AI and Machine Learning Applied to Policy and Program Design: Integrating Evidence for Better Outcomes

Chris Callaghan, M.Sc.
President and Principal Consultant
chris.callaghan@lotic.ca
https://www.linkedin.com/in/chrislcallaghan
+1-613-295-2870

Summary

Leveraging the same artificial intelligence and machine learning concepts and technologies that power leading business and scientific applications, we are a small Canadian group now forging an innovative way to design interventions and tackle complex policy problems. In this article, I argue that better intervention causal models are the key to evidenced-based learning and improved outcomes. I describe an approach that synthesizes these models from multiple evidence streams, including deliberative stakeholder narrative, bodies of literature, and available data sets (including open and big data). I further describe how my group's approach integrates these data to tame complexity and help decision-makers and other stakeholders visualize how systems work. I then go on to explain how the approach supports adaptive learning by facilitating model testing through more rational and efficient selection of performance measures, and how the construction of better models enables policy-makers to enter the realm of quasi-experimentation and causal inference. The article concludes by pointing out that complex intervention realities, rapid change, and the need to be more accountable, efficient and effective with limited resources, all point to a pressing need to use the best and most innovative tools to find solutions to both new and persistent problems.

All policy, program or management interventions are designed to achieve one or more outcomes. They are also usually based on ideas about the cause-and-effect sequences through which intervention actions are presumed to produce desirable outcomes and avoid undesirable outcomes. If these ideas are accurate, then it is more likely that the intervention will be effective. In short, to "work" (*i.e.* produce desirable outcomes and avoid undesirable outcomes), interventions must be based on ideas that are - at least approximately - true.

The causal assumptions that lie at the heart of interventions are also fundamental to powering so-called results-based management (RBM) cycles. RBM cycles are, in essence, adaptive learning cycles that involve modeling, design, implementation, evaluation and evidence-based redesign. This actually closely resembles the basic scientific method. In both cases, ideas about how a system works are formulated, data are collected about how the system behaves while it is operating, and the data are then used to validate (or invalidate) the original causal ideas. This in turn provides the information needed to produce a better model of how the system works, informing how and what levers should be pulled in the future to achieve improved outcomes.

In principle, this type of adaptive learning, involving successive refinements to foundational ideas, should improve the predictability and reliability of outcomes. However, in practice, where time and resources are limited, and where complex human and organizational dynamics are at play, moving through even one of these cycles can be difficult. This is perhaps why many organizations find it so challenging to fully reap the benefits of results-based management. So, if we agree that more accurate intervention models have the potential to support RBM-style learning, but that moving through a large number of learning cycles is impractical, it starts to become clear that initial starting points matter. In other words, initial causal ideas that approximate intervention realities as closely as possible have the potential to put interventions on a betting footing early, effectively jump-starting adaptive learning and accelerating the achievement of results.

With this in mind, it seems reasonable that any approach capable of producing better models early in the intervention cycle represents a potentially major advantage for institutions concerned with achieving set outcomes. This is especially true for a method capable of addressing the kind of complexity typically found in large or complicated policy and program contexts. To be practical, such an approach must be able to create, evaluate and refine rigorous and testable causal ideas, and it must be transparent, widely accessible, and intuitive to understand. Moreover, because the best intervention models are those that are well-informed by the available evidence, any such approach should be able to capture and integrate evidence from multiple sources, including from knowledge holders (stakeholders), experts, published literature and relevant data sets (including open and big data). And because the willingness of stakeholders to consider the evidence rests, at least in part, on whether models reflect their beliefs about how systems work, such an approach should provide an effective way to capture stakeholder values and integrate these values into decision-making. In sum, an effective approach must allow for the integration and weighing of different types of evidence, but must also provide for a credible deliberative process where alternative models can be represented, dissected and debated.

In light of these specific challenges, our group has developed an approach to support rapid construction and refinement of intuitive, yet highly rigorous, intervention causal models based on multiple evidence streams, including deliberative dialogue among knowledge holders.

Our interactive, workshop-based methods foster deep deliberation about the causal factors that drive policies and programs, and the cause-effect linkages among important system variables. Using evidence gathered from the range of available sources in any given context, our methods can be used to tame complexity and identify concepts that have the greatest influence on outcomes. Our approach enables stakeholders to build detailed visual narratives of how their systems work, quickly and intuitively. Alternative narratives are represented in a common format using a common toolset, enabling information and knowledge exchange among stakeholders and decision-makers. This permits the identification of knowledge commonalities (shared causal relationships), knowledge conflicts (logical causal contradictions) and knowledge gaps, and further creates the conditions necessary for the expression of shared visions. Such visions are crucial to eliciting buy-in, nurturing effective communication and building enhanced understanding. Explicit representation of stakeholder narrative also facilitates insight into stakeholder beliefs, and insight into how these beliefs motivate behaviour. The overall approach eliminates the need to choose between models derived from research-based information, and bottom-up, deliberative stakeholder dialogue by augmenting stakeholder insight with information from additional sources of evidence. The ability to compare models in this way generates deep insight into intervention causal relationships, providing designers and decision-makers with powerful tools to understand even the most challenging policy and program problems.

Methodologically, our data gathering and analysis toolset uses the same concepts and technologies that power leading scientific and business platforms and applications. By leveraging the mathematical and algorithmic agents that are currently being employed in the areas of artificial intelligence and machine learning, we bring cutting-edge methods and analytics into the policy and program realm. The rapid evolution of these tools, increasing interest in deliberative dialogue around policy-making, and the increasing availability of open and large data sets, all create unique and timely opportunities to bring policy and decision-making into a more modern era.

Articulating better causal ideas using this toolset further supports evidence-based learning by facilitating a more rational and efficient approach to the identification of performance indicators. With the development of superior models, specific and robust metrics can be selected that not only track performance but also support the rigorous testing of underlying causal ideas. This is crucial for long-term learning, and provides decision-makers with the right information to better distinguish whether observed changes can be attributed to intervention actions. Lastly, the synthesis of better models based on strong evidence, coupled with measures specifically designed to probe models, sets the stage for treating interventions as quasi-experiments (experiments without random assignment). Experimentation in the policy and program realm has long been perceived as a somewhat unwieldy, expensive and difficult proposition, putting its benefits out of reach for many organizations. Our toolset, which, as described above, permits the rapid development of alternative, competing causal models, helps our clients to wade into the realm of experimentation and causal inference with comparative ease.

Complex intervention realities, rapid change, and the need to be more accountable, efficient and effective with limited resources, all point to a pressing need to use the best and most innovative tools to find solutions to both new and persistent problems. We believe government and non-government institutions can benefit from the use of more modern, rigorous methods to address the social, environmental and development issues that face us at multi-jurisdictional scales. With the approach we now bring to the community, we feel that organizations no longer have to make a choice between rigor and clarity. Our approach permits a return to fundamentally important principles, such as value-driven engagement, long-term learning, causal inference, and experimentation, in ways that are intuitively appealing to clients and stakeholders. Our purpose and mission is to help organizations leverage cutting edge tools to identify the detailed intervention causal structures that drive behavior and change, ultimately supporting more credible strategic design and better outcomes.