Presented by
Daniel Almirall, PhD

Primary Aim Analyses in a SMART

Part II

Module 5

60 min

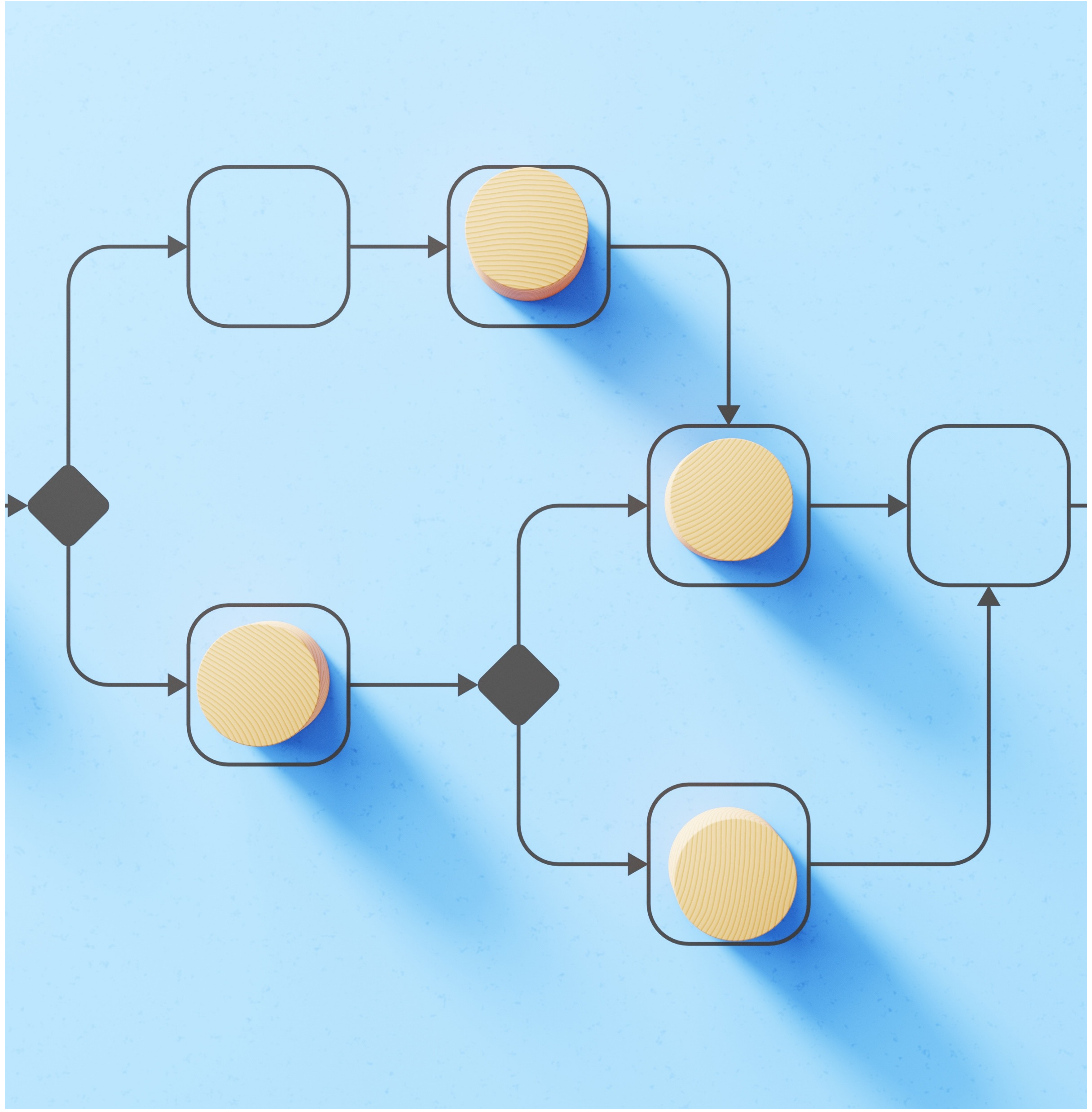
catie d3c

Learning Objectives

You will have a better understanding, and will continue learning how to frame, the typical Primary Aims in a SMART

