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The multiphase optimization strategy (MOST) in child maltreatment prevention research

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Abstract

Each year hundreds of thousands of children and families receive behavioral interventions designed to prevent child maltreatment; yet rates of maltreatment have not declined in over a decade. To reduce the prevalence and prevent the life-long negative consequences of child maltreatment, behavioral interventions must not only be effective, but also affordable, scalable, and efficient to meet the demand for these services. An innovative approach to intervention science is needed. The purpose of this article is to introduce the multiphase optimization strategy (MOST) to the field of child maltreatment prevention. MOST is an engineering-inspired framework for developing, optimizing, and evaluating multicomponent behavioral interventions. MOST enables intervention scientists to empirically examine the performance of each intervention component, independently and in combination. Using a hypothetical example of a home visiting intervention and artificial data, this article demonstrates how MOST may be used to optimize the *content* of a parent-focused in-home intervention and the *engagement* strategies of an intervention to increase completion rate to identify an intervention that is effective, efficient, economical, and scalable. We suggest that MOST will ultimately improve prevention science and hasten the progress of translational science to prevent child maltreatment.

Keywords

home visiting; multiphase optimization strategy (MOST); child maltreatment; intervention science; behavioral intervention

In the U.S. 12.5% of all children are referred to child protective service systems by age 18 (Wildeman et al., 2014); indeed, in 2019 child protective service systems across the U.S. received concerns for the safety and well-being of more than 7.8 million children and youth (DHHS, 2021). A core function of the child protective service system is to identify high-risk families and provide services including parent education programs, which are designed to bolster parenting skills, knowledge, and attitudes as well as improve home environments

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(Herrenkohl et al., 2016). Despite financial support for parent-focused programs designed to prevent maltreatment, prevalence rates of physical abuse, neglect, and sexual abuse have not changed in over a decade (Finkelhor et al., 2019). In fact, the most recent national data indicate an uptick in the prevalence of sexual abuse (Finkelhor et al., 2020). This underscores the need to critically examine parent-focused programs used within the child protective service system.

Home visiting programs are one of the most common parent education strategies employed by child protective service systems. Indeed, in the U.S. since 2010, nearly $1.9 billion of federal funds have been earmarked for home visiting program support. The goal of a home visiting program is to foster parent knowledge and skills, social support, coping and problem-solving, and access to community referrals (e.g., developmental specialists) to improve children's developmental trajectories (Guterman, 2001). The effectiveness of home visiting programs varies (Avellar & Supplee, 2013; Chaffin, 2004; Euser et al., 2015; Filene et al., 2015; Peacock et al., 2013; Sweet & Appelbaum, 2004; van der Put et al., 2018). For example, a recent meta-analysis indicated a moderate (d =.29) reduction of risk for child maltreatment, but, notably, effects varied widely among child protective service system referred samples, who are at highest risk (d =.018 to .53; Chen & Chan, 2016).

Even among home visiting programs that have demonstrated effectiveness in preventing child maltreatment, the way in which the programs were developed and evaluated limits scientific understanding of how the intervention produces the desired effect. For example, is one aspect of the intervention entirely driving the outcome? Is the performance of one aspect dampened by the presence of another? Are all ingredients of the intervention needed to produce the desired effect? Because of this limited scientific understanding, it is unknown what next steps should be taken to make prevention programs more effective, affordable, scalable, and efficient.

One potential approach to increasing scientific understanding and improving the impact of interventions designed to prevent child maltreatment can be found in the multiphase optimization strategy (MOST). MOST is an engineering-inspired framework for developing, optimizing, and evaluating multicomponent behavioral interventions so that they are not only effective, but also affordable, scalable, and efficient (Collins, 2018). The purpose of this article is to introduce MOST to the field of child maltreatment prevention. The aim is not to review the effectiveness of and differences between the myriad of existing home visiting programs nor is it to suggest that home visiting is the only prevention strategy appropriate for parents referred to child protective service systems. Rather, the aim is to use home visiting as an illustrative example to demonstrate one of the many ways MOST could be applied to advance prevention science. MOST is neither an off-the-shelf procedure nor is it limited by public health priority or prevention strategy. Over the past 15 years, over 100 projects applying MOST have been funded by the National Institutes of Health across many institutes and centers across a number of public health priority areas including smoking cessation (e.g., Piper et al., 2016), obesity (e.g., Spring et al., 2020), heart disease (e.g., Celano et al., 2018), HIV (e.g., Caldwell et al., 2012; Gwadz et al., 2017), and the prevention of sexually transmitted infections (STI; Tanner et al., 2021; Wyrick et al., 2020). For example, in an online intervention to prevent STI among first year college students five theoretically and empirically supported components were identified and tested following the MOST framework (Wyrick et al., 2020). Experimental data from a highly efficient randomized experimental trial indicated that only two components had a significant effect on the outcome of interest. This enabled removal of inert components, thereby increasing the efficiency of the intervention.

