OLCA 101: a primer

OLCA: Outcome Likelihood and Causal Analysis

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By Stuart Astill and Simon Henderson

OLCA 101: a primer



OLCA estimates the likelihoods of outcomes

Maps of causality, beliefs about influence and success feed advanced quantitative methods

Analysing strategy based on a better understanding about causality

OLCA combines structured mapping with expert beliefs about the causal relationships underpinning a programme strategy to provide insight. Using innovative quantitative approaches our software compiles this evidence – using the Bayes algorithm – to leverage incomplete knowledge (uncertainty).

Strategy can then be stress-tested in an easy to understand visual format and 'what if' and 'why' questions can be interrogated live in the online interface.
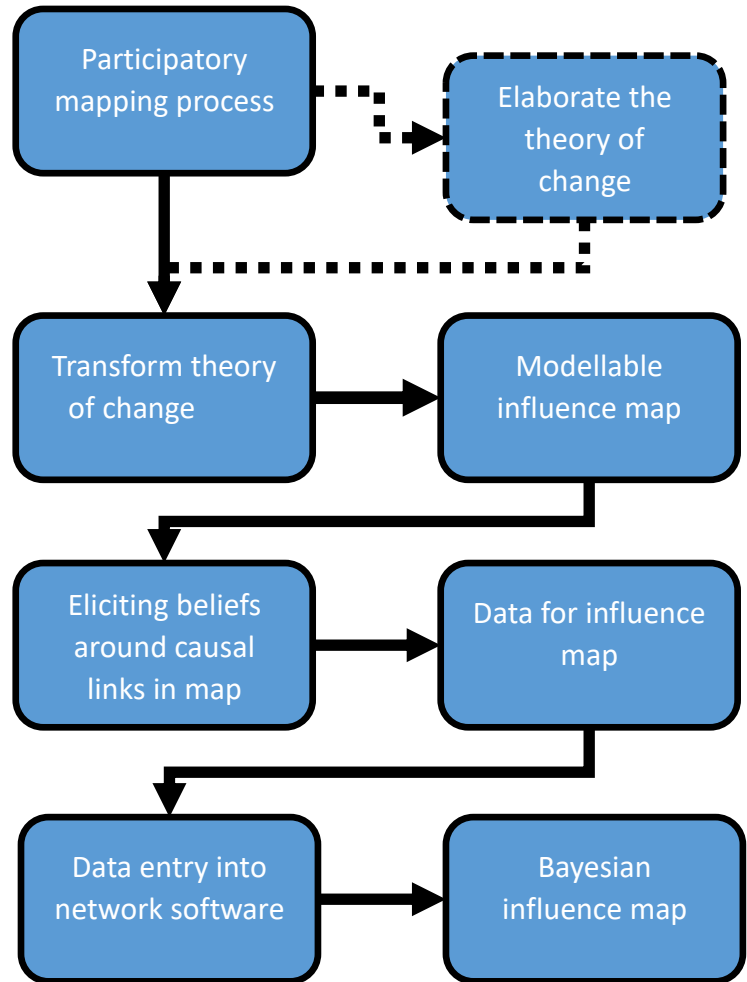
- What's the likelihood that the activity will have its planned effects?

- If an activity does (or doesn't) succeed, how does that affect other critical steps on the way to the final outcome?

- What are the chances for overall success and how do changes in the operating environment affect them?
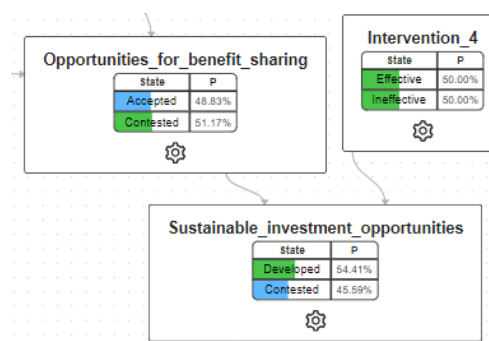
In complex contexts, OLCA is an interactive tool for mangers to test the sensitivity of their strategy to key assumptions and project prospects of success.