You will learn about key statistical considerations in Primary Aim analyses in a SMART

You will learn how to interpret the output for the different Primary Aim Analyses in a SMART



Outline

Illustrative Example: ADHD SMART Study (PI: Pelham)

Prepare (again) for a third primary aim analysis by
(d): Estimate and compare the mean outcome under two of the embedded AIs using weighted least squares

Use a single weighted-and-replicated least squares regression approach capable of address any/all three primary aims in a SMART

Outline

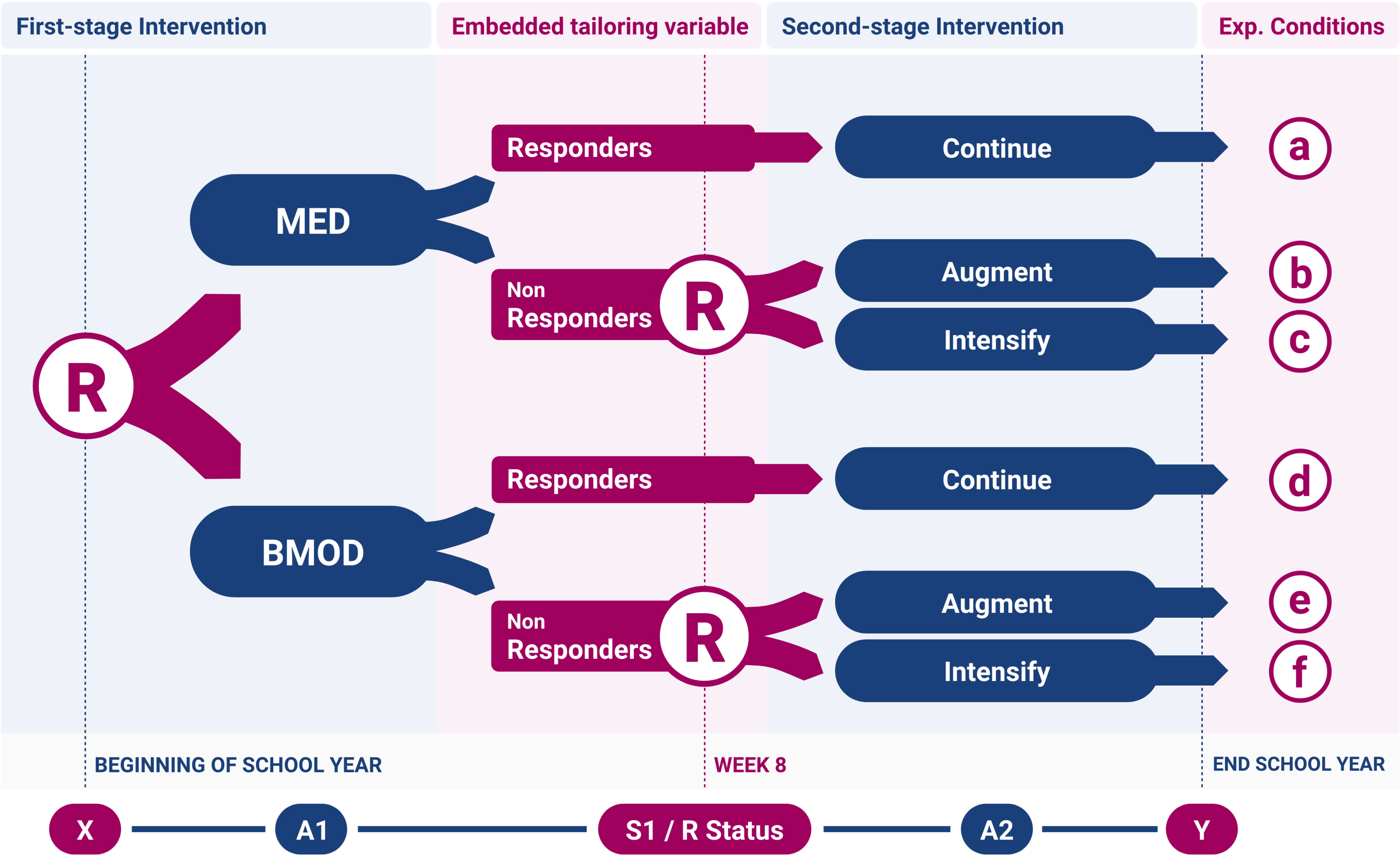
Illustrative Example: ADHD SMART Study (PI: Pelham)

