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Evaluating the Effectiveness of Complex, Multi-component, Dynamic, Community-Based Injury Prevention Interventions: A Statistical Framework

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Abstract

Dynamic violence and injury prevention interventions located within community settings raise evaluation challenges by virtue of their complex structure, focus, and aims. They try to address many risk factors simultaneously, are often overlapped in their implementation, and their implementation may be phased over time. This article proposes a statistical and analytic framework for evaluating the effectiveness of multilevel, multisystem, multi-component, community-driven, dynamic interventions. The proposed framework builds on meta regression methodology and recently proposed approaches for pooling results from multi-component intervention studies. The methodology is applied to the evaluation of the effectiveness of South African community-centered injury prevention and safety promotion interventions. The proposed framework allows for complex interventions to be disaggregated into their constituent parts in order to extract their specific effects. The potential utility of the framework is successfully illustrated using contact crime data from select police stations in Johannesburg. The proposed framework and statistical guidelines proved to be useful to study the effectiveness of complex, dynamic, community-based interventions as a whole and of their components. The framework may help researchers and policy makers to adopt and study a specific methodology for evaluating the effectiveness of complex intervention programs.

Keywords

community-based participatory research, peace promotion, multilevel, dynamic interventions, safe communities

Community-centered injury and violence prevention and containment interventions, framed from within the social–ecological model and the Haddon (1972) matrix logic, aim to intervene on multiple risk and protective factors at multiple levels (individual, peers and relationships, organizations, community, and society) and through multiple systems (e.g., schools, families, social networks, places of leisure, and workplaces). Such interventions may also seek to identify and act on relevant factors at the pre-, during-, and post-phases of injurious events.

The multifactor, multisystem, and event-phase focus introduces complexities that require careful consideration throughout the different aspects of intervention design, implementation, monitoring, and evaluation. Within such complexity, the evaluation approach needs to deliberate on how best to assess the impacts and outcomes of the overall intervention effort, since they may seek to address many risk and protective factors simultaneously and have components that overlap in their implementation. Implementations are also dynamic and conducted over time as per the priorities of communities and budgetary constraints.

The multifaceted drivers of violence and unintentional injuries that necessitate complex intertwining strategies and approaches also call for evaluation methods that can assess the effectiveness of intervention programs either as a whole or of its discrete components. In addition, standard experimental research designs involving controlled comparisons and the use of randomization are often not practical. Randomization may be possible when there are opportunities for delayed intervention in select communities (e.g., stepped-wedge design). Since communities are particularly unique in their circumstances, replication is also often not possible. The use of non-standardized research designs can thus be useful for evaluating interventions implemented in the absence of stringent research conditions (Shadish, Cook, & Campbell, 2002). The evaluation is complicated further when the number of events to be measured in the community, before and after the interventions, is small (Bangdiwala, Villaveces, Garrettson, & Ringwalt, 2012).

A systematic review of complex, multi-component interventions (Guise et al., 2014) noted the difficulties in describing and characterizing complex interventions and provided a framework for how to report such studies. Bangdiwala et al. (2016) review some statistical analytic approaches for such complex intervention programs. Schensul and Trickett (2009) characterize community-based interventions with the term "multilevel intervention–multilevel evaluation" or M-M to emphasize that both the intervention and the evaluation are conducted at community and member levels. Charns and colleagues (2012) propose the use of hierarchical modeling methods to guide the design and evaluation of M-M in order to control for individual-level variation while systematically evaluating community-level effects. In the Communities That Care model, researchers used three-level hierarchical models to account for variation between students, communities and matched-paired communities (Kim, Gloppen, Rhew, Oesterie, & Hawkins, 2015; Shapiro et al., 2013), and within the district changes in cohorts of students and variations in program status (Gloppen, Arthur, Hawkins, & Shapiro, 2012). However, Nastasi and Hitchcock (2009) raise important challenges related to M-M designs: acceptability and social or cultural validity of evaluation procedures; implementer, recipient, and contextual variations in program success; interactions among levels of the intervention; unanticipated changes or conditions; multiple indicators of program success; engagements with multiple stakeholders in a participatory process; and evaluations of sustainability and institutionalization.