Although MOST has been described and applied across a variety of public health topics, to our knowledge, MOST has yet to be applied to the field of home visiting to prevent child maltreatment. Building upon decades of prior work, a host of available home visiting programs with varied levels of effectiveness, and a consistent number of children reported to child protective service systems each year amid limited implementation budgets, the field of child maltreatment prevention is primed for application of the MOST framework.

The Classical Treatment Package Approach

The vast majority of behavioral interventions, including home visiting programs, have been developed and evaluated in what we will refer to as the 'treatment package approach'. In this approach, the intervention scientist uses theory and empirical literature to identify intervention components that are believed to affect the desired outcome, then immediately assembles these components into a package and (after suitable pilot work) tests the package in a randomized controlled trial (RCT). The RCT remains the gold standard for determining the effectiveness of an intervention; however, as discussed above, the treatment package approach leaves unanswered questions. The RCT, like any clinical trial, is highly resource intensive (i.e., time, money, person-time) and is conducted in a highly controlled, well-resourced (i.e., grant funded) environment that does not necessarily represent the practicalities of 'real world' implementation. Because implementation constraints are not considered when the intervention is designed or evaluated, it is not surprising that many effective interventions are not available widely to the population they are designed to help, or may even never reach this population, because they are ultimately too expensive or too complicated to be implemented on a wide scale.

The Multiphase Optimization Strategy (MOST): A Brief Introduction

MOST is not a specific experimental design, nor is it an off-the-shelf method or procedure. Rather, MOST is a framework for the development, optimization, and evaluation of multicomponent interventions. An intervention component is any aspect of an intervention that can be separated out for study (e.g., content related to emotion regulation, text message prompts to use skills between sessions, etc.). In this regard, virtually any intervention may be conceptualized as multicomponent. *Optimization* is the process that identifies the set of intervention components that produces the best expected outcome obtainable given key constraints imposed by the need for affordability, scalability, and efficiency. Constraints constitute anything that might hinder implementation (e.g., cost of the intervention per participant, provider time to deliver the intervention, or participant burden). The goal of an optimized intervention is to achieve *effectiveness*, but also *affordability* (i.e., degree to which the intervention produces a good outcome without exceeding budgetary constraints), *scalability* (i.e., the degree to which an intervention can be implemented exactly as it was evaluated; Collins, 2018), and *efficiency* (i.e., degree to which an intervention produces a favorable outcome while avoiding the wasting of resources)

MOST is comprised of three phases: preparation, optimization, and evaluation (Figure 1). Researchers will be familiar with many of the activities of the preparation and evaluation phases, as these are the basis of the treatment package approach. In the preparation phase, a theoretically and empirically derived conceptual model is developed, a set of candidate intervention components are identified, and pilot testing of components is conducted as needed. The evaluation phase, in which hypotheses about the effect of the assembled intervention compared to a suitable control are tested, typically uses the RCT experimental design.

MOST diverges from the treatment package approach by introducing the optimization phase between the preparation and evaluation phases. In the optimization phase, a highly efficient, adequately powered randomized experiment, called an *optimization trial*, is conducted to determine the individual performance of each component on the outcome of interest and whether the presence or absence of a component affects the performance of other components. The results of the optimization trial are used to identify the combination of components that produces the best expected outcome while satisfying the *optimization objective* (i.e., the goal of optimization; described in detail below). This combination represents the optimized intervention that will subsequently be evaluated in an RCT in the evaluation phase of MOST. If the optimized intervention is not expected to be sufficiently effective, then adhering to the *resource management principle* of MOST, the investigator would return to the preparation phase and begin the process of optimization again as opposed to moving onto the evaluation phase (Figure 1). The resource management principle holds that the intervention scientist “must strive to make the best and most efficient use of available resources when obtaining scientific information” (Collins, 2018, p. 17). If the optimized intervention is not expected to be sufficiently effective, to conduct an RCT would not be the most efficient use of resources. Optimization is a process and, according to the *continual optimization principle*, even the optimized intervention that has made it through the evaluation phase can be further optimized. New advances in technology, updated basic science, or emerging theories will provide the basis of continued optimization. Those who may be interested in a comprehensive tutorial on MOST are directed to Collins’ 2018 book.

In the following sections, we use artificial data to illustrate the development, optimization, and evaluation of a hypothetical home visiting program using the MOST framework. The hypothetical example is based on a scenario in which an intervention scientist is interested in developing a home visiting program designed to reduce the potential for child maltreatment. The example will walk through the three phases of MOST, using simulated data from a hypothetical factorial optimization trial to illustrate nuances of experimental design and empirically driven decision-making. This hypothetical example should not be considered the only way MOST can be applied in the field of child maltreatment. Rather, the example is meant to inspire the wide application of MOST to address long-standing issues in the field of child maltreatment prevention and produce child maltreatment interventions that are better equipped to achieve public health impact.