Prepare (again) for a third primary aim analysis by
(d): Estimate and compare the mean outcome under two of the embedded AIs using weighted least squares

Use a single weighted-and-replicated least squares regression approach capable of address any/all three primary aims in a SMART

SMART Example ADHD Study

PI: Pelham



4 Embedded Adaptive Interventions

Adaptive Intervention 1

At the beginning of the school year **Stage 1 = {MED};**
then, every month, starting week 8
if response status = {NR},
then, **Stage 2 = {AUGMENT}**;
else if response status = {R},
then, **Continue Stage 1**

Adaptive Intervention 2

At the beginning of the school year **Stage 1 = {BMOD};**
then, every month, starting week 8
if response status = {NR},
then, **Stage 2 = {AUGMENT}**;
else if response status = {R},
then, **Continue Stage 1**

Adaptive Intervention 3

At the beginning of the school year **Stage 1 = {MED};**
then, every month, starting week 8
if response status = {NR},
then, **Stage 2 = {INTENSIFY}**;
else if response status = {R},
then, **Continue Stage 1**

Adaptive Intervention 4

At the beginning of the school year **Stage 1 = {BMOD};**
then, every month, starting week 8
if response status = {NR},
then, **Stage 2 = {INTENSIFY}**;
else if response status = {R},
then, **Continue Stage 1**