In brief, the complexity of multilevel intervention and evaluation designs challenges traditional notions of evaluation research and experimental designs. Overcoming these challenges is critical to effective translation of research to practice. Drawing on the field of criminology, Sampson (2010) argues that practicality and ethical considerations often render randomization unsuitable and notes that researchers who employ experimental methods must address what really occurs in the social world. He suggests that a more suitable approach to criminological science would be an integrated approach that combines observational with experimental methods. Thus, recognizing that standard randomized experimental research study designs are not possible in most community-centered intervention situations (Shadish et al., 2002) and the challenges noted above, this article describes an approach for evaluating the effectiveness of complex community-based or heterogeneous interventions. Specifically, following the work of Bangdiwala and collaborators (2016) and Meléndez-Torres, Bonell, and Thomas (2015), this article describes and applies a methodological framework embodying an analytic statistical approach for retrospectively evaluating the effectiveness of multilevel, multi-component, community-driven, dynamic interventions.

In a pilot feasibility study, Bangdiwala, Villaveces, Garrettson, and Ringwalt (2012) showed that a meta regression methodology could be used to evaluate heterogeneous community-based, non-randomized, uncontrolled efforts that have a common intervention and a common outcome of interest. Meléndez-Torres and colleagues (2015), who recently reviewed the applicability of meta-analytic approaches, suggest two ways to model the complexity and heterogeneity using meta regression methodology. One approach is to group interventions by modality into "clinically meaningful units" based on their underlying theory of change criteria, while the other is to disaggregate interventions into their constituent components so as to extract their effects. The latter technique would require defining a taxonomy that characterizes and groups the components of the interventions, as suggested by Michie et al. (2013).

As a proof of concept, the proposed framework is applied to the retrospective evaluation of South African community-centered injury prevention and safety promotion efforts implemented by a South African research institute in partnership with a science council research outfit (henceforth referred to as the Institute). The Institute has concentrated on multilevel, multiple system interventions that are implemented in close partnerships with communities over an extended time period in different geographical communities (Seedat, McClure, Suffla, & Van Niekerk, 2012). Below is a description of the proposed statistical methodology and analytical framework, followed by details of the database structure, and a description of the institute's violence and injury prevention interventions. Real data of "contact crimes" recorded by the South African Police Service (SAPS) for the catchment areas of the intervened communities are modeled. The article concludes by reiterating evaluation challenges related to complex community-based injury and violence prevention interventions and reasserting the benefits of the evaluation framework proposed herein.

Statistical Methodology and Analytical Framework

We propose to use the methodology of linear mixed effects regression models to estimate the effectiveness of interventions and their components using a meta-analytic-based approach. In meta-analysis, a study contributes a single observation of the effectiveness of a common intervention. The effectiveness of an intervention is commonly estimated by the difference between the outcome of interest in the intervention arm and the same outcome of interest in the control or comparison arm in a randomized controlled experimental study. When assuming the "fixed effects" approach, the assumption is that every study's observed intervention effect G_i is an estimate of the common intervention effect μ. In randomized studies, these estimates G_i are considered unbiased estimates of μ. Thus,

$$G_i = \mu + e_i,$$

where the errors e_i are assumed to follow a $N(0, \sigma^2)$ distribution and $i = 1, \ldots n$ studies. Given the heterogeneity in studies' design, population, and implementation of the common intervention, one often assumes that each study may not be estimating a common effect μ, but rather its own effect θ_i, where the θs are normally distributed with a mean of 0 around the common overall effect μ and a variance of τ^2. Thus, the "random effects" meta-analysis is a "multilevel model" for the observed effects:

$$G_i = \mu + \theta_i + e_i.$$

The above random effects meta-analysis can be expanded to include study-level covariates and is then referred to as a meta regression. Let W_i

denote a characteristic of the ith study; then, a study's observed effect can be modeled by

$$G_i = \mu + \phi W_i + \theta_i + e_i,$$

where the inclusion of the study-level covariate W_i may explain some of the observed study effect. Meta regression, just like meta-analysis, is designed to estimate the common effect μ, assuming that all studies are implementing exactly the same intervention.

In the absence of a control arm, as is the case in many community-based interventions and in our situation, randomization to intervention is not a consideration. Interventions are simply implemented or not in a community. In such situations, one is unable to calculate an effect G_i, and thus one models the outcome of interest Y_i of the study itself. In this context, we propose to adapt the meta regression model as suggested by Bangdiwala et al. (2012), to studies that do not have a control arm by modeling the observed outcome Y_i:

$$Y_i = \beta_0 + \beta_1 I_i + \phi W_i + \theta_i + e_i,$$

where the common effect μ has been replaced by a linear term for the intervention effect. The effect of the intervention is now assessed by the fixed parameter β_1 attached to the dummy variable I_i that indicates the implementation or not of intervention I by the ith community.