The Preparation Phase

The preparation phase lays the groundwork for optimization. The activities of the preparation phase – depiction of a conceptual model, identification of candidate components, pilot testing, and specification of the optimization objective – are essential in the process of optimization. A thorough preparation phase will provide a clear path forward through the iterative process and subsequent phases of MOST. Aspects of the preparation phase will inform actions in the optimization and evaluation phases.

Conceptual Model and Identifying Intervention Components

The conceptual model depicts the 'engine' driving the intervention (Collins, 2018). A conceptual model should be thorough, but its purpose is not to depict every possible relationship among components, mediators, and outcomes; thus, the conceptual model is neither a logic model nor a structural equation model. The purpose of the conceptual model is to depict the hypothesized way the intervention will affect behavior leading to the desired outcome. Figure 2 depicts a hypothetical conceptual model in which the theoretically and empirically derived intervention components are identified as well as the causal pathway comprised of proximal and distal mediators that produce the desired outcome. In our hypothetical example, the intervention scientist decides to consider components related to the intervention content and parental engagement with the home visiting program informed by common component analyses (Filene et al., 2015; Kaye et al., 2018). As identified on the far right of Figure 2, the desired outcome is to reduce potential for child maltreatment, as measured by the Child Abuse Potential Inventory (Chaffin & Valle, 2003; Milner, 1986), by targeting parenting behaviors of parents referred to child protective service systems. The left of Figure 2 specifies candidate intervention components that were selected based on theory and empirical literature: parenting knowledge and skills, child sexual abuse prevention, peer mentoring, problem-solving, and check-ins between visits. We use the term candidate intervention component because the components in Figure 2 are under consideration, or candidates, for inclusion in the optimized intervention.

The parenting knowledge and skills component is designed as a constant component. A constant component is appropriate when there is specific intervention content that must be provided for ethical or logistical reasons, or because prior research has established its effectiveness (Collins, 2018). A constant component is not experimentally manipulated in the optimization trial (i.e., everyone receives it); therefore, the optimization trial does not provide any information on the effect of that component on the desired outcome. The component is designed to teach parents what behaviors are appropriate for their child's developmental stage and corresponding activities that can help promote social-emotional, cognitive, or motor development. This is accomplished by enhancing parent-child interactions such that parents create an emotional investment in their child, focusing specifically on creating positive interactions that reinforce parental bonding with the child. The parenting knowledge and skills component represents the common content used across most home visiting programs, and, thus, the intervention scientist decides this content must be delivered to all parents.

Of the remaining four components that will be experimentally manipulated in the subsequent phase of MOST, three are related to the content of the intervention. The child sexual abuse (CSA) prevention component is a module with demonstrated effectiveness in improving parents' CSA-related awareness and use of protective behaviors (Guastaferro et al., 2020). The peer mentor component connects the parent with a peer mentor to provide a form of social support. The peer mentor, someone who has previously completed the intervention, will help reduce the stigma of enrolling in a parenting program, and will provide social reinforcement of skills taught and opportunities for practice of parenting skills (Kaye et al., 2018). The problem-solving component is designed to teach parents strategies to overcome perceived stressors (e.g., disruptive child behaviors, lack of child care). The fourth component is designed to improve parental engagement with the home visiting intervention. The check-ins between visits component is designed to target the parents' perceived support. For example, the home visitor might send a text message to the parent between visits: "It is beautiful outside today – a great day to go to the park! What activity do you have planned that you and your child could do today outside?"

As depicted in Figure 2, each component directly targets one proximal mediator: CSA-related awareness and protective behaviors, social support, stress/coping strategies, and concrete support. The pathways that follow specify the hypothesized mechanisms through which the intervention targets the distal outcome. The conceptual model can be read as a series of causal pathways. For example: *information about CSA will increase parental CSA-related awareness and use of protective behaviors which will then directly improve parenting behaviors/skills leading to a reduction in the potential for child maltreatment.* It is not necessarily the case that the intervention scientist believes that the peer mentor component will not affect any other mediators, such a parent's stress level; rather, the conceptual model specified the intended target of the peer mentor component, in this case social support. The effect of components on other mediators can be examined post hoc.

Pilot Studies

If any components needed to be developed or adapted, the intervention scientist would conduct necessary pilot testing in the preparation phase. We define a pilot test as one in which hypotheses are generated, not tested and, therefore, a pilot test is not powered to estimate effects (Leon et al., 2011). A pilot study might seek to understand the acceptability and feasibility of a component, establish the logistical feasibility of a complex experiment, or be useful in the finalization of intervention protocols. There is no specific experimental design that is recommended for the preparation phase. A pilot test is not equivalent to an adequately powered, randomized optimization trial (described below). For the purpose of the hypothetical example, suppose that we conducted simple pretest-posttest study with the CSA prevention focused component to determine if it could feasibly be delivered in 1-hour and the acceptability among parent participants. In this pilot, the results confirmed feasibility and acceptability, but also the team was able to practice the delivery of the assessment corresponding to the mediator in the conceptual model. A second pilot study used focus groups with parents and providers to inform the development of the text messages sent in the check-in component. At the end of the pilot studies, the investigator team is ready to subject the components to rigorous experimentation in the optimization trial.