Compare 2 Embedded AIs

Adaptive Intervention 1

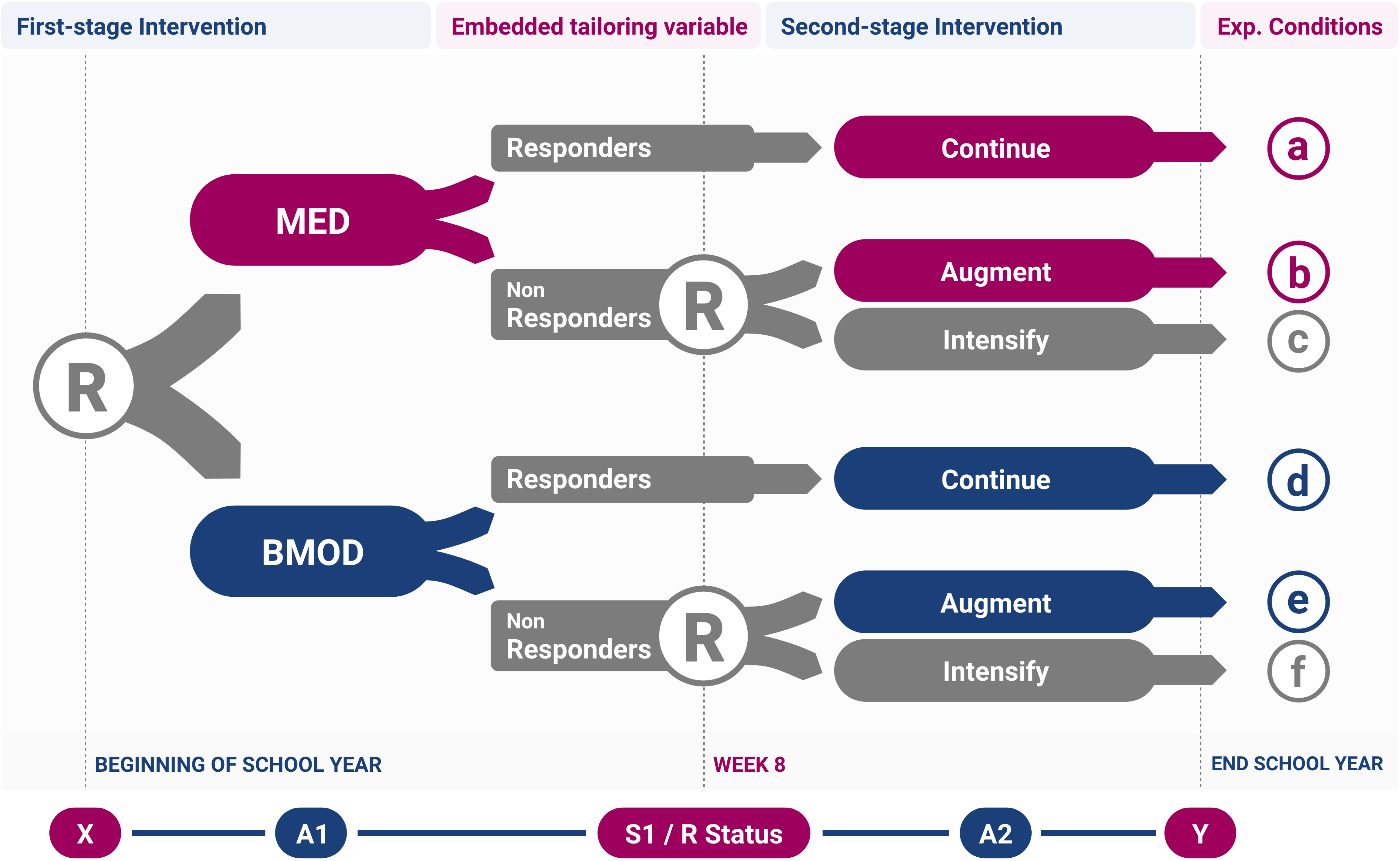
At the beginning of the school year
Stage 1 = {MED};
then, every month, starting week 8
if response status = {NR},
then, Stage 2 = {AUGMENT};
else if response status = {R},
then, Continue Stage 1

