

# compmed: A new command for estimating causal mediation effects with non-adherence to treatment allocation

*Anca Chis Ster, Sabine Landau, Richard Emsley*

*Department of Biostatistics and Health Informatics, King's College London, United Kingdom*

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**STATA**

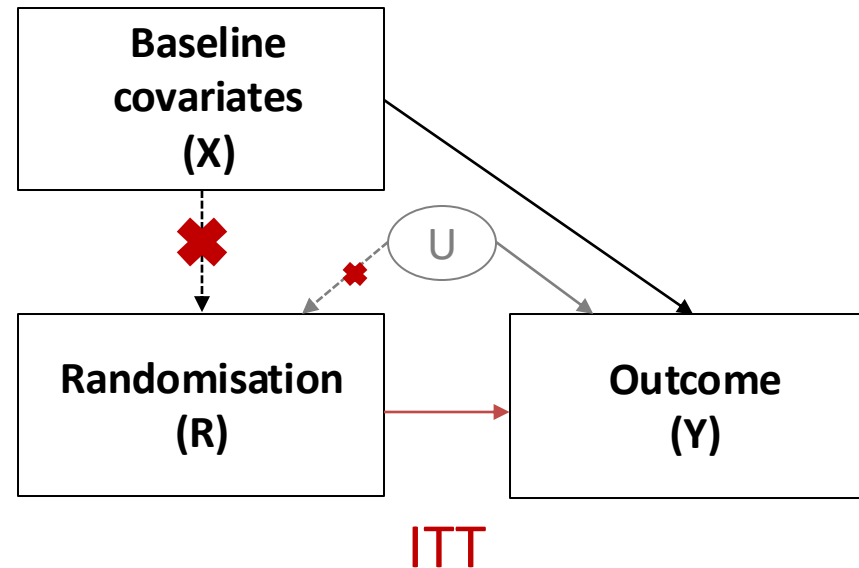
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# Motivation for handling nonadherence in mediation

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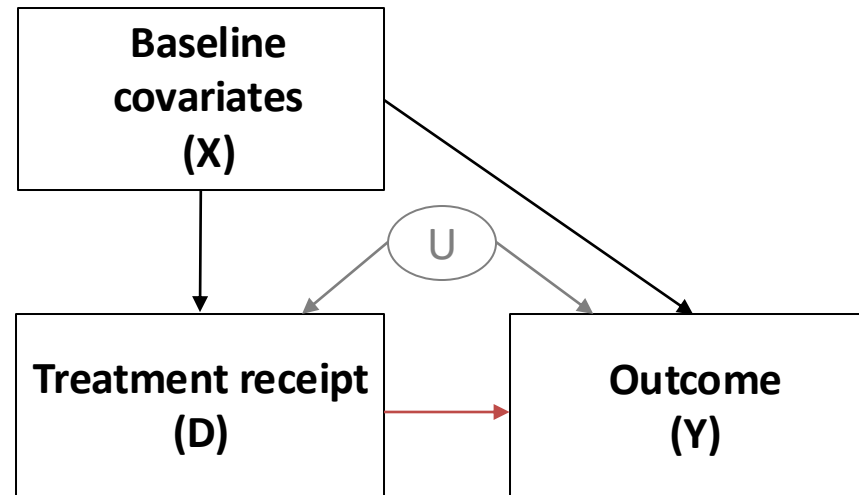
- Trials in mental health often evaluate **complex** interventions, such as therapy or psychotherapy
- One guideline for evaluating complex interventions is to understand the treatment **mechanism**, i.e., understand how the treatment works in practice
- Trials in mental health are faced with the challenge of **nonadherence** to treatment allocation
- It's currently unclear how to account for nonadherence in a mechanism evaluation, or how to practically implement this within a statistical package, e.g., **STATA**