Optimization Objective

Selected based on the objectives of the intervention and in consideration of the constraints of the setting within which the intervention will be delivered, the optimization objective specifies the goal to be achieved through optimization. In many cases, an appropriate starting point is the *all active components* optimization objective; that is, the set of intervention components that produces the best expected outcome irrespective of cost. Under the all active components optimization objective, only an intervention component that produces a positive and meaningful effect on the outcome of interest will be included in the optimized intervention. In our hypothetical example, suppose the intervention scientist selects the all active components objective. This choice is made because the hypothetical optimization trial represents the first attempt to optimize a home visiting intervention, and, in line with the continual optimization principle, a subsequent iteration of MOST could include constraints (e.g., upper limits on participant costs or provider time) in the optimization objective.

The Optimization Phase

In the optimization phase, the objective is to conduct a highly efficient experiment (i.e., optimization trial) to assess the individual and combined performance of the candidate intervention components. Any reasonable experimental design is a possibility for the optimization trial, as long as it answers the research questions and adheres to the resource management principle.

Optimization Trial

Experimental Design.—The research question for the hypothetical example seeks to determine which of the four candidate components show a detectable reduction in the potential for child maltreatment and therefore should be included in the optimized intervention. This question is best answered by the factorial experimental design (Collins, 2018). In a factorial experiment, candidate components are operationalized as factors with two or more levels. These factors are manipulated in a systematic manner to identify the individual effect of each factor on average on the desired outcome (i.e. main effect) as well as whether the effect of a factor varies depending on the level of other factors (i.e., interaction). The levels of the factors can represent the inclusion or exclusion of a factor (yes vs. no or on vs. off) or may designate different intensities of the factor (e.g., high vs. low). Although it is possible to conceptualize a factor with more than two levels, this should be considered carefully because adding a third level will substantially increase the required sample size. Space precludes full detail about the design and efficiency of factorial experiments; readers are referred to Collins and colleagues (2014), which provides an introduction to factorial experiments for those trained primarily in the RCT, and Collins (2018), which provides a more detailed introduction to the use of factorial experiments as optimization trials.

In the hypothetical example, because there are four candidate components (CSA prevention [*CSAP*], peer mentoring [*PEER*], problem-solving [*PS*] and check-ins [*CHECK*]) each with two levels, the intervention scientist selects a 2^4 (2x2x2x2) factorial experiment yielding the 16 experimental conditions listed in Table 1. Factor levels are conceptualized as yes (included) versus no (excluded). As the table shows, a participant randomized to experimental condition 4 would receive the parenting knowledge and skills, CSA prevention, and peer mentoring components, but not the problem-solving or check-in components. In contrast, a participant randomized to experimental condition 10 would receive the parenting knowledge and skills, peer mentoring components, and problem-solving components, but not the CSA prevention or check-in components.

Statistical power.—A power analysis using the SAS macro FactorialPowerPlan (Dziak et al., 2013) indicates that $N = 351$ subjects are sufficient to achieve a power of at least .80 to detect $d \geq .30$ with $\alpha = .05$. To achieve balance of participants across the 16 experimental conditions, a total of 352 participants are needed such that each condition has 22 participants (Table 1). Depending on expected attrition rates, ranging from 20-67% in empirical studies (Damashek et al., 2011), the intervention scientist may elect to over-recruit for the optimization trial, just as they might in any experiment. Randomization may be done using any reasonable randomization paradigm (e.g., random number generator), as long as any special nuances are accounted for in the procedure (e.g., block randomization; see Gallis et al., 2019). Management of experimental conditions can be accomplished through software such as REDCap (see Cleland, 2018).

Analytic Plan.—We recommend analyzing the data from the optimization trial using a regression approach to a classic factorial ANOVA, which requires the use of effect coding (Kugler et al., 2018). We recommend using effect coding compared to dummy coding as it has important advantages in interpretation of effects (see Collins et al., 2009). Each regression weight corresponds to either a main effect or an interaction. Main effects represent the effect on the outcome of interest of a component on average across the levels of all remaining factors (Collins, 2018). For example, the main effect for the CSA prevention module is the mean of conditions 1-16 (wherein subjects receive the CSA prevention module) compared to the mean of conditions 17-32 (wherein subjects do not receive the CSA prevention module). The main effect for the problem-solving component is the mean of conditions 1-4, 9-12, 17-20, and 25-28 compared to the mean of conditions 5-8, 13-16, 21-24, and 29-32. A two-way interaction occurs when the effect of one factor is different depending on the level of a second factor.