VS

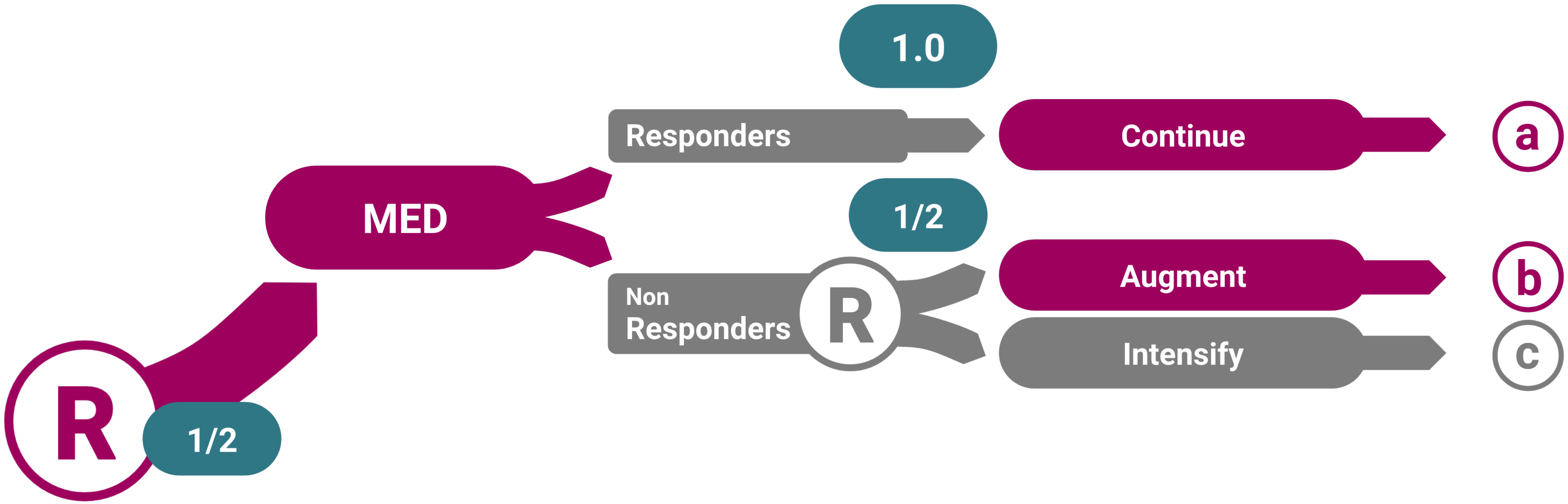
Adaptive Intervention 2

At the beginning of the school year
Stage 1 = {BMOD};
then, every month, starting week 8
if response status = {NR},
then, Stage 2 = {AUGMENT};
else if response status = {R},
then, Continue Stage 1

This Aim is a Comparison of the Mean Outcome under AI#1 vs. the Mean Outcome of AI#2



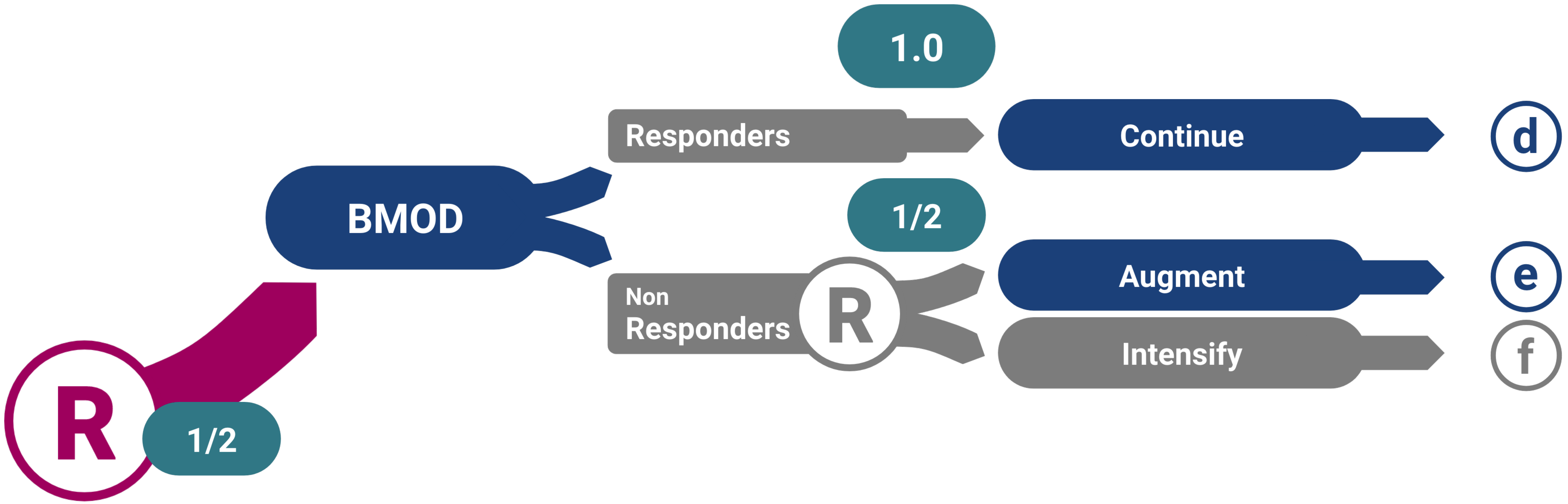
We Know How to Account for Imbalance in Non-Responders Following AI#1



- Assign W = weight = 2 to responders to MED → 2* ½ = 1
- Assign W = weight = 4 to non-responders to MED → 4* ¼ =1

- Then we take W-weighted mean of sample who ended up in circles A+B.