# Background: The challenge of non-adherence in trials

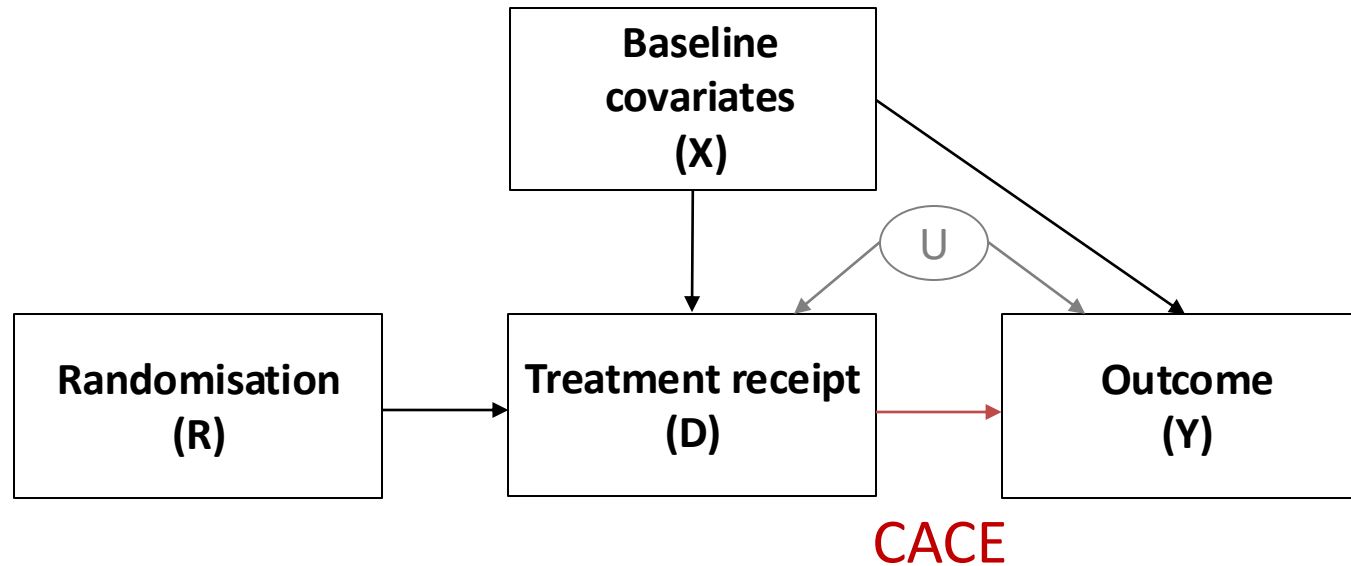


X, U = measured or unmeasured variables  
ITT = Intention-to-treat  
CACE = Complier Average Causal Effect  
NDE = Natural Direct Effect  
NIE = Natural Indirect Effect

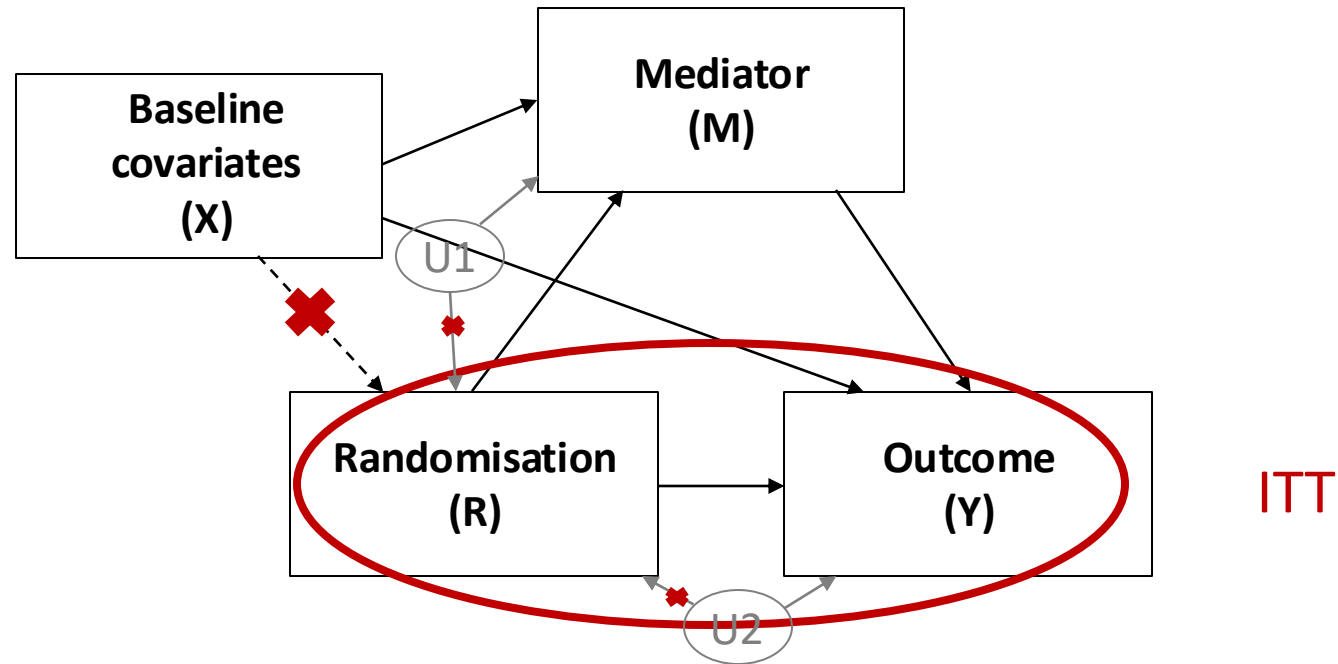
# Background: The challenge of non-adherence in trials