The OLCA recipe card

OLCA follows a simple set of steps to create an interactive tool that provides insights about strategy

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┌─────────────────────┐          ┌─────────────────────┐
│   Participatory     │ ·····>   │   Elaborate the     │
│  mapping process    │          │    theory of        │
│                     │          │     change          │
└─────────────────────┘          └─────────────────────┘
           │
           v
┌─────────────────────┐          ┌─────────────────────┐
│  Transform theory   │  ───>    │    Modellable       │
│    of change        │          │   influence map     │
└─────────────────────┘          └─────────────────────┘

┌─────────────────────┐          ┌─────────────────────┐
│  Eliciting beliefs  │  ───>    │  Data for influence │
│  around causal      │          │        map          │
│  links in map       │          │                     │
└─────────────────────┘          └─────────────────────┘

┌─────────────────────┐          ┌─────────────────────┐
│  Data entry into    │  ───>    │     Bayesian        │
│  network software   │          │   influence map     │
└─────────────────────┘          └─────────────────────┘
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Starting out with OLCA

OLCA can make a breakthrough contribution to strategic management

How is OLCA innovative?

OLCA relies on well-established components but it is innovative in how it combines and applies these. Participatory mapping has been around for some time, as a rigorous method to help better understand people's beliefs about causal systems. Similarly, Bayesian networks aren't new. They have been used and proven in diverse fields such as medicine, IT and natural resources management, for diagnosis of problems and prediction of likely outcomes.

OLCA's innovation is in combining best practice elicitation, analytical practice and communication from these two approaches and systematically applying the whole to the assessment of complex social programmes, policy environments, systems and organisations.

Where do we begin?

OLCA uses participatory processes as a starting point to develop (or refine) the logic model (sometimes called a Theory of Change) underpinning a strategy.

This initial mapping produces a crisp structured description of relevant aspects of the real world and what *you* are doing, or plan to do, to achieve your desired strategic outcomes. It is grounded in the whole 'system' and important factors apart from your actions are very much in scope. But the key focus is always on how your activity interacts with this system.

OLCA creates a robust causal model of how change is believed to happen

People we work with find this a valuable and enlightening step in its own right: a structured reflection about cause and effect, the chain of consequences - and where their actions touch the real world and what that implies.

Mapping for analysis

The design and content of OLCA's map needs to be technically fit-for-purpose.

Names and nodes must be framed appropriately for the elicitation phase to be meaningful and robust