The complicating issue faced in community studies is that interventions are not the same across communities, so that the effect of intervention I provided by the ith community is only a single observation for our meta regression. To overcome this issue, Bangdiwala et al. (2012) suggested incorporating multiple observations over time from each community, by considering a community's intervention program over several years not as a single study, but each annual experience as if it were a single study. The repeated measures of the observed outcome over time Y_{it} are now autocorrelated measures, and thus our model must include further random effects for the studies:

$$Y_{it} = \beta_0 + \beta_{0i} + (\beta_1 + \beta_{1i}) I_{it} + \phi W_i + e_{it},$$

where the random study effect θ_i is now replaced by the random intercept β_{0i}, and the unique aspects of the ith community's implementation of intervention I are modeled by the random slope β_{1i}. Note that the intervention I is allowed to change over time, since the intervention does not have to be offered every year.

The interesting complexity that arises in violence and injury prevention research is that multiple types of interventions $I1$, $I2, \ldots,$ are conducted simultaneously and dynamically in a given community, and if a given intervention is conducted in different communities, they often are implemented quite differently given different resources and interests. Guise et al. (2014) noted that reviewers of complex interventions often consider interventions to be composites of "components" that can be mixed and matched, that is, a "suite" of actions/activities as denoted by Seedat, McClure, Suffla, and Van Niekerk (2012). Because components co-occur or overlap, it is difficult to estimate the effect of each component or of groups of components using standard methods based on the observed intervention effects and component combinations. Thus, multiple-treatment meta-analysis (e.g., network meta-analysis) is not appropriate in this context.

Our approach of modeling the observed outcome rather than the observed intervention effect in a meta regression does allow for proper estimation of relative effects of the various components and was also suggested by Guise et al. (2014) and Bangdiwala et al. (2012). It is first necessary to "decompose" an intervention into its components $C1$, $C2, \ldots$ following a common taxonomy for behavioral change interventions as suggested by Michie et al. (2013). Thus, if we assume we have k components C and m study-level covariates W, we can model the observed outcome in community i in year t by

$$Y_{it} = \beta_0 + \beta_{0i} + \sum\nolimits_{j=1}^{k} (\beta_{j1} + \beta_{j1i}) C_{jit} + \sum\nolimits_{l=1}^{m} \phi_l W_{li} + e_{it}.$$

The basic assumptions of our linear mixed effects model are the standard assumptions of linearity, homoscedasticity, and normal distribution of the errors. In addition, we have the standard assumptions of random effects models, namely, that the random errors e_{it} are uncorrelated with the random intercept β_{0i} and slope β_{j1i} effects (see McCulloch, Searle, & Neuhaus, 2008). Covariance parameters can be included if this latter assumption is not met.

The model above could be further complicated by allowing the community-level covariates to change over time and by introducing random slopes for the effects of the community-level covariates. One can also include interaction terms among the various components. Also, one can incorporate "lag effects," so that the observed outcome value Y_{it} in year t in the ith community could be explained by intervention components in prior years, say $C_{ji\,(t\,-\,1)}$ or even $C_{ji(t\,-\,2)}$.

Furthermore, if individual data were available—for example, when cohorts of individuals are followed over time in each community—the model could also be expanded to incorporate individual-level information as in "multilevel meta regression." Here, however, we only consider community-level information.

Table 1. Hypothetical Time Line for Illustrative Example: $p = 3$ Communities, $k = 4$ Intervention Components, and Intervention Programs Over a 6-Year Period.

Community	Year 01	Year 02	Year 03	Year 04	Year 05	Year 06
001	—	*C1*	*C1, C3*	*C3*	—	*C4*
002	*C2*	*C1*	*C4*	—	—	*C1, C2*
003	*C3*	*C3*	*C3*	*C3*	*C3*	*C3*

Database Structure for Proposed Framework

We now illustrate what the structure of a database would look like that could be used to fit the model described above. Let there be $p = 3$ communities, $k = 4$ components, $l = 2$ community-level covariates, and possible data over a 6-year period. An example time line of implementation may be as given in Table 1.

An example database (see Table 2) would accompany the example time line of implementation (see Table 1). Each row is an observation in this theoretical data set.

From Table 2, we notice that, in this hypothetical example, the maximum number of observations is $p \times$ years $= 18$. In some years, a community may not have collected information—because of lack of budget or interest, community dynamics, or because they did not know that they had to collect information on the outcome of interest. Notice that all components are not carried out in all communities every year, nor are they consistently conducted in a given community over time. The community-level covariates do not change over time in this example, and thus are constant within a community.