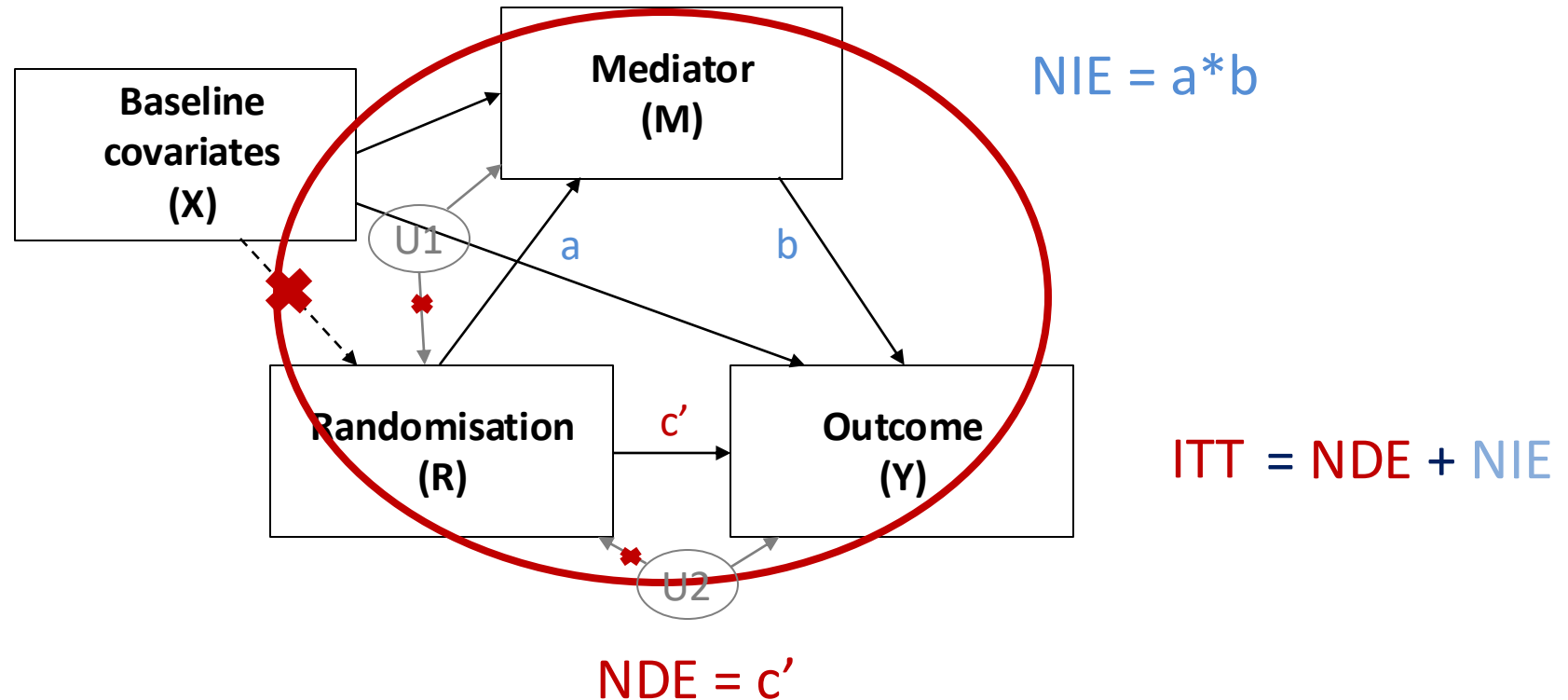
# Background: The challenge of non-adherence in trials