Identifying the Optimized Intervention

The outcome is the potential for maltreatment as measured by the CAPI, a 160-item actuarial assessment widely used to indicate the potential for child maltreatment (Chaffin & Valle, 2003) where higher scores signify a greater potential for maltreatment. For simplicity of interpretation in this hypothetical example, the outcome variable is operationalized as change in the potential for child maltreatment across two timepoints: at baseline and at the end of the hypothetical optimization trial. Change is defined as the CAPI score at baseline minus the CAPI score post-intervention, i.e. such that a higher—or more positive—difference indicates more desirable change. Again, all data described here are simulated for demonstration purposes.

The intervention scientist has specified that, for a component to be eligible for inclusion in the optimized intervention, the factor associated with that component must either: (a) have a statistically significant main effect (p <. 05) in the desired direction or (b) be involved in a statistically significant (p <. 05) interaction effect that indicates that the factor boosts the effect of another factor. Any component that does not meet these eligibility requirements would not be included in the optimized intervention. Table 2 depicts simulated results of the factorial ANOVA (recall, these data are hypothetical and should not be interpreted as true empirical findings). The main effects of factors *CSA* and *PEER* meet the cut-off of p <. 05 suggesting that on average the inclusion of these factors significantly reduced the potential for maltreatment. The *CSA* and *PEER* factors are tentatively designated for inclusion in the optimized intervention. The *PS* and *CHECK* factors did not meet the cut-off of p <. 05 and thus are tentatively designated for exclusion from the optimized intervention.

Next, significant interaction effects are considered. It is important to closely examine significant interactions to distinguish those that are synergistic (i.e., the combined effect of two or more factors is more favorable than would be expected based on the main effects alone) from those that are antagonistic (i.e., the combined effect of two or more factors is less favorable than would be expected based on the main effects alone). This is easily done by plotting the marginal means for all significant interactions. As indicated in Table 2, the interaction of *PEER* and *PS* factors is significant and plotting the marginal means (not shown) we identify a synergistic interaction (p <. 05) between the *PEER* and *PS* factors. Though the *PS* factor did not have a significant main effect, it is included in a synergistic interaction with the *PEER* factor and, thus, it must be considered for inclusion. No other interactions met the specified cut-off of p <. 05.

Recall in this example we are using the all active components optimization objective. Using the results from the optimization trial, the intervention scientist identifies the optimized intervention as one that includes the parent knowledge and skills, CSA, peer mentoring, and problem-solving components. Importantly, the check-in component is not included in the optimized intervention in this cycle of MOST. Note that in this hypothetical example the factor levels were set to yes or no. If the levels were set to high versus low, the optimized intervention would retain the lower level of components rather than eliminating them from the intervention.

The Evaluation Phase

If the identified optimized intervention is expected to be sufficiently effective against a suitable control, then the investigator may move on to the evaluation phase. The optimized intervention is then evaluated in an RCT (or another experimental design that allows for comparison of the optimized intervention against a suitable control). In the evaluation phase of MOS, in contrast to the RCT in the classic treatment package approach, the intervention being evaluated is one that has already been found empirically to contain components that produce the desired outcome. Alternatively, if at the end of the optimization phase the intervention is not expected to be sufficiently effective, then adhering to the resource management principle, the intervention scientist would return to the preparation phase. Given the vast resources needed to conduct an RCT, the resource management principle suggests that if the intervention is not expected to be effective, then it is best to return to the preparation phase, revise the conceptual model, perhaps modify intervention components or identify new ones, and conduct another optimization trial. An insufficiently effective intervention subjected to the RCT produces many of the same unanswered questions and unclear next steps described previously related to the classic treatment package approach. The information garnered in the optimization trial, even if the intervention is not sufficiently effective or if an ineffective component is identified, provides a guide for immediate improvement, aligned with the continual optimization principle.

Returning to our hypothetical example, at the end of this cycle of MOST, the intervention scientist has identified an intervention that is efficient in the sense that it is trimmed of components that do not have an effect on the outcome of interest (i.e., check-in). In this example, the intervention scientist used theory and empirical literature to identify four components, plus a constant component, that were hypothesized to be important in reducing the potential for child maltreatment. Using a highly efficient factorial experiment, the intervention scientist was able to determine that the check-ins component had no effect on the outcome of interest, and thus was dropped from the optimized intervention. The intervention scientist would not have known that the check-in component was not contributing to the outcome had we just tested these components following the treatment package approach in a two arm RCT. The optimized intervention thereby balances the desired qualities of effectiveness with efficiency. Affordability, degree to which the intervention produces a good outcome without exceeding budgetary constraints, could be pursued using economic evaluation methods such as a cost analysis (Crowley et al., 2018). Scalability, the degree to which the optimized intervention is delivered as it was evaluated, might be assessed in the evaluation phase using the Stages of Implementation Completion tool (Chamberlain et al., 2011; Saldana, 2014). Over multiple cycles of MOST, the intervention can be made more effective, affordable, scalable, and efficient.

