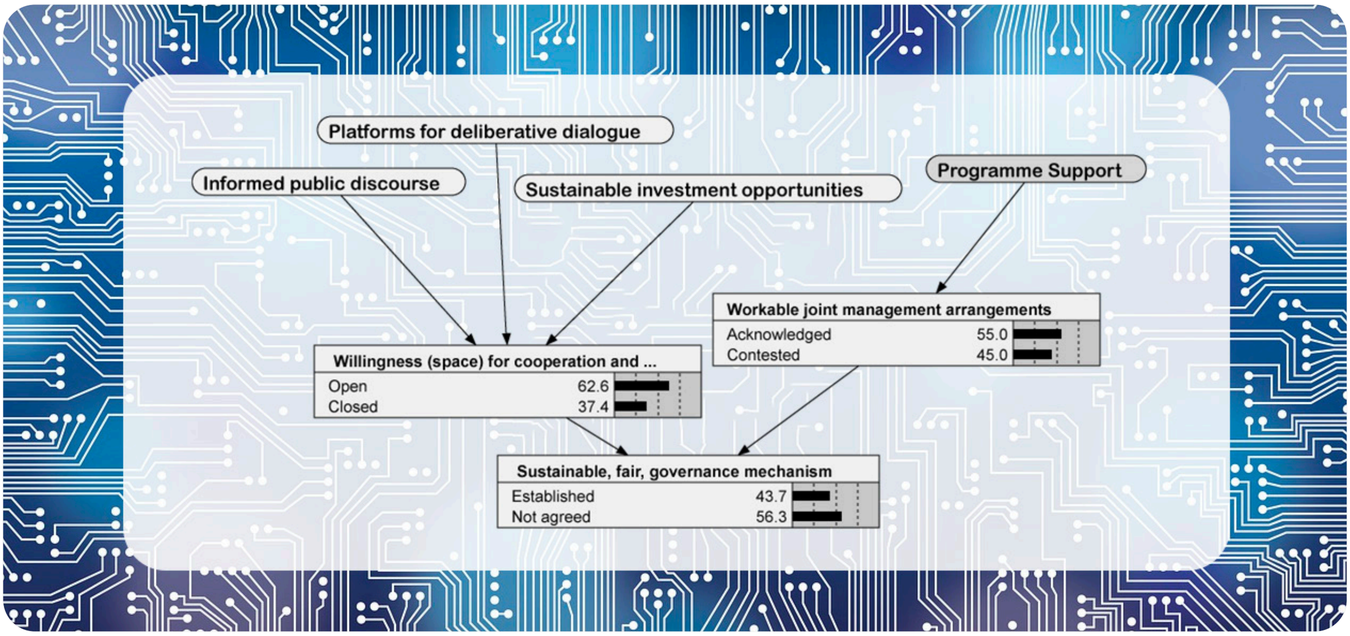
Note No. 19
Spring 2022

Outcome Likelihoods and Causal Analysis (OLCA)

Structured influence mapping and Bayesian belief networks for evaluating outcome likelihoods

A CECAN Evaluation and Policy Practice Note for policy analysts and evaluators



Technological and societal change is creating a more connected and rapidly shifting world. When an organisation acts in that world and tries to understand the consequences this often means understanding a complex system. This is particularly exemplified by the world of public policymaking and evaluation of public policy – although it is far from limited to that context.

To understand the world of complexity we require non-linear ways of appreciating change, impact and influence and we look for new tools to use. Outcome Likelihoods and Causal Analysis (OLCA) is a method to support theory-based evaluation in complex contexts especially when (a) the cause-and-effect being modelled is subject to significant uncertainty and, hence, must be described probabilistically; and when (b) objective data on the causal relationship between factors of interest are not readily available so therefore significant reliance must be placed on informants' views.

By using Bayesian Belief Networks (BBNs), OLCA also turns a logic model or Theory of Change (ToC) for an intervention into a powerful and flexible analytical tool that can be used to generate quantitative estimates of the contribution of different factors and conduct 'what-if' analyses. The model allows forward-looking (ex-ante) reasoning to examine the prospects of success, backward-looking (ex-post) reasoning to examine the influence of different factors, and intercausal reasoning, to explore efficiently the implications of interactions between factors of intervention and/or context.

As BBNs are strongly visual OLCA lends itself to use with non-specialists and can communicate results through demonstration.