# Background: Mechanism evaluation

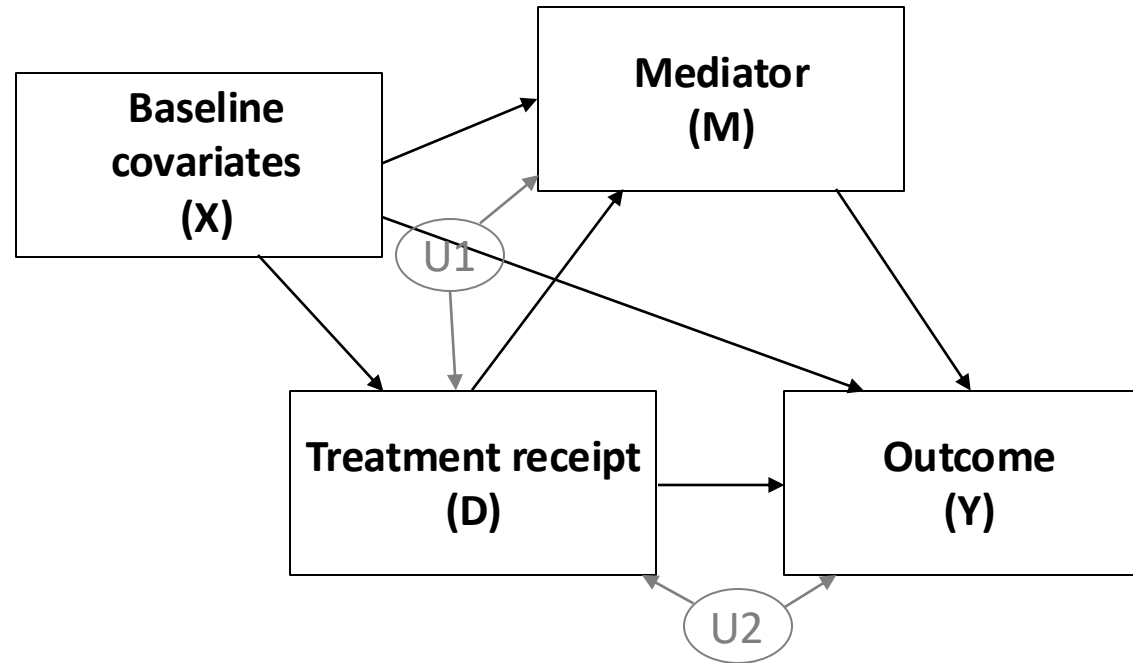


# Background: Mechanism evaluation



X, U = measured or unmeasured variables  
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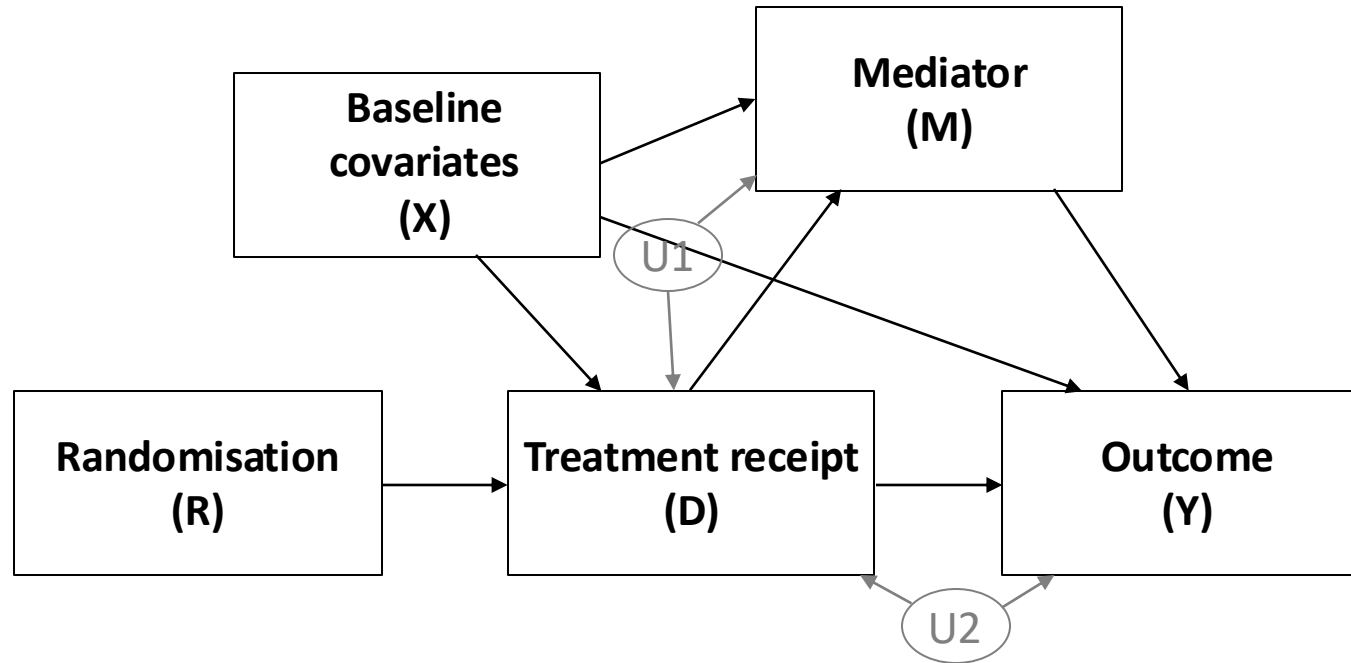
# Background: Mechanism evaluation



