BRIEFING

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Disentangling the impact of Active Labour Market Programmes to inform the new and improved Youth Employment Toolkit

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In 2021 Youth Futures Foundation engaged a consortium from Monash University, the Centre for Evidence and Implementation, and the Institute for Employment Studies to make sense of the existing research on which interventions help young people enter the labour market.

The research was used to inform the Youth Employment Toolkit, a digital resource translating evidence into practical information for decisionmakers. The first edition was launched in 2023.

We learned a lot from that initial work and have now rebuilt the analysis that sits behind the Toolkit from the ground up.

Here we explain what's changed, and why it matters.

Programmes rarely come in neat boxes

Pinning down what improves employment outcomes for young people is surprisingly hard.

Programmes that aim to get young people into work come in lots of shapes and sizes, and they might even bundle several different things together – perhaps a bit of classroom training, some careers advice and job search support.

When everything is delivered at once like this, the standard tools of evidence synthesis do not work well for isolating which elements of the programmes are effective.

Network meta-analysis can help untangle 'what works'

A network meta-analysis (NMA) is a way of comparing a whole family of programmes at once.

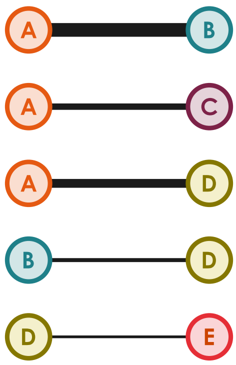
It pools:

- *direct* evidence – where two programmes have been compared head-to-head
- *indirect* evidence – where comparison between two programmes is inferred by routing through one or more other programmes that both have been tested against (Petropoulou et al. 2021; Chaimani et al. 2022)

This matters because so many youth employment programmes are complex interventions – bundles of two or more components delivered together.

By estimating each component's effect, a CNMA gets at the question we started with: not just whether a programme works, but which parts of it are actually doing the work.

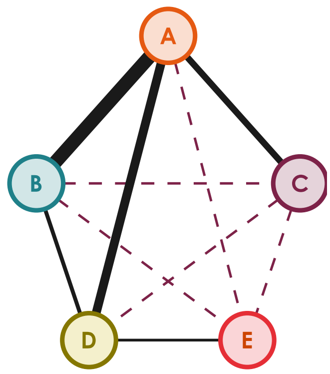
This is easier to see with a picture…

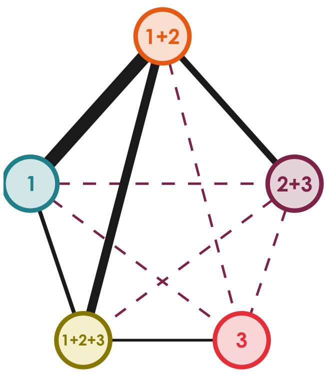


A **pairwise** meta-analysis *directly* compares pairs of youth employment interventions. For example A vs. B.

A **network** meta-analysis lets us compare interventions head-to-head (A vs. B etc.), *and* to compare interventions that no study has tested against each other directly.

We can *estimate* B vs. C, by routing through A, which both B and C have been directly compared against.





A **component** network meta-analysis (CNMA) goes a step further by:

1. breaking every intervention down into its building blocks – its components
2. estimating the contribution of each one, pooling across every study in which that component appears.

Direct comparison (line width = # of studies) Indirect comparison

Figure 1: Illustrative network map

What's new for Toolkit 2.0?

There are two major changes between the work we did to inform the first Youth Employment Toolkit and the latest edition:

1. How we defined, included and split interventions

In the 2026 edition, we took a broader look at overarching interventions and included any study that used appropriate causal methods to evaluate the impact of an active labour market programme (ALMP) – that is, any publicly funded programme (other than mainstream education) designed to help people find work or boost their earnings.

When dividing interventions into their components, it's important to define these components carefully. Apart from being mutually exclusive, they need to be detailed enough to be useful but not too detailed as to make it difficult to determine their presence (from often limited information) in published studies.

After reviewing how previous high-quality meta-analysis (Puerto et al. 2022) split ALMPs, we followed a similar path and split them into five overarching groups comprising seventeen active components):

Skills development	Basic skills training	Soft skills training	Behavioural skills training	Job-specific skills (off-job training)	
Self-employment support*	Business skills training	Business advisory & mentoring	Financial & start-up support		
Employment support services	Job search preparation	Job search assistance	Employment counselling	Employment coaching	Financial assistance
Employment experience	Job-specific skills (on-the-job training)	Paid work experience	Unpaid work experience		
Subsidised employment	Wage subsidies	Public works			

Figure 2: How we defined intervention components.