Discussion

A number of home visiting programs exist and some have even demonstrated a significant reduction in risk for maltreatment; however, the magnitude of the problem, as indicated by the number of children and families in need of or accessing preventive services, necessitates an innovative approach to intervention science. Applying the MOST framework may be beneficial for the field of child maltreatment prevention. MOST provides a framework used to guide the systematic improvement of the effectiveness of evidence-based programs. Many applications of MOST can be planned using well-known experimental designs and data analysis methods. This article has illustrated a hypothetical example of how MOST can be used to examine the content of a home visiting program as well as strategies to support parental engagement with the home visiting program. Using simulated results from a hypothetical factorial experiment, the optimized intervention identified was comprised of three components (CSA, peer mentoring, and problem-solving), and one component (check-in) was screened out. If the check-in component were reconceptualized in the preparation phase, it could potentially be examined in the optimization phase of a subsequent iteration of MOST, along with other candidate components. Over time, this iterative process will produce an optimized intervention that steadily becomes more effective, affordable, scalable, and efficient.

Given the multitude of existing home visiting interventions, particularly those that have met criteria to be determined evidence-based, it should be noted that MOST can be used to optimize existing interventions. If an intervention scientist is willing to base the inclusion or exclusion of components on empirical findings and potentially remove components that do not show adequate performance in the optimization trial, over time MOST can be used to improve the effectiveness, affordability, scalability, and/or efficiency of existing evidence-based programs. MOST has the ability to hasten the progress of translational science and increase the public health impact of interventions (Guastaferro & Collins, 2019). We suggest that in applying the MOST framework, the field of child maltreatment prevention can advance intervention science to better meet the needs of children and families that encounter child protective service systems. Moreover, we believe the incorporation of implementation constraints in the development of optimized interventions can be particularly informative to decision-makers across organizations or systems who must decide what program to select for their context as well as policy-makers who are responsible for the allocation of financial resources to support program evidence-based dissemination and implementation across contexts.

Every application of MOST is unique and specific to a given set of constraints. Space precludes a comprehensive review of all possible considerations of the MOST framework, readers are referred to Collins (2018). However, briefly we want to highlight two possibilities within the MOST framework. First, the hypothetical example included four experimental components. However, in theory, there is no limit to the number of components that could be examined. Rather, the number of components included is limited by the feasibility of executing an experiment with a large number of experimental conditions (see Collins et al., 2009 for experimental design options). Relatedly, while the hypothetical example discussed content and engagement related components, MOST could also be used to enhance other qualities of interventions such as implementation fidelity or the delivery of the intervention. Identifying the best strategy for delivering an intervention could provide important information for what type of delivery works best for whom (Supplee & Duggan, 2019), thereby creating a more efficient and affordable intervention (see Broder-Fingert et al., 2019). The hypothetical example did not include elements related to fidelity because the intended target of content and engagement strategies (e.g., parents) differs from that of implementation fidelity components (e.g., providers). This makes it challenging, but not impossible, to examine implementation-focused components alongside content or engagement related components in the same optimization trial. Second, though the example focused on a fixed intervention (i.e., one in which all participants are offered the same treatment), there is also the potential to develop adaptive interventions. An adaptive intervention is one in which decision rules guide alterations to the intervention design, content, dose or approach (Collins, 2018). Adaptive interventions require specific experimental designs for the optimization trial, including but not limited to the sequential multiple assignment randomized trial (Almirall et al., 2014; Almirall et al., 2018) or the micro-randomized trial (Klasnja et al., 2015). An adaptive intervention might offer the potential to scale up the intensity or type of treatment based on the response of a participant at a specified time point. As every participant may not require the same touch, an adaptive intervention allows for the reallocation of resources, either to provide more intensive treatment to those who will benefit, or to extend the reach of the intervention to more people. Adaptive interventions may be important in the field of child maltreatment prevention, but we caution intervention scientists from jumping into the adaptive intervention arena too quickly.

Some intervention scientists who consider conducting a factorial optimization trial are concerned by the large number of experimental conditions that the factorial experiment requires. In the hypothetical example, we included four components yielding 16 experimental conditions. We could have conceptualized a fifth component deciding to conduct a 2^5 factorial experiment with 32 experimental conditions. If the intervention scientist determined it was not feasible to execute a randomized experiment with a high number of conditions (e.g., 16 or 32), there are three alternatives that could be considered. First, it may be possible to examine one fewer component. Second, and closely related to the first point, components could be re-conceptualized so as to combine two components into one (thereby changing the granularity of the components; see Collins, 2018). Third, the intervention scientist could select a fractional factorial design that would reduce the number of conditions while enabling examination of all components. However, it must be noted that the addition or removal of a factor does not change the number of subjects required (Collins et al., 2009).

Another common concern in the child maltreatment prevention field is the challenge of having home visitors deliver different combinations of components to different families in a factorial experiment. The potential for protocol violations increases when a home visitor is asked to deliver different combinations of components to different families on their caseload. One solution might be to have different home visitors trained to different conditions, but this may confound home visitors and conditions. A related approach might be to randomize at the agency or site level, which would mean that all home visitors within the agency would implement the same condition. This would require clustering resulting in a multilevel factorial experiment (see Collins et al., 2014; Nahum-Shani et al., 2018). Though these concerns are valid, MOST and the factorial experiment have been applied to a number of public health topics, so while perhaps daunting, the concerns are manageable.

