GINI index of income inequality, or high variance, such as the percentage of adults reporting excessive drinking or children in single-parent households that precluded their inclusion. The model could not be reliably identified when these indicators were included. However, the theoretical pathways of how these variables could lead to increased child maltreatment risk are still proximally represented in the current set of indicators. For example, we assert that children in single-parent households are still represented through our inclusion of female-headed households with children, as female headed households are typically single-parent households. Additionally, we represent the concept of risky substance use that would have been indicated by excessive drinking through our overdose death rate indicator.

We obtained NC child maltreatment outcomes from the University of North Carolina Management Assistance for Child Welfare, Work First, and Food & Nutrition Services in North

Carolina. Rates were calculated per 10,000 county residents using population estimates from the ACS 5-year estimates. We explored four child maltreatment outcomes: *Total child maltreatment reports,* including all reports in a county in the state's fiscal year, regardless of whether the claim is substantiated and the type of abuse reported (i.e. physical abuse, sexual abuse, emotional abuse, neglect). Multiple reports can be filed for the same child, so the reports are not equivalent to the number of children involved. *Abuse* and *Neglect* rates are those reports which are substantiated as either type of maltreatment. *Total child maltreatment reports* were also explored by child victim's race or ethnicity, with only *Black* and *Hispanic* children having sufficient non-zero rates across counties to be estimable. Finally, we tested whether families *received services* as recommended by social services.[47]

Analytic Plan

To determine which observable child maltreatment risk and protective factors are associated with latent county subgroups, we employed Latent Profile Analysis (LPA) using a pseudoclass classification-analyze approach.[48,49] LPA is a type of Latent Class Analysis (LCA) that uses continuous indicators to predict latent profiles based on combinations of factors that cluster together. Resulting latent profiles are homogeneous within but heterogeneous across profiles. In contrast to variable centered approaches, LCA is a person-centered approach to discern heterogeneity between populations that has been shown to take a more holistic approach to understanding how a constellation of factors relate to outcomes.[10,48] There are two key assumptions required for LPA in the current research.[50] The first is normality of the distribution of each indicator within each latent profile. We estimate this to be met because we have sufficient sample size (n=3141) to allow for multiple counties within each profile. Second, measurement invariance of the key latent constructs, the measures of abuse and neglect. Any measurement error is likely to be constant across sites due to the collection methodology, as noted by the data repository.[47] Further, LCA-based approaches "explicitly model(s) measurement error" while also modeling the structural relationships among variables.[50]

The LPA model structure took the following form:[48]

$$P(Y = y) = \sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{r_j=1}^{R} \rho_{j,r_j|\,c}^{I(y_j=r_j)}$$

The probability of membership in latent profile *c* is denoted by γ_c, where γ is a vector of latent profile membership probabilities. The true membership to subgroups is unknown.[51] The probability of response r_j to item j, conditional on membership in latent profile p represented by $\rho_{j,r_j|\,c}^{I(y_j=r_j)}$, where ρ is a matrix of item-response probabilities conditional on latent profile membership. Figure 3.2 depicts an overview of the LPA theoretical framework.

Analytic Procedures

We employed a five-stage procedure for a theory-driven latent profile analysis in Mplus version 8.1.[45,52] First, we fit a baseline LPA model without covariates. Adding covariates gradually allowed us to understand whether class interpretations are changing and more clearly understand how the covariates are impacting the model.[53] Second, we ran a multi-level LPA accounting for clustering of counties at the state level, though these models did not converge after two profiles. Third, we returned to the LPA in step one and added the covariate for the proportion of the population that is rural, comparing the AIC, BIC, Lo-Mendell Rubin Test (LMR), Bootstrapped Likelihood Ratio Test (BLRT), and overall model performance to the baseline model in step one, described in detail below. The models in step one produced qualitatively similar results, so we focused our analyses on comparing model fit statistics for those models with our key covariate from step three.[2]

We selected the optimal model by comparing fit statistics including the Akaike Information Criteria (AIC) and Bayesian information criterion (BIC), which are recommended for assessing balance between model fit and parsimony.[48,54,55] The AIC tends to favor more complex models, and thus the model with the smallest AIC represents the maximum number of profiles that one should consider. In contrast, the BIC often under-extracts profiles and the model with the lowest BIC represent the fewest number of profiles that should be considered. These information criteria do not provide a statistical test of model fit, however. Thus, the BLRT was used to test the null hypothesis that the given latent class model is sufficient to describe the data compared to the alternative hypothesis that an additional class is required.[56,57] The BLRT compares two models at a time, bootstrapping the difference in the log likelihood between the model with *k* parameters and *k-1* parameters.[50] Models with a statistically significant BLRT value suggest that the significant model has statistically better fit compared to the model with one less profile.[58] In addition to consulting these statistical tests of model fit and parsimony, we also weighed theoretical interpretability and practical usefulness of the associated profiles such as the relative prevalence of each profile.[10,59] Once the preferred model was selected, we re-ran the model with twice the number of starts to ensure that the maximum likelihood was replicated.

Fourth, we associated pseudoclass assigned latent profiles with child maltreatment outcomes for North Carolina counties (n=100). Strict classify-analyze approaches have been shown to be biased due to overclassification of observations to the most prevalent latent profile.[48,53] To reduce this bias, we created four pseudoclasses in which observations were

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[2] Additional results available upon request. Most item-response estimates identical to the thousandth place, with some differing at the hundredth. AIC and BIC were lower in these models (see Appendix 3.1).

assigned to the latent profiles by: 1) generating a unique random number draw from a uniform distribution for each observation, 2) assigning observations to a latent profile based on matching the randomly drawn number to the observation's class-assignment probabilities that had been calculated in Mplus. This approach is comparable to multiple imputation approaches for missing data.[49] Our four pseudoclasses resulted in similar proportions of observations assigned to each latent profile, so we only present one here, which was the most inclusive across latent profiles. Additionally, we had high entropy across our initial latent profile models (.871), suggesting that class-assignment probabilities were relatively high and consistent, increasing our confidence that the pseudoclass assignment would be sufficiently unbiased.

Finally, we estimated the relationship between profile membership and the four child maltreatment outcomes using a negative binomial approach and delta method standard-error estimation for marginal effects. We selected a negative binomial because the distribution of the outcome did not have an equivalent variance equal to the mean and we were estimating a rate-dependent variable.[60,61] Pseudoclass and Negative Binomial analyses were estimated in Stata 14.2.[62]

Sensitivity Analyses

We conducted several sensitivity analyses to ascertain the reliability of our latent profile model and identified profiles. Due to the skewed nature of our data and thus high variance in some of our preferred indicators, we also ran two additional latent class models: 1) a latent profile model with logged versions of each indicator, and 2) a latent class model with the indicators transformed into quintiles, yielding 10 categories per indicator. These models both suggested a four-class solution, with an additional high-risk class compared to our presented results (Appendices 3.2 and 3.3, respectively). We elected not to select these models, as they were not as practically interpretable and were not sufficiently distinct from the presented model to warrant differential conclusions or implications. Further, we compared our primary latent profile model results with the item-response variables representing percentages on 0-1 and 0-100 scales. Results for class probabilities and item-response indicators were identical to the hundredth place in most instances. Using our selected model, we calculated the difference in predicted class membership for observations with and without the covariate included in the model, and found little to no difference across observations.

To test the sensitivity of our results to our model of choice and the pseudoclasses, we conducted two sets of sensitivity analyses. To compare our distal outcome association with profile membership, we used a model-based approach to relate child maltreatment outcomes to latent profiles in the restricted sample of US counties for which we had outcome data (n=820). The insights from these sensitivity analyses were comparable (Appendix 3.4). Further, we estimated our negative binomial regressions across the alternative three pseudoclasses and found no meaningful difference in the magnitude or significance of our estimates (Appendix 3.5).

Results

Descriptive Characteristics

Overall, counties had less variation in the included protective factors, such as social associations, compared to the variability within risk factors such as the percentage of female-headed households in poverty and the high school drop-out rate (Table 3.1). Total child maltreatment report rates varied significantly by county size and geography (Figure 3.3), with notably less variability in neglect rates due to the low baseline rate of this adverse outcome (Figure 3.4)

Latent Profile Membership Probabilities

Based on the comparatively low AIC and BIC, and the representativeness of each profile (Table 3.2), we selected a three-profile solution. In the four-profile solution, the fourth class that emerged had a prevalence of only .5% in the national sample. The four-profile solution separated the highest risk profile (and lowest prevalence profile) from the three-profile solution into two. The fourth profile that resulted was also high-risk, but to a lesser degree.

Latent profile membership probabilities with the pseudoclass approach are presented in Table 3.3 for the North Carolina observations only (n=100). Profile two was the most prevalent in North Carolina, while profile one was the least common with only seven counties with a high probability of random assignment. The profiles were associated with geographic clustering (Figure 3.5).

For each additional percentage of the population that lived in a rural area, the odds of membership in the two lower-risk profiles compared to profile three, the highest risk profile, was slightly lower, though only the second profile had a statistically significant lower odds (OR .994, *se* .002; Table 3.3).

Latent Profile Composition

The second parameter of interest, item-response probabilities, estimates the mean predicted level of each indicator for observations within the respective latent profile (Table 3.4). These probabilities thus characterize the nature of each profile, which can be described as follows: Profile one is labeled as **Low overall risk** because there were the lowest predicted mean levels of risk factors across all indicators with the exception of drug overdose deaths, which were the second highest predicted level across profiles. Profile two was labeled as **Moderate overall risk, high overdose.** This profile had the second highest level of mean predicted risk indicators with the exception of the predicted mean drug overdose death rate, which was the highest across profiles. Profile two had 15.90 predicted overdose deaths per 100,000 residents compared to 10.90 and 11.87 in profiles one and three, respectively. Profile three was defined as the **High overall risk** profile. This profile had the highest mean item-response indicators across all risk-factors among the profiles with the exception of predicted drug overdose deaths. Counties in this profile had approximately three times the level of risk across factors compared to profiles one and two, on average. To facilitate comparison, we show the variation in key indicators by pseudoclass profile in Figure 3.6.

Latent Profile Association with Predicted Child Maltreatment Outcomes

Figure 3.7 depicts the variation in mean predicted total child maltreatment reports by pseudoclass. Compared to being in the **Low-risk** profile**,** observations in **High-risk** profile were predicted to have approximately 12.00 more child maltreatment reports per 10,000 residents, although this result was not statistically significant (95% CI -9.67 – 33.67). Despite having lower predicted mean of most risk factors compared to the High-risk profile, the **Moderate risk, high overdose** profile had the highest number of total predicted child maltreatment reports with an additional 20.12 predicted reports per 10,000 residents compared to profile one (95% CI 1.38-38.86; Table 3.5).

There was not a statistically significant difference between any of the latent profiles compared to the **Low-risk** profile for substantiated neglect rates. Counties in the **Moderate risk, high overdose** and **High-risk** profiles had lower predicted rates of substantiated abuse reports compared to the **low-risk** profile, although these effects were not statistically significant (Table 3.5).

Services and Race/Ethnicity Disparities

Neither the **Moderate risk, High overdose** nor **High-risk** profiles had service receipt rates that were statistically significantly different compared to those levels observed in the **Low-risk** profile, holding all else constant. The **High-risk** profile was the only profile with a statistically significantly higher rate of child victims that were Black compared to the **Low-risk** profile, with 20.91 more predicted Black child victims per 10,000 residents (95% CI 6.78-35.04). None of the profiles were associated with a statistically significant difference in the predicted rate of Hispanic child victims.

Discussion

This study was unique in its utilization of a national dataset that included observations of all counties to obtain latent profiles of child maltreatment risk across the ecological domains affecting child development, as opposed to previous studies that have focused on a specific domain or subpopulations or that have used variable-centered approaches. As hypothesized, counties had varied levels of risk factors related to child maltreatment that clustered together in empirically meaningful ways. Contrary to our expectations, risk factors mostly moved together in the same direction, creating profiles of low, moderate, and high risk, with few risk factors deviating from classification as low to high risk across profiles with the exception of drug overdose deaths. For this risk factor, we found that the moderate risk level profile had the highest predicted mean drug overdose deaths. This profile was also associated with the highest child maltreatment report rate and the second lowest number of families receiving services as recommended by social services. These results suggest that, despite moderate risk, families are still not receiving sufficient support to care for children and promote child and family well-being. Further, simply having high-risk factors does not imply that families are the most likely to have high rates of child maltreatment, adding to the literature suggesting that the story of risk and protective factors is not always straightforward, with the risk associated with some factors outweighing the effect of others, and significant heterogeneity in the prevalence and combination of factors.[63,64] The **Low-risk** and **High-risk** profiles had relatively similar levels of drug overdose deaths with high and low-income indicators, respectively; whereas, the Moderate risk/High overdose profile had a high level of drug overdose deaths with a moderate income indicator. This finding contributes to the growing literature showing that overdose deaths, in particular, are not limited to low-income communities and may by affecting middle-class, White communities.[65–68] While we are not able to distinguish drug type underlying the drug overdose death rate, previous research has shown that the alarmingly high rates of drug overdose deaths in the United States are being driven by an increase in opioid-related drug overdoses.[69–71]

Our finding that families in the highest-risk profile received the fewest services is concerning and warrants further research. While this profile was not associated with the highest rate of any type of child maltreatment, these families are still in high-risk environments that place them at risk for a range of adverse childhood experiences and adverse health and social outcomes across the life course. Service provision could help ensure that these families need the support that is required to protect families against the effects of adverse environments and ensure that child maltreatment reports are followed up and substantiated when appropriate, in order to protect children.

Limitations

There are several limitations to the current study. First, we did not account for county membership by state, which is likely associated with higher standard errors. However, since our outcomes focused on North Carolina counties alone, we were not concerned about generalizability of the profiles across states. Further, during model testing we found no significant difference among profiles due to state versus county run social service systems, the primary hypothesized factor that would differentiate profiles at the state-level. Although other highly heterogeneous state-level factors such as state governance and norms could also be hypothesized to affect county profiles, but are more difficult to measure and we were thus unable to assess them. Second, missing data was more common among counties with smaller populations, ostensibly due to lower resources for responding to the surveys utilized for the latent profile indicators and concerns over county confidentiality. Interpretation of the results for smaller counties, in particular, should be made with this limitation in mind. This missing data also limited our ability to explore additional hypothesized micro and exo level factors of interest such as the degree to which housing segregation by race or ethnicity was observed, which could stand as a proxy for considerations of social cohesion and perceived racism. Due to the high variance of some of our proposed risk-factors, we were unable to include them as item-response indicators for our latent profiles. This may have limited our ability to understand the impact of indicators with a more direct relationship between risk and child maltreatment outcomes, thus leading to less variation across the profiles and weaker associations between the profiles and predicted maltreatment rates. Our ability to explore issues of equity in depth was thus limited. We were also unable to explore macro level indicators such as community norms or prevention services funding. Finally, our indicators were for all households in the county, not just those who had children under age 18. Thus, we may have underestimated the association between risk and child maltreatment for families.

We emphasize that county profile membership is a measure of association, not causation, and urge public health practitioners and their partners to bear in mind that county membership within a particular class does not imply a certain level of child maltreatment rates with certainty. Rather, the three presented profiles should be used as a tool to guide discussions around what factors on the county level may be impacting family and child level processes, as well as the impact of interventions that target those micro family and child level factors.

These profiles suggest three important take-aways. First, a high level of risk factors does not necessarily coincide with a high predicted level of child maltreatment. Second, drug overdoses continue to be prevalent across risk profiles. Considering the increasing number of children being placed in foster care due to parental substance misuse, this finding warrants further research with respect to child and parental well-being.[72–75] Finally, observable factors on the county level can be indicative of child maltreatment risk in a community, and may be especially helpful for monitoring communities in which high levels of multiple risk factors are observed. The three empirically derived profiles that we presented in this paper align with the three tiers of county distress proposed by the North Carolina Department of Commerce and last updated in 2018.[76] Similar to our profiles, the fewest number of counties were placed into their lowest distress tier (n=20), although an equivalent number of counties were in the middle and highest tiers of distress (n=40). The primary difference between their tiers and our risk profiles lies in that the distress tiers only include four indicators of economic risk, and do not include additional domains of child maltreatment risk such as health factors and family organization that our profiles take into account. In the same manner that the distress tiers are factored into state-level decision making to guide the development of economic activity through state programs, our risk profiles could be helpful for prioritizing state and county programming to support child and family well-being.

Considering the strength of the emerging literature around community protective factors[77–79] and community resilience[80] to promote community, family, and child well-being, future research should explore the impact of additional protective factors in latent profile composition and latent profile relationships to various child well-being outcomes. Empirical analyses such as those presented here will always fall short of capturing the complete set of risk and protective factors that affect families and should be interpreted with caution, but community decision makers can use studies such as these to guide their understanding of how to potentially monitor risk and intervene accordingly in their communities.