*Ultimately we had to combine the self-employment support components into their over-arching category, as there weren't enough studies looking at each of the individual components.

2. A Bayesian engine under the hood

We rebuilt the underlying model using a Bayesian framework (Dias et al. 2018), rather than the original Frequentist one, because it handles the complex evidence on youth employment more flexibly.

Usable, nuanced insights

A traditional frequentist analysis tends to hand back a binary verdict: an effect was either statistically significant or it was not.

A Bayesian model trades that yes-or-no answer for a more nuanced look at how certain we are of the finding – how confident we can be that a programme actually helps (rather than does nothing, or harms), and how large that benefit is likely to be (Gelman, Hill, and Yajima 2012).

We believe that when making decisions about where to allocate funding to help vulnerable youth, it's more useful to say "we are fairly confident this helps, by about this much" rather than "its statistically significant, with an estimated effect size of …".

Multiple outcomes considered at once

The first Toolkit edition modelled outcomes one at a time, so we had to aggregate different measures of employment together.

The new Bayesian model estimates a whole family of them together – whether young people are in work now (or anytime in the last year), what they earn, how many hours they work, how long they have been working and their progress in furthering their education and skills – so that a study reporting on both jobs and wages contributes to each within a single, consistent model, rather than being analysed outcome-by-outcome in isolation.

The new framework lets us treat the outcomes as they were reported and gives us a more complete picture of employment, wage and education outcomes.

Appropriate handling of the available evidence

The revised framework means we can use the evidence we have.

Much of the published research on youth employment programmes is non-randomised (Puerto et al. 2022), and such studies are generally considered more prone to bias than randomized trials, which means they can overstate or understate a programme's true effect.

Faced with this, meta-analysts usually pick one of two options:

1. exclude the non-randomised studies and rely on the experimental ones alone, which discards a large share of the available evidence;
2. Include the non-randomised studies alongside the randomised studies, which risks treating weaker evidence as though it were just as trustworthy.

The first edition of our NMA took the second route, in effect assuming a non-randomised study was as reliable as a randomised trial.

The Bayesian framework lets us do something in between – adjusting for differences in study design and quality rather than ignoring them.

We classified each study by its design:

- **a randomised study** – assigning people to receive a programme by random chance so that the two groups start out alike in every other respect and any later differences in outcomes can be attributed entirely to the programme itself.
- **selection on observables** – comparing participants with otherwise similar non-participants after statistically matching them on measured traits such as age, schooling and past work history, so the programme's effect can be teased apart from those background differences – provided nothing important that also shapes the outcome has been left unmeasured (Cunningham 2021).
- **design-based identification** – exploiting a feature in how a programme was rolled out, such as an arbitrary eligibility cut-off or a staggered launch across locations, to create two otherwise-similar groups whose differing outcomes can then be put down to the programme itself. (Angrist and Pischke 2010).

We used standardised risk-of-bias tools to grade each study as either low-quality or not low-quality.

The model can then estimate whether studies of a particular design or quality tend to overstate or understate effects relative to a randomised study, and correct for it – adjusting more where the data suggest bias, and leaving estimates as they are where they do not. This reduces the risk of bias from weaker evidence rather than discarding it entirely (Efthimiou et al. 2017; Verde 2021). This process is detailed in Figure 3.