A Similar Approach (and SAS Code) Can be Used to Obtain Mean Under AI #2



- Assign W = weight = 2 to responders to BMOD → 2* ½ = 1
- Assign W = weight = 4 to non-responders to BMOD → 4* ¼ =1

- Then we take W-weighted mean of sample who ended up in circles D+E.

Results for Estimated Mean Outcome had All Participants Followed AI#2 (BMOD, AUGMENT)

Results are from simulated data.

Analysis Of GEE Parameter Estimates			
Parameter	**Estimate**	**Standard Error**	**Pr > |Z|**
Intercept	3.149	0.1477	<.0001
Z1	0.6836	0.1477	0.0001

Contrast Estimate Results					
		95% Confidence Limits			
Label	**Mean Estimate**	**Lower**	**Upper**	**Standard Error**	**Pr > ChiSq**
Mean Y under AI #2 (BMOD, AUGMENT)	**3.833**	3.363	4.303	**0.24**	**<.0001**

Interpretation: The estimated mean school performance score for children consistent with AI #2 is ~3.83 (95% CI: (3.36, 4.30)).

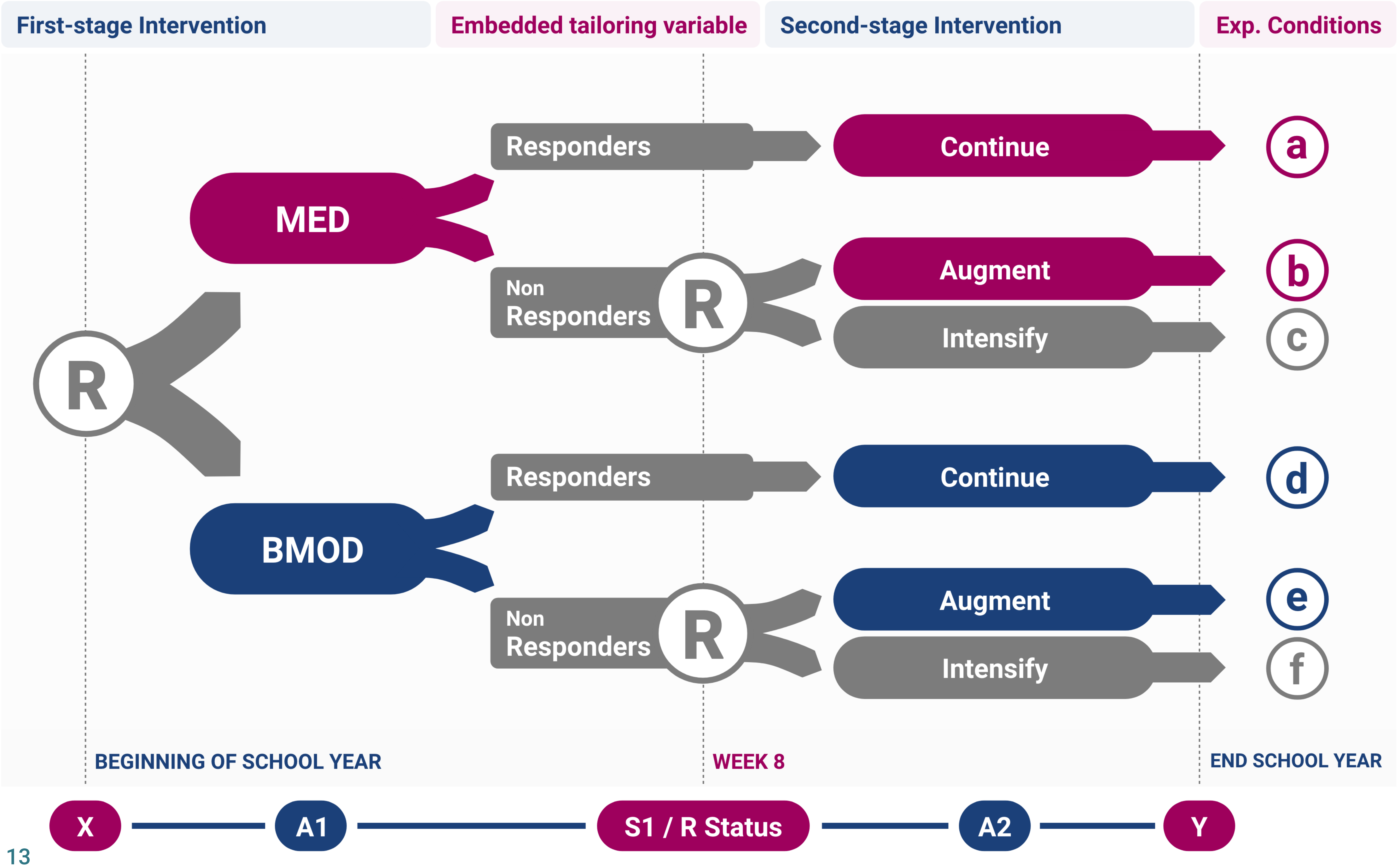
Outline

Illustrative Example: ADHD SMART Study (PI: Pelham)

Prepare (again) for a third primary aim analysis by
(d): Estimate and compare the mean outcome under two of the embedded AIs using weighted least squares

Use a single weighted-and-replicated least squares regression approach capable of address any/all three primary aims in a SMART

An Intuitive [Yet Less Efficient] Approach to Comparing AI#1 vs. AI#2



An Intuitive [Yet Less Efficient] Approach to Comparing AI#1 vs. AI#2

```
data dat7; set dat1;
 Z1=-1;
          if A1*R=-1 then Z1=1;
          if (1-A1)*(1-R)*A2=-2 then Z1=1;
 Z2=-1;
          if A1*R= 1 then Z2=1;