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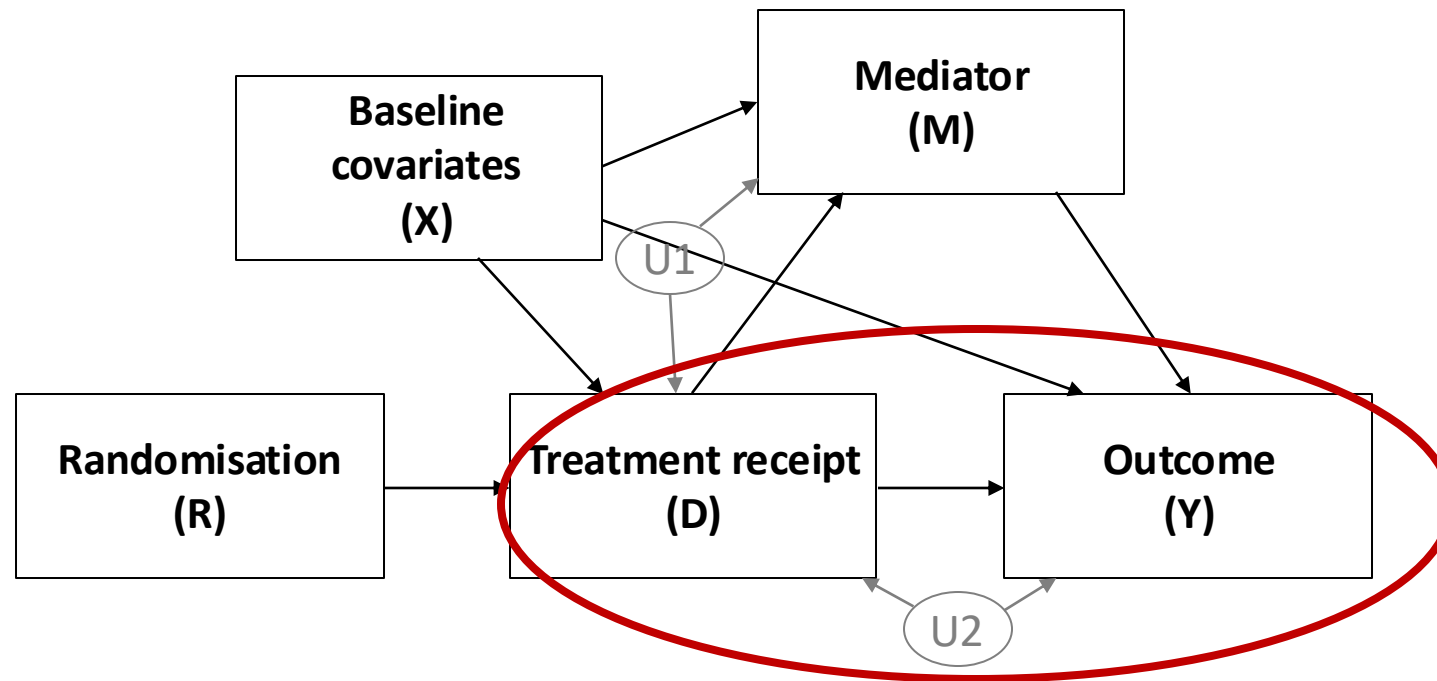


# Background: Mechanism evaluation



X, U = measured or unmeasured variables  
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# Combining mediation and non-adherence: Identification