Prepping your map for the model

While the causal structure obtained from the previous stage is comprehensive, it needs to be transformed into a model to permit more extensive analysis. The model retains the relevant causal relationships identified but allows the significance of different factors and evidence about likelihoods to be incorporated. This is where experience and understanding of the method comes in. In particular, to make sure the design of the model nodes and their potential outcomes (their 'states') are framed appropriately to enable probabilities to be attached and to ensure the next stage (elicitation) works well.
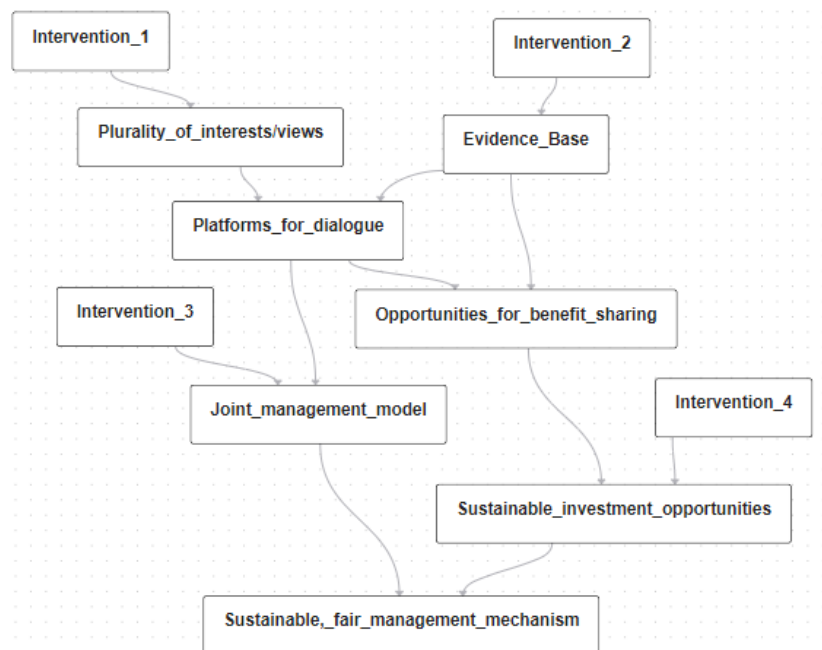
And when we have created the initial model we test this with experts (very likely you!) to make sure it still reflects their view of the reality on the ground.
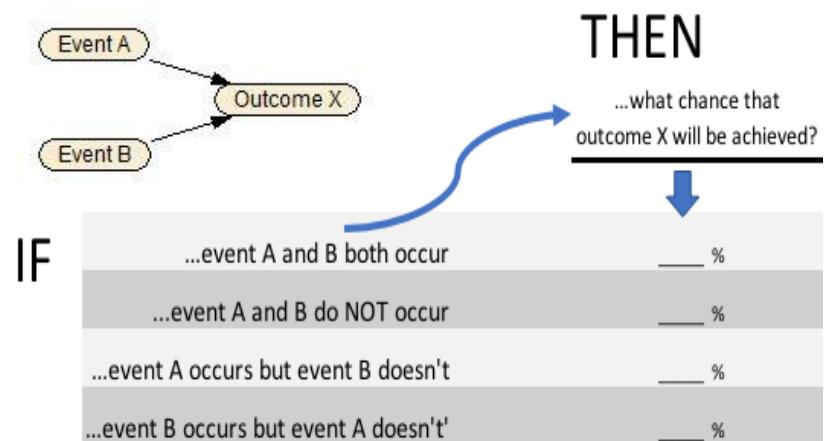
Eliciting probabilities

Breaking it down

OLCA creates a robust causal model of how change is believed to happen

A great strength of the OLCA approach is that it 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 we atomise the map and ask directed specific questions about each stage. Then, only at the end are these responses compiled to create the analytical conclusion.

Elicitation is ideally conducted face-to-face but can be run remotely or even through a guided step-by-step 'offline' process. It can be conducted through consultations with individuals or as a group exercise.

The result of this elicitation stage is a set of conditional probabilities which assess what the probability is that the next step in the causal chain will be achieved, given the possible outcomes of the preceding step(s).

The stepwise nature of the elicitation process means that it is virtually impossible for experts to tailor individual responses with a view to creating the overall answer they would prefer to see.   And the transparent nature of the process means that elicited probabilities can be reviewed

As the method steps through to produce the concrete result it also helps to develop a rich qualitative view

in real-time to identify anomalies.

Notes are taken of discussions and rationales so that if questions arise or views change in the future, we can revisit the underlying reasoning and evidence. Indeed, the ability to quantify changes in views over time, and identify the reasons why, makes OLCA so useful as a monitoring and reporting tool in programmes operating under high uncertainty.

Feedback on the elicitation sessions tells us that stakeholders build knowledge and create new insights from the guided reflection on the strength of causal relationships. For this reason, OLCA can be as useful for planning as for managing on-going implementation.

An important point to note here: while elicitation focuses on the causal relations within the model, these are conditioned by many other factors not explicitly referenced. In providing their assessments, experts will take these into account, and when explaining their judgements, we obtain valuable insights into key "other" factors in the broader system. This helps develop a rich qualitative understanding that surrounds and contextualises the model and its results.

Model and algorithm

The initial model in the software shows straight away the experts' views and the outcome likelihood

Building a visual model

The dedicated software we use for OLCA is not only smart but good-looking. Using the refined structure, appropriately framed, we enter the elicited experts' probabilities.