A useful method to visualize the multilevel nature of the data is to present the levels and the variables collected at each level using the "multilevel diagram" (Bangdiwala, 2012b). If we assume that the communities in our hypothetical example are from two separate regions/provinces, we would have a three-level diagram as shown in Table 3.

Let Y_{jit} represent the primary outcome of interest, which may be the number of violent events or assaults registered by the police in the ith community from the jth region in time period t, or a process outcome such as the participation rate of community members in safety promotion programs in the ith community from the jth region in time period t, for example. The time periods could be on any scale, but we elect to use years for our example. In our model, it is not necessary to have variables measured at a level to have the "effect of the level" considered in the analysis.

Table 2. Hypothetical Database to Accompany the Hypothetical Time Line of Table 1, with $p = 3$ Communities, $k = 4$ Intervention Components, $l = 2$ Community-Level Covariates, and Intervention Programs Over a 6-Year Period.

Community (i)	Year (t)	Y_{it} (No. of Assaults)	$C1$	$C2$	$C3$	$C4$	$W1$ (Most Common Type of Housing—Informal/Formal)	$W2$ (Proximity to Lighted Roads—Yes/Partial/No)
001	01	$y_{001,01}$	0	0	0	0	Informal	Partial
001	02	$y_{001,02}$	1	0	0	0	Informal	Partial
001	03	$y_{001,03}$	1	0	1	0	Informal	Partial
001	04	$y_{001,04}$	0	0	1	0	Informal	Partial
001	05	Missing	0	0	0	0	Informal	Partial
001	06	Missing	0	0	0	1	Informal	Partial
002	01	$y_{002,01}$	0	1	0	0	Informal	No
002	02	$y_{002,02}$	1	0	0	0	Informal	No
002	03	$y_{002,03}$	0	0	0	1	Informal	No
002	04	Missing	0	0	0	0	Informal	No
002	05	$y_{002,05}$	0	0	0	0	Informal	No
002	06	$y_{002,06}$	1	1	0	0	Informal	No
003	01	Missing	0	0	1	0	Formal	No
003	02	$y_{003,02}$	0	0	1	0	Formal	No
003	03	$y_{003,03}$	0	0	1	0	Formal	No
003	04	$y_{003,04}$	0	0	1	0	Formal	No
003	05	$y_{003,05}$	0	0	1	0	Formal	No
003	06	$y_{003,06}$	0	0	1	0	Formal	No

Table 3. Illustrative Multilevel Diagram for the Hypothetical Example of Table 1 With Added Region/Province.

Level	Index	Variables
Region/Province	$j = 1, 2$	
Community	$i = 1, 2, 3$	$W1_{ji}$ $W2_{ji}$
Time	$t = 1, 2, \ldots 6$	$C1_{jit}$ $C2_{jit}$ $C3_{jit}$ $C4_{jit}$ Y_{jit}

Methods for Proof of Concept: Application of the Framework

The Institute has been engaging in violence and injury prevention activities over three decades, including varying combinations of behavioral, social, and environmental interventions, across various communities in South Africa and select other African countries. The Institute's approach to injury prevention and safety and peace promotion is underpinned by a community engagement strategy that fosters community participation, formation of partnerships, and the strengthening of community prevention–related competencies and infrastructure (Eksteen, Bulbulia, Van Niekerk, Ismail, & Lekoba, 2012).

For two decades, the South African work has concentrated on selected communities in south Johannesburg. These communities are marked by inadequate municipal services, poverty, high unemployment, and violence. Community A is situated between Soweto and Lenasia. The area is made up of a combination of middle- to low-income households and was reserved for a specific population group as per apartheid segregationist policies. The recent 2011 census estimates around 65,700 people live in the area (Statistics South Africa, 2011). Community A also includes an adjacent informal settlement with about 3,359 shack households with an average of about four to five people per house (Statistics South Africa, 2011). Informal settlements consist predominantly of shacks or temporary dwellings made from wood and corrugated zinc. Although local government provides limited services for water and sanitation, such as piped water inside the yard or on a communal stand and the installation of pit latrines, informal settlements typically have no electricity; roads are untarred; and there are few formalized amenities like shops, clinics, schools, and recreation facilities.