          if (1+A1)*(1-R)*A2=-2 then Z2=1;
 W=2*R + 4*(1-R);
run;
```

Create Z1 –> indicator for whether or not the person is consistent with AI#1

```
data dat8;
 set dat7; if Z1=1 or Z2=1;
run;
```


This analysis is with simulated data.

An Intuitive [Yet Less Efficient] Approach to Comparing AI#1 vs. AI#2

```
data dat7; set dat1;
 Z1=-1;
          if A1*R=-1 then Z1=1;
          if (1-A1)*(1-R)*A2=-2 then Z1=1;
 Z2=-1;
          if A1*R= 1 then Z2=1;
          if (1+A1)*(1-R)*A2=-2 then Z2=1;
 W=2*R + 4*(1-R);
run;
```

Create Z2 –> indicator for whether or not the person is consistent with AI#2

```
data dat8;
 set dat7; if Z1=1 or Z2=1;
run;
```


This analysis is with simulated data.

An Intuitive [Yet Less Efficient] Approach to Comparing AI#1 vs. AI#2

```
data dat7; set dat1;
 Z1=-1;
          if A1*R=-1 then Z1=1;
          if (1-A1)*(1-R)*A2=-2 then Z1=1;
 Z2=-1;
          if A1*R= 1 then Z2=1;
          if (1+A1)*(1-R)*A2=-2 then Z2=1;
 W=2*R + 4*(1-R);
run;
```

Assigned Weights

```
data dat8;
 set dat7; if Z1=1 or Z2=1;
run;
```


This analysis is with simulated data.

An Intuitive [Yet Less Efficient] Approach to Comparing AI#1 vs. AI#2

```
data dat7; set dat1;
 Z1=-1;
        if A1*R=-1 then Z1=1;
        if (1-A1)*(1-R)*A2=-2 then Z1=1;
 Z2=-1;
        if A1*R= 1 then Z2=1;
        if (1+A1)*(1-R)*A2=-2 then Z2=1;
 W=2*R + 4*(1-R);
run;


data dat8;
 set dat7; if Z1=1 or Z2=1;
run;
```

Delete data from participants not consistent with either AI#1 or AI#2

This analysis is with simulated data.