Table 3.1: Latent Profile Indicators and Descriptive Statistics

				North Carolina			National sample		
Ecological Level	**Domain**	**Latent Indicator**	**Definition**	**Mean**	**SD**	**Range**	**Mean**	**SD**	**Range**
Micro- Child and Parent									
	Health Care Access	Uninsured children (%)	Children under age 18 without any health insurance	6.10	2.46	(1.95-17.44)	6.89	5.10	(0-54.60)
	Parental Substance Misuse	Drug overdose deaths rate[+]	Based on National Health Statistics Overdose deaths modeled per 100,000 residents[+]	15.42	5.16	(7-21)	13.73	5.19	(7-21)
	Parent Mental Health	Mentally unhealthy days[+]	Average number of mentally unhealthy days reported over the past 30 days (age adjusted)	3.88	.26	(3.3-4.9)	3.67	.62	(2.1-5.6)
	Economic and Educational Status	High School drop-out (%)	For population aged 16-19	5.59	3.64	(0-25.59)	5.35	5.00	(0, 53.22)
		Unemployment (%)	Among civilian population over aged 16	5.22	1.25	(2.59-8.38)	4.02	1.67	(0, 18.76)
	Financial Support Services	Children receiving public insurance (%)	Children under age 18 receiving public insurance of any type	50.19	10.46	(24.57-74.10)	41.47	13.80	(0-100)
		Households receiving public assistance (%)	Households receiving public assistance of any type (e.g. WIC, SNAP, SSI)	2.10	.69	(.62-4.01)	2.46	1.72	(0-30.65)

Micro- Family									
	Family Structure (and Economic Distress)	Female-headed households in poverty (%)	Tax households with female head of house meeting federal poverty standards	6.17	2.81	(1.54-16.54)	5.16	3.10	(0-27.31)
	Material Resources	Food insecure (%)	Based on coefficient estimates from "Map the Meal Gap" analyses relating estimates of food insecurity and indicators at the county level to estimate rates for the child level	17.84	3.11	(11.80-26.30)	15.06	3.93	(4.2-33.40)
		Severe housing problems (%)	Households with overcrowding, high housing costs, or lack of kitchen or plumbing facilities	16.42	2.94	(10.60-27.70)	14.48	4.86	(2.2-71.3)
Exo- Community									
	Rurality	Rural Population (%)	2010 Census Designation	61.20	28.17	(1.1-100)	58.62	31.50	(0-100)

+ This variable was originally modeled by the RWJF County Health Rankings based on National Data and reported as a range for each observation. We converted it to a continuous variable based on the range rank based on the median value of the reported range (e.g. 6.1-8 = 7 and >20 = 2)

Table 3.2: LPA Model Fit Statistics

Model	Entropy	AIC	BIC	BLRT p-value	Lo-Mendell Rubin	Lo-Mendell Rubin p-value
2 profile	.815	134918.935	135094.451	.00	5581.310	.00
3 profile	.871	131923.545	132165.637	.00	4659.441	.00
4 profile	.895	130592.865	130901.532	.00	1337.579	.30
5 profile	.848	129537.525	129912.767	.00	1065.313	.09
6 profile	.840	128949.611	129391.428	.00	603.105	.70

Table 3.3: Odds of Profile Membership by Rurality

	Percentage of the population that lives in rural area		
Pseudoclass	**OR**	**SE**	**p-value**
1	*Referent*	-	-
2	.997	.002	.220
3	.994	.002	.014

Table 3.4: Item-Response Probabilities for North Carolina Counties (Mean (se))

	Profile 1	Profile 2	Profile 3
Probability (N) (Total N=100)	***.07 (7)***	***.75 (75)***	***.18 (18)***
Drug Overdose Fatality Rate	10.90 (.19)	15.90 (.17)	17.006 (.255)
Mental Health Distressed Days	3.14 (.02)	3.95 (.02)	4.44 (.03)
High School Drop-out Rate	4.36 (.16)	5.76 (.3)	7.39 (.40)
Unemployment Rate	2.95 (.06)	4.42 (.05)	6.48 (.27)
Publicly Insured Children	29.81 (.45)	46.77 (.62)	52.62 (.86)
Households receiving public assistance	1.89 (.04)	2.70 (.04)	3.63 (.30)
Female Headed Households in Poverty	3.07 (.07)	5.64 (.13)	11.89 (.54)
Food insecure households	12.02 (.12)	16.12 (.15)	22.59 (.53)
Housing Insecure households	12.32 (.17)	15.28 (.12)	19.51 (.67)

Table 3.5: Predicted Child Maltreatment Rates by Pseudoclass

Pseudoclass	**Marginal Effect**	**Delta-method Standard Error**	**95% CI**
Total			
1	*Referent*	-	-
2	20.12*	9.56	1.382, 38.86
3	12.00	11.06	-9.670, 33.66
Neglect			
2	.50	.30	-.08, 1.09
3	.23	.34	-.44, .90
Abuse			
2	-.13	.36	-.84, .58
3	-.20	.40	-.98, .58
Services Provided			
2	5.09	4.86	-4.43, 14.61
3	-3.85	4.89	-13.43, 5.74
Black Child			
2	1.98	3.77	-5.41, 9.36
3	20.91	7.21	6.78, 35.04
Hispanic Child			
2	-.05	1.58	-3.16, 3.05
3	2.43	2.01	-1.51. 6.37

*p<.05

Figure 3.1: Theoretical Framework of Child Maltreatment Risk for Latent Profile Analysis

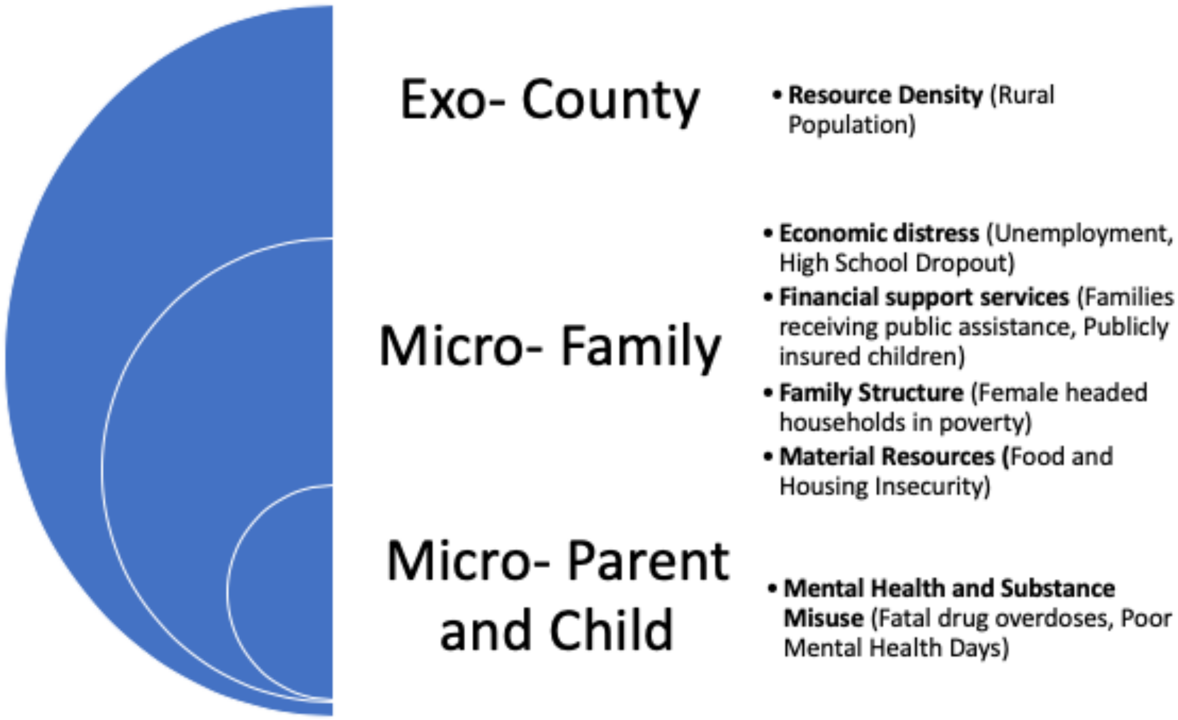


Figure 3.2: Latent Profile Analysis Analytic Model

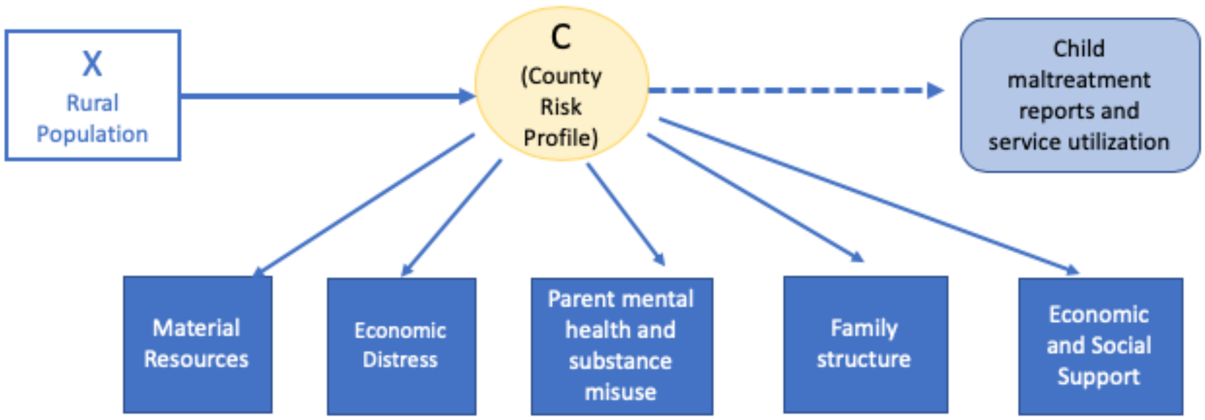


Figure 3.3: Total Child Maltreatment Report Rates by North Carolina County

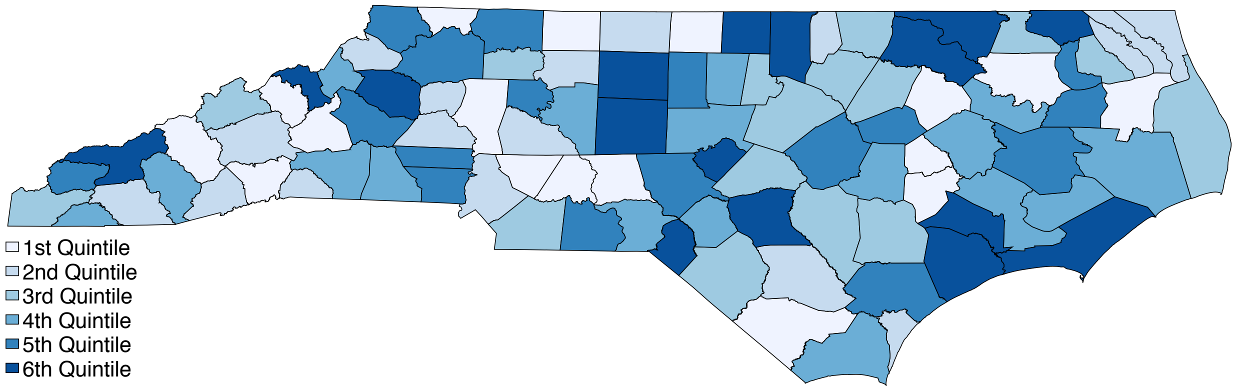


Figure 3.4: Substantiated Neglect Rates Expressed as Quartiles in North Carolina

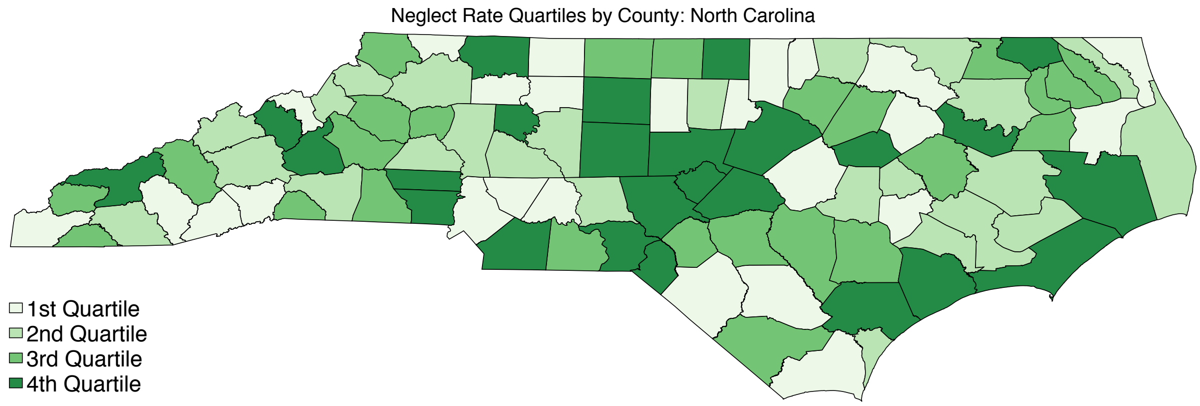
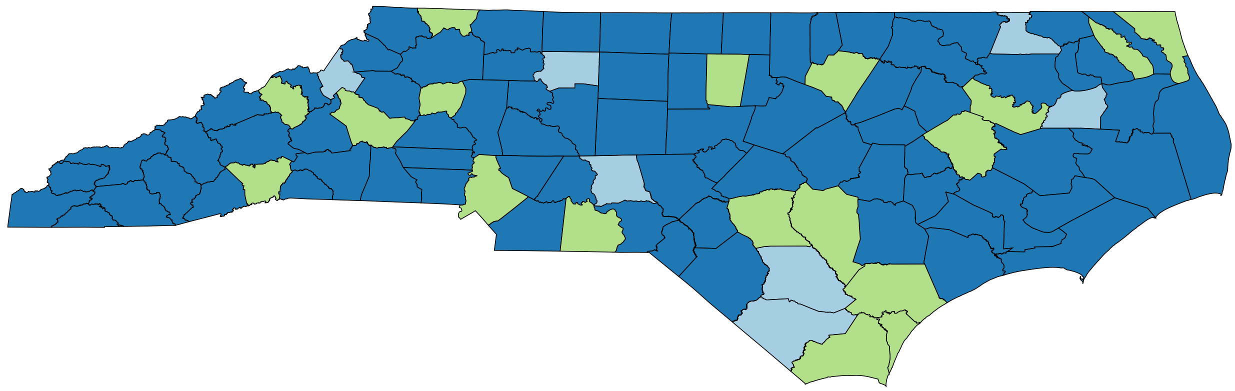


Figure 3.5: Latent Profile Representation in North Carolina



1 Low-Risk
2 Moderate Risk, High Overdose
3 High Risk

Figure 3.6: Item-response Means by Pseudoclass

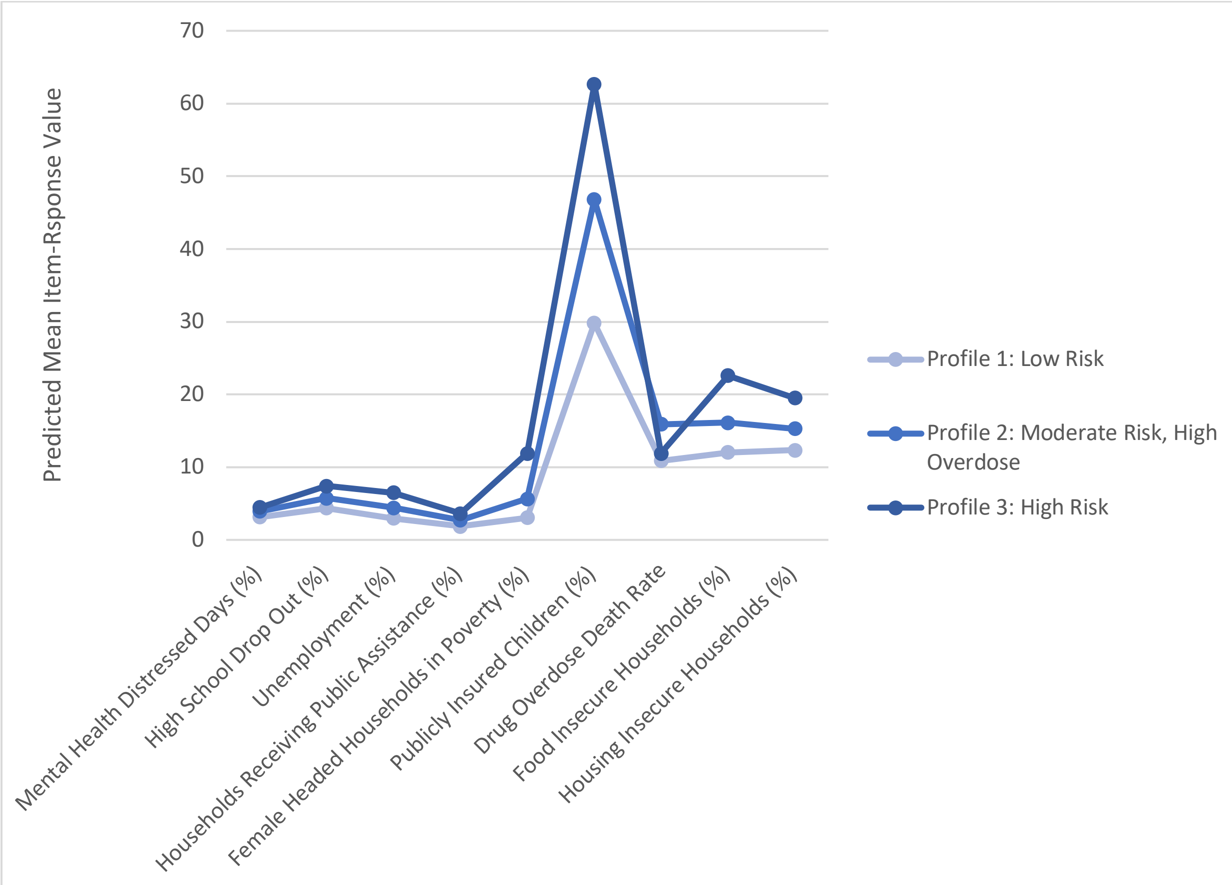
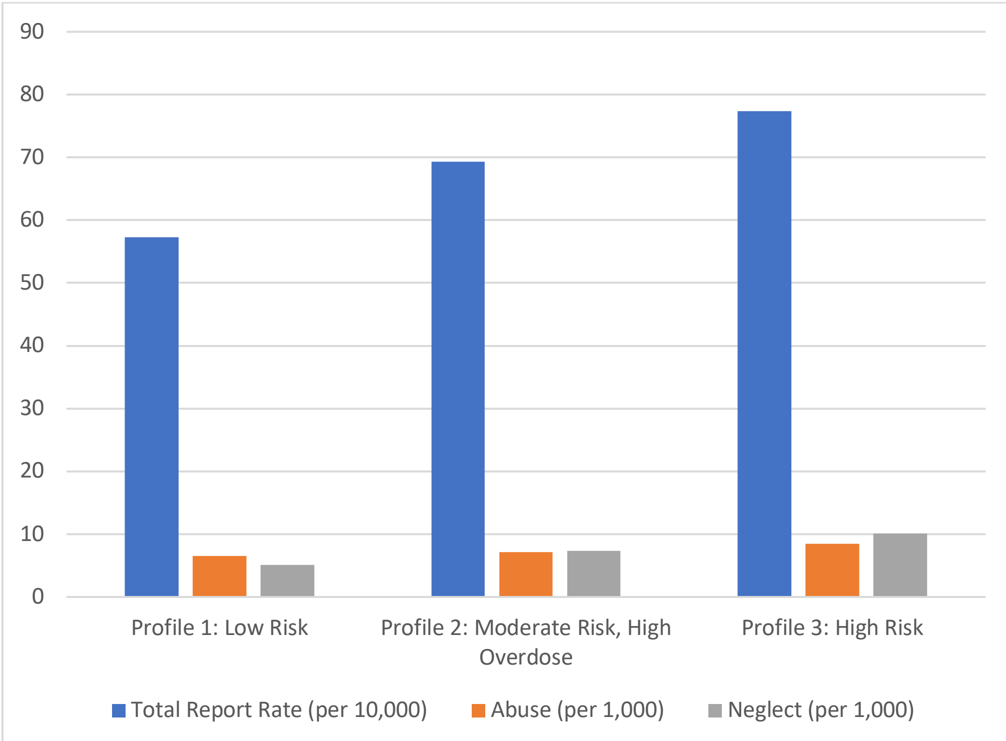


Figure 3.7: Mean Child Maltreatment Report Rates by Pseudoclass



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Chapter 4 : COLLABORATIVE THEORY BUILDING FOR COMMUNITY PLANNING TO PREVENT CHILD MALTREATMENT

Background

Public health practitioners are often asked to address health and social outcomes shaped by complexity. Complexity is defined by the theory that "everything is connected to everything else," and these interconnections are not only subtle, but often difficult to understand due to the interconnectedness of effects once discrete changes occur. Change can result in nonlinear effects, dynamics that occur over varied but parallel timelines, and feedback loops that drive further change.[1,2] This dynamic complexity creates surprising behavior; the sum of piecewise effects is different from the whole.[3] Failing to understand complexity often leads to "fixes that fail," inefficient resource allocation, and even iatrogenic effects.[1,3] Systems thinking can help characterize this complexity so as to identify points of intervention, often referred to as "leverage points," that can change the levels of existing system components or restructure the system.[3–5] While there have been numerous calls to increase the utilization of systems thinking and modeling in public health,[6–11] less attention has been given to how researchers or practitioners can do so.[12] This paper presents one method for increasing community knowledge about systems thinking and incorporating community knowledge into systems models known as Group Model Building (GMB), exemplified through an application to child maltreatment prevention research.

GMB has been used for nearly forty years as a method for engaging stakeholders in systems thinking and modeling to a) facilitate group learning and b) to solve problems through consensus. During GMB, a modeling team with experience in systems thinking and systems dynamics modeling facilitates structured activities codified by “scripts” to create a space for shared communication and learning so as to plan actions.[13–15] GMB encourages stakeholders to make their mental models, or internal heuristics about how the world works, explicit.[14,16,17] Mental models shape how people behave and understand reality.[14] Thus, without having a common understanding of the problem, reaching consensus about how to solve the problem can be difficult. Most early applications of GMB were in businesses or structured organizations, but it has increasingly been utilized in communities an inter-organizational settings.[18–21] The GMB process can be used to plan action steps,[22,23] develop simulation models,[1,17,24] or act on an identified leverage point.[25] GMB methods can be generalized across settings, topic areas, and stakeholders for public health theory building and action planning[26–28] so as to support resilient communities.