Community B is an informal settlement which was established in the mid-1980s. As the settlement is located on dolomitic land, making development potentially risky and expensive, government decided in 2002 to relocate the residents to Community C, further south of Johannesburg (Clark, 2014). Many residents resisted relocation with there being approximately 21,100 residents reported in 2011 (Statistics South Africa, 2011). However, some residents from Community B relocated to Community C. Community C was established in 2001 and is a formalized area that consists of low-cost permanent housing structures with services like water, sanitation, and electricity. In 2011, Community C had approximately 27,300 residents (Statistics South Africa, 2011). Community D is an informal settlement, established in the early 1990s and consists of an estimated total population of about 4,400 with a fair amount of informal small businesses in the area (Van Niekerk, Govender, Hornsby, & Swart, 2016).

Integral to conceptualizing the evaluation methodology, a series of workshops were conducted to first visualize the time line of activities undertaken in each community and then to populate a database retrospectively. A group Delphi method, a collaborative technique that adopts independent analysis and the iterative processes of feedback to obtain consensus among experts, was used to create a conceptual structural path model and to identify the components of the interventions that could be labeled as "similar." The process was guided by the theory of change principles (Weiss, 1997) that help explain how and why changes are produced by complex interventions. A theory of change helps to strengthen planning and implementation, clarify how and when to collect data and serves to map out how delineated activities will produce change, as well as describe the contextual factors that may influence the processes of change and the intended outcomes.

The various components of the activities—some were not "formal interventions"—as implemented in each community were grouped into the following nine mechanistic taxonomic groups (Michie et al., 2013; Walter, Nutley, & Davies, 2003):

- Information dissemination (INFO)—presenting or circulating information (research summaries, brochures, guidelines, and oral presentations) not active education (creating awareness)
- Education (EDUC)—traditional lectures, interactive sessions, and courses (increasing knowledge and understanding)
- Training (TR)—skills development (increase capacity)
- Engagement (ENG)—dialogue and interaction, holding meetings, and creating relationships
- Environmental modification (ENV)—changing the physical or social context
- Enforcement (ENF)—supervision, monitoring
- Network development (NET)—creating linkages involving stakeholders
- Advocacy (ADV)—actively involving government authorities and stakeholders in community activities
- Economic activity (ECON)—funding

Within this taxonomy, engagement (ENG) refers to the processes of building trustful relationships that are critical for obtaining consent, support, and ongoing participation for intervention research. Whereas information (INFO) entails the distribution and dissemination of reading resources and materials, education (EDUC) refers to face-to-face interactions with participants as part of the process of increasing knowledge about specific issues.

These interventions were implemented in the south of Johannesburg in the early 1990s through various safety initiatives, including the Three Neighborhood Study, a women-led safety promotion volunteer program, home visitation programs, and early childhood and youth interventions (Swart, Van Niekerk, Seedat, & Jordaan, 2008). The Institute and its community partners identified community priority injuries (especially violence, burns, and traffic injury) and implemented interventions through delivery systems based on the existing evidence of effective or promising interventions (Seedat et al., 2012). These included combinations of collaborative creation of local injury information; education and training of community members, often as volunteers, to serve as safety promotion advocates; the engagement of community activists and agencies to form networks for advocacy; and safe environment modifications or resource mobilization. Such interventions emphasized activities to protect local vulnerable groups and mitigate against at-risk environments. The Institute's suite of interventions were delivered through family and extended social and living systems through communitywide and home interventions. The community interventions include education and sensitization activities, psychoeducational activities at early childhood development centers and schools, advocacy and emergency services offered by responsive resource persons, and community mobilization. The home interventions were offered through home visits and provided core health and safety curricula to primary caregivers on child health, family functioning, and child abuse and unintentional injury (traffic, burns, and poisoning) prevention components (Seedat et al., 2012).

The proposed methodology allows for the incorporation of community-level covariates. For example, it would be possible to consider social assets at the societal, community, relationship, and individual levels and determine whether they changed or remained constant over time. These would be potential confounders to consider in this meta regression model. However, some of the societal assets such as job opportunities, educational centers, religious institutions, and drug rehabilitation units are measurable, while others like compassion, empathy, and mindfulness are intangible. Since retrospective assessment was not possible or subject to recall bias, we have not incorporated them in the example in this article.

The actual mechanistic taxonomic components of the multiple intervention activities carried out in the communities in Johannesburg are presented in Table 4—by year.

As can be seen in Table 4, there was considerable variability as regards the mechanistic approaches used in the different communities and over time. Information dissemination, education, and training have been approaches quite commonly used, while others have been more sporadic in their implementation. Some communities applied a large number of approaches, while others concentrated on a few approaches. Many of the

Table 4. Matrix of Activities (Components) Carried Out at Each of the Communities Over Time.