## CACE

X, U = measured or unmeasured variables

ITT = Intention-to-treat

CACE = Complier Average Causal Effect

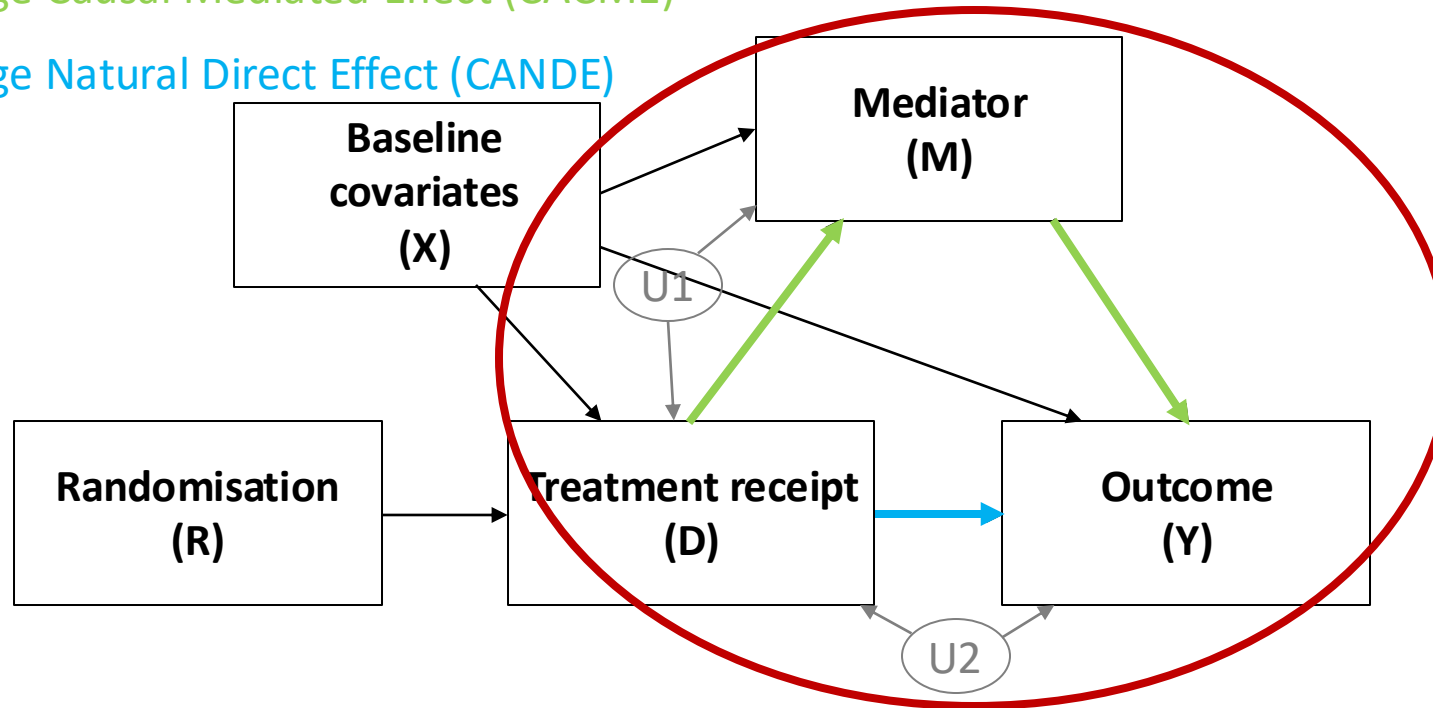
NDE = Natural Direct Effect

NIE = Natural Indirect Effect

# Combining mediation and non-adherence: Identification

The CACE can be partitioned into a:

- **Complier-Average Causal Mediated Effect (CACME)**
- **Complier-Average Natural Direct Effect (CANDE)**



$$\text{CACE} = \text{CACME} + \text{CANDE}$$

X, U = measured or unmeasured variables

ITT = Intention-to-treat

CACE = Complier Average Causal Effect

NDE = Natural Direct Effect

NIE = Natural Indirect Effect

# Combining mediation and non-adherence: Assumptions

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The CACME and CANDE can be identified under:

(1) Conditionally ignorable treatment assignment

- No variables that influence the randomisation variable

(2) Monotonicity

- No individuals who would receive the opposite intervention to the one offered

(3) Exclusion restriction for non-compliers

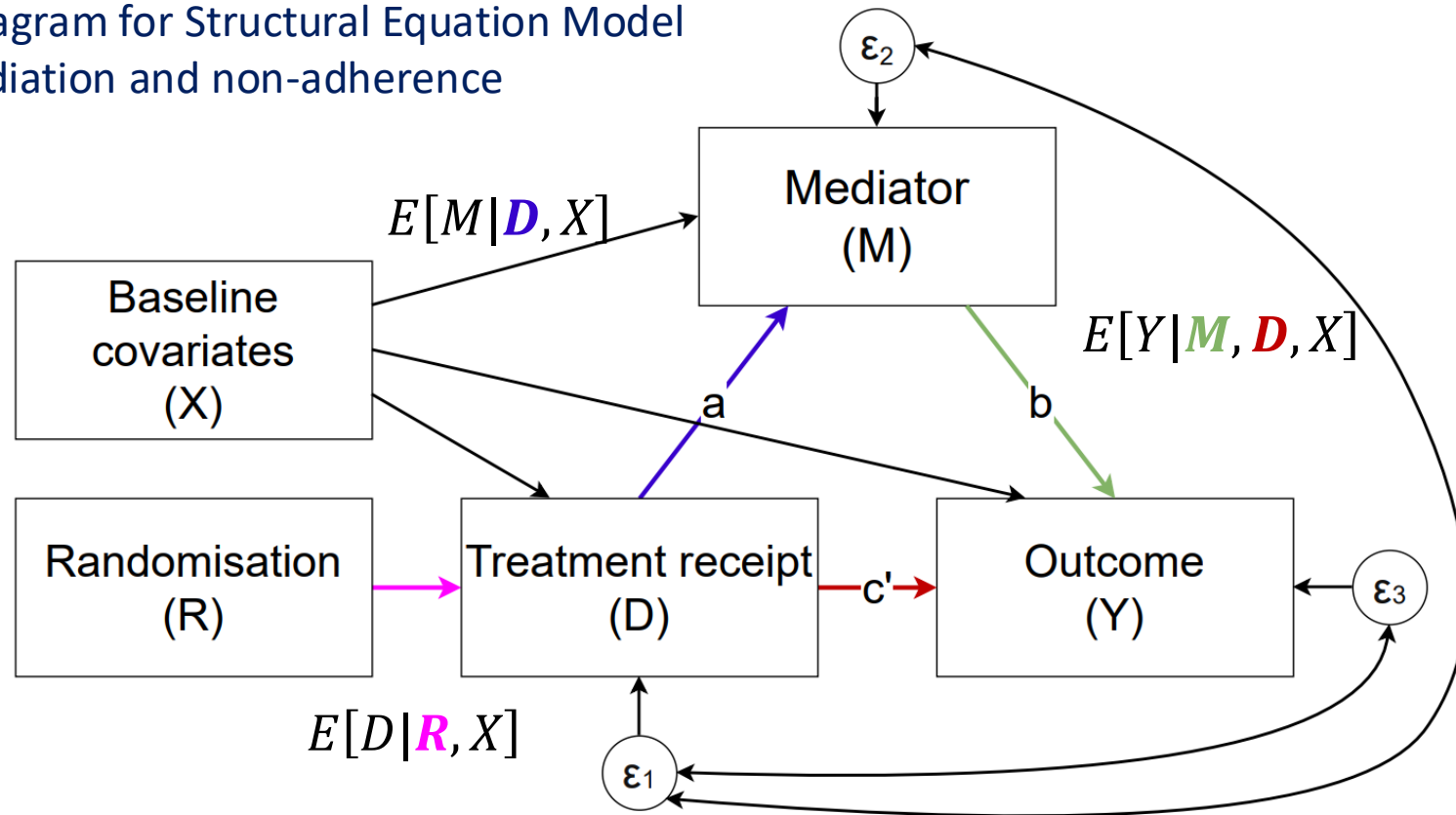
- Randomisation cannot directly influence the mediator or outcome variables