In this paper, we present the overall structure, activities, and products from a GMB project aimed at informing decision making around child maltreatment prevention. Specifically, we aimed to support decision making around the selection of evidence-based prevention programs (EBPs) that could be implemented to prevent child maltreatment. We review the roles of the modeling team, as well as how the activities within each GMB session led to discrete products.

Research Question and Approach

We aimed to understand the complexity underlying risk and protective factors across the bioecological levels of child development[29] as they relate to child maltreatment in order to develop a systems informed conceptual model, or dynamic hypothesis, explaining child maltreatment trends over time. Numerous frameworks have been utilized to examine discrete sets of factors or pathways to child maltreatment,[30–32] but traditional frameworks often are limited in their ability to show the relationships between more than a few factors, or to capture non-linear relationships (e.g. when variables have delayed effects, or effects that vary by context).[32,33] Because of the potential for systems science methods and thinking to articulate complex problems such as child maltreatment,[34–36] we used system dynamics modeling and a GMB process to develop the qualitative dynamic hypothesis and an early-stage associated quantitative simulation model of child maltreatment. We hypothesized that we can better understand the potential impact of EBPs if we had a systems-based framework.

Methods

We engaged eight North Carolina (NC) stakeholders from June 2018 through February 2019. These stakeholders were selected via direct outreach and through recommendations from key funders and leaders in child maltreatment prevention in NC. We prioritized recruiting stakeholders from various parts of the state with a diversity of administrative responsibilities, practice-based experience, and who either directly served children and families or worked as administrators at family serving organizations. Stakeholders were initially offered up to $200 dollars for their participation, with $50 reduced for each session missed, and were consented as research participants (UNC IRB 18-0659). After stakeholders were consented, we obtained a stakeholder engagement grant through the modeling team's university translational science center and were able to compensate stakeholders or their organizations up to $350.

The final GMB team included an administrator from a group home/foster care hybrid model, the director of a children's advocacy center, a county non-profit administrator, social workers, a school support specialist and a certified evidence-based program facilitator, and a non-profit director. Five stakeholders also brought their perspective as parents. They were mid-career professionals (10-15 years of experience minimum), and primarily identified as female (n=6). One individual identified as a member of the LGBTQ community. The majority of stakeholders identified as White/Non-Hispanic, as only one identified as African-American.

The core modeling team (GC, KHL, LF) with experience in systems science met to shape the focus of each session and assign modeling team members' roles.[3] This including identifying the number of sessions, session frequency and length, and accompanying activities (Table 4.1). There were approximately eight hours of planning time for the project overall over the course of six months and an additional three hours per session.

Key considerations at this planning stage included 1) the time that participants can be expected to stay engaged in a project that is not a part of their occupational responsibilities, and 2) the time the modeling team would require to distill information and build models between sessions, 3) the final products that we wanted to develop, 4) requisite interim products. The modeling team initially bounded the project to child maltreatment in NC, although the GMB would later define child maltreatment and the type(s) of maltreatment to focus upon (Table 4.2).

We designed the activities to iterate between the GMB principles of divergence and convergence. Divergent individual and group activities focused on eliciting diverse insights and expanding the breadth of our understanding of child maltreatment risk. Convergent activities brought the unique insights together and bounded the simulation model based on group priorities.[4]

[3]For further discussion of the types of roles that can be represented in a GMB project, the interested reader is referred to Hovmand (2016), Vennix (1996), and Luna Reyes et al. (2014).
[4]See Appendix 4.1 for a list of principles that guided or were refined during our process.

Session 1: Preparation

The first session was designed to achieve three goals: define the problem, teach stakeholders key system dynamics concepts, and make stakeholders' mental models explicit. A common challenge in decision-making is for individuals to skip to solution identification based on biased mental models without first developing a shared understanding of the problem to be solved and what a solution should accomplish.[14] Establishing a shared understanding of the problem can improve outcomes and commitment to decisions made in collaboratives.[37–39] However, we also wanted to avoid potential power differentials or 'group think' that could limit some stakeholders from sharing their mental models. Thus, we decided to have GMB stakeholders first share their mental models in individual sessions so that they could freely share their models without having peers in the room who may have had different priorities, experiences, and theories. We also asked stakeholders to share their definitions for four key concepts: systems, child maltreatment, maltreatment prevention, child well-being, as well as their goals and expectations for how we would engage and what we would accomplish, the latter of which shaped our project vision.

Session 1: Activities

Session 1 was held with each stakeholder individually. The lead modeler (GC), facilitated each individual meeting at a place of the stakeholder's convenience, often at their place of work. The modeler first reviewed systems concepts and posed the project objectives to the stakeholders. The modeler then guided the participants to share their mental models using causal loop diagramming (CLD), a system dynamics method for illustrating the interconnections between factors that lead to emergent behavior over time.[6,40,41] Stakeholders drew their first CLD (see Figure 4.1 for example), then learned additional systems concepts. The remainder of the session was primarily spent expanding their CLD. While creating this second, detailed CLD, stakeholders told stories behind the interconnections and feedback loops that were emerging in their CLD (Figure 4.2). The facilitating modeler used the qualitative data from these stories to fill in gaps in the CLDs that were discussed but not drawn. We closed the individual sessions by asking stakeholders to share their values around child maltreatment prevention and their hopes and fears for the project.[15]

Session 2: Preparation

Prior to session two, the lead modeler (GC) reviewed notes from session one and synthesized the four key definitions by compiling a list of unique components for each and identifying repeated themes. She reviewed notes about stakeholders' values and hopes to distill a concise vision statement (Table 4.2). Finally, she converged the second CLD from each stakeholder into one by identifying overlapping factors and adding factors that had been either discussed or drawn (Figure 4.3).

Session 2: Activities

Session two was our first meeting as a group. Thus, we prioritized building a sense of community among GMB stakeholders by first sharing the synthesized key definitions and project expectations (Table 4.2; Figure 4.4). The stakeholders requested several changes to the synthesized definitions and vision. Next, the core modeling team presented the synthesized CLD. The modelers highlighted key feedback loops and asked stakeholders to *correct* inaccuracies and to *add* missing factors in the synthesized CLD. Stakeholders had access to a poster-sized print out of the CLD as well as a web-based version that allowed them to zoom in on factors and interconnections (Figure 4.3). The web-based version was strongly preferred due to the ability to isolate factors and connections. Finally, the modeling team used the "Behavior over time" script to elicit additional stories about the challenges facing families that may contribute to child maltreatment.[15]

Session 3: Preparation

The core modeling team translated the CLD into a stock and flow structure that formed the basis for the quantified simulation model by 1) reflecting on salient driving factors that stakeholders identified, 2) determining the unit of analysis (e.g. household, child, community), and 3) considering how the key outcome would be computed. For example, because stakeholders emphasized that trauma was a key factor, the initial structure separated households by whether they had experienced trauma and had received trauma treatment.

The modelers bounded the model to focus on child neglect because 1) the key factors that the GMB team had focused upon could be wholly incorporated, 2) neglect entails factors that are typically targeted by prevention EBPs and as well as outside of the targeted factors of EBPs, enabling us to model not only EBP theories of change, but the GMB's more holistic theories of change, 3) the factors associated with neglect were almost always associated with those related to abuse, thus priming the model to incorporate additional types of child maltreatment, and 4) it is the most prevalent type of child maltreatment.[42–45] The GMB stakeholders were amenable to this focus. To incorporate the potential impact of EBPs, we prepared materials for the GMB team to reference when selecting EBPs that would be operationalized in the simulation model (see Appendix 4.2 for exemplar EBP characteristics provided). We distributed these materials electronically one week before the meeting, along with login information to the virtual conference platform that we used for sessions 3 and 4, which were facilitated virtually.

Session 3: Activities

Session three focused on gathering GMB feedback on the system dynamics model structure (Figure 4.5) and selecting the EBPs. At this point, we had fostered sufficient trust with and between our GMB stakeholders that they readily asked questions of the modeling team and one another. This questioning process furthered the structural validity and boundary adequacy of the model, and resulted in an updated CLD (Figure 4.6).[1]

EBPs were selected through a three-step process detailed in Table 4.1.[15] One EBP, Incredible Years, was not initially in the list because it was listed as secondary prevention, but was added due to stakeholder preference for a program with a peer support component.[46,47]

Session 4: Preparation and Activities

The modeling team updated the CLD that informed the simulation model structure and the model structure based on stakeholder feedback.[5] Session four focused on gathering GMB team reactions to the updated CLD and the updated simulation model structure. Figure 4.7 shows the CLD with feedback from session four. Again, the GMB provided feedback akin to member checking in qualitative research by identifying missing factors and interconnection.[48] Figure 4.8 depicts the product development flow across sessions.

Results

There were several themes or key factors that the GMB team perceived as crucial to understand the dynamics of child maltreatment: 1) multi-level trauma, including providers who interact with families, such as educators and medical practitioners, as well as parents, 2) parent stress due to emotional stressors or basic needs deprivation, 3) lack of treatment for parent and

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[5]Due to model size, the structure is best viewed online through a story telling feature of the modeling software, Stella, that can be viewed here: https://exchange.iseesystems.com/public/gcruden/childneglectlearningmodel/index.html#page2

child mental health and substance misuse concerns, and 4) the crucial need for parent support, especially peer and crisis. As one stakeholder noted, "stress causes neglect but no one wants to neglect."

Stakeholder insights were instructive for the core modeling team and improved model accuracy, as has been shown in previous community engaged modeling,.[17,19] For example, the GMB stakeholders pointed out that parent stress and parent trauma can have both direct and indirect effects on child behavior, and that it was important to model both sets of pathways, whereas the modeling team had only modeled the indirect pathway.

Our process of revising a simulation model based on stakeholder feedback is not only common, but a crucial part of model validation.[1,49] Without stakeholder structural assessment and feedback on the boundary adequacy of the model,[1] the simulation would not have captured complexity as completely. For example, when reviewing the initial simulation model structure, one stakeholder pointed out that a low risk household with a trauma history did not make sense, as trauma increased risk to high. Figure 4.9 captures our mental model of this feedback process, akin to triangulating qualitative data alongside existing theories and resources.[50–52]

There are two categories of lessons learned about the Group Model Building process through this project. These include adaptations to the meeting and activity modalities and how interpersonal dynamics can be shaped by these modalities.

During our first sessions with individual stakeholders, we observed that the one-on-one time allowed the modeler to build rapport with each individual, which was crucial to forging trusting, sustainable relationships based on mutual self-interest.[53] The modeler was able to be more attuned to what concepts and activities resonated with each participant. For example, giving stakeholders the flexibility of being able to move around sticky notes when creating their second CLDs was crucial to some stakeholders' comfort with completing the activity. Our observations mirror those reported in other collaborative simulation design processes.[37,54,55]

We also adapted the GMB process by conducting sessions three and four virtually. While GMB activities are often designed to be "hands-on," and thrive when in-person facilitation and interaction can occur, we had two limitations to in-person interaction. First, travel time was a significant concern. Second, stakeholders noted their discomfort with and the difficulty of meeting at the university campus. For one, there were concerns due to the historical power imbalance between the university and community. Additionally, there were logistical concerns around parking and navigating a large university campus. Since the modeling team and GMB stakeholders had established rapport during the first two sessions, the final virtual sessions were still engaging. The modeling team employed three procedures to facilitate this virtual delivery: explaining why the transition was being made, utilizing video conferencing so that the GMB stakeholders could see one another and the modeling team's screens, and sharing documents beforehand.

Conclusion

Most GMB projects can and should begin with the community identifying the problem that they wish to solve, but it is not uncommon for researchers to approach a group of stakeholders who are tackling messy problems and propose GMB as a shared undertaking.[17,18,56] Since our project was researcher initiated and the GMB team did not exist as a formal group prior to the project, some of the process insights may differ in processes initiated through existing collaboratives. However, the quality and depth of conversations and insights that we were able to elicit among these stakeholders speaks to the strength of the GMB approach for fostering collaborations and theoretical insights. Additionally, due to time limitations, we may not have identified all relevant factors or completed all feedback loops in the CLDs.

This paper presented a case study of how GMB can be replicated to develop a dynamic hypothesis of child maltreatment and an associated system dynamics simulation model.[57] We fostered agreement on action plans amongst stakeholders and showed how our partners shared their mental models, two key group level outcomes in GMB.[57]

The resulting products can be utilized as a starting point for future community-based models of child maltreatment to support cumulative knowledge building and action planning around maltreatment prevention.[57] The breadth of the dynamic hypotheses that we co-developed lends to insights around how EBPs may target only some risk factors or subgroups of families, compared to policies that target leverage points at more encompassing levels of the ecological model. Without attempting to explicitly model dynamic processes through a simulation model, we may fail to understand how these observations generalize to other settings.[49] Next stages of this project include validating the simulation model behavior and assessing stakeholder learning in reaction to the model.[56]

Acknowledging such tradeoffs is crucial to shaping effective policies and improving community health. For example, one stakeholder noted that "lack of understanding…connects to everything." Statements such as these highlight the need for systems engaged thinking to improve community health and this thinking can be fostered through GMB approaches so that consensus and commitment to action is obtained to avoid getting "distracted by the shiny."

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Table 4.1: Group Model Building Process Overview

Session	Goals	Activities in Session	Time	Preparation Activities (Modeling Team)	Follow-Up Activities (Modeling Team)	Resulting Products
1	Develop a shared level of system dynamics and systems thinking vocabulary and concepts	"Concept Models" script, Learning Lab with lead modeler using exemplar resources from Donella Meadows[50] and previous core modeling team projects such as the flu. Key concepts included "fixes that fail," dynamic relationships developed through feedback loops, surprising behavior, and system archetypes. We reviewed key definitions such as stocks, flows, leverage points, and feedback loops.	30 minutes	Prepare example causal loop diagram and stock and flow diagram around child flu spread in a classroom.	None	Individual Definitions of systems, child maltreatment and well-being, and prevention that were later synthesized.
	Create individual "mental maps"	"Variable Elicitation" Script; Stakeholders were asked to place the phrase "child maltreatment" or "child well-being" in the center of a small white board. They selected whichever concept aligned with their perspective. Next, they were asked to write a few (approximately 5-10) key factors that influenced the concept on their board and arrows of influence between them, denoting whether the relationship was characterized by variables moving in the same	90 minutes	Obtain individual sized white boards for stakeholders to utilize as they draw initial CLD	Transfer physical maps to modeling software for preservation and then synthesize in online modeling software into one CLD across participants.	Individual Mental Maps: Initial and "Deep Dive" on 3-4 factors (Figures 4.1, 4.2) Synthesized CLD (Figure 4.3)

		(+) or opposite (-) direction. Stakeholders could use either +, - or "S", "O" notation. We chose the generic language of "factors" because saying "risk and protective factors," which are often referred to in the scientific literature, did not resonate with most stakeholders. They then extended three to four concepts or key factors from the first high-level CLD on whiteboard to poster paper and expanded on the number of interconnections to have their second CLD depicting a mental model of child maltreatment risk and protective factors in their community.				
	Develop shared definition of problem to be solved and shared vision for project/participation	Adaptation of "Creating a Shared Vision" script for individual format. Participants were asked questions from the script and verbally reported answers to the modeling facilitator. The modeler then synthesized these answers to obtain the shared vision statement.	15 minutes	Adapt "Creating a Shared Vision" script for current project that was focused on child maltreatment prevention	Synthesize individual statements.	Shared vision statement
	Understand stakeholder perspectives about project participation	Adaptation of "Hope and Fears" Script for individual format. Participants were asked questions from the script and verbally reported answers to the modeling facilitator.	5 minutes	Synthesize stakeholder vision statements.	None	Shared vision statement

2	Reflect on synthesized project vision, focus population, and shared definition of prevention	Group discussion after presentation of proposed definitions and vision.	15 minutes	Synthesize individual definitions.	Update definitions based on feedback.	Shared vision statement.
	Reflect on synthesized “mental maps” or Causal Loop Diagram	“Structure Elicitation Script”; GMB stakeholders interacted with paper and online versions of synthesized CLD to trace feedback loops, correct inaccuracies, and identify missing links and factors.	45 minutes	Prepare synthesized CLD in online modeling software and print paper copies for team to engage with.	Modify existing synthesized causal loop diagram based on immediate feedback and create new, simplified CLD and associated Stock and Flow structure to begin translating the CLD into a quantified simulation model.	Refined CLD https://kumu.io/gcruden/synthesized-initial-cld#working-map-simplified
	Identify key stories shaping trends of child maltreatment	“Behavior Over Time Graphs” Script	30 minutes	Prepare example behavior over time graph example (child grades) and obtain paper and pens for stakeholder use during session.	Adapt existing CLD based on new stories.	Refined CLD (Figure 4.3)

3	Review initial structure of a stock and flow system dynamics model	"Presenting the Reference Mode" Script. The modeling team shared the model structure in a piece wise fashion, noting first the key stock and flow structure that was replicated throughout the model and then showing the expanded structures to 1) demonstrate how the group's synthesized CLD was translated into a system dynamics simulation model, and 2) obtain feedback on the model boundaries and structural decisions. The modelers also presented key modeling decisions that were made, including which types of maltreatment were modeled, how maltreatment rates would be calculated, the population being modeled, and time step as well as the time horizon.	45 minutes	Prepare stock and flow structure and associated Powerpoint slides for walking through model.	Adapt CLD and Stock and Flow structures	Refined Stock and Flow structure for quantified simulation (Supplemental Link: https://exchange.iseesystems.com/public/gcruden/childneglectlearningmodel/index.html#page1)
	Select evidence-based prevention programs for simulation	"Dots" "Initial Policy Options" and "Action Ideas" scripts. First, stakeholders reviewed the Excel spreadsheet and the original links to the registries from which the information was drawn. Second, stakeholders completed an online survey that asked them to rank their top four preferred interventions, to share their logic for why they selected each intervention, and to propose their	45 minutes	Prepare descriptions of evidence-based prevention programs to be reviewed from multiple resources and compile into an Excel spreadsheet, and create online survey to complete.	Review online survey to see top three programs prioritized and incorporate program targets into Stock and Flow structure.	3 identified evidence-based programs: Incredible Years, Nurse Family Partnership, SafeCare

		top four leverage points or action ideas, such as parent stress or child care subsidies, which may or may not have been targeted by the EBPs. Finally, the modeling team reviewed the surveys to select two of the three EBPs (Nurse Family Partnership[61] and SafeCare62) based on stakeholder rankings. A third EBP (Incredible Years)[47] was selected from outside of the initial list by the stakeholders due to its peer support component.				
4	Reflect on current system dynamics model structure and missing pathways or factors	Present new Stock and Flow structure and refined CLD (Figure 4.5). The modeling team highlighted how the previous structure fed into the current one, the same key modeling decisions, such as the population being modeled and time horizon, and key stock and flow structures as well as parameters that influenced those structures.	60 minutes	Translate refined CLD into Stock and Flow Structure based on Session 3 feedback.	Refine Stock and Flow Structure.	Refined Stock and Flow structure for quantified simulation (Supplemental Link: https://exchange.iseesystems.com/public/gcruden/childneglectlearningmodel/index.html#page1)

Table 4.2: Key Project Definitions

Topic/Concept	Definition
Child Maltreatment	Includes not only physical, sexual, and emotional abuse, but also medical, physical, and emotional neglect, as well as "anything that harms the well-being of the child."
Child Maltreatment Prevention	Child maltreatment prevention was defined via both specific actions and general statements reflective of an overall ethos. We kept these as a list of statements so as to reflect the breadth of prevention. The broadest statement, reflecting universal prevention,[58] stated that prevention entailed activities that are "as far upstream as we can go…before the baby is even in the water," referring to the common analogy of upstream interventions that intervene to prevent adverse outcomes. Similarly, GMB stakeholders spoke about ensuring that families had "access to everything" and the need for family engagement, defined as a sense of trust between families and family serving organizations, as well as the development of crisis and peer support networks. Stakeholders also focused on well-being promotion and the insurance of protective factors. Figure 4.7 shows a depiction of the group's prevention components. The range of these components shows that stakeholders believed in the importance of understanding prevention along a continuum, which aligns with prevention science literature.[59,60]
Project Vision	Systems strengthening in this space means creating systems that respond to *all* children's and families' needs and creating positive environments for children to thrive. We will focus on ensuring that children are able to live in an environment that fosters their well-being and does not put them in danger of witnessing or experiencing violence or neglect, and that each child and parent in North Carolina is connected to optimal support systems.
Systems	GMB stakeholder definitions of systems showed how readily they thought about core concepts in systems thinking and how these concepts were often a part of discussions in their everyday practice. They often included a focus on either the actions or structure of systems. Structures were most often defined by describing either collaborations or silos. Participants highlighted the purposeful and interconnected nature of a system, stating that a system is "a lot of complex issues and or organizations working on issues… to [solve] a social problem." Other participants noted the ambiguity of systems and the multiplicity of actors, stating "I don't know if there is *a* system." We utilized the operationalized definition from Meadows (2008) for systems as follows: A set of elements or parts that is coherently organized and inter-connected in a pattern or structure that produces a characteristic set of behaviors, often classified as its "function" or "purpose."