The integration of optimization into the field of child maltreatment prevention has the potential to create a new generation of interventions that will be more effective, affordable, scalable, and efficient and that will continue to be improved over time. A suite of optimized interventions designed to prevent child maltreatment in the first place and others designed to reduce the risk for recidivism among those already involved in child protective services will increase the likelihood of affecting rates of maltreatment and impacting public health.

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Highlights

- To reduce prevalence rates of child maltreatment an innovative approach to prevention is needed
- Home visiting programs can be developed or refined to not only be more effective but also efficient, economical, and scalable
- Using the multiphase optimization strategy can improve the public health impact

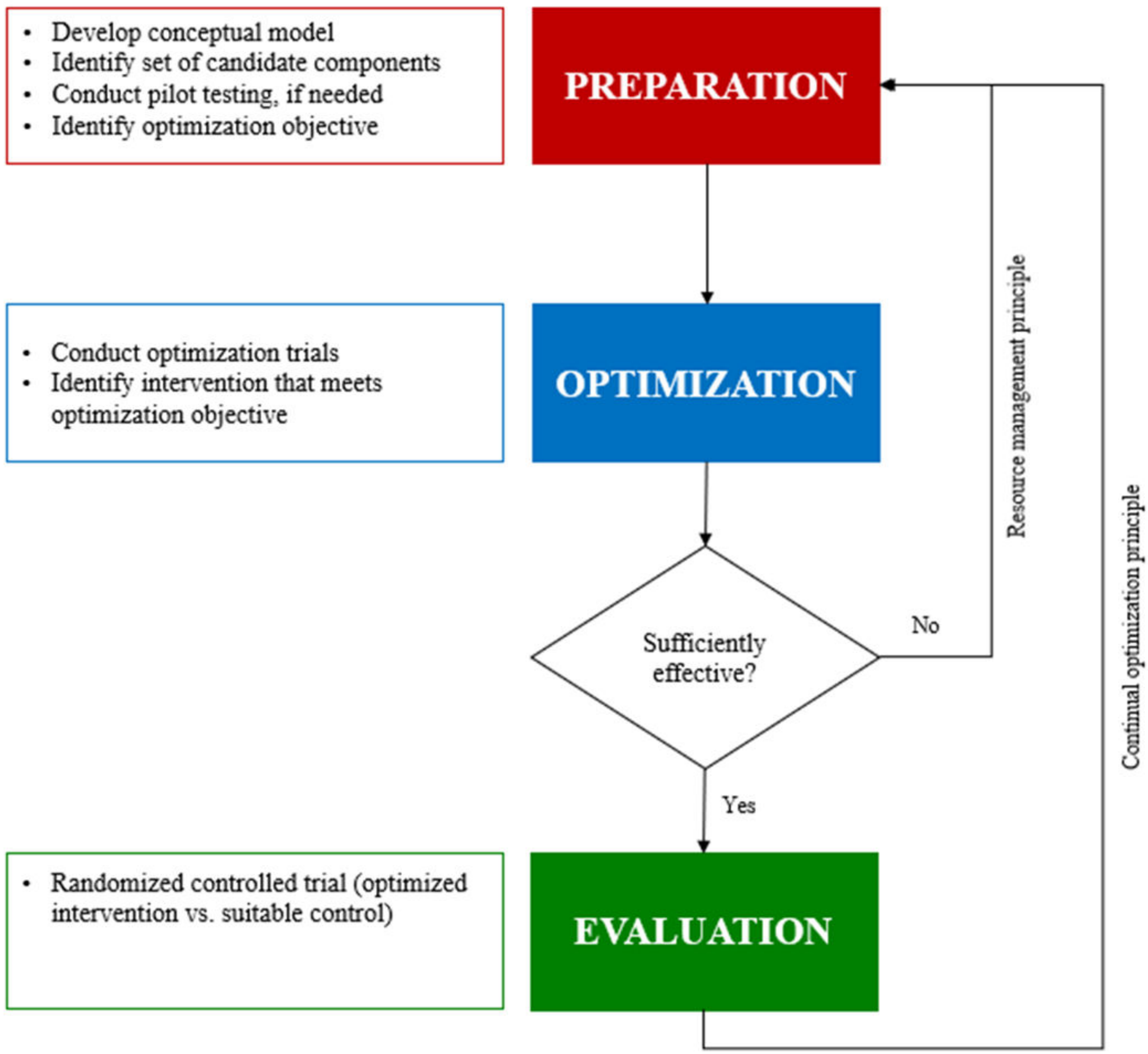

Figure 1.
The Multiphase Optimization Strategy (MOST)