OLCA combines structured mapping with expert beliefs about the causal relationships underpinning a programme strategy. Quantitative approaches and software compile this participatory elicited evidence – using the Bayes algorithm – to provide insight into likelihoods and to explore causality. The insight can then be systematically explored and stress-tested in an easy-to-understand visual format. The approach also enables 'what if' and 'why' questions to be interrogated live in the software interface.

How does OLCA contribute to better evaluation?

Theory-based (generative) evaluation approaches such as contribution analysis and process tracing can provide a compelling case about whether or not a causal claim 'stacks up'. However, unpacking that claim to gain insights about the degree of influence of different factors is much harder.

Based on stakeholders' understanding of the context, OLCA can model how the presence or absence of an intervention, subsets of an intervention and indeed factors outside the intervention that may shift the likelihood of achieving the outcome of interest. OLCA handles causation in complex settings characterised by uncertainty, effects resulting from a combination of causes (conjunctural causation), equifinality, 'INUS' (**I**nsufficient, but **N**ecessary part of an **U**nnecessary but **S**ufficient) conditions and asymmetry (where the presence or absence of causes does not have equal and opposite effect).

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. OLCA enables these different pathways and their individual steps to be linked in an overarching model to be examined and analysed in combination and simultaneously – reflecting better the real-world interactions. This ability to explore 'what-if' questions interactively can address ex-ante or real-time strategic management decisions.

While this might initially sound like a complicated approach, the software available to present the findings means that in practice OLCA can be more accessible to non-specialists than long text-based reports or complicated equations. Furthermore, OLCA's use of the Bayes algorithm is efficient, leveraging relatively few elicited probabilities to create a very rich model. Furthermore, OLCA 's probabilistic approach allows differing levels of uncertainty to be explicitly reflected in the analysis.

When OLCA is used in ex-post evaluation it offers a distinct perspective: events and outcomes are typically known but the notion of likelihood, often overlooked in qualitative ex post evaluation, is still there in the sense that even observed outcomes are typically uncertain up to the point when they occur. OLCA asks how likely it was that they occurred allowing decision-makers to understand whether results achieved were highly probable or the product of, say, an unusual configuration of fortunate (or unfortunate) events – as well as the likely difference an intervention made to those results. This is important if we want to generalise and learn lessons from a single unique, or a limited number of, implementations.