Figure 4.1: Initial Causal Loop Diagram: Example from Participant 1

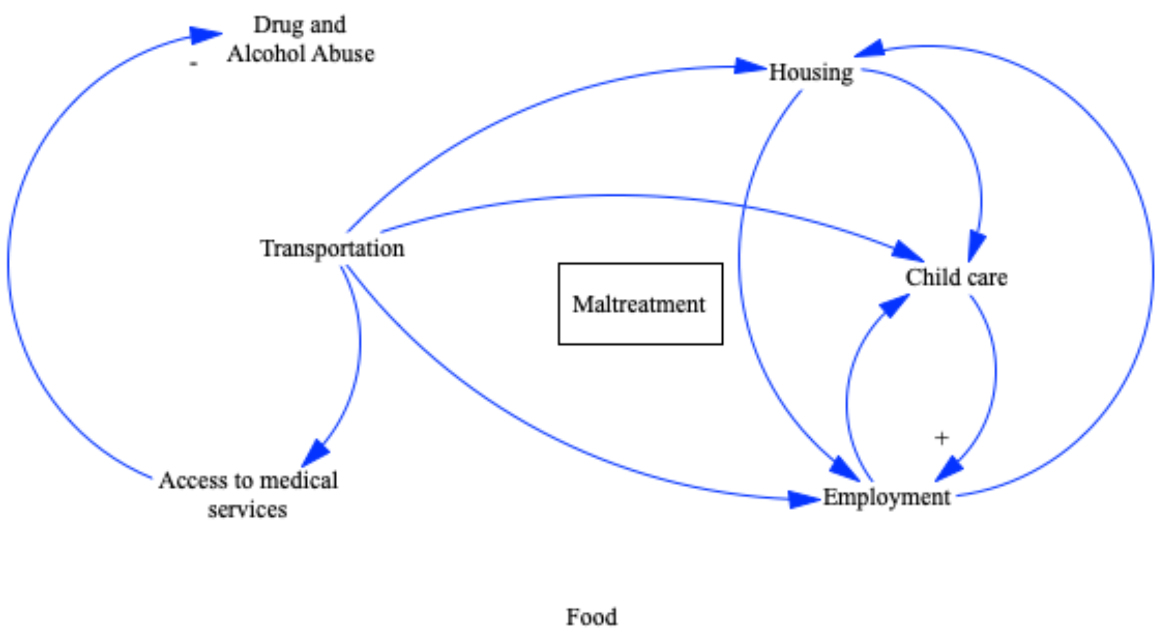


Figure 4.2: Second Causal Loop Diagram: Example from Participant 1

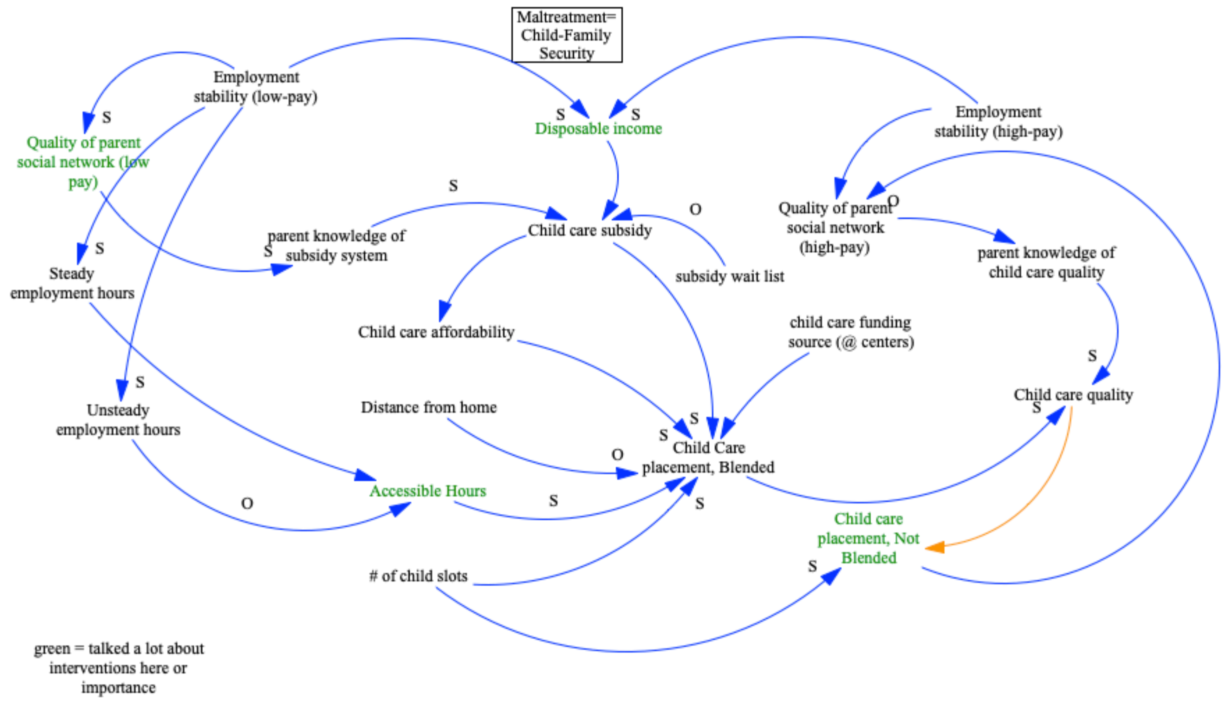
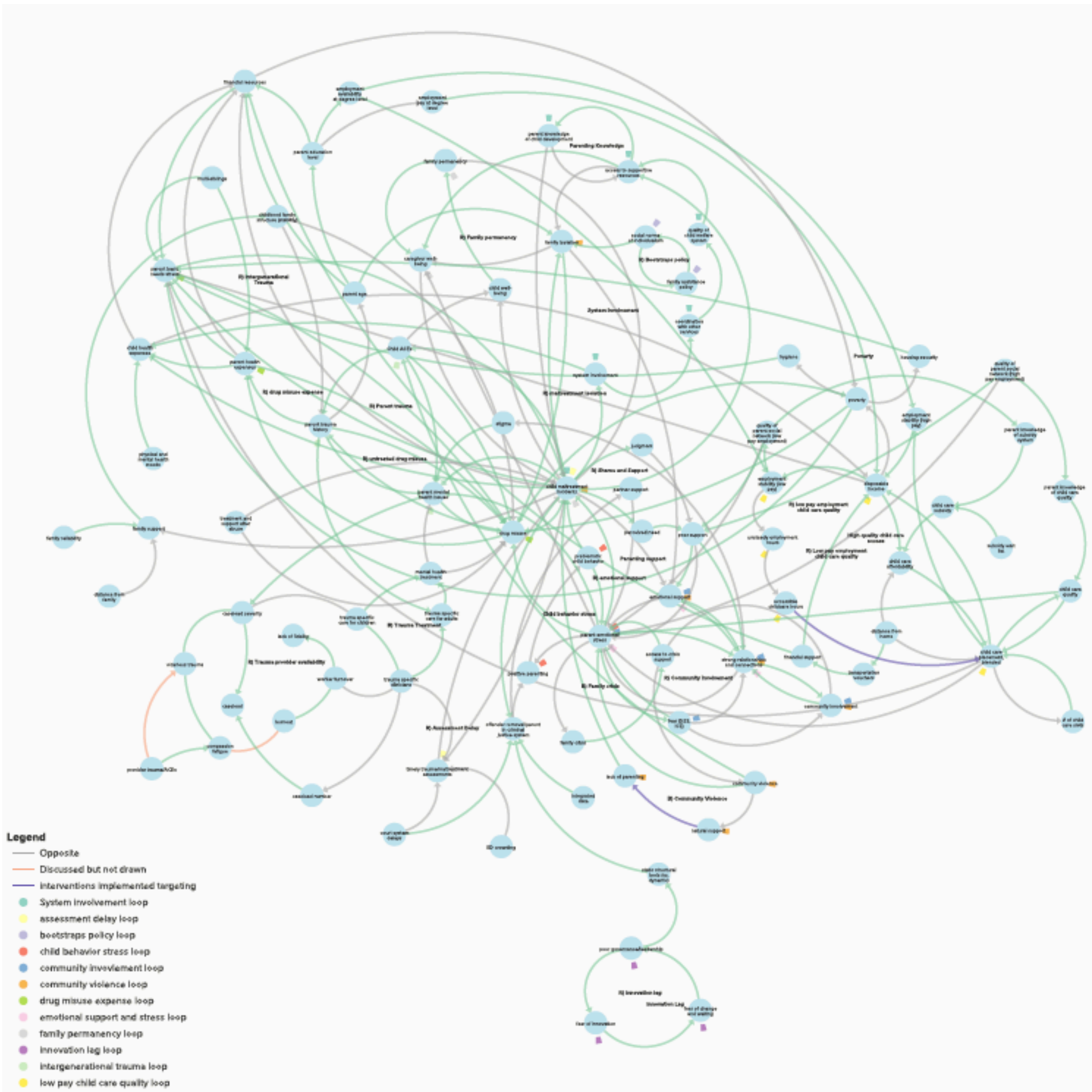


Figure 4.3: Overall Causal Loop Diagram



This diagram can be viewed interactively at: https://kumu.io/gcruden/synthesized-initial-cld#working-map-simplified/colored-loops

