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Strengthening ex-post evaluation

OLCA: Outcome Likelihood and Causal Analysis

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Evaluating causality in complex settings

OLCA estimates the contribution of the intervention by estimating the increased likelihood of the desired outcome

Interest in finding better methods to evaluate the effectiveness of complex interventions continues to grow. This, in part, reflects the limitations of quantitative designs in complex setting. But also the growing willingness by agencies to support programmes with complex ambitions. Outcomes in these programmes often depend on the collective action of multiple actors beyond any single sphere of control and are typically highly political.

Evaluation in such settings is by definition 'hard-to-measure'. So how might OLCA help in these situations?

The significance of contribution

Theory-based (generative) evaluation approaches such as contribution analysis and process tracing can provide a compelling case as to whether or not a causal claim 'stacks up'. However, the scale of that influence is much harder to establish. Criticism of contribution analysis from policy makers is that concluding a programme made 'no' contribution is unlikely, while the insight of knowing it made 'some' contribution is limited.

OLCA adds something here. Based on stakeholders' understanding of the context, OLCA estimates how the presence or absence of an intervention shifts the likelihood of achieving the observed outcome of interest.

Engaging complexity

OLCA creates an overall causal model integrated with thousands of joint probabilities calculated from an efficient elicitation of expert knowledge

Complex causation

Causation in complex settings is characterised by uncertainty, conjunctural causation, equifinality, 'INUS' conditions and asymmetry. Theory-based evaluations will typically examine the individual steps in different causal 'pathways' in order to determine which, if any, offers the strongest evidence of influence. These pathways may reflect different elements of programme of support or other, non-programme related explanations of change.

OLCA's approach

However, OLCA enables these different pathways and their individual steps to be linked in an overarching causal model (or 'theory of change') and examined and analysed in combination and simultaneously – reflecting better how they operate and interact in the real world. And OLCA's use of the Bayes algorithm means it does this incredibly efficiently – for example, eliciting just 50 subjective probabilities in a typical causal model enables over 30,000 joint probabilities to be analysed simultaneously. Furthermore, OLCA's probabilistic approach allows differing levels of uncertainty to be explicitly reflected in the analysis.

And while this might sound complicated, in practice, the software available to present the findings means OLCA is often much more accessible to non-specialist audiences compared to typical long text-based reports or complicated equations.

How can OLCA help?

OLCA can help draw more generalisable lessons from qualitative evaluations

Using OLCA's robust causal model you can explore causal mechanisms systematically and in an open and challengeable way

Analysing the theory of change

Let's imagine an evaluation finds that a key intermediate step in an expected causal pathway wasn't achieved. How should we interpret this? It *could* mean that the theory of change is flawed and that the programme intervention does not influence the intended outcome as intended. But what if the programme did exert an influence - just in this case, it wasn't sufficient? If the evaluation is intended to illuminate only this specific case then such questions may not matter. But such findings are highly relevant if the evaluation is to identify lessons to inform application elsewhere.

OLCA offers the scope to understand the causal importance of parts of a theory of change, even if the evidence points to *non*-achievement of an outcome in a particular case. More generally in ex-post evaluation, even when the events and outcomes are actually known, we still want to know if they were highly likely or the result, say, of an unusual configuration of fortunate (or unfortunate) events. This is important if we want to generalise. To do this we have to understand the underlying causal mechanisms… and these are inherently uncertain.

Understanding the causal mechanisms

Theory-based evaluation methods focus on observable events as proxy building blocks for causal relationships. But analysing causality directly means not just describing how events are linked but why one event triggers the responses that generate the next event.

This is challenging for evaluation and OLCA doesn't resolve it entirely. But, unlike most solutions, the approach systematically examines why stakeholders believe one event led to another, in a structured way. Exploring stakeholders' reasoning in this manner can help identify causal mechanisms and the causal logic much more clearly.

Final thoughts

Through careful application, OLCA can provide causal insights in contexts where other ex-post evaluation methods struggle

It is important to note that OLCA is not a substitute for established, theory-based methods. Rather, it builds on the logic of these approaches. As such, OLCA can significantly augment a conventional Contribution Analysis. Similarly, OLCA can itself benefit from Process Tracing's careful identification and weighing of evidence needs and its probative value.

There are also some importance considerations in how to apply OLCA in an ex-post setting and interpret the results. As in all well carried out evaluations, careful thought is needed: not least defining counterfactuals for actual events and interpreting known outcomes in probabilistic terms, for generalisable learning purposes.

OLCA is at its most valuable when other (quantitative or qualitative) methods are unlikely to be adequate. In such situations, OLCA has the potential to add significant understanding in the face of what has before looked like insurmountable barriers. This is a major advantage for programmes operating in complex settings, where cause and effect is most meaningfully understood in probabilistic terms.