Year	Community A	Community B	Community C	Community D
1996	INFO, EDUC, TR, ENG, NET, ADV			
1997	INFO, EDUC, TR, ENG, NET, ADV			
1998	INFO, EDUC, TR, ENG, ENV, NET, ADV			
1999	INFO, EDU, TR, ENG, NET	INFO, EDUC, TR, ENG, NET		
2000	INFO, EDUC, TR, ENG, NET, ENF, ADV	INFO, EDUC, TR, ENG, NET		
2001	INFO, EDUC, TR, ENG, NET, ENF, ADV	INFO, EDUC, TR, ENG, NET		
2002	INFO, EDUC, TR, ENG, NET	INFO, EDUC, TR, ENG		
2003	INFO, EDUC, TR, ENG	INFO, EDUC, TR, ENG	ENG	
2004	INFO, EDUC, TR, ENG, ENF, ADV		INFO, TR, ENG	
2005	INFO, EDUC, TR, ENG, ENF,		ENG	
2006	ENG, NET		ENG, NET	
2007	INFO, EDUC, TR, ENG, NET, ADV		INFO, EDUC, ENG, NET, ADV	
2008	INFO, EDUC, ENG, NET, ADV		INFO, EDUC, ENG	
2009	INFO, EDUC, ENG, NET, ADV		INFO, EDUC, ENG, NET, ADV	
2010	INFO, ENG, NET, ADV		INFO, EDUC, ENG, NET, ADV	
2011	INFO, EDUC, TR, ENG, NET, ADV		INFO, NET, ADV	
2012	INFO, EDUC, TR, ENG, NET, ADV		INFO, NET, ADV	
2013	INFO, ENG, NET, ADV	ENG, NET	INFO, NET, ADV	INFO, EDUC, TR, ENG
2014	INFO, ENG, TR, NET, ADV	INFO, EDUC, ENG, NET	NET, ADV	INFO, EDUC, ENG, ENV
2015		INFO, EDUC, ENG, NET, ADV		

Note. INFO = information dissemination; EDUC = education; TR = training; ENG = engagement; NET = network development; ENV = environmental modification; ENF = enforcement; ECON = economic activity; ADV = advocacy.

activities were guided by budgetary constraints and community perceived priorities and were therefore inconsistent in their application.

We were able to obtain crime statistics from SAPS in the Johannesburg communities only for the years 2003–2013. The catchment areas of some SAPS forced us to collapse the analyses to four communities and thus we had a limited number of data points ($n = 44$) for this analysis. We thus were forced to collapse the nine intervention approaches into three main groups: Category 1 (CAT 1) included INFO, EDUC, and TR (educational); Category 2 (CAT 2) was comprised of ENV and ENF (environmental), while Category 3 (CAT 3) was ENG, NET, and ADV (engagement). ECON was not used as an intervention component in those years in the studied communities and thus not considered in the models.

Our proposed framework for evaluating the effectiveness of the various approaches was operationalized by the following linear mixed effects (multilevel) model for the outcome Y of interest:

$$Y_{it} = \beta_0 + \beta_{0i} + (\beta_1 + \beta_{1i})\text{CAT } 1_{it} + (\beta_2 + \beta_{2i})\text{CAT } 2_{it} + (\beta_3 + \beta_{3i})\text{CAT } 3_{it} + \beta_4 \text{ year}_t + e_{it},$$

where Y_{it} is the number of contact crimes in the ith community at time point t, and the various component "indicator variables" are 1 if the approach was used in a given year in a given community and 0 if not, for $t = 2003, \ldots, 2013$. The inclusion of the random slopes β_{1i}, β_{2i}, and β_{3i} provides each community with its own "trajectory" or regression. The model was further enhanced with the variable *year* in order to accommodate a linear trend of declining contact crimes over time after descriptive analyses showed a trend (see Figure 1). Note that two sets of models were fit; Set A that modeled the effect of current efforts on current contact crimes and Set B which included a "lag" of 1 year, thus assuming that the actions carried out in year $t-1$ are reflected in the contact crimes of year t:

$$Y_{it} = \beta_0 + \beta_{0i} + (\beta_1 + \beta_{1i})\text{CAT } 1_{i(t-1)} + (\beta_2 + \beta_{2i})\text{CAT } 2_{i(t-1)} + (\beta_3 + \beta_{3i})\text{CAT3}_{i(t-1)} + \beta_4 \text{ year}_t + e_{it},$$

for $t = 2003, \ldots, 2013$, thus $t - 1 = 2002, \ldots, 2012$.