Figure 4.4: Stakeholder Defined Child Maltreatment Prevention Framework

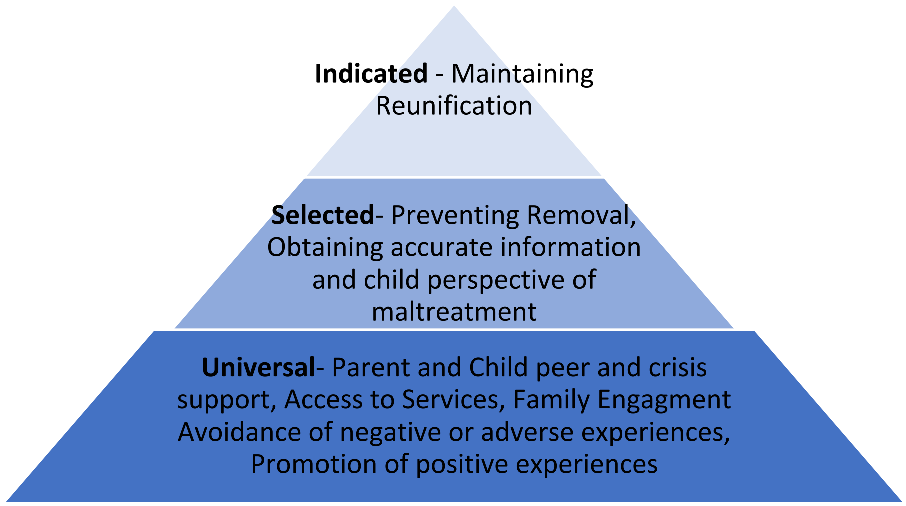


Figure 4.5: Initial Stock and Flow Simulation Structure Presented in Session 3

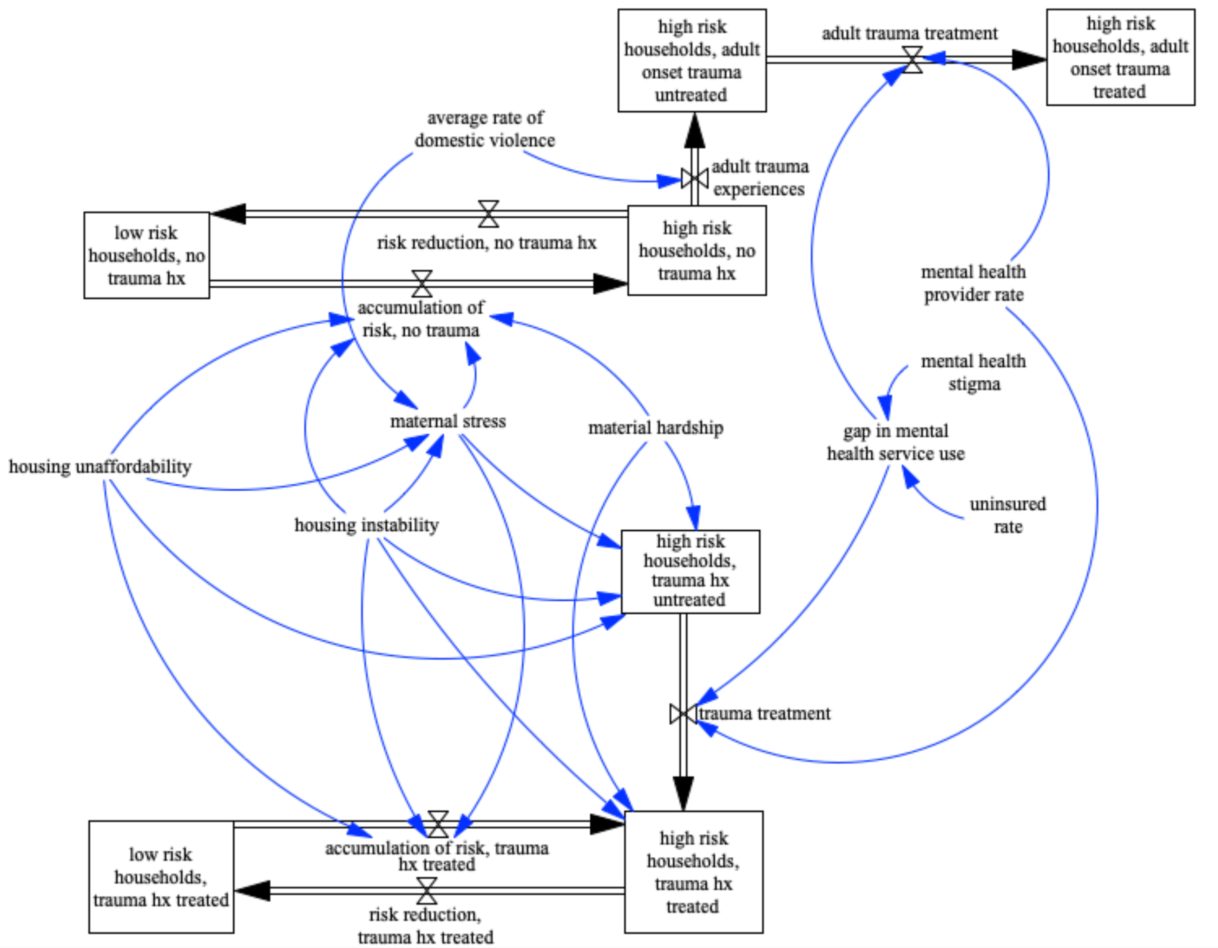


Figure 4.6: Initial Synthesized Causal Loop Diagram Underlying Simulation Model

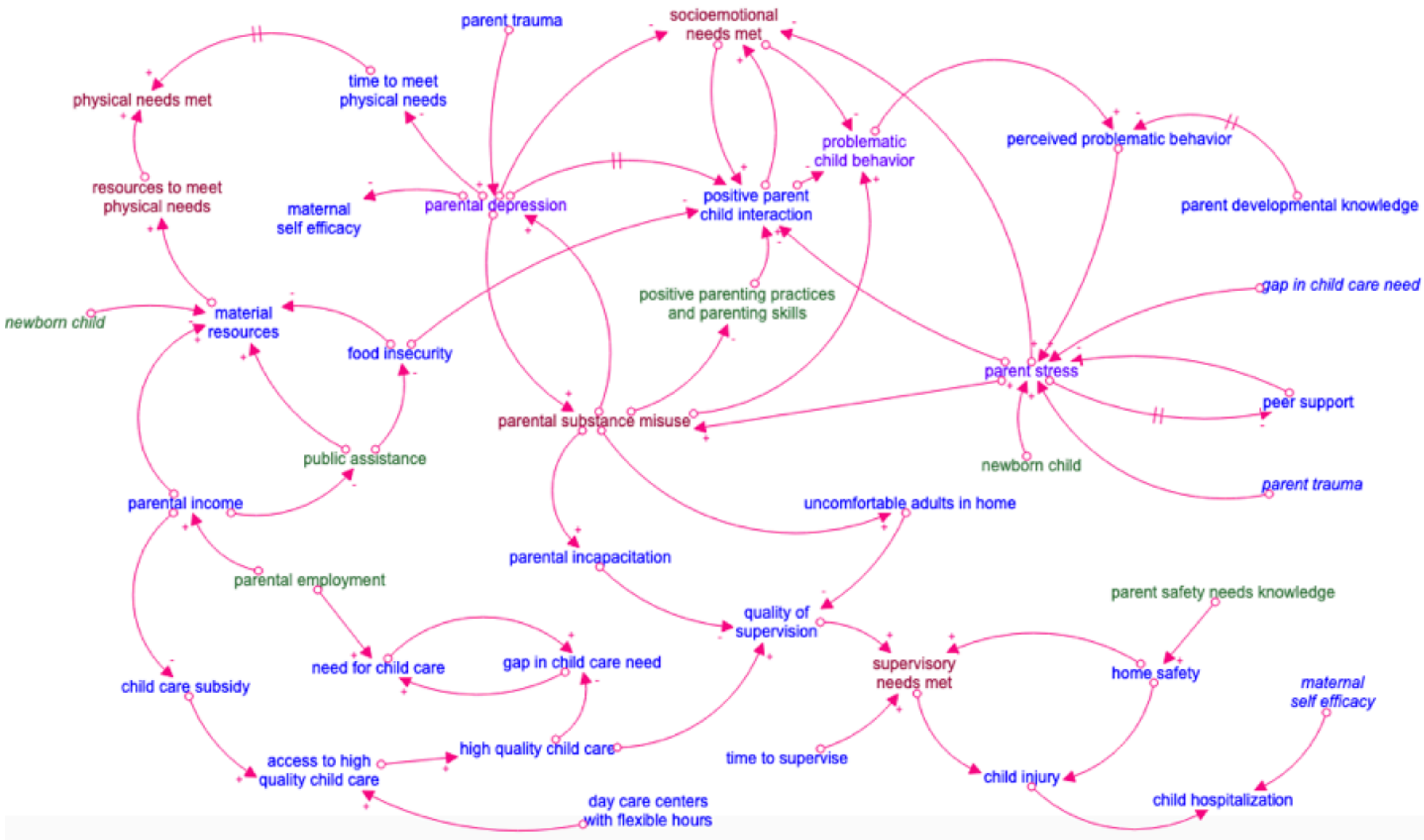


Figure 4.7: Iterated Causal Loop Diagram Underlying Simulation Model

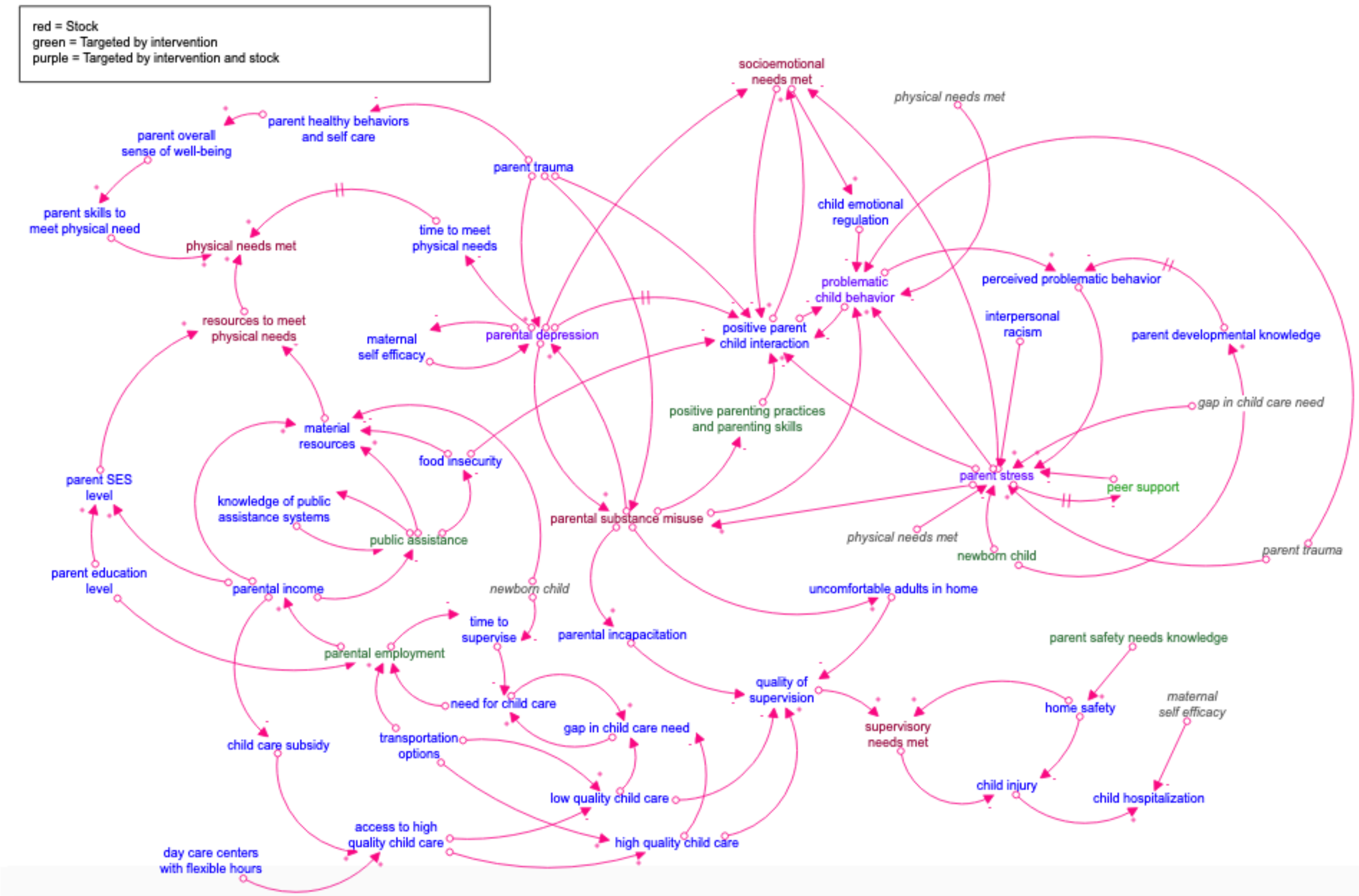


Figure 4.8: Session and Product Development Flow

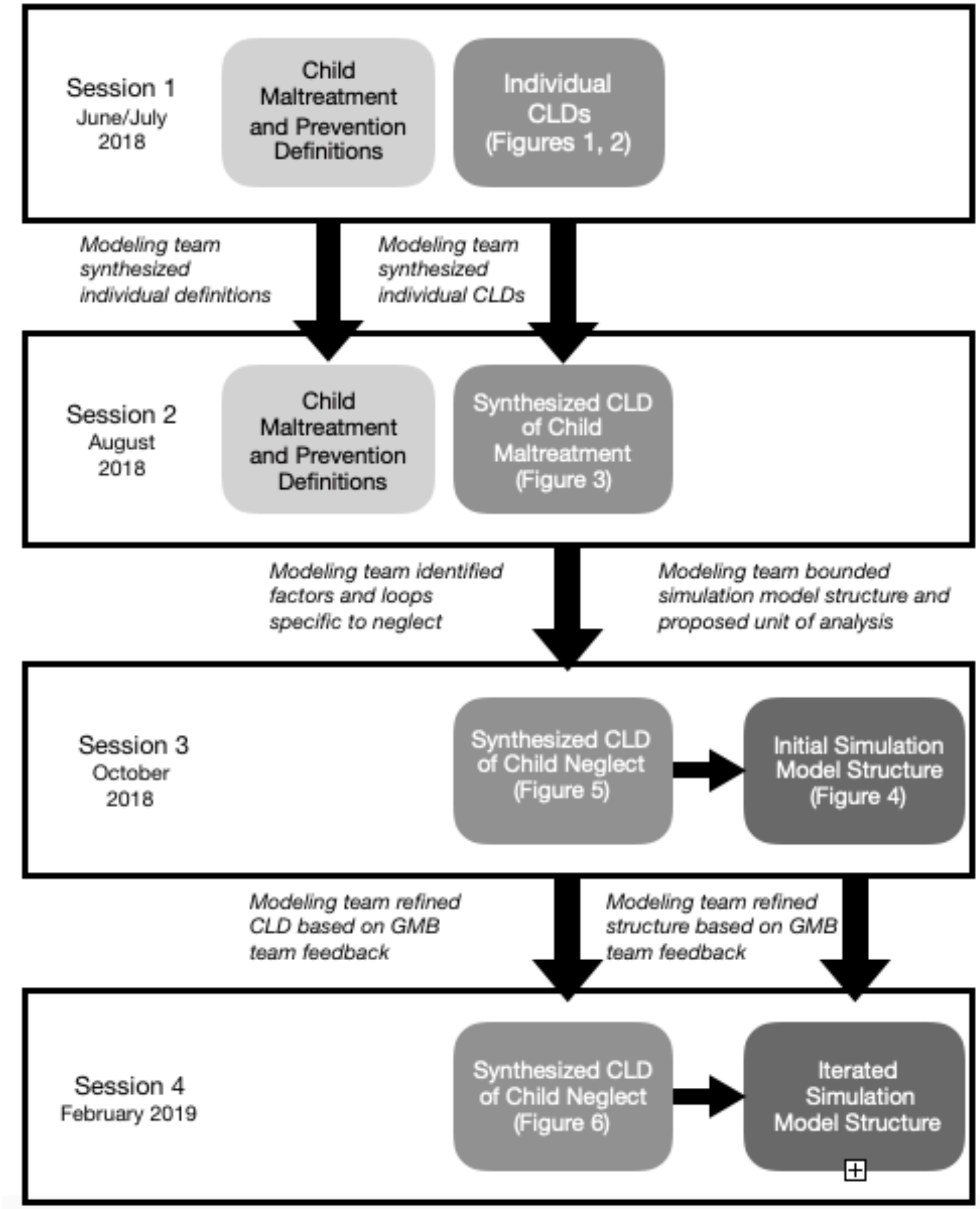
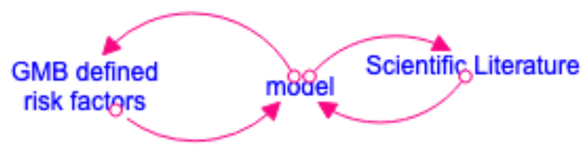


Figure 4.9: Model Refinement Feedback Loop



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Chapter 5 : DEVELOPING A MULTI-CRITERIA ANALYSIS TOOL TO SUPPORT THE SELECTION OF EVIDENCE-BASED CHILD MALTREATMENT PREVENTION PROGRAMS FOR COMMUNITY IMPLEMENTATION

Introduction

Numerous evidence-based prevention programs (EBPs) exist to prevent child neglect, yet decision makers face barriers while deciding exactly where and how to intervene to prevent this adverse childhood experience. Decision makers must decide which EBPs are most appropriate for preventing neglect by considering many criteria such as available resources and community needs. In addition, child neglect is a complex issue that has a multitude of risk factors across the socioecological levels,[1,2] and interventions may target only a subset of risk factors or high-risk subgroups.[1,3,4] Further complicating the decision-making process, EBPs may not have been tested in a setting similar to the context in question, and decision makers must make assumptions about the likelihood that the interventions will have the same level of positive effects in their context.[4–6]

Decision Support Tools

To support decision making around how to solve complex, messy problems such as child maltreatment, researchers use theoretical frameworks [7–10] and develop tools predicated upon methods that account for complexity such as multi-criteria decision analysis (MCDA) methods [11,12] and the balanced scorecard approach.[13] MCDA tools ask decision makers to consider a variety of selection criteria and assign differential weights for each criteria that reflect their relative importance.[14] The preferred intervention is identified using one of a range of available quantitative or mixed-method approaches to help decision makers acknowledge the problem complexity and attributes of potential solutions.[15] MCDA tools aim to limit the extent to which decision makers employ extensive heuristics that artificially simplify the problem and the resulting solutions they identify.[14,16]

MCDA tools have most frequently been applied to decision making for discrete, intra-organizational processes [17,18] and environmental [19,20] or engineering type problems.[21] Far fewer tools have been developed for generalized use across settings in health care or public health decision making. The few existing tools have often focused on health care service delivery, not community-based intervention selection, leaving a crucial gap in the field.[14,22,23]

MCDA holds promise as a framework for community health planning. State and community decision makers are increasingly responsible for selecting programs to respond to identified health priorities, such as those identified via community health assessments. Further, state, federal, and private funding requirements increasingly require the utilization of evidence-based programs. Decision makers need tools to support their decision-making process when selecting evidence-based program for preventing adverse outcomes at the population level, yet scientific development and testing of such tools is a gap in the current scientific literature.

Community Health Decision Making Context

A primary distinguishing factor between organizational decision making, such as for a particular health care system or mental health clinic, compared to decision making at the community level is the breadth of the population to be served.[24–26] When serving an entire community, decision makers must consider the broader cultural and political context, as well as population health needs that may vary by subpopulations and jurisdiction, such as public health regions. Qualitative analyses based on individual interviews and focus groups have found that local health department decision makers' use of evidence-based decision making approaches, including reviewing available evidence to inform decision making and applying program-planning frameworks, is affected not only by workforce and financial resources, but also the uncertainty around which interventions fit community context.[27]

Context not only affects how decisions are made, but which interventions are best aligned with needs in that context. Best et al found that a key factor of importance to health system decision makers is the ability to adapt programs to local need.[28] This finding aligns with that of Aarons et al who used group concept mapping to identify important factors related to the implementation of EBPs for mental health such as EBP fit with system readiness, cost, and political climate. Importantly, Aarons et al. found that the degree to which factors mattered to decision makers varied by context.[29] In an extensive literature review, Buffett, Ciliska, and Thomas found that the transferability and feasibility of interventions, implementation strategies, and public health policies were related to political factors, social acceptability, available resources for implementation, organizational expertise, target population characteristics, and the extent of health issues in the local context.[30] They noted the need for decision makers to collaborate with stakeholders and researchers to not only ensure that strong evidence for programs exist, but that the evidence is available, useful, and relevant locally. They further emphasized the importance of considering local context and developed a brief tool for assessing program fit with local context, although the tool was based on their literature review, not an ongoing stakeholder-engaged process, and it was limited to six items assessing two primary constructs: applicability (feasibility) and transferability (generalizability). The items included the following: political leverage, social acceptability, available resources, magnitude of the health problem, potential reach of the intervention to the current population, and comparability of study population to the current one.

The Necessity of Defining Complexity: Systems Science Approaches

Decision support must take into account the variety of factors that decision makers consider when selecting an intervention[31] as well as the complexity of the problem at hand. Schoeneborn reflected on the limitations of approaches that fail to account for problem complexity, and argued that the balanced scorecard approach, an alternative tool for supporting decision making, found a preferred strategy based on short-term outcomes that were substantially different from the choice preferred over the long-term by a quantified system dynamics model.[32] He posited that this discrepancy could be explained by the difficulty that decision makers have in understanding how the various elements of the scorecard connect and are related to outcomes, thus leading them to omit consideration of crucial pathways that may affect outcomes. There is a need for more comprehensive approaches that can accommodate such complexities when comparing alternatives that have different implications over both the short and long-term.

Decision maker's understanding of a problem's complexity affects how they perceive the optimal prevention intervention. Systems science has shown that failure to understand and adequately define a problem can limit stakeholders' ability to improve it and can lead to the implementation of "fixes that fail."[33,34] Incompletely or incorrectly defining a problem can lead to the misidentification of the most important leverage points to be intervened upon to improve outcomes, as well as failure to anticipate the full implications of a given intervention.[34–36] Systems science takes into account the interdependency of risk and protective factors that shape population health outcomes and the nature of these interdependencies such as nonlinear relationships.[34,37] Maps and models of these interdependencies, which can are often referred to as "dynamic hypotheses," are akin to theoretical frameworks in prevention intervention designs. However, dynamic hypotheses can depict the delayed effects that may appear after altering one component in the system and the feedback loops that may produce otherwise unanticipated effects. Such dynamic hypotheses and the accompanying stories can guide decision makers to intervene in ways that are less prone to policy resistance in which unintended, negative, or null effects arise in response to well-intentioned prevention efforts.[38]

Community-based prevention support processes have been increasingly developed over the past twenty years to help community members identify the scope of the problem they are trying to address and collectively determine how to intervene.[39–43] While these evidence-based processes for community engagement have been shown to be highly effective in improving community collaboration outcomes, trust, and population health outcomes, they often require development of new tools for each implementation or have decision support tools that are unique to the respective process. Generalizable tools that can be used within existing community partnerships and organizations that may not have access to larger collaboratives, such as rural health departments, are needed.

Current Study

This study aimed to support decision makers as they compare evidence-based child neglect prevention interventions to select for community implementation by a) collaboratively developing a MCDA tool with stakeholders to support EBP selection and b) pilot testing the MCDA with a set of decision makers to refine the tool. We accomplished this through a four-step process. First, we utilized an approach for facilitating team learning and collaborating based on systems science known as Group Model Building with North Carolina stakeholders to define child neglect risk and the factors that influence EBP selection to prevent neglect.[33,44,45] Second, we built on insights from step one and worked with the same set of stakeholders to develop a multi-criteria decision analysis support tool. The tool was designed to facilitate contemplation of the unique criteria of an EBP, EBP fit with the local context, the relative importance of each component, and comparison of these criteria across EBPs. Third, we completed a pilot evaluation of the MCDA tool with a separate set of decision makers. During the pilot, we had decision makers complete the MCDA tool and provide feedback before and after a systems science based brief intervention that was designed to a) test whether the MCDA tool was sensitive to variation in decision makers' understanding of the targeted problem's complexity and b) engage stakeholders in a broader discussion around the factors that they consider when selecting EBPs. The current study is innovative in its goal to develop a tool that can be easily transferred across settings to assist with comparing and evaluating evidence-based interventions.

Methods

Part I: Multi-Criteria Decision Analysis (MCDA) tool development

To develop the MCDA tool, we worked with eight stakeholders who are currently responsible for selecting EBPs or implementing EBPs in their local community to improve child well-being or prevent maltreatment. We engaged them between July 2017 and February 2018 as part of a larger project that aimed to support decision making around evidence-based prevention program selection to prevent child maltreatment in North Carolina.[46] The stakeholders were compensated for their time, which was approximately eight hours over four sessions. The latter two sessions included activities directly related to the MCDA tool development.

The stakeholder engagement process is described elsewhere, but we briefly detail it here. An overview of the MCDA development process is in **Error! Reference source not found.**. A group model building (GMB) approach was utilized to engage stakeholders to develop a systems-science informed framework of risk and protective factors related to child maltreatment. Stakeholders included practitioners trained in delivering EBPs for children and families, individuals who serve families who have been referred to child protective services, foster care youth, and local child agency administrators. Using structured GMB activities, we first identified each stakeholder's definition of child maltreatment and prevention, then synthesized these definitions. Problem identification is a crucial first step in MCDA tool development so as to ensure a shared vision for the question to be deliberated and shape the associated criteria.[14,16] Child maltreatment was defined broadly as "anything that harms the well-being of a child," but also specifically included delineation by physical, sexual, emotional abuse and neglect. As neglect is the most common type of maltreatment, is associated with risk factors that are shared across other types of maltreatment, and has seen the least decline in recent decades compared to other types of maltreatment,[1] we chose to focus on child neglect for the current tool. Neglect was defined as encompassing physical, home safety, socioemotional, and supervisory needs based on conversations with stakeholders and consultation with the peer-reviewed literature.[1,47]

Prevention was defined across the three tiers of prevention, ranging from more universal interventions that target all families to selected or indicated approaches that target families at high risk for maltreatment or who have previously been involved with Child Protective Services. There was a strong desire, however, to focus efforts on the universal level so as to prevent adverse experiences from ever occurring and so as to promote positive experiences.

Considering this universal prevention orientation, the research team prepared a list of seven evidence-based child neglect prevention interventions for the GMB stakeholders to review based on three sources. Information regarding intervention details such as the targeted population, length of the intervention, whether implementation supports were available, and where the intervention was originally tested were drawn from the California Evidence-Based Clearinghouse for Child Welfare and the Blueprints Registry for Healthy Youth

Development.[48,49] Interventions identified as primary or universal child neglect interventions across the two highest tiers of evidence in these evidence-based registry were included. Information on intervention costs and cost-benefit analysis was presented as available.[50] A complete list of the presented criteria is in Appendix 5.1.

The purpose of creating this intervention list was twofold; First, since this tool was being developed outside the scope of an existing organization or immediate decision inflection point, we wanted to bound the decision options to be presented in the MCDA tool, and 2) we used insights from the GMB stakeholders as they prioritized interventions from the list to begin identifying the MCDA criteria. During the third GMB stakeholder engagement session, we asked participants to review the intervention descriptions. Next, they were asked to complete a survey in which they identified, 1) their top four choices of an intervention to be considered in the MCDA tool, 2) why they selected the intervention, and 3) what child neglect risk and protective factors they would want to prioritize for intervention, should those factors not be targeted by the presented interventions. The stakeholders prioritized two programs, Nurse Family Partnership and Safe Care, from the original list. A third program, Incredible Years, was identified through the third step in which stakeholders emphasized the importance of parent peer support that was offered through Incredible Years but was absent in the alternatives. This intervention had not been included in the original list because it was categorized as a selected prevention intervention in the evidence-based registry.

An initial list of potential MCDA criteria was drawn from the survey as stakeholders explained why they selected their prioritized interventions. Several of the criteria were repeatedly mentioned. Some stakeholders viewed specific criteria as a factor that positively influenced prioritization of an intervention that other stakeholders viewed negatively, which indicated the need for differential weighting. For example, having the program implemented elsewhere in North Carolina was encouraging to some stakeholders, and others preferred to select programs that were not currently available in North Carolina so as to fill a gap.