Platforms_for_dialogue

Name: Platforms_for_dialogue   [Add State]

Scenarios			Platforms_for_dialogue State Likelihood	
Plurality_of_interests/views	Evidence_Base		Operatingeffecti	Operatingpoorly
Limited	Limited	→	0.2	0.8
Limited	Enhanced	→	0.35	0.65
Enhanced	Limited	→	0.4	0.6
Enhanced	Enhanced	→	0.92	0.08

With the model complete we can then produce an 'as is' view of the whole system – external context and the planned strategy – that leads to the estimated likelihood of overall success.

This first cut of the model can be examined to see what is most influential and whether the effect of the planned activities on overall chances of success is worthwhile.
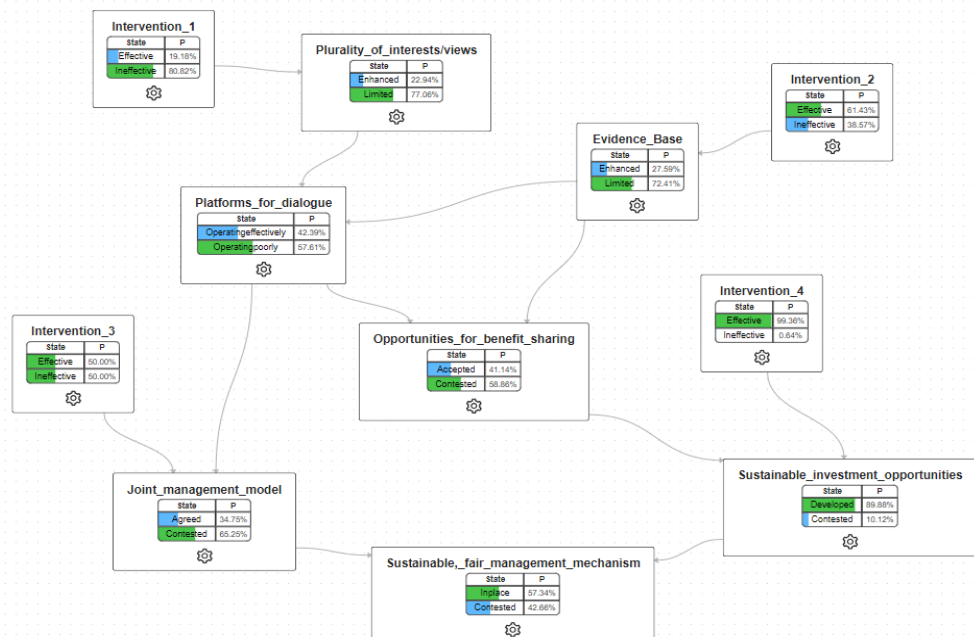
Bayesian Belief Networks: the background

A Bayesian belief network (BBN) can be seen essentially as a graphical model of causal interactions among a set of variables, represented as a network of nodes that are linked by probabilities.
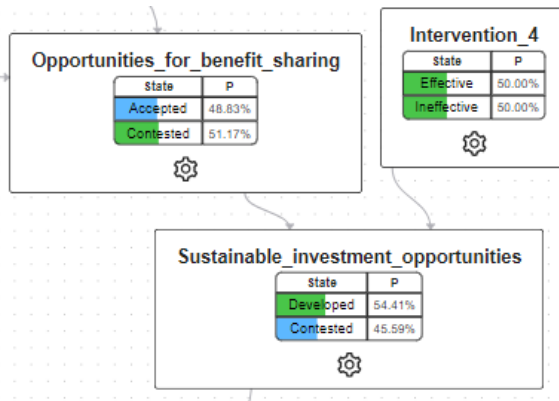
A BBN is an acyclic graph, that is, a network with no feedback loops, where the "predictor" nodes are direct or indirect causal factors of the outcome variable(s).

Opportunities_for_benefit_sharing

State	P
Accepted	48.83%
Contested	51.17%

Intervention_4

State	P
Effective	50.00%
Ineffective	50.00%

Sustainable_investment_opportunities

State	P
Developed	54.41%
Contested	45.59%

The nodes represent factors that affect outcome(s) of interest and the links represent how the factors interact.

A BBN has a **qualitative** and **quantitative** element.