Contact crimes were as defined by the SAPS and included the types of crime in which there was physical contact between a perpetrator and a victim, mostly of a violent nature. These included murder and attempted murder, sexual crimes, assault with the intent to inflict grievous bodily harm, common assault, common robbery, and robbery with aggravating circumstances.

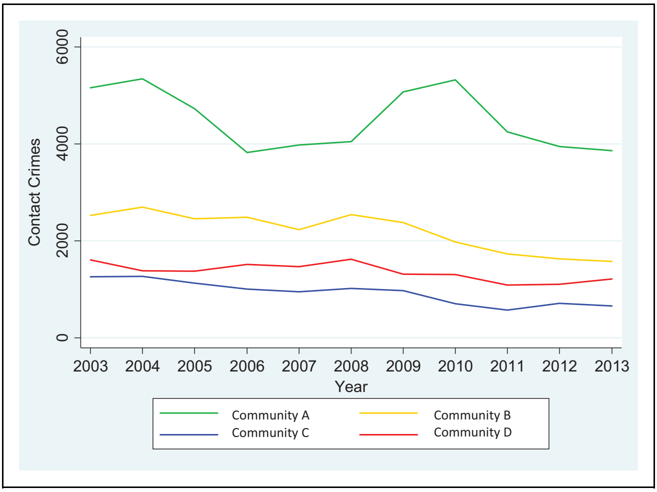

Figure 1. Counts of contact crimes in the four studied communities over time.

Results

It should be pointed out that the strongest statistically significant factor related to the number of contact crimes in all models was the linear trend for decrease over time (see Table 5). However, our framework enabled us to show that for current year contact crimes, the overall efforts carried out in the communities, labeled as "being present" (i.e., having the Institute engaged with the community in any fashion), was an independent factor leading to an important reduction in annual contact crimes, although not statistically significant (Model A2). The component CAT 3 turned out to be exactly the same variable as being present, so only one of the two variables was included in the final model. Furthermore, the correlation between CAT 1 and CAT 3 was quite high, leading to possible collinearity issues and thus the preferred final model is the one that includes only CAT 2 and CAT 3 (Model A3).

For the effect on next year contact crimes, we note that CAT 2, that is, environmental changes and enforcement, is related to a reduction in contact crimes and have a larger coefficient than being present or engagement (CAT 1) in the previous year (Model B3).

Conclusion

Intervention effectiveness within complex intervention arrangements requires a theoretical understanding of the behavior of the complex system

Table 5. Multilevel Random-Intercept Models for Assessing the Effectiveness of Dynamic, Complex Safety Promotion Interventions on the Number of Contact Crimes in Four South Johannesburg Communities, 2003–2013.

Variable	Model 1	Model 2	Model 3	Model 4
A. Current year contact crimes				
Year	−76.0 ± 14.9 [−105.3, −46.8]	−75.9 ± 15.1 [−105.4, −46.3]	−70.0 ± 15.3 [−99.9, −40.1]	−77.4 ± 15.0 [−106.8, −48.1]
CAT 3—"engagement"		−12.2 ± 196.7 [−397.8, 373.4]	−24.5 ± 192.1 [−401.1, 352.1]	−228.5 ± 208.0 [−636.1, 179.2]
CAT 2—"environmental"			364.1 ± 247.2 [−120.5, 848.6]	295.5 ± 237.8 [−170.5, 761.5]
CAT 1—"educational"				319.6 ± 155.4 [15.1, 624.1]
B. Next year contact crimes				
Year	−76.0 ± 14.9 [−105.3, −46.8]	−75.2 ± 15.0 [−104.5, −45.8]	−81.1 ± 14.4 [−109.3, −52.9]	−87.0 ± 14.2 [−114.8, −59.1]
CAT 3—"engagement"		96.2 ± 195.6 [−287.1, 479.6]	84.5 ± 184.5 [−277.1, 446.2]	−193.6 ± 234.8 [−653.9, 266.6]
CAT 2—"environmental"			−515.3 ± 234.0 [−974.0, −56.6]	−567.3 ± 227.0 [−1,012.2, −122.4]
CAT 1—"educational"				300.6 ± 166.7 [−26.1, 627.2]

Note. Coefficients ± standard error with 95% confidence intervals placed immediately below estimate. CAT 1 = Category 1; CAT 2 = Category 2; CAT 3 = Category 3.

in which the interventions are implemented (Matheson, Dew, & Cumming, 2009). Spinks, Turner, Nixon, and McClure (2009) argue that the science of community-centered injury prevention is compromised by the diversity and minimally demonstrated efficacy of safe community approaches and activities, the relative dearth of evaluations undertaken, methodological limitations in community-based evaluations, and the distinct variation in observed injury rates across identified communities. We suggest that the use of the framework, as proposed and illustrated in this article, will provide methodological rigor for both the retrospective and prospective evaluation of community-centered interventions in injury and violence prevention and speak to the gaps in the injury prevention evaluation that Spinks and colleagues (2009) refer to.

