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Journal of Clinical Epidemiology ■ (2014) ■

Journal of Clinical Epidemiology

ORIGINAL ARTICLE

A novel approach used outcome distribution curves to estimate the population-level impact of a public health intervention☆

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Accepted 18 December 2013; Published online xxxx

Abstract

Objectives: To provide an analytical framework within which public health interventions can be evaluated, present its mathematical proof, and demonstrate its use using real trial data.

Study Design and Setting: This article describes a method to assess population-level effects by describing change using the distribution curve. The area between the two overlapping distribution curves at baseline and follow-up represents the impact of the intervention, that is, the proportion of the target population that benefited from the intervention.

Results: Using trial data from a parenting program, empirical proof of the idea is demonstrated on a measure of behavioral problems in 355 preschoolers using the Gaussian distribution curve. The intervention group had a 12% [9%−17%] health gain, whereas the control group had 3% [1%−7%]. In addition, for the subgroup of parents with lower education, the intervention produced a 15% [6%−25%] improvement, whereas for the group of parents with higher education the net health gain was 6% [4%−16%].

Conclusion: It is possible to calculate the impact of public health interventions by using the distribution curve of a variable, which requires knowing the distribution function. The method can be used to assess the differential impact of population interventions and their potential to improve health inequities.

Keywords: Public health; Intervention studies; Normal distribution; Area under the curve; Primary prevention; Parenting education

1. Introduction

Generating population health improvement in ways that produce more equitable health outcomes is difficult [1]. Interpreting the results of interventions to achieve these goals is equally challenging [2]. Using analytical methods developed for clinical randomized controlled trials (RCTs) to investigate naturally complex interventions in dynamic and complicated settings carries the danger of controlling out of the investigation the very factors that are of intrinsic interest and of focusing on individual and not population-level change. The essence of trial design is to isolate single causes and effects when, in reality, linear causal pathways are seldom relevant for public health practice [3]. Trials of public health interventions are often disappointing; effect sizes are small and sometimes they do not reach statistical significance [4−6], although publication bias probably conceals most trials that do not show significant effects. This article demonstrates a different technique for considering effects in public health trials by looking at the data through a population health lens.

We propose a method to look at population outcomes in their own right in the quest of understanding how public health interventions work. Rather than considering the effects of interventions on the individual level, we view the level and distribution of a certain outcome measure in the

Conflict of interest: A.S. conceived of the idea and concept of the article; was Principal Investigator in the case example; and drafted the first version of, edited and finalized the manuscript. M.P.K. helped formulate the individual−⊖ population distinction as the key research question for the article, helped to develop the structure of the article, and drafted and edited the manuscript. F.S. assisted in the calculations of the case examples, drew the graphs, and helped edit the manuscript. I.F. designed and performed the methods of the study including the mathematical analyses and interpretation of results, was responsible for calculating the case examples, and helped draft the manuscript. The authors do not have any conflicts of interest to disclose.

Funding: The study was supported by the National Institute of Public Health grants # HFÅ 2008/214 and HFÅ 2010/93 and the common grant of major Swedish research funders termed "Mental health of children and adolescents", FORMAS 259—2012-68. The funders were not involved in the writing of the manuscript. The first author is supported by a senior lecturer research grant by the Gillbergska Foundation in Uppsala.

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0895-4356/$ - see front matter
http://dx.doi.org/10.1016/j.jclinepi.2013.12.012

What is new?

- It is possible to calculate the impact of public health interventions by using the distribution curve of a variable before and after the intervention.
- The method can be used to assess the impact of population health measures and their potential to improve health inequities.
- The proposed analytical framework takes the complexity of public health interventions and their potential pathways of effect into account, allowing for multiple causality and network effects.
- We encourage authors to use this analytical framework in studies that aim to improve population health—including possibly reconsidering previous trial data.

population as the unit of interest. We do not apply the idea of representativeness on a subsample to then project these effects on a population: instead we aim to understand the underlying mechanisms [7] by which population effects play out when different interventions are applied.

2. Background

2.1. The population health approach

Rose [8] popularized the population health approach. Overall population change, in, for example, average hypertension, was the goal, rather than individual outcomes. Taking this approach seriously requires researchers to describe causal pathways that are not yet fully understood. Consider the large network study by Christakis and Fowler [9] where positive effects in the whole social network of those quitting smoking were registered, along with the marginalization of smokers in the network. The social-level explanations underpinning these results (such as the mechanisms whereby networks produce these effects) are much less well understood than the etiology of lung cancer for example, yet are critical if we are to advance population-level approaches [10].

2.1.1. The goal of modern public health interventions

There is an increasing body of evidence suggesting that health equity within a population benefits the population as a whole. A goal of many contemporary health policies is just that—closing the health inequity gap [11]. A common way of describing a variable on the population level is using the distribution function with the mean and standard deviation (SD) values of a certain relevant measure determining the shape of the curve. The most often used distribution function is the normal (Gaussian) distribution (Fig. 1A—C), but it is increasingly recognized that not all variables of importance in public health are normally distributed, but can be described by another function, for example, by a gamma-type curve (Fig. 1D).

The goal of a public health intervention is then—simply put—to move the population distribution curve of the targeted outcome or risk factor (the exposure) toward healthier levels and to decrease the distribution of the outcome, implying higher proportions of the population being within the healthy intervals (Fig. 1A—D), or being less exposed to a certain risk factor. Both the health state of the population and its exposure to risks can be expressed by indicating which percentage of the population is above or below any certain value of interest by calculating the area under the curve cutoff by a vertical line drawn at that value of the x-axis, exactly as it is done by the verticals indicating the SD values of a population mean. We propose a method that does exactly this: expresses health improvement in the percentage of the population improved.

2.1.2. Evaluating public health interventions

For most major public health issues, there is a cluster of indicators, rather than a single outcome that signifies health. However, one of the unintended consequences of the application of the principles of evidence-based medicine to public health has been a tendency to focus on determining effect size and significance levels in individual-level variables rather than thinking about the issue in population terms [10,12]. Also, in the quest for statistical significance, surrogate measures rather than direct patient outcomes are sometimes used [13].

Studies in the area of public health often collect information on variables that can be presented on a continuous scale. Although both the mean value and SD measures are necessary for the analyses presented in RCTs, it is rather unusual to actually draw the population distribution curves and estimate the outcomes based on these.

Let us suppose that Fig. 1A—D represent the distribution curves of outcome variables of hypothetical public health interventions. Fig. 1A describes a scenario where the population mean was effectively decreased without affecting the distribution of the variable. This could be possible through a universal program that actually manages to reach all the different segments of the population equally, but not proportionately depending on need. Thus, inequities would still remain, but the population health would improve (see the size of the gray area).

Fig. 1B represents a scenario where the SD of a variable has decreased, but the population mean is unaltered. This could be the result of a targeted intervention that has successfully addressed the needs of a population at risk for the studied outcome. Inequities in health for this outcome have then decreased, but the health gain for the population as such is less, as indicated by the smaller size of the gray area than in Fig. 1A. This scenario introduces some possible ethical concerns as decreases in values/areas on the right side of the curve necessarily imply increases on