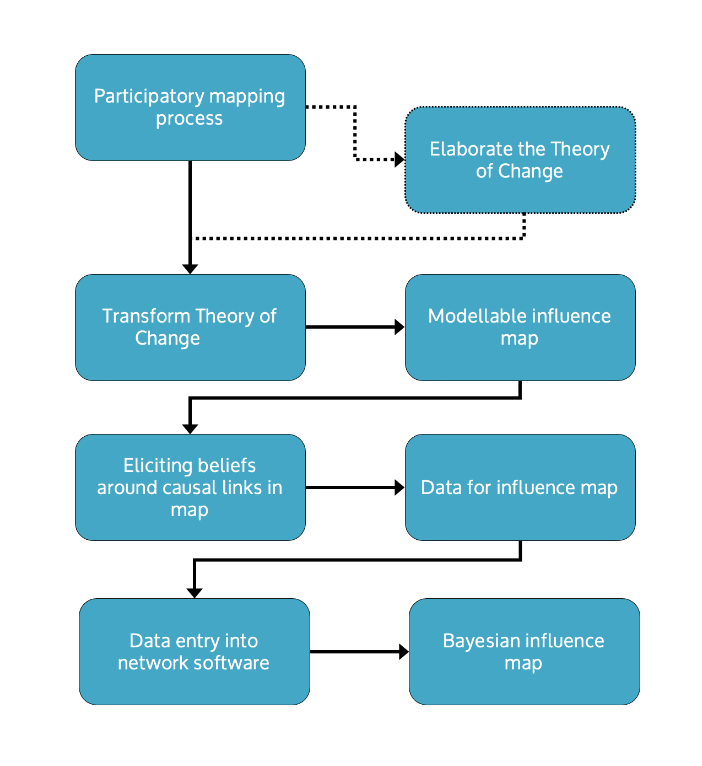
Building the OLCA model

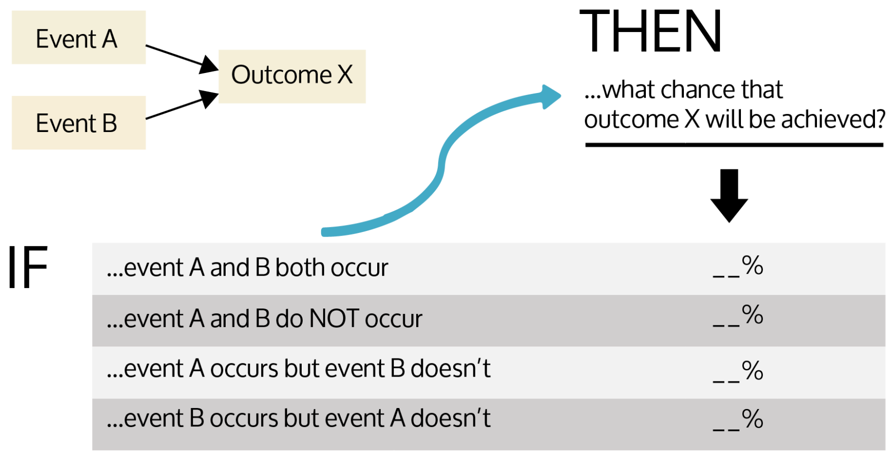
OLCA relies on well-established components but it is innovative in how it combines and applies these. The first step of OLCA is developing the logical causal mechanisms for an intervention (they may already exist, perhaps as a Theory of Change.) The aim is to obtain a whole system 'influence map' where factors in addition to the intervention actions are in scope.

OLCA uses participatory processes as the starting point. Then, taking the initial participatory mapping a step further, the causal model is put into a graphical and interactive form that finally becomes a modellable 'map'.

The model retains the relevant causal linkages and adds elicited likelihood evidence for the different elements.

To make sure the subsequent elicitation stage works well, names of the nodes (bubbles on the map) and their potential outcomes (their 'states') must be framed appropriately to enable probabilities to be attached. Collection of these data and entry into appropriate software produces the Bayesian influence map that can be used for analysis.





The OLCA approach creates a replicable result using objective analysis and compilation of subjective views, even from experts who have a close relationship to – or a hand in – the activities that are being examined. This is possible, in part, because in the elicitation step the questions asked ensure that the informant's view is almost entirely atomised by focusing on directed specific questions about each stage of the causal chain. Only at the end are these responses compiled to create the analytical conclusion. This process means that it is very unlikely that informants could tailor responses to create any overall answer they would prefer to see.

As with many participatory modelling approaches, people find that applying OLCA is an enlightening process in its own right: a structured reflection about cause and effect and the implications of their actions in the real world.