After reviewing the qualitative data to derive initial criteria, the research team mapped the criteria onto an implementation framework, RE-AIM. RE-AIM was used to explore the comprehensiveness of the criteria as defined by factors known to affect intervention selection and implementation in the peer-reviewed literature.[51,52] The RE-AIM framework is widely used to guide the dissemination and implementation of evidence-based interventions, and its generalized focus on both organizational and intervention characteristics in contrast to implementation frameworks that focus more on particular organizational processes or contexts made it ideal for our purposes. The stakeholders had identified criteria across the RE-AIM domains except for one, Maintenance. The maintenance phase refers to how an intervention is sustained once implementation has begun. Thus, the research team proposed one criterion to address this phase before presenting the full list back to the stakeholders. During the final meeting, the GMB stakeholders reviewed the criteria list and proposed four additional criteria. They also suggested refinement of current criterion phrasing. Figure 5.1 depicts the criteria by RE-AIM domains.

The scoring alternatives and weights for each criterion were developed after session three through a similar process as the criteria. Based on the qualitative survey data, the research team proposed a Likert-type scoring alternative from 1-5 for the criteria, with 1 indicating “Strongly Disagree” and 5 indicating “Strongly Disagree,” indicating how much the decision maker agreed with that criteria for the specific intervention being scored. We proposed this range to allow for differentiation between alternatives but not so much that decision makers were burdened by distinguishing between more granular levels. This scoring range has been used for similar tools as well.[30]

Next, based on the frequency of criterion mentions in the qualitative survey data and existing knowledge about intervention characteristics that are important for implementation, the research team proposed weights for each criterion. This was not an exact process. Rather, the most frequently cited criteria were given the highest weights that could be assigned given the number of criteria and the need for all weights to sum to one, while keeping the weights simple with no more than two decimal places. The weights are designed to be universal across all EBPs to allow for comparison of the criteria responses and thus EBP scores. In other words, while criteria scores may vary by EBP, the degree to which each criterion contributes to the overall EBP score is consistent across EBPs.

Both the scoring alternatives and weights were reviewed by stakeholders during the final meeting to ensure that the alternatives were understandable and that the weights seemed appropriate. During this meeting, the stakeholders noted that up to twenty criteria could be feasible for decision makers to consider, but we decided to keep the tool more parsimonious initially and expand it as needed. The MCDA criteria and weights are presented in Table 5.2. The first listed weight is the weight as agreed upon by the stakeholder and research team after the stakeholders reviewed the initial weights as proposed by the research team. The averaged proposed weight is the average of the difference between the initial weight and the weight assigned by pilot study participants.

Part II: Decision Maker Pilot

We conducted a pilot study with North Carolina (NC) decision makers (n=11) to test 1) the acceptability of the MCDA tool's criteria and weights and 2) the capacity of the tool to assist in considering the extent of risk and protective factors for child neglect and how EBPs target these factors. We recruited participants from NC only to reduce confounding of contextual considerations by state level factors and because the MCDA was developed with NC stakeholders. The decision makers were either responsible for directly implementing family-based child maltreatment or parenting focused interventions or for selecting interventions for implementation due to their administrative duties. Decision makers included local health department directors, executive directors of county partnerships for children, non-profit administrators, current and previous NC state legislators, and NC Department of Health and Human Services employees. Participants were mid to late career, primarily female (n=9), and non-Hispanic White. This project was considered exempt by the UNC-Chapel Hill IRB. Recruitment occurred through referrals from decision makers who had already completed the pilot and through direct contact by the research team due to their professional roles.

Participants completed a sixty to ninety minute, five-step process as part of this pilot study (Figure 5.2). First, they were asked to read about the three evidence-based child neglect prevention interventions (Nurse Family Partnership, Incredible Years, Safe Care) in the California Evidence-Based Clearinghouse for Child Welfare. Second, they recorded their initial manual ranking of their first, second, and third choice of an intervention for implementation should they have a $3 million block grant for implementing the intervention in their community (county or state, as applicable) over the next three years. The ranking was completed without the MCDA tool. Each stakeholder was asked to rank the interventions in order, i.e., their first, second, and third choice, based solely on the descriptive information.

Next, the participants completed the MCDA tool in an Excel spreadsheet for each of the three EBPs. The tool listed the proposed weights for each criterion. The decision makers were told they could alter the weights assigned for each criterion in a column adjacent to the initial proposed weights, which allowed for comparison. An error message appeared if their altered weights did not sum to one. Decision makers were also given space in the tool to add an additional criterion that they felt was extremely important to consider but was otherwise not reflected in the tool.

After they completed their initial manual ranking and the MCDA tool for each EBP, decision makers watched a brief video[6] that was developed based on the systems science informed framework of child neglect developed with the GMB stakeholders. The purpose of showing the video was to improve decision maker understanding of the complex interconnections between child neglect risk and protective factors and highlight how the EBPs being considered in the MCDA tool aimed to impact these factors. Specifically, the video focused on the relationship between child behavior and parent stress, and how these factors can both directly relate to neglect risk and indirectly relate through interconnectedness with risk factors such as material resource deprivation, trauma, and child care availability. A detailed overview of the stakeholder engaged process behind developing the video and the resulting dynamic hypothesis that informed the video is available in Cruden.[46]

Fourth, in order to assess if the MCDA tool was sensitive to changes in decision makers understanding of the problem and potential impact of the EBPs, decision makers were asked to review their initial responses in the MCDA tool and change any weights or criteria scores. The MCDA tool allowed participants to see their initial responses and then easily enter a new response in an adjacent column. Because the video focused on the risk and protective factors targeted by the intervention, we hypothesized that only those criteria related to interventions

[6]https://youtu.be/XzGcdafW87M

targets such as the *Program targeted* (criterion 3), *Important Outcomes/Goals* (criterion 6), and *Local Fit/Impact* (criterion 9) would be altered. Finally, decision makers completed a brief semi-structured interview, the details of which will be reported in a forthcoming manuscript.

MCDA Analyses

The score for each intervention was derived through a weighted sum approach, multiplying the criteria score of 1-5 by the criteria weight at each timepoint. Thus, the overall lowest possible score for each intervention was 1 and the highest was 5 at each timepoint.

Results

Evidence-Based Intervention Ranking

Most decision makers were familiar with Nurse Family Partnership (NFP) and Incredible Years prior to the pilot study. NFP was most frequently ranked as the first-choice intervention during the manual ranking" (n=6) followed by SafeCare (n=3). Six participants ranked interventions differently with the MCDA tool compared to their initial manual ranking. Four of these participants ranked all three EBPs differently in their manual ranking compared to the weighted sum scores in their baseline MCDA responses and two participants had two interventions rank differentially, with one of these participants ranking two EBPs in a tied score in the MCDA tool. Thus, five participants' rankings matched between these two initial rankings. Based on MCDA scores, NFP and was still the highest ranking, on average (Table 5.3). Among providers who did not rate NFP highly in either the manual ranking or MCDA, they cited the high costs of the EBP and lack of nurses in their community.

After watching the video, four participants changed their MCDA criteria responses. Three of these participants changed their responses to an extent that changed the overall EBP rankings as scored in the MCDA tool. Criteria scores never changed by more than one on the 5-

item scale after watching the video, and typically moved upward (e.g. from "agree" to "strongly agree" or "neutral" to "agree."). The most frequently changed criteria were those related to the intervention specifically, such as *Cost-benefit balance*, *Program targets*, *Local fit/impact*, and *Sustainability* (criteria 2, 3, 9, and 12, respectively; see Table 5.2 for complete criteria language).

Figure 5.3 offers a graphical representation of the degree to which each criterion contributed to the weighted sum score for each EBP at the baseline MCDA scoring and post, after the video intervention. Because of their high relative weights, criteria 2 and 5, i.e., the *Cost-benefit balance* and the *Strong Evidence-Base*, drove most of the overall score. The next criteria that contributed most to the weighted sum score was criteria 8, *Implementation resources*.

Proposed Weight Changes

Decision makers were invited to change weights at baseline and post-video intervention, although all changes occurred at baseline. The most frequently changed weights were those assigned to criterion 2, "*This program is likely to have an acceptable balance of cost to potential benefit (Cost-benefit balance, n=5),"* which was typically increased by .05, and criterion 1, *Existing Program*, (n=4), which was both up and down-weighted. Criteria 4-6 (*Familiarity*, *Strong Evidence-base*, *Important Outcomes/Goals*), 10 (*Available Intervention Resources*), and 12 (*Sustainability)* were changed by at least two decision makers. Criteria 7, *Program Duration*, was the only weight that was not manipulated by at least one decision maker. When calculating the mean change in weights, we computed weight reductions as a negative value and increased weights as positive (Table 5.2). Three decision makers noted that they did not change the weights because they trusted the stakeholder input and tool development. Figure 5.4 offers a graphical representation of the degree to which each weight changed from the proposed to altered values and which criteria carried the greatest weights.

Proposed Additional Criteria

Decision makers suggested additional criteria related to implementation context, implementation capacity, and sustainability. Only one participant wrote her additional criterion in the tool in the space provided; The remainder of suggestions came out during the semi-structured interviews. Every decision maker from a rural area (n=4) noted concerns about how interventions are often tested in urban areas, and it is unclear if they will have the same effects when used “off-label” (i.e., in a rural area) as one stakeholder put it. Thus, rural decision makers wanted to weigh interventions that had been tested in rural communities differentially. Further, decision makers wanted to reflect intervention fit not only within the community demographics and needs, but within the array of current programs offered. That is, they considered whether the program could fill a gap in a continuum of care across the levels of prevention and treatment. Implementation capacity was perceived as capacity to initially implement the intervention, such as through existing infrastructures from previous EBP delivery, as well as funding for implementation planning and active implementation, not just training. Finally, suggestions for sustainability were broken into two broad components: 1) financial sustainability, such as the potential for additional funders and reimbursement mechanisms to take ownership of the program after the initial funding source, 2) organizational sustainability in terms of organizations who would be willing to come on or continue as partners for implementation.

MCDA Tool Usability

We found five features of the MCDA tool needed to be refined to make the tool easier to use. First, it was important to clarify that the responses to individual criteria should vary across interventions, but the weights would be carried across each intervention. It was unclear to some stakeholders that the weights were the same for each intervention but that the criteria should be manipulated. Second, it was helpful to point out to decision makers what the lowest and highest rated criteria were so that they could easily interpret how important a given criterion was in the MCDA context. Third, although we had built in a warning that weights needed to sum to one to alert decision makers as they varied their weights, it would have been more helpful to distinguish whether the weights were incorrect because they were summing over or below one. Fourth, decision makers wanted a "Don't know" response instead of "Neutral" so as not to skew criteria scores. Finally, some decision makers noted that it would have been easier for them to change the weights if we had them presented as whole numbers, thus summing to 100 instead of 1. One participant wanted a notes section to record her logic behind why she selected particular answer or how she interpreted criteria.

MCDA Tool Acceptability

All but two decision makers reported that they would use a tool such as this again. The two who would not did not report an explicit reason why, but both were involved in legislative positions or acted as advocates to the legislature and thus may not have felt that they had time for such a tool or did not foresee themselves being responsible for such a distinct decision. One decision maker noted that it was "extremely user friendly," and another recalled that her non-profit had developed a similar rubric for comparing interventions, though not with a rigorous development approach. She liked the idea of the MCDA since it had been systematically developed and tested with multiple stakeholders. Of the decision makers who would use the tool again, all noted that the tool would be helpful for facilitating conversations and for "forcing" both funders and local leaders to think about EBPs and fit with local context, but could not replace collaboration and engagement with community partners during the decision-making process.

Limitations

This tool and accompanying pilot study have several limitations. First, the tool was developed with a relatively small (though diverse) group of stakeholders from North Carolina. While the criteria were not developed to be specific to North Carolina and align with considerations that have been highlighted in other states and organizational settings, there may be unique considerations in other state contexts.

Second, we designed the tool to assist with comparing EBPs for implementation, not for comparing the evidence or distinct components underlying each EBP. Thus, the tool may not be generalizable to all phases of EBP selection. For example, the individuals who review intervention research and compile evidence to inform decision making may not always be the individuals who ultimately select the intervention for implementation or funding. In some smaller settings, such as a local non-profit or rural health departments, the decision makers shared that they conducted their own research, and in larger settings such as the state legislature, decision makers acted upon synthesized information that was prepared by their staff or community and research partners. However, the criteria resonated with both individuals who are responsible for *selecting* or *funding* interventions and those who are responsible for *implementing* them.

Third, the small sample size of our pilot study limits our ability to make inferences about the strength of changes in the MCDA tool before and after the brief video intervention. Due to the similarity in changes across stakeholders, we posit that our sample was sufficient for testing the tool in its current form. The limited changes in MCDA responses after the intervention may be indicative that the decision makers were already adequately conceptualizing the complexity of child neglect prior to the video or that the video was not sufficiently in-depth or instructive.

Future research will test these hypotheses. Finally, we emphasize that the EBP rankings in the current study are not representative of all stakeholders in North Carolina or the value of the potential programs for implementation in North Carolina or other locations.

Discussion

This paper presented an overview of the replicable development process of a MCDA tool for comparing evidence-based child neglect prevention programs, and reviewed results of a pilot study intended to validate the tool and to test the difference between initial manual intervention selection ranks compared to ranks determined through MCDA scores. The pilot study demonstrated the feasibility and acceptability of the tool by decision makers, and the tool will continue to be refined based on decision maker feedback.

Our pilot allowed us to test the comprehensive of the criteria and how well the criteria resonated with both implementers and decision makers. Additional criteria that should be considered for inclusion included community history with EBP implementation or the potential for additional funding to sustain the program over time, and ways in which to present the tool in an easily understandable format. The diversity of our stakeholders helped us develop more comprehensive criteria that is relevant both to decision makers and practitioners, two groups that overlap frequently, but not always. Decision makers repeatedly asked for clarification around criteria 1 and 13 (“Existing Program” and “Training Transferability,”) and these two criteria were always down-weighted when they were changed. This suggests that these criteria may not need considerable focus.

Future research should explore the differential utility of the MCDA tool for comparing interventions during various stages over the intervention selection process and by individuals with varying levels of decision-making authority in a pragmatic context. For example, we will test a second version that removes the two criteria that seemed the least important to stakeholders, *Familiarity* and *Training Transferability* (criteria 4 and 13, respectively). We will also include more criteria specific to sustainability and implementation components based on the semi-structured interviews.

The results of this pilot suggest that decision makers may be biased toward ranking EBPs that they are familiar with more highly than those with which they are less familiar, as evidenced by the consistent finding the decision makers ranked SafeCare as the least preferred intervention overall, the EBP with which they were the least familiar. However, decision makers consciously weighted some criteria, such as the *Cost-Benefit Balance* and *Implementation Resources* (criteria 2 and 8, respectively), more highly than the *Familiarity* criteria. This finding suggests that internal heuristics and biases as well as salient decision-making processes are at work when considering intervention alternatives. Further, our findings around the differential weights assigned to our criteria highlight that decision makers were considering factors beyond effectiveness and evidence, suggesting that funders should take such factors into account when considering financial support for specific EBPs.

Although we weighted them highly to begin, the two criteria that most pertained to cost-benefit potential and resources available for implementation, (criteria 2 and 10) were often upweighted, suggesting that we underestimated the extent to which these criteria mattered. As one participant recalled, "there is nothing worse than getting a great program started and running out of funding." Decision makers need information not only about program effectiveness, but implementation costs over time to improve confidence of sustainability. Thus, more research is needed on the cost for implementing programs at various stages of implementation,[53–55] as well as in different contexts that have varied levels of resources at baseline. Cost calculators specific to evidence-based interventions, as well as generic ones that follow the stages of implementation could be particularly useful.[53,56,57]

Future research should assess whether interventions that are selected with the help of the MCDA tool have differential effectiveness and implementation outcomes compared to interventions selected without the use of the MCDA tool. However, we stress that the tool should only be viewed as a decision aid, not a final arbitrator, for two key reasons. First, MCDA tools cannot replace sustained, engaging conversations with practitioners and community partners when assessing intervention fit for a given community. The pilot project decision makers consistently stressed the collaborative nature of their decision-making processes, and how the quality of these collaborations affected the quality of decision making and implementation outcomes. Three decision makers had identical MCDA tool scores for two of the three interventions; Conversations would be required to break such ties. Second, decision makers may not always be required to select only one intervention, and the presentation of a discrete rank may represent a false choice for the community. Several decision makers noted the need for a continuum of prevention interventions to serve families. MCDA tools could help with prioritizing interventions across prevention levels, as well.

Our study developed and refined a MCDA framework that allows decision makers to compare evidence-based prevention interventions for child neglect. The framework could be easily transferable to other community health outcomes and evidence-based prevention programs, offering another important area for future research. Importantly, stakeholder developed MCDA tools such as ours that involve flexible, accessible formats (i.e., Microsoft Excel spreadsheets) allow for community decision makers to adapt and use the tools to facilitate collaborative decision making. Such tools are not intended to replace important community collaborative processes, but to supplement discussions around problem definitions and the optimal solutions given local context. Our results add to the existing literature that warns against "trusting your gut," thus supporting the need for structured tools and decision making processes.[58]

Table 5.1: Multi-Criteria Decision Analysis Tool Development Process

Step	Description	Study Activities
Defining the decision problem	Define child maltreatment, child maltreatment prevention, scope of problem, boundaries of systems that may serve children, relevant stakeholders, and potential alternatives	Review individual and synthesized definitions during Sessions 1 and 2 of GMB team sessions.
Selecting and structuring criteria	Identify the relevant criteria for each intervention alternative and refine with stakeholders and Implementation Science literature	Review qualitative responses explaining intervention selection from GMB Session 3, revise and expand to accommodate Implementation Science framework (Re-AIM), and refine list with stakeholder feedback in GMB Session 4.
Measuring performance	Gather data about effectiveness of each intervention alternative	Research team review of peer-reviewed evidence-based databases (Blueprints for Healthy Youth Development and California Evidence-Based Clearinghouse for Child Welfare Policies) to gather data on program characteristics for GMB team to select three interventions for primary consideration. (See Appendix for characteristics presented for comparison)
Scoring Alternatives	Establish ranges of scores for each criteria and intervention overall, as well as how alternatives will be presented in the MCDA tool	Research team proposed range and definitions based on qualitative GMB survey and reviewed proposal with GMB team in Session 4.
Weighting criteria	Elicit stakeholder preferences for how much weight to assign each criterion	Research team proposed weights after Session 3 GMB team survey which were revised during GMB Session 4.
Calculating aggregate scores	Calculate total value of each intervention	Study team independently calculated using weighted sum approach
Dealing with uncertainty	Test robustness of MCDA results using uncertainty analyses	Research team conducted pilot study with secondary set of decision makers.