The particular approach we propose is to expand the meta-analysis methodology of obtaining an estimate of an intervention's effect, when the intervention is not randomized, community-centered, and complex. We first model the outcome variable rather than the effect. We then consider each year of intervention as providing a separate (but correlated) outcome assessment. Given that interventions are subject to unique idiosyncrasies of communities, we propose using a random effects meta regression to incorporate measurable and nonmeasurable community-level covariables. If one wishes to understand the relative contribution of the multiple components of these complex interventions, one can decompose the intervention into components and estimate the relative effect of the components of the interventions.

Our proposed framework is not meant to imply a preference for non-randomized intervention study designs. We do acknowledge that randomized study designs are best for obtaining unbiased estimates of the effectiveness of a single intervention. However, in community-based studies, where complex, multi-component, dynamic and overlapping non-randomized interventions are commonly implemented, we propose researchers consider using our novel methodological approach. As all approaches, it has limitations. First, for simplicity, we are modeling using a linear regression model and not the possibly nonlinear complex relationship. Second, we use data at the community level, thus we are not using data at the individual level. As in all models, we are limited by the availability of data, which is a particular concern due to communities' lack of routinely collecting pertinent information (see below). Fewer data points may lead to missing important relationships due to reduced statistical power. We use linear mixed effects models that assume a normal distribution for the error distribution and independence between the random errors and the random intercept and slope effects. Additional covariance parameters can be included to account for the lack of independence. Finally, the modeled outcome is measured in a given community over time and the correlation among these measurements can be miss-specified. The example used for illustration of the methodology is simply a "proof of concept" and not meant to imply that the number of assaults has been fully studied by the models constructed. The framework proposed can certainly be used with more frequent time points of outcome data as well as more communities, both of which would allow the possibility of considering more potential community-level covariates.

Our proposed model is resonant with writers (Morales-Asencio, Gonzalo-Jiménez, Martín-Santos, & Morilla-Herrera, 2008) who make a case for non-randomized studies, controlled studies, and/or observational studies, and the recent recommendations provided by Transparent Reporting of Evaluations with Non-randomized Designs (TREND), Strengthening the Reporting of Observational studies in Epidemiology (STROBE), and Meta-analysis of Observational Studies in Epidemiology (MOOSE). Consistent with the call for consolidated critical appraisal tools, the framework proposed herein provides guidance and a tool for assessing the quantitative evidence within community-based intervention studies. The proposed framework may therefore help grow the "practice-based evidence" (Bangdiwala, 2012a) in the injury and violence prevention sector and, in particular, support academics, researchers, and prevention practitioners who are under increasing pressure to demonstrate the relevance of their community engaged work. The framework can help produce empirical evidence for grant and programmatic applications. As such, it offers applied research institutions a framework for growing the scope of their evaluation approaches. Likewise, this framework would enable intervention agencies, including government and nongovernment programs, to frame their activities according to the proposed taxonomy so as to render them amenable to evaluation for purposes of funding and community support. Partnership-based and collaborative research approaches can help develop capacities and institutionalize a culture of evaluation in violence and injury prevention work.

Actual implementation of the proposed framework may be limited due to communities' lack of resources and gaps in competencies related to the collection of meaningful outcome data useful for research purposes; likewise, relevant covariates are often not assessed by municipal authorities. Nongovernmental organizations involved in safety and peace promotion activities are "doers" and often not "investigators"; thus, documentation of implementation and timing of the components of the interventions may be limited. However, nowadays there is increased availability of administrative data, and with increased understanding of its utility for evaluation purposes and thus for effective management of limited resources, there is increased potential for adoption of the proposed framework and collection of relevant data. Partnerships between researchers and service agencies may help strengthen competencies and expertise and overall appreciation for documentation and evaluation work.

Notwithstanding the potential challenges, this article provides a useful framework and statistical guideline to understand the spectrum of conceptual and analytic approaches and an initial list of critical reporting elements (taxonomy of mechanisms) for primary and secondary studies of multicomponent, dynamic interventions. The framework may help researchers to adopt and study a specific methodology for evaluating the effectiveness of complex intervention programs.

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