(4) Conditionally ignorable observed mediator among compliers

- No unmeasured confounding between the mediator and outcome

# Combining mediation and non-adherence: Estimation

**Figure:** Path diagram for Structural Equation Model combining mediation and non-adherence



$$\text{CACME} = a * b$$

$$\text{CANDE} = c'$$

# Illustrating example: The AVATAR study

- 150 participants randomised 1:1 to receive **AVATAR therapy** or supportive counselling for psychosis related symptoms
- The primary outcome was the total score on the **Psychotic Symptom Rating Scales** at 12 weeks and was analysed with the **ITT principle**
- 84% compliance (attended  $\geq 3$  of 6 sessions)
- Mediator of interest is the participants **acceptance-based attitudes** in relation to their auditory hallucinations



# Estimation via `-sem-`

```
sem (R -> D) (D -> M) (D M -> Y) ,  
cov(e.D*e.M) cov(e.D*e.Y)
```

- The path `(R -> D)` implements IV theory and accounts for the endogeneity in D
- The covariances `cov(e.D*e.M)` and `cov(e.D*e.Y)` are essential as they allow for unmeasured confounding between D-M and D-Y

```
estat teffects
```

- Produces many results and paths – many are not relevant
- Can be difficult to identify which paths correspond to the CACME and CANDE

# Estimation via the `-sem-` command

The screenshot displays the Stata/MP 18.0 software interface. The main window is titled "Stata/MP 18.0 - C:\Users\k2036498\OneDrive - King's College London\Documents\PhD\Anca's PhD\AVATAR files for ANCA\Dataset\AVATAR\_analysis set\_July17.dta". The menu bar includes File, Edit, Data, Graphics, Statistics, User, Window, and Help. The toolbar contains icons for file operations, viewing, and analysis. The main workspace is empty, showing a list of variables on the left. The Command window at the bottom is titled "Command" and is currently empty. On the right side, the Variables and Properties panels are visible. The Variables panel shows a list of variables: Name, Label, Personid, REG\_03, REG\_04, REG\_05, REG\_06, EX\_05, and a partially visible "REG\_07". The Properties panel shows the properties for the selected variable, "Label".

Variables	
Name	Label
Label	Subject Label
Type	str50
Format	%50s
Value label	
Notes	

Data	
Frame	default

The status bar at the bottom shows the file path: "C:\Users\k2036498\OneDrive - King's College London\Documents\PhD\Anca's PhD\AVATAR files for ANCA\Dataset" and the variable list: "CAP NUM INS".



# The `–compmed–` command: Motivation

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- Estimating the CACME and CANDE requires
  - (1) Knowledge of SEMs and the SEM Stata package
  - (2) Fitting the correct Structural Equation Model
  - (3) Identifying the correct pathways that correspond to the CACME and CANDE
- `compmed` offers a standardised approach for estimating the CACME and CANDE in Stata using a single, more intuitive, and user-friendly programme.