*The steps of MCDA tool development are derived from Thokala et al. (2016)

Table 5.2: MCDA Tool Criteria Overview

	Criteria	Weight	Average Proposed Weight Change
1	This program is already implemented elsewhere in North Carolina. (Existing Program)	.1	-.04
2	This program is likely to have an acceptable balance of cost to potential benefit (Cost-Benefit Balance).	.15	.01
3	This program targets a population that I think is important (for example, young children, low-income mothers) (Program Targets)	.1	.05
4	I am familiar with this program. (Familiarity)	.05	-.05
5	This program has a strong evidence-base. (Strong Evidence-Base)	.15	.02
6	This program focuses on an outcome or set of short and long-term goals that I think is/are important. (Important Outcomes/Goals)	.09	-.03
7	The duration or timeframe for this program is appealing. (Program Duration)	.05	0
8	This program seems to provide sufficient implementation support or resources. (Implementation Resources)	.1	-.04
9	This program is missing one or more essential components that will reduce or limits its impact in my community. (Local Fit/Impact)	.05	-.01
10	The resources required for this intervention are available in my community. (Available Intervention Resources)	.05	.05
11	Organizations in my community would be excited to implement this intervention. (Community Enthusiasm)	.03	.02
12	This intervention is likely to be sustainable in my community. (Sustainability)	.07	-.01
13	People trained in this intervention will be able to train others to do it over time. (Training Transferability)	.01	-.01

Table 5.3: Evidence-Based Prevention Intervention Rankings

Evidence-Based Intervention	Modal Manual Ranking	Average Aggregate Score on MCDA, Baseline (Minimum, Maximum)	Average Aggregate Score on MCDA, Post (Minimum, Maximum)
Incredible Years	2	4.04 (3.66, 4.7)	4.05 (3.85, 4.7)
Nurse Family Partnership	1	4.16 (3.56, 4.69)	4.18 (3.56, 4.65)
SafeCare	3	3.78 (3.07, 4.41)	3.79 (3.02, 4.49)

Figure 5.1: Multi Criteria Decision Analysis Tool Initial Criteria by RE-AIM domains

+ Indicates that this particular concept and related question was proposed by the research team after it was identified as a missing concept from the initial list of considerations given by the GMB team. The GMB team then responded and refined the concept.

+ This was a new concept that was proposed during the refinement stage of the tool by the research team while mapping the initial criteria to the Re-AIM framework. This entire domain, Maintenance, was not represented in the initially proposed criteria.

Figure 5.2: Decision Maker MCDA Pilot Process

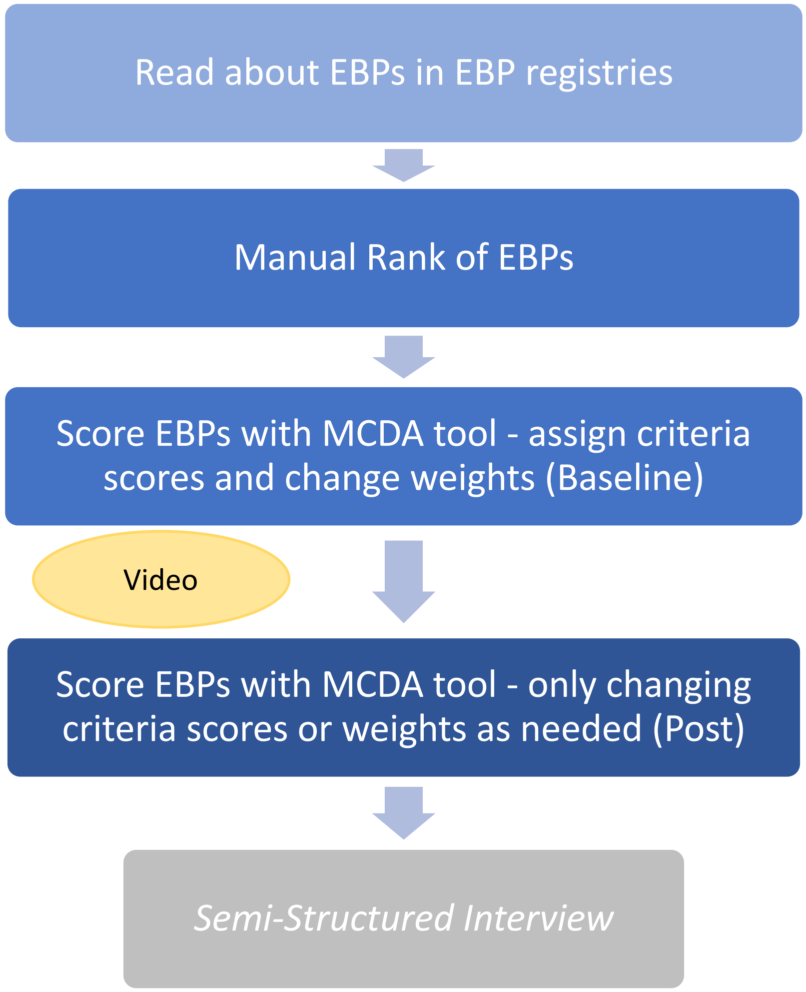


Figure 5.3: Weighted Sum for Criteria by Evidence Based Prevention Program and Timepoint

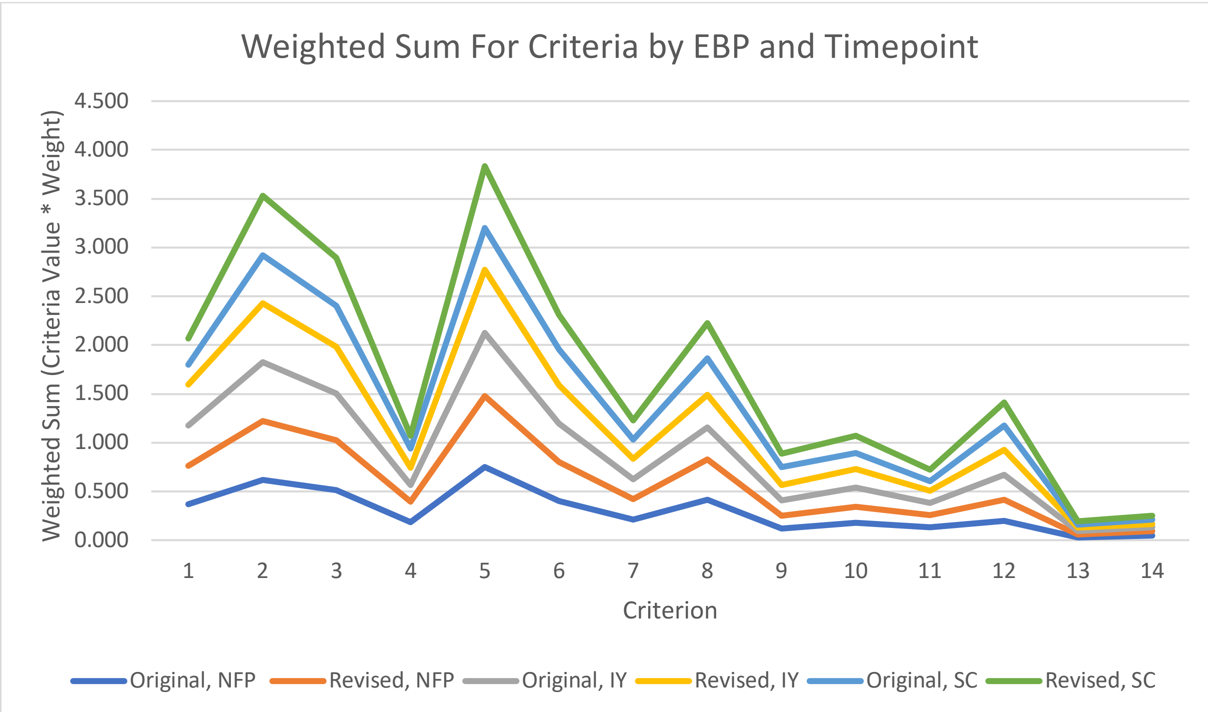
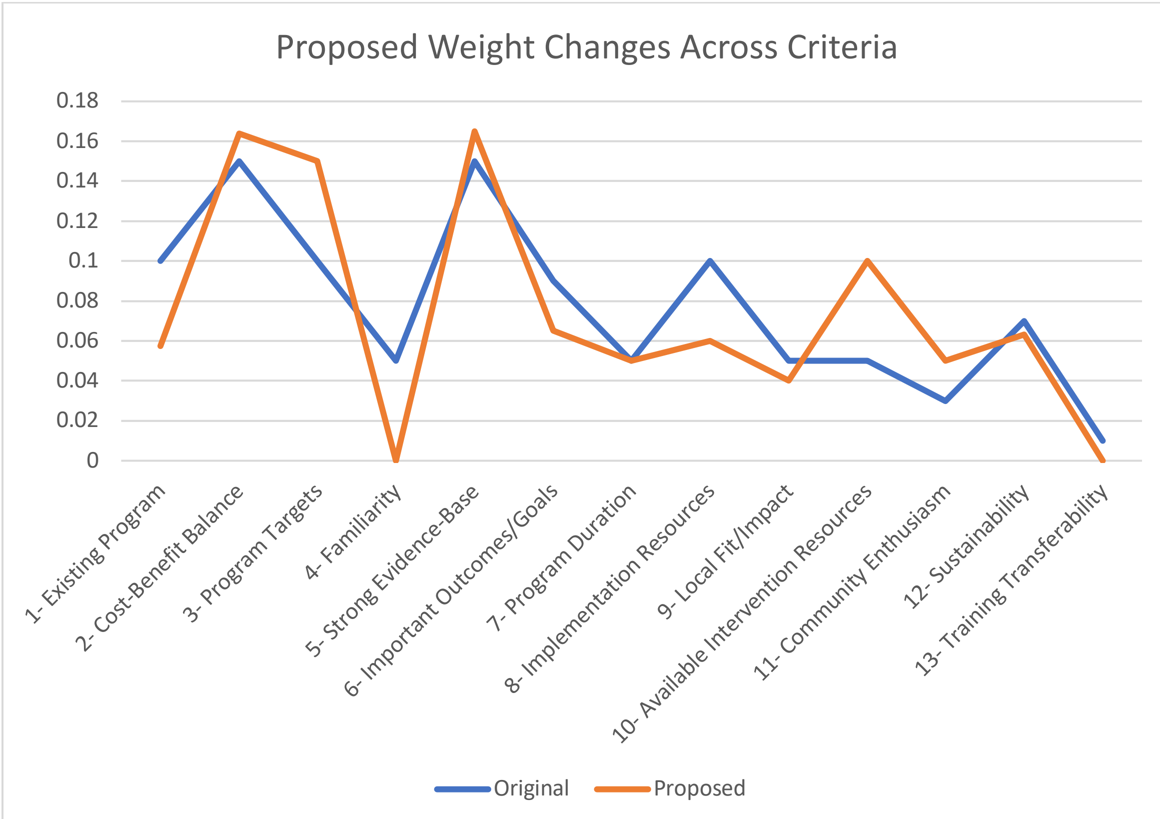


Figure 5.4: Proposed Weight Changes Across Criteria



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Chapter 6 : **CONCLUSION**

Summary

This dissertation was motivated by the central hypothesis that intervention effectiveness and ultimately implementation outcomes are shaped by local context; To understand the differential impact of evidence-based interventions once they are implemented in new contexts, we must understand 1) what contextual factors shape risk, and 2) what contextual factors decision makers consider beyond the strength of the interventions' evidence base when considering intervention alignment with their community needs. As I discussed in Chapter 1, child maltreatment is a significant adverse child experience with lifelong consequences. Evidence-based prevention interventions exist and are increasingly required as the preferred alternative by funders, but communities have to make their best guesses about which interventions may work best in their community given limited information. In Chapter 2, I reviewed the existing literature around the extent to which a variety of factors across the ecological levels of child development can be associated with child maltreatment risk, and highlight how a unified dynamic hypothesis or associated simulation model that can help us to understand the interconnectedness of factors through the lens of complexity is currently lacking in the literature. However, these chapters highlighted our acknowledgment in the literature that intervention effectiveness, as well as the acceptability and sustainability of interventions in community also vary across a variety of contextual influences. Previous studies of the influence of context on implementation processes and outcomes have primarily focused on the implementation of a specific EBP or setting type, such as mental health clinics. To build upon the current literature, this dissertation was motivated by four primary questions:

1) How do county-level observable risk factors for child maltreatment cluster together and relate to predicted child maltreatment rates?
2) How do local stakeholders conceptualize child maltreatment risk, and how do these risk and protective factors overlap with those targeted by child maltreatment evidence-based prevention programs?
3) Do decision makers compare evidence-based child neglect prevention interventions for implementation in their community more effectively with the support of a multi-criteria tool compared to an unassisted decision?
4) What local, organizational, and intervention specific factors should be considered when selecting between evidence-based prevention intervention alternatives when prioritizing interventions for implementation to prevent child maltreatment in a local community?

In the following section, I summarize the general insights from our activities to answer these questions and related limitations, followed by suggestions for immediate and long-term research activities to continue the current line of research, as well as implications for practice. I conclude this chapter with an overview of my insights from this learning process.

Main Findings

In Chapter 3, we used a person-centered analytic approach that aimed to characterize how key risk and protective factors for child maltreatment observable at the aggregate, county-level cluster together, and how these clusters, or latent profiles, relate to predicted child maltreatment rates. We found that counties clustered into low, moderate, and high-risk profiles characterized by the levels of predicted mean item-response indicators of child maltreatment risk. One notable exception to the factors that otherwise moved in the same direction was drug overdose fatality rates, which were highest in the moderate risk profile. Predicted child maltreatment rates were also highest in this moderate risk profile, and families in the highest risk profile had the least services received. These results suggest that high risk is not necessarily associated with higher rates of child maltreatment, and that particular attention should be given to counties with high levels of drug misuse and related fatalities.

In Chapter 4, we presented a case-study of how a community engagement approach based in systems science, Group Model Building, can be used to 1) generate a dynamic hypothesis of a complex population health problem, child maltreatment, and 2) iteratively build a simulation learning model based on insights from the Group Model Building team. There were two primary findings here. First, the Group Model Building stakeholders helped to develop an expansive, complex understanding of child maltreatment risk that went beyond the leverage points typically targeted by evidence-based child maltreatment prevention interventions. However, the stakeholders also identified most of the leverage points and related feedback loops that are targeted by evidence-based child maltreatment prevention interventions, thus easily facilitating a cross-walk between stakeholder insights and historical knowledge from the scientific literature. Second, we built upon the existing body of literature that highlights the necessity of involving stakeholders throughout the model building process so as to fully capture the required dynamics and build a model that is understandable and acceptable to decision makers and community stakeholders.

In Chapter 5, we reviewed the development of a multi-criteria decision analysis tool that was co-developed with the Group Model Building team from Chapter 4. This tool was motivated through an implementation science framework and designed to compare evidence-based prevention interventions for implementation in a specific population health serving context such as a county or county serving organization such as a health department. After developing the tool with the Group Model Building team, we recruited an additional sample of stakeholders from across North Carolina who had decision making authority or experience with respect to intervention selection and implementation in local settings. We found that decision makers generally liked the tool, although they suggested 1) several additional criteria for inclusion, 2) modifications to the weights assigned to current criterion, and 3) modifications for usability of the tool. The additional suggested criteria were primarily related to specifying the original context of where interventions were tested, as well as criteria related to the implementation process and sustainability. Six of the eleven decision makers in the pilot study ranked interventions differently when they ranked interventions without the tool compared to the weighted sum scores that they assigned through the tool, suggesting that the tool elicited additional considerations and may lead to differential decision making compared to decisions made without the tool. Relatedly, it was clear that the tool could not replace important conversations within implementation organizations and between their implementing and funding partners throughout the community. Finally, we had decision makers complete the tool again after watching a video that highlighted some of the key feedback loops identified by the Group Model Building team. Few decision makers changed their criteria scores after the video, and only one changed their criteria to the extent that an intervention was ranked differentially.

Limitations

There are several limitations to the potential of this dissertation to contribute to the literature. First, our data for Aim 1 was not ideally suited to the chosen analytic approach, latent profile analysis, due to the skewed nature of many of the identified risk and protective factors and the limited availability of child maltreatment data for small counties. This limited our ability to develop rich profiles that were characterized by complex combinations of risk and protective factors, as we only included risk factors and found profiles that had all factors moving in the same direction and with the same magnitude (e.g. low, medium, high) with the exception of drug overdose fatalities. Further, our generalizability to smaller population counties is limited. Second, we did not evaluate the adaptations to the Group Model Building process or participant perceptions of the process in a rigorous manner, limiting our ability to concretely add to the literature around Group Model Building methods, even though we demonstrated the potential of this approach for generating complexity based hypothesis related to adverse child experiences such as child maltreatment. Relatedly, we did not evaluate the video that was used in Aim 3 in a manner that allowed us to understand absolute change in the way that decision makers may have experienced in their conceptualization of the root causes of child neglect and potential leverage points. Thus, our mostly null results around whether intervention ranking changes after watching the video may be related to a ceiling effect for complexity understanding or a ceiling effect related to how this understanding relates to intervention potential for implementation, but we are not able to distinguish between these alternatives. Finally, we used North Carolina stakeholders for both Aims 2 and 3, which may limit the generalizability of our results to other states. While stakeholders rarely identified factors that are unique to North Carolina, the weight of each factor as a risk for child maltreatment or consideration for intervention fit may vary by state, or other states may have additional factors to consider that our stakeholders did not mention.

Implications

Research: Immediate Next Steps

There are three immediate next steps to expand upon this dissertation. First, I will further test and evaluate the potential insights from the learning model based on traditional tests for system dynamics learning models and simple baseline model behavior experiments. For example, I have begun reviewing the differential impact of parental depression at various baseline levels of depression on child neglect risk over time, finding that there is a fairly low threshold at which parental depression has increasing risk for child maltreatment over time due to the reinforcing feedback loop that characterizes depression trajectories. Second, I will revise the MCDA tool based on the proposed criteria from pilot study participants. Third, I will use a three-step approach to analyze the semi-structured interviews in Aim 3. The first step will be to assign themes from the knowledge translation framework in Ellen et al[1] to characterize how each question maps onto an evidence-utilization process in decision making. Next, I will develop second level themes within these knowledge translation domains based on my initial notes from the interviews. Finally, I will apply these second level themes when listening to the interviews again to derive any additional third level themes that will adequately characterize participant experiences to complete my codebook.

Research: Future

I propose the following lines of research motivated by this dissertation:

- How can implementing organizations better share information about their implementation experiences for other organizations to reflect upon?
- How can we better share family experiences during evidence-based intervention participation for both researchers and practitioners to better understand their experiences?

- How can we develop community-wide crisis, social, and financial supports for families?
- What is the potential impact of leverage points that are not targeted by evidence-based interventions? How does this impact relate to that expected to be achieved through discrete evidence-based interventions?
- How can we support communities and organizations in developing evidence for promising interventions or community generated interventions that meet community needs but may not be otherwise reimbursable or funded due to their lack of evidence-based?
- How can we promote trusting, sustainable community partnerships that serve families and children across the life course?

Policy

There are three potential policy implications that can be inferred from this dissertation. First, based on the latent profiles that emerged in Chapter 3 and the complexity of factors reviewed in Chapters 2 and 4, it is clear that a population health approach to child maltreatment intervention will require not only micro-level interventions at the child and family level, but community level interventions that may take the form of public health interventions such as communication campaigns that aim to reduce stigma around receiving parenting interventions, or policy interventions aimed at exo and macro level factors such as family access to transportation and child care subsidies. Second, decision makers in Chapter 5 consistently reiterated the importance of community partnerships for selecting, implementing, and sustaining evidence-based interventions for child maltreatment and well-being in their communities. This suggests that there should be supports for facilitating such partnership, such as through creating physical spaces for such partnerships or funding community-wide collaborations. Third, considering the breadth of the dynamic hypothesis developed in Aim 2 and the way that risk factors in Aim 1 moved together, policy makers need to consider the totality of risk and how policies and related funding can be expected to target or fail to target not just one factor, but all related factors. For example, targeting parenting stress through a parenting program alone may be insufficient to reduce stress in a way that measurably reduces child maltreatment risk compared to approaches that also incorporate policies to reduce material resource deprivation distress. As one Group Model Building participant notes, “no one wants to neglect.” Understanding that families require resources and community support to meet their children’s needs will be crucial to providing the spectrum of support that families require to nurture children and families.