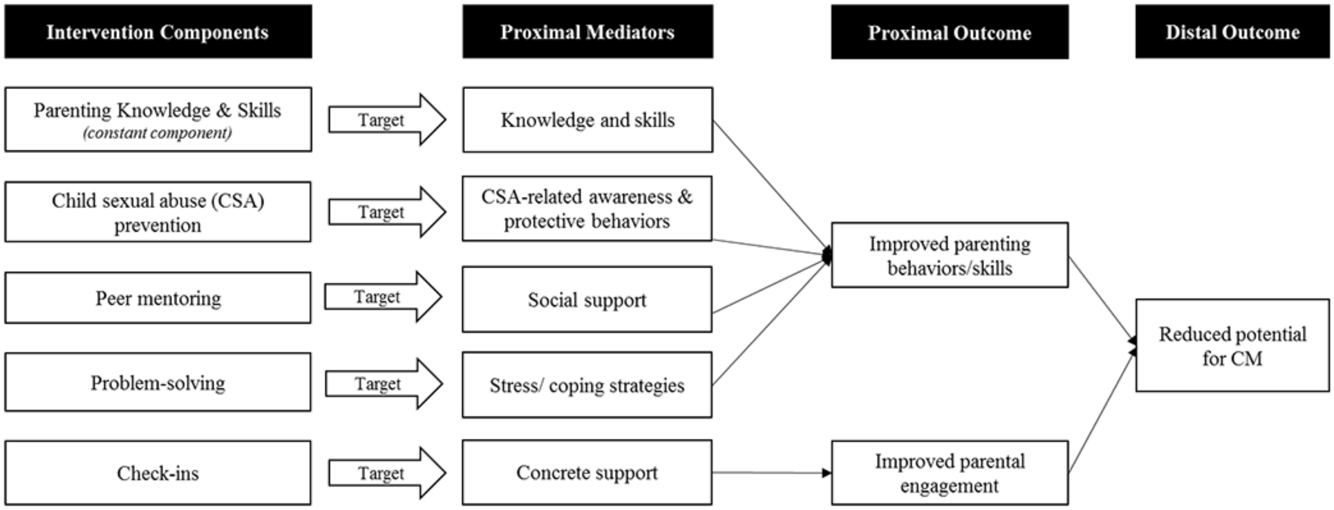

Figure 2.

Conceptual model for a hypothetical home visiting intervention designed to reduce the potential for CM among parents referrred to child protective services.

Table 1.

Experimental Conditions in Hypothetical 2^4 Factorial Design (N= 352)

Experimental Condition	Parenting Knowledge & Skills	CSA prevention	Peer Mentoring	Problem-solving	Check-Ins	*n*
1	Yes	Yes	Yes	Yes	Yes	22
2	Yes	Yes	Yes	Yes	No	22
3	Yes	Yes	Yes	No	Yes	22
4	Yes	Yes	Yes	No	No	22
5	Yes	Yes	No	Yes	Yes	22
6	Yes	Yes	No	Yes	No	22
7	Yes	Yes	No	No	Yes	22
8	Yes	Yes	No	No	No	22
9	Yes	No	Yes	Yes	Yes	22
10	Yes	No	Yes	Yes	No	22
11	Yes	No	Yes	No	Yes	22
12	Yes	No	Yes	No	No	22
13	Yes	No	No	Yes	Yes	22
14	Yes	No	No	Yes	No	22
15	Yes	No	No	No	Yes	22
16	Yes	No	No	No	No	22

KEY: Yes indicates the component is included in the intervention; no indicates it is not included in the intervention. *n* indicates the number of subjects per condition.

Table 2.

Simulated results of analysis of variance on data from a hypothetical 2^4 factorial experiment.

		***b*-weight**	***t***	***p***
	Intercept	12.98	86.62	<.0001
Main Effects				
	CSAP	0.83	5.53	<.0001
	PEER	0.89	5.95	<.0001
	PS	−0.04	−0.28	0.78
	CHECK	0.094	0.63	0.53
Interactions				
	CSAP × *PEER*	0.09	0.59	0.56
	CSAP ×*PS*	−0.15	−1.01	0.32
	CSAP × *CHECK*	−0.13	−0.85	0.39
	PEER × *PS*	0.50	3.31	0.001
	PEER × *CHECK*	0.05	0.32	0.75
	PS × *CHECK*	0.03	0.17	0.86
	CSAP × *PEER* × *PS*	0.12	0.82	0.42
	CSAP × *PEER* × *CHECK*	−0.03	−0.17	0.86
	CSAP × *PS* × *CHECK*	−0.09	−0.63	0.53
	PEER × *PS* × *CHECK*	0.05	0.32	0.75
	CSAP × *PEER* × *PS* × *CHECK*	0.01	0.06	0.95

Note: Results are based on simulated data and should not be interpreted as empirical findings. Standard error (all effects) = 0.15. Shading indicates that the effect meets the main effect or interaction criterion; in this example both criteria are p <.05.

KEY: *CSAP* = child sexual abuse prevention; *PEER* = Peer mentoring; *PS* = problem solving; *CHECK* = Check-in.