The qualitative element relates to its structure, which involves mapping the factors considered relevant to the outcome(s) of interest and the dependencies or links between them, (including the order or direction of causality. This may be equivalent to the theory-of-change.

The quantitative element is the inclusion of probabilities that quantify the relationships between the factors.

Probabilities need only be specified for factors that are linked (i.e. direct relationship). This makes a BBN efficient in terms of the data required to populate the network and a very powerful reasoning tool for evaluation purposes.

Probabilities that quantify the relationship between a factor and its indirect causes or effects are computed automatically by inference algorithms.

Platforms_for_dialogue

Name: Platforms_for_dialogue   [Add State]

Scenarios			Platforms_for_dialogue State Likelihood	
Plurality_of_interests/views	Evidence_Base		Operatingeffecti	Operatingpoorly
Limited	Limited	→	0.2	0.8
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Enhanced	Enhanced	→	0.92	0.08

Depending on the context, probabilities may be derived from observed ('objective') data about the relationship between factors. More commonly, they are subjective probabilities reflecting the beliefs of key informants. A BBN can, however, accommodate both objective and subjective data.

Exploring with OLCA

OLCA augments existing adaptive management practices

It capturing beliefs about the strength of influence and levels of uncertainty,

Understand changing prospects and communicate your knowledge

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 exactly what difference the changes make and why, providing insights for corrective or mitigating action focused on areas likely to have most effect. The results can be tracked over time, helping managers engage stakeholders and communicate performance clearly.
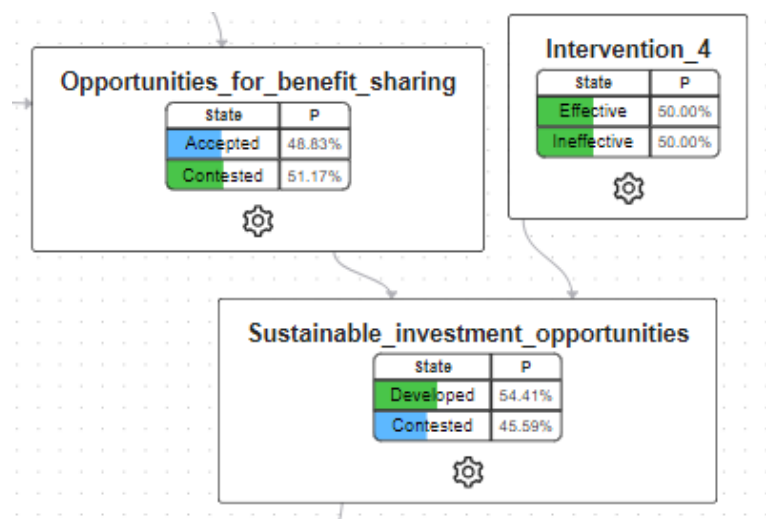
As an interactive tool, OLCA enables mangers to test the sensitivity of their strategy to key assumptions.

- is the programme effort focused where it can achieve the greatest traction?
- What are the implications of if support is ineffective at different points of intervention?

Navigating with OLCA

OLCA's key advantage is the ability to incorporate in-flight learning in rigorous, informative ways.

Updating beliefs with new evidence and learning

Managers can update the model as they learn and their knowledge becomes more complete. As a result, conclusions become more solid. During implementation, strategic implications of new information can be explored, along with their predicted effect on the prospects for success.

In-flight updating can take different forms:

- Confirming the (previously unknown) status of key events/factors with new evidence
- Revising previous beliefs about the strength of causal influence to reflect learning from experience
- Redesigning the model entirely to reflect a major shift in strategy.

In all three instances, the updating process takes a structured approach to treatment of new information and fosters reflection and learning. In all three, OLCA facilitates assessment of the implications for strategy.

An indicator to track and communicate improving prospects over time

OLCA also provides revised estimates of the likelihood of success over time. With this, managers have an indicator that they can track over time to highlight evolving prospects and engage stakeholders.

Prospects of achievement

75%

Expert
Group X

50%

Expet
Group Y

25%

Expert
Group Z

0%

Baseline   **Year 1**   **Year 2**