Insights

Aside from the research and policy implications above, I learned several invaluable lessons throughout this process. First, research often requires revision in response to surprises in the data, intermediate findings, and participant needs. I needed to adapt my analytic approach several times for the first aim after reviewing the data and understanding not only what data was available, but the underlying distributions and quantitative limits of my selected methodological approach given the nature of the data. The latent class and profile analytic approaches were new to me, and I learned that some of the challenges I encountered are common in that analytic domain and I can better anticipate them in the future. Relatedly, I had to adapt the Group Model Building process to meet my stakeholders’ needs at every stage of the process, and adapt my plans for each session based on what we were able to accomplish during and between each session. Similar to the challenges noted for Aim 1, when creating the simulation model and attempting to quantify it, we realized that the model we needed to build based on stakeholder insights and associated available data in the literature was slightly different that the one that we had originally intended. Finally, I learned how to manage a stakeholder engaged project with respect to communicating with and responding to my stakeholders as well as navigating the complexity of stakeholder engagement in a university setting. For example, in Aim 3 I learned not to try and schedule interviews with legislators while the legislature was in session, and that even when stakeholders are excited about a project, they may not fully be able to engage due to administrative responsibilities. With respect to the university, I learned that some of the transparency and power-sharing that I would have like to share with my stakeholders during the Group Model Building process was not possible because I had to treat them as consented research participants. Not only did I feel that there was an inherent power imbalance that was created by having to situate myself as a university researcher when we signed consent forms, I also felt that I had to monitor my communications very carefully with the participants and not contact them in a personable manner. Instead, I had to have several communications approved by the IRB, so the email communication about their payment, for example, felt templated instead of personalized. This concern about respecting the IRB regulations also affected logistics and interactions. Prior to session two, I knew that two of the GMB stakeholders who had to travel the furthest to our meeting location were located near each other and likely could have carpooled. Because we had not yet met as a group, I did not feel permitted to introduce them over email and propose the carpooling. In session two, they recognized each other and commented that they knew each other from working together almost 15 years prior and commented that they should have carpooled. In the future, I will write more flexibility for myself into the Institutional Review Board (IRB) that will allow for more frequent communication, for example, while still respecting the rights of my stakeholders. Overall, I was not surprised by the depth of stakeholder knowledge that was shard with me through both Aims 2 and 3, but I was slightly surprised at how much research does not seem to be meeting the needs of community stakeholders and practitioners.

It is crucial to bear in mind that research must be developed with stakeholders in order to better meet their needs and set reasonable expectations about what roles that research can fill during the decision-making and implementation processes. As previously noted, the tools developed in Aims 2 and 3 should be viewed as *support* tools- not a replacement for the natural decision-making process or a resource for delivering decisions, but tools that support conversation among stakeholders and those with decision making authority. The tools can serve to help individuals understand the problem, understand why they think a solution would be appropriate or not, and to weigh the potential ramifications and tradeoffs that may be inherent to a given decision. This dissertation supported previous insights from decision science and psychological literature around the internal biases that shape decision making- I now appreciate how much this is true, and can see the potential of decision tools, from the simple to complex, that can introduce rigor and help to manage conflicting opinions or ambiguity when determining an appropriate solution. Tools should be general, such as the ones developed here, with room for adaptation to support community ownership of the tool, belief in the utility of the tools, and to align with unique community needs. Encouragingly, it seemed in Aim 3 that even developing these tools with stakeholders initially increased the degree to which decision makers were willing to accept the tool and trust its utility, again pointing to the need for engaging stakeholders at every stage of decision support tool development.

Conclusion

Child maltreatment prevention will require a population health approach that acknowledges the complexity that shapes child, parent, and family well-being. Such an approach will likely entail a variety of strategies across the prevention continuum, and these strategies will need to vary by the needs of the local population, as well as the physical and relationship-based resources in the community that serves the local population. In Aim 1, we saw that risk can vary greatly by geography, although risk factors often cluster together, pointing to the necessity of targeting multiple factors through shared mechanisms. We extended this insight in Aim 2 by co—developing a dynamic hypothesis of how risk and protective factors for child maltreatment interrelate in a dynamic way, thus making explicit how efforts to target a particular factor may either simultaneously target additional factors or fail to affect factors that are otherwise driven by interrelated processes, thus alerting us to when efforts at reducing risk may be undermined when we are not targeted the driving factors of risk. We then carried forward our hypothesis that factors should vary differentially when considering alternative solutions to Aim 3, where we found support for the hypothesis that decision makers not only consider a variety of factors when deciding which interventions are best suited to their community, but the degree to which these factors matter varies by organization, geography, and practice. Further, we found in both Aim 2 and Aim 3 that the preferred alternative may vary when we consider the totality of factors and their impact with the aid of a decision support tool as compared to unassisted decisions that are made without explicit probing into the differential weight of each factor. Further, we demonstrated that Group Model Building can be an effective way to facilitate community stakeholder and researcher learning around how to prevent child maltreatment. Decision support tools can facilitate conversations around which intervention alternatives may best fit a community, but they cannot replace such conversations. Both engaged processes and concrete tools such as the one developed in this dissertation can serve vital but complementary roles while working to improve population well-being across the life-course.

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APPENDIX 3.1 MODEL FIT STATISTICS AND ITEM-RESPONSE PROBABILITIES FOR FULL LATENT PROFILE MODEL WITHOUT COVARIATE

Model Fit					
Profiles (#)	**Entropy**	**AIC**	**BIC**	**BLRT p-value**	**LMR p-value**
3	.871	162514.122	162768.319	.000	.005
4	.895	161183.675	161504.447	.000	.001
5	.848	160127.536	160514.883	.000	.100
Profile Membership Probabilities			**3-profile model**	**4-profile model**	**5-profile model**
			.39	.38	.20
			.52	.00	.40
			.08	.52	.33
				.09	.06
					.00

Item-Response Probabilities for 3-profile solution						
	Profile 1		**Profile 2**		**Profile 3**	
Item	**Mean**	**S.E.**	**Mean**	**S.E.**	**Mean**	**S.E.**
Mental Health Distressed Days (%)	3.136	0.024	3.95	0.024	4.443	0.032
High School Drop Out (%)	4.357	0.161	5.755	0.129	7.387	0.403
Unemployment (%)	2.95	0.057	4.423	0.047	6.482	0.271
Households Receiving Public Assistance (%)	1.881	0.04	2.702	0.039	3.633	0.3
Female Headed Households in Poverty (%)	3.067	0.067	5.642	0.129	11.891	0.538
Publicly Insured Children (%)	29.808	0.451	46.774	0.623	62.619	0.859
Drug Overdose Death Rate	10.897	0.191	15.895	0.173	11.874	0.473
Food Insecure Households (%)	12.016	0.123	16.119	0.153	22.585	0.526
Housing Insecure Households (%)	12.322	0.165	15.276	0.119	19.511	0.668
Mental Health Distressed Days (%)	59.824	1.11	57.097	0.87	62.558	1.934

APPENDIX 3.2: ALTERNATIVE MODEL MEMBERSHIP PROBABILITIES AND FIT: ITEMS LOG-TRANSFORMED (LATENT PROFILE)

Profiles (#)	Entropy	AIC	BIC	BLRT p-value	LMR p-value
No Covariate					
3	.830	28506.129	28784.535	.0000	.0000
4	.858	27088.594	27439.628	.0000	.0002
5	.853	26155.971	26579.631	.0000	.2911
6	.846	25285.925	25782.214	.0000	.0142
Covariate					
3	.831	19696.000	19961.752	.0000	.0002
4	.846	18593.430	18931.659	.0000	.0015
5	.843	17657.243	18067.950	.0000	.0086
6		Did not run because of miniscule class size and associated practical utility			
Profiles Proportions, no covariate		**3- profile model**	**4- profile model**	**5- profile model**	**6- profile model**
1		.18	.43	.21	.05
2		.48	.16	.04	.23
3		.34	.35	.07	.06
4			.07	.41	.29
5				.27	.17
6					.11
Profiles Proportions, covariate		**3- profile model**	**4- profile model**	**5- profile model**	**6- profile model**
1		.18	.24	.04	.
2		.48	.27	.24	.
3		.34	.04	.17	.
4			.45	.11	.
5				.43	.
6					.

APPENDIX 3.3: ALTERNATIVE MODEL MEMBERSHIP PROBABILITIES AND FIT: ITEMS TRANSFORMED TO TEN QUINTILES (LATENT CLASS)

Classes (#)	Entropy	AIC	BIC	BLRT p-value	LMR p-value
No Covariate					
3	.830	160181.773	160460.178	.000	.000
4	.833	159016.917	159367.951	.000	.001
5	.816	158263.546	158687.207	.000	.002
6	.820	157544.051	158040.339	.000	.000
Covariate					
3	.830	145549.408	145815.709	.000	.000
4	.834	144383.216	144722.144	.000	.001
5	.816	143637.695	144049.251	.000	.001
6	.820	142978.962	143463.146	.000	.000
Class Proportions, no covariate		**3-class model**	**4-class model**	**5-class model**	**6-class model**
1		.37	.31	.21	.19
2		.30	.30	.27	.10
3		.33	.14	.20	.22
4			.24	.18	.14
5				.14	.18
6					.17
Class Proportions, covariate		**3-class model**	**4-class model**	**5-class model**	**6-class model**
1		.30	.30	.21	.09
2		.37	.31	.14	.14
3		.33	.24	.20	.22
4			.14	.18	.19
5				.27	.17
6					.19

APPENDIX 3.4: LATENT PROFILE MODEL WITH RESTRICTED SAMPLE (N=820): MODEL-BASED (BAKK VERMUNT 3-STEP) METHOD

Classes (#)	**Entropy**	**AIC**	**BIC**	**BLRT p-value**	**LMR p-value**
With Covariate					
2	.888	31990.327	32282.304	.000	.73
3	.926	30318.587	30742.424	.000	.65
4	.911	29736.557	29889.128	.000	.12
5	.909	28921.457	29524.248	.000	.38
Class Proportions	**2-class model**	**3-class model**	**4-class model**	**5-class model**	
1	.58	.55	.39	.09	
2	42	.16	.14	.15	
3		.29	.38	.18	
4			.09	.25	
5				.33	

APPENDIX 3.5: ALTERNATIVE PSEUDOCLASS RESULTS FOR CHILD MALTREATMENT OUTCOMES IN SELECTED MODEL

Pseudoclass 2						
Pseudoclass	**Total Reports**	**Abuse**	**Neglect**	**Black**	**Hispanic**	**Services Received**
2	31.07* (9.09)	-.17 (.43)	.54 (.33)	2.17 (4.38)	.14 (1.84)	4.61 (5.67)
3	24.98* (10.99)	-.28 (.37)	.21 (.37)	22.22* (8.11)	2.28 (2.25)	-4.17 (5.76)
Pseudoclass 3						
2	22.94* (8.71)	-.10 (.34)	.66* (.25)	1.07 (3.72)	1.12 (1.30)	6.66 (4.21)
3	13.43 (10.25)	-.19 (.37)	.33 (.30)	20.81 (7.24)	3.80 (1.73)	-2.88 (4.20)
Pseudoclass 4						
2	34.06* (7.57)	-.00 (.34)	.77* (.23)	3.57 (3.31)	2.05 (1.69)	7.66 (4.10)
3	25.70* (9.44)	-.12 (.38)	.39 (.28)	23.51* (7.30)	3.73* (1.67)	-2.14 (4.10)

Note: Pseudoclass 1, **low-risk** profile, is the referent in all analyses above. Marginal effects and Delta-method standard errors presented.
*p<.05

APPENDIX 4.1: PRINCIPLES FOR GMB ENGAGEMENT

Below, we propose a collated selected of principles for planning and facilitating Group Model Building projects based on our own experiences, and those proposed by Luna-Reyes[1] and Vennix.[2] We offer these in order to support cumulative knowledge development as proposed by Andersen and Richardson.[3] This list is not comprehensive, and the interested reader is encouraged to see out other seminal texts, including Vennix,[2] Hovmand,[4,5] and Luna-Reyes.[1]

Planning Principles

1) Be willing to iterate the products within and between sessions
    a. Group Model Building is a dynamic process that is intended to foster learning on behalf of the stakeholders and modeling team. Internal heuristics held by the modelers may shape how information is captured, and group dynamics, activities, or time limitations may limit what is originally shared. Thus, the GMB process should be designed to be iterative, allowing for activities that may elicit the same information through different avenues within the sessions. The modeling team should also review the models developed in previous sessions before the next session to identify places areas that may be contradicting one another or need further evaluation and discussion in the ensuing sessions. This review between sessions is important to improve the efficiency and quality of insights of each session.
2) Give multiple ways for people to engage and to elicit information.
    a. This principle builds upon the idea of iteration in principle one. Here, we emphasize that providing alternative avenues for eliciting information may not

only come from various scripts that use different prompts to ask about important variables or stories to be modeled, but multiple modalities that may resonate more with some individuals compared to others. Similar to pedagogical approaches that emphasize multiple modalities of learning, we proposed having some activities that are individually based, some that are group or conversationally based, written activities, and virtual activities as needed. Some group model building scripts combine these modalities, such as the "Hopes and Fears" script, where individuals write down their hopes and fears on their own, and then share them aloud one at a time with the group.

3) Keep sessions simple and focused.
    a. Be keenly aware of the time available for each session. Most activities take at least 45 minutes to 1 hour, and the activities will not have the intended effects on the group dynamics or lead to in-depth insights when rushed. Thus, allow for ample time for each activity as suggested in the scripts, or build in extra time into your detailed agenda for activities that have not been consistently attempted or timed.
4) Keep examples simple, generic, and consistent.
    a. As groups are learning about systems principles, it is helpful to pick simple, relatable examples such as how the flu can be spread in a classroom or how a student's grades change over time, that almost everyone can understand or relate to, before moving into examples more specific to the project at hand. It should be the goal of the modeler to help people understand the principles behind the example, and not get caught up in trying to understand the problem if it is too

obtuse, or correct the problem if it is too similar to the one that the group is trying to solve.

5) Plan ample time for establishing a group vision and problem definition.

    a. We have found that this can be a time-consuming step in the process, but one that is essential for everyone in the room to feel that they belong as part of the process and will be heard, as well as that they will benefit from the process. This is especially important for groups that have power imbalances such as different levels of administrators within an organization, lay community members and administrators with power such as the police, or individuals from organizations that may be vying for limited resources or populations, or organizations that may be mandated to work within constricted spaces. For example, one group spent an entire session defining the age range of youth that would be discussed for collaborative care because of the difficulties in navigating legislation and funding that restricted funds and activities to certain age ranges that did not always fully overlap. Establishing shared definitions and visions help to establish ownership of the project and thus foster positive engagement, as well as mutual self-interest so that everyone in the project feels that they are obtaining results that are worthy of their time and respectful of their vision and values.[2,6–9]

<u>Facilitating Principles</u>

1) Beware of modeling team paradigms.

    a. The modeling team should aim to be as neutral as possible when facilitating sessions so as to explore and extract the insights important to the GMB group as they see them. Otherwise, the project may end up being a validation of the modeling team's mental models. The iterative processes can help combat this, as can having a diversity of individuals on the modeling or facilitation team, including someone from the community or organization who is participating in the GMB activities. The modeling team should also consistently reflect on the existing scientific literature to see how the GMB insights map onto the literature, and can rely upon the literature as a starting point for clarifying any concepts in the developing GMB model. However, we emphasize that the scientific literature should not be held as the standard upon which the GMB should be assessed, but as a tertiary tool for framing insights and the depth of the problem.

2) Encourage **both** convergence and divergence.
    a. This principle is one of the foundations of GMB, in that the sessions and activities should be designed to help the group go broad in their definition of a problem and its solutions in order to eventually converge and collaborative decide upon a solution through consensus. By first converging, the process allows each stakeholder to share their mental models and feel heard, but the facilitated process of converging these mental models and potential solutions helps stakeholders not only to determine a solution or feel that they compromised on a solution, but to selection a solution through consensus as they walk through the logic of why that solution affects their problem in the way that they intend.
3) Name variables in causal loop diagram using stakeholder nomenclature and making directionality clear as necessary to complete the CLD.

a. Luna-Reyes et al[10] suggest omitting mathematical terms from variables such as "ratio" in order to make the variables and model more approachable for populations that are not focused on mathematical concepts and analyses.
b. It may be necessary to add qualifying words to some concepts in order to characterize the connecting arrows as + or -. For example, *positive* parent child interactions may be affected differently than *negative* parent child interactions, and may need to be modeled separately. Additionally, some factors may be too vague without a directional qualifier. For example, if you want to describe the relationship between a policy and healthy food access, it would be difficult to show whether the policy positively or negatively affected health in the diagram without denoting the relationship between policy and health food access, in particular (versus "food" or "food access").

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APPENDIX 4.2: CHARACTERISTICS OF EVIDENCE BASED PREVENTION PROGRAMS PRESENTED FOR PROGRAM SELECTION

Topic/Concept	**Definition**
Intervention Name	As designated by program developers
Type of Prevention	Qualitative description of prevention program targeted population and outcomes
Child age range targeted	Child age for inclusion
Parent outcomes targeted	Final or interim (mediating) parent-level targets of parental intervention
Child outcomes targeted	Final or interim (mediating) child-level targets of parental intervention
Session Description	Including session length, modality (individual, group) and number of sessions.
Timeframe for Delivery	Time frame over which intervention is delivered (length and point of engagement)
Level of Evidence	Strength of evidence as designated by evidence-based registry
Testing site	Location(s) where intervention effectiveness and implementation trials conducted
Implementation Setting	Location where intervention is delivered
Intervention Deliverers	Practitioner responsible for delivering intervention and associated professional or education degrees
Benefits minus cost, per participant, per year	Drawn from Washington State Institute for Public Policy (WSIPP)
Chances benefits will exceed costs	Drawn from Washington State Institute for Public Policy (WSIPP) based on simulation experiments of assumed parameters
Available languages other than English	Languages that program is offered in other than English
Pre-implementation training or assessment	Yes/No, based on program registry
Manual available	Yes/No, based on program registry
Source	Evidence based registry from which information drawn

APPENDIX 5.1: INTERVENTION CHARACTERISTICS FOR COMPARING EVIDENCE-BASED PREVENTION PROGRAMS

Characteristic	Definition	Examples	Source
Type of Prevention	Primary target of prevention as defined through evidence-based registry, defined through population targeted or outcome targeted	Prevent child abuse and neglect; Prevent removal from home after investigation	CEBC, Blueprints
Child age range targeted	Age range of child eligible for receiving intervention	0-5, 0-17	CEBC, Blueprints
Parent outcomes targeted	Final or interim (mediating) parent-level targets of parental intervention	Disciplinary skills; self-efficacy	CEBC, Blueprints
Child outcomes targeted	Final or interim (mediating) child-level targets of parental intervention	Externalizing behavior; internalizing symptoms	CEBC, Blueprints
Session description	Including session length, modality (individual, group) and number of sessions.	1.5 hours/week	CEBC, Blueprints
Timeframe for delivery	Strength of evidence as designated by evidence-based registry	90 days after initial case plan for individual families	CEBC, Blueprints
Level of Evidence	Location(s) where intervention effectiveness and implementation trials conducted	2- Supported by research evidence	CEBC, Blueprints
Testing Site	Location where intervention is delivered	Memphis, TN; urban neighborhood	CEBC, Blueprints
Implementation Setting		School	CEBC, Blueprints
Implementation Deliverer		Master's level mental health clinician	CEBC, Blueprints
Benefits minus cost, per participant per year		$712	WSIPP
Chances benefits will exceed costs		98%	WSIPP
Available language(s)		Spanish, Hebrew	CEBC, Blueprints
Pre-implementation training or assessment?		Yes/No	CEBC, Blueprints
Training available?		Yes/No	CEBC, Blueprints

Manual available?		Yes/No	CEBC, Blueprints
Program name		Nurse Family Partnership	CEBC, Blueprints

- WSIPP – Washington State Institute for Public Policy
- CEBC- California Evidence-Based Clearinghouse for Child Welfare
- Blueprints- Blueprints for Healthy Youth Development