An Intuitive [Yet Less Efficient] Approach to Comparing AI#1 vs. AI#2

The Regression and Contrast Coding Logic:

Recall:

Z_1 is now an indicator for whether the person is consistent with AI#1 or with AI#2:

→ $Z_1 = 1$ = AI#1

→ $Z_1 = -1$ = AI#2

To compare the 2 AIs, we can fit the Model:

$$Y = \beta_0 + \beta_1 Z_1 + e$$

Overall Mean Y under AI#1 = $\boldsymbol{\beta_0 + \beta_1 \times 1}$

Overall Mean Y under AI#2 = $\boldsymbol{\beta_0 + \beta_1 \times -1}$

Diff Between AIs = $\boldsymbol{\beta_0 + \beta_1 - (\beta_0 - \beta_1) = 2\beta_1}$

This analysis is with simulated data.

An Intuitive [Yet Less Efficient] Approach to Comparing AI#1 vs. AI#2

```
proc genmod data = dat8;
  class id;
  model Y = Z1;
  scwgt W;
  repeated subject = id / type = ind;
  estimate 'Mean Y AI#1(MED, Add BMOD)' intercept 1 Z1  1;
  estimate 'Mean Y AI#2(BMOD, Add MED)' intercept 1 Z1 -1;
  estimate 'Diff: AI#1 - AI#2'                      Z1  2;
run;
```

Mean Y under AI#1	= $\boldsymbol{\beta_0 + \beta_1 \times 1}$
Mean Y under AI#2	= $\boldsymbol{\beta_0 + \beta_1 \times -1}$
Diff Between AIs	= $2\beta_1$

This analysis is with simulated data.

An Intuitive [Yet Less Efficient] Approach to Comparing AI#1 vs. AI#2

Analysis Of GEE Parameter Estimates

Parameter	Estimate	Standard Error	Pr > |Z|
Intercept	3.25	0.1613	<.0001
Z1	-0.583	0.1613	0.0003

Contrast Estimate Results

Label	Mean Estimate	95% Confidence Limits		Standard Error	Pr > ChiSq
		Lower	Upper		
Mean Y under AI #1 (MED, AUGMENT)	**2.666**	2.242	3.0892	**0.216**	**<.0001**
Mean Y under AI #2 (BMOD, AUGMENT)	**3.833**	3.363	4.3028	**0.240**	**<.0001**
Diff: AI#1 – AI#2	**-1.167**	-1.799	-0.5347	**0.323**	**0.0003**

Notice SE

This analysis is with simulated data.

An Intuitive Approach to Comparing AI#1 vs. AI#2

```
proc genmod data = dat8;
 class id;
 model Y = Z1  Y0c oddc;
 scwgt w;
 repeated subject = id / type = ind;
 estimate 'Mean Y AI#1(MED, AUGMENT)' intercept 1 Z1  1;
 estimate 'Mean Y AI#2(BMOD,AUGMENT)' intercept 1 Z1 -1;
 estimate 'Diff: AI#1 - AI#2'                  Z1  2;
run;
```

Adding baseline control covariates (mean centered)

An Intuitive Approach to Comparing AI#1 vs. AI#2

Analysis Of GEE Parameter Estimates

Parameter	Estimate	Standard Error	Pr > |Z|
Intercept	3.26	0.1148	<.0001
Z1	-0.45	0.1160	<.0001
Y0	2.13	0.2464	<.0001
oddc	0.09	0.2511	0.715

Contrast Estimate Results

Label	Mean Estimate	95% Confidence Limits Lower	95% Confidence Limits Upper	Standard Error	Pr > ChiSq
Mean Y under AI #1	**2.806**	2.5198	3.0927	**0.146**	**<.0001**
Mean Y under AI #2	**3.713**	3.3491	4.0787	**0.186**	**<.0001**
Diff: AI#1 – AI#2	**-0.907**	-1.3776	-0.4376	**0.240**	**0.0001**

Notice SE: Slightly smaller compared to the analysis without control covariates

This analysis is with simulated data.