Getting answers

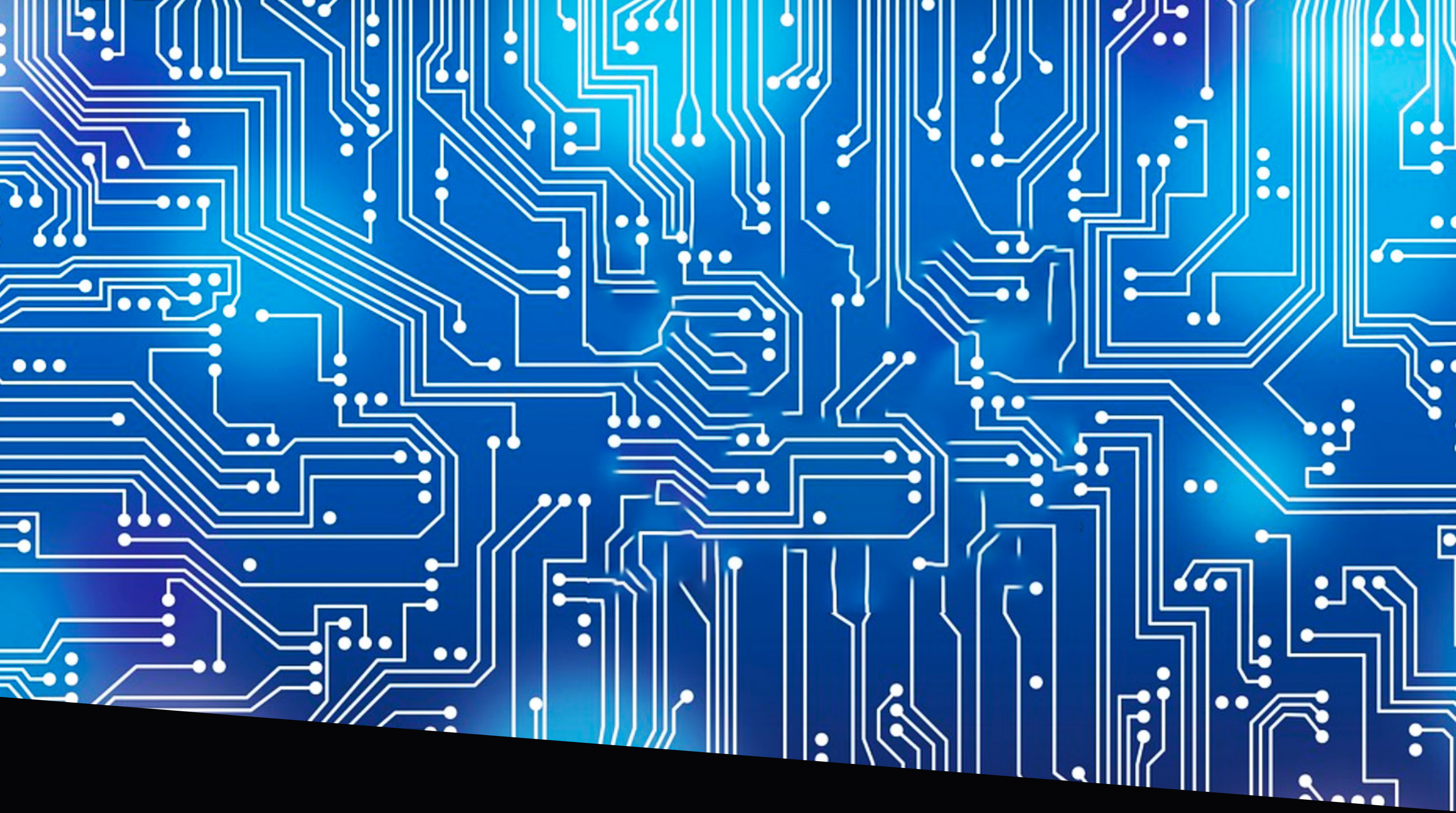
This first cut of the model can be examined to see what factors appear to be most influential in the process and what is the effect of activities, in totality or various sub-combinations , on overall chances of success. In making any judgement about the acceptability of those chances, decision-makers' risk appetite is also factored into the exercise. Once that initial model has been understood there is scope to explore further 'what if' and 'what does' questions by varying the scenarios examined within the basic model.

Changes frequently occur in the external environment and these can impact the prospects of success. OLCA helps clarify understanding about exactly what difference the changes make and why, providing insights for corrective or mitigating action focused on areas likely to have most effect. Assigning cost data can facilitate analysis of value for money. The results can be monitored over time to track changing prospects and help managers engage stakeholders and communicate performance clearly.

How it fits with other complexity methodologies

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.

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.



Further reading

- Charniak, E (1991) Bayesian Networks without tears. *AI Magazine*. Winter
- Sloman, S (2005) *Causal Models: How people think about the world and its alternatives*. Oxford University Press.
- Henderson, JS, and R Burn (2004) Uptake Pathways: the potential of Bayesian belief networks to assist the management, monitoring and evaluation of development research. *Agricultural Systems* 79, 3-15
- Marcot, B (2017). Common quandaries and their practical solutions in Bayesian network modelling. *Ecological Modelling* 358, 1–9

- **More information on OLCA at the website of the authors www.quantqual.net**

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The Centre for the Evaluation of Complexity Across the Nexus (CECAN) is a £3m national research centre hosted by the University of Surrey, which brings together a unique coalition of experts to address some of the greatest issues in policy making and evaluation.

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CECAN has developed a set of co-produced case studies, working with government departments and agencies to tackle their intractable evaluation challenges in complex policy area. These case studies have involved sustained dialogue and an orchestrated succession of activities and relationship building. They are providing experiments in bringing together the expertise of evaluation practitioners, methods and domain specialists, social and natural scientists and policy analysts to develop shared understandings of evaluation challenges and to identify evaluation needs and solutions.

CECAN receives funding from the Economic and Social Research Council

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