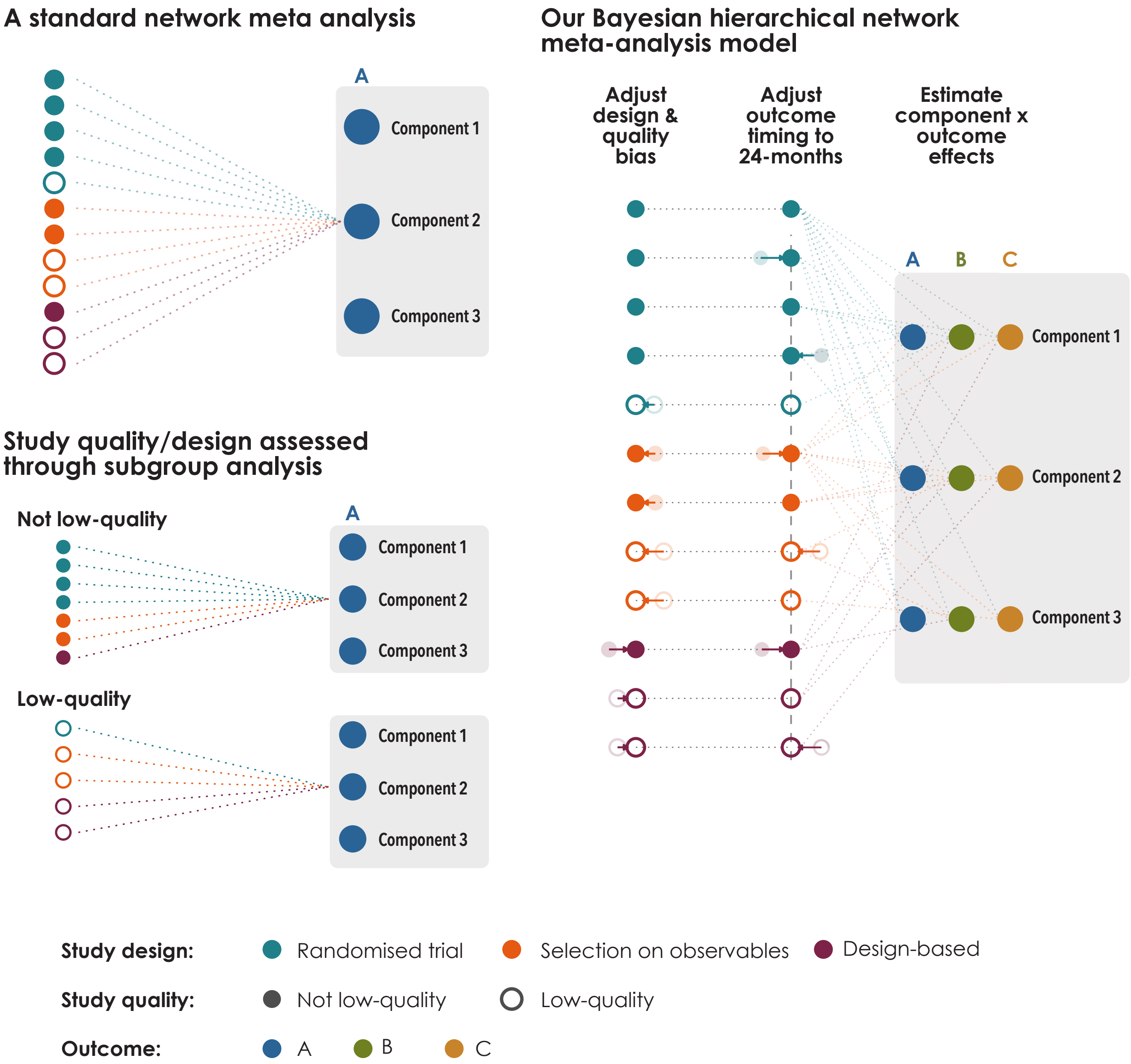


Figure 3: How the Bayesian hierarchical network meta-analysis model disentangles the evidence.

Importance of timing

Studies measure success at wildly different points – some a few months after a programme starts, others several years later.

To compare like with like, we needed a single point in time to measure from. Looking across the studies, we found that outcomes were most commonly reported at 24 months, so we made that our reference point.

Where a study reported at that mark we use its estimate directly; where it did not, we took the closest available time point and let the model adjust it to the common 24-month endpoint.

What this all means

All of this work feeds back into providing actionable evidence to inform practice.

The new analysis underpins an update to the Youth Employment Toolkit which speaks to a richer set of programme components, and a wider range of outcomes, than the first edition could reach.

Learn more about the latest edition.

Compare outcomes for…	Impact	Strength
Education ?	−	🔒🔒
Employment ?	+ +	🔒🔒
Training ?	+	🔒

Cost ? ££

3 additional young people in work

For every 100 NEET young people who can take pc … c skills training as a targeted youth employment intervention, three are … et a job in 12-24 months from the start of the intervention who wo … lone so without the intervention.

This intervention could increase recent employm … 3 percentage points.

The ambition is unchanged from the outset: to turn a sprawling, untidy evidence base into something a policymaker or a programme designer can read, interpret and act on, in a way that reflects the types of services young people may encounter within programmes and some of the challenges facing young people it is meant to serve.

If you're interested in learning more about our methods check out our technical guide.

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