# The `—compmed—` command: Syntax

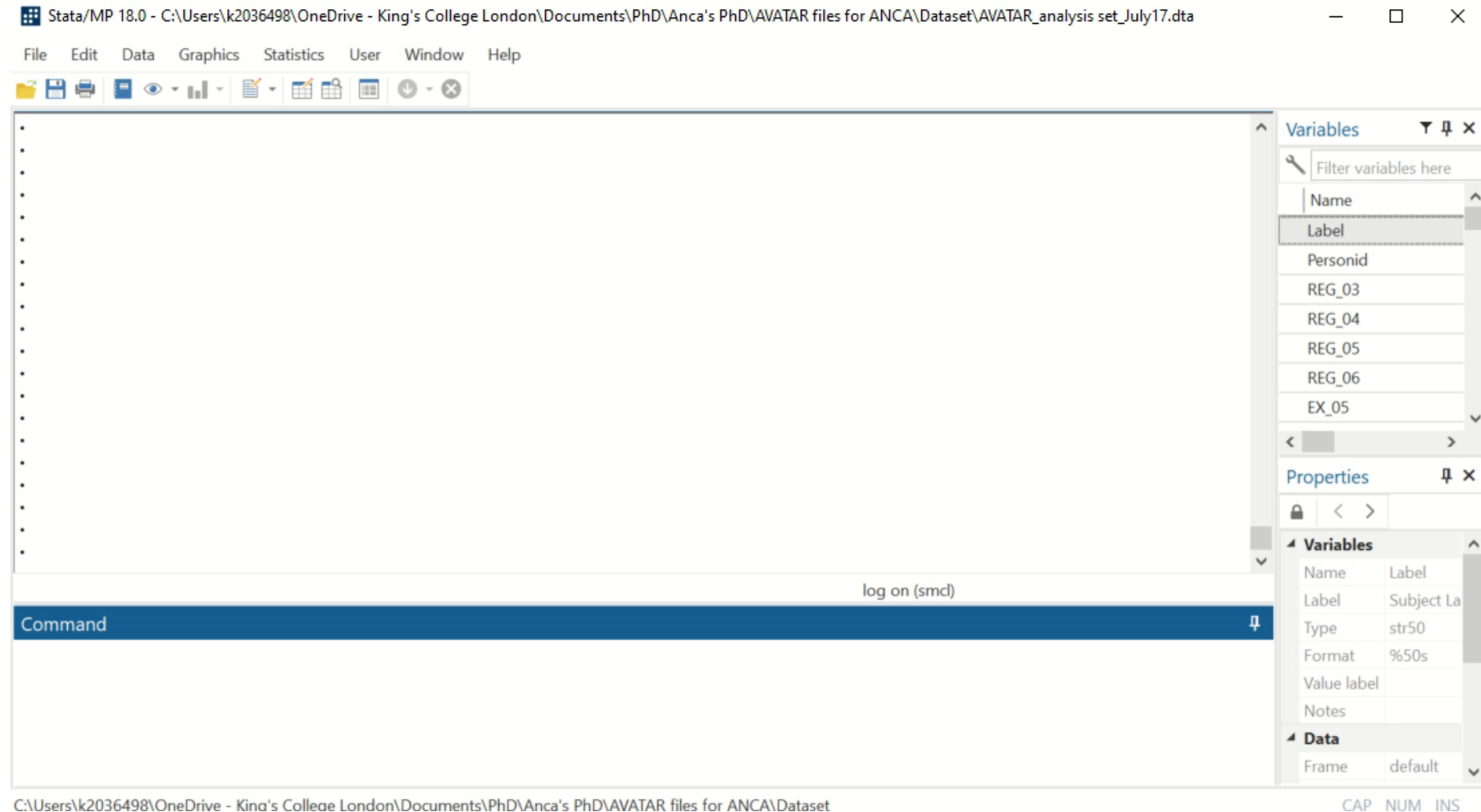
```
compmed Y, mvar(M) dvar(D) rvar(R) cvars(varlist)  
[, vce(vcetype) FULLoutput]
```

**cvars(varlist)** determines the list of covariates that are included in the outcome and mediator models.

**vce(vcetype)** calculates the standard error of the estimator. `vcetype` can be `oim` (observed information matrix), `robust` (Huber/White/sandwich estimator), `bootstrap`, or `cluster` (generalized Huber/White/sandwich estimator). If the option is not specified, the default is `oim`.

**FULLoutput** reports the full decomposition of effects into total, direct, and indirect effects, along with standard errors obtained by the delta method (Sobel, 1987). This option is equivalent to the `'estat teffects'` command that is for use after running an the `sem` command in Stata.

# The `—compmed—` command: Demonstration



# Missing data consideration

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- Both `-sem-` and `-compmed-` undertake a **complete-case analysis**, i.e., observations with missing values are dropped from the analysis
- The analysis is therefore valid provided the missing data are **MCAR**, or **MAR** (provided all variables that drive missingness are in the analysis model)
  - ✓ Information on non-adherence, a common predictor of missingness, is already included in the analysis model
- A Monte Carlo simulation study demonstrates that unbiased estimates of CACME, CANDE, and CACE can be obtained under the MCAR and MAR scenarios explored (full results and details not described here)

# Final remarks

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- The CACE can be partitioned into a CACME and CANDE under a given set of assumptions and can be estimated with linear SEMs
- A new Stata program, `compmed`, provides a practical tool for undertaking causal mediation analysis with non-adherence
  1. Fits the correct SEM model
  2. Automatically identifies the paths that correspond to the CACME and CANDE
  3. Outputs a nice and simple table with these estimates

# Questions

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anca.m.chis\_ster@kcl.ac.uk  
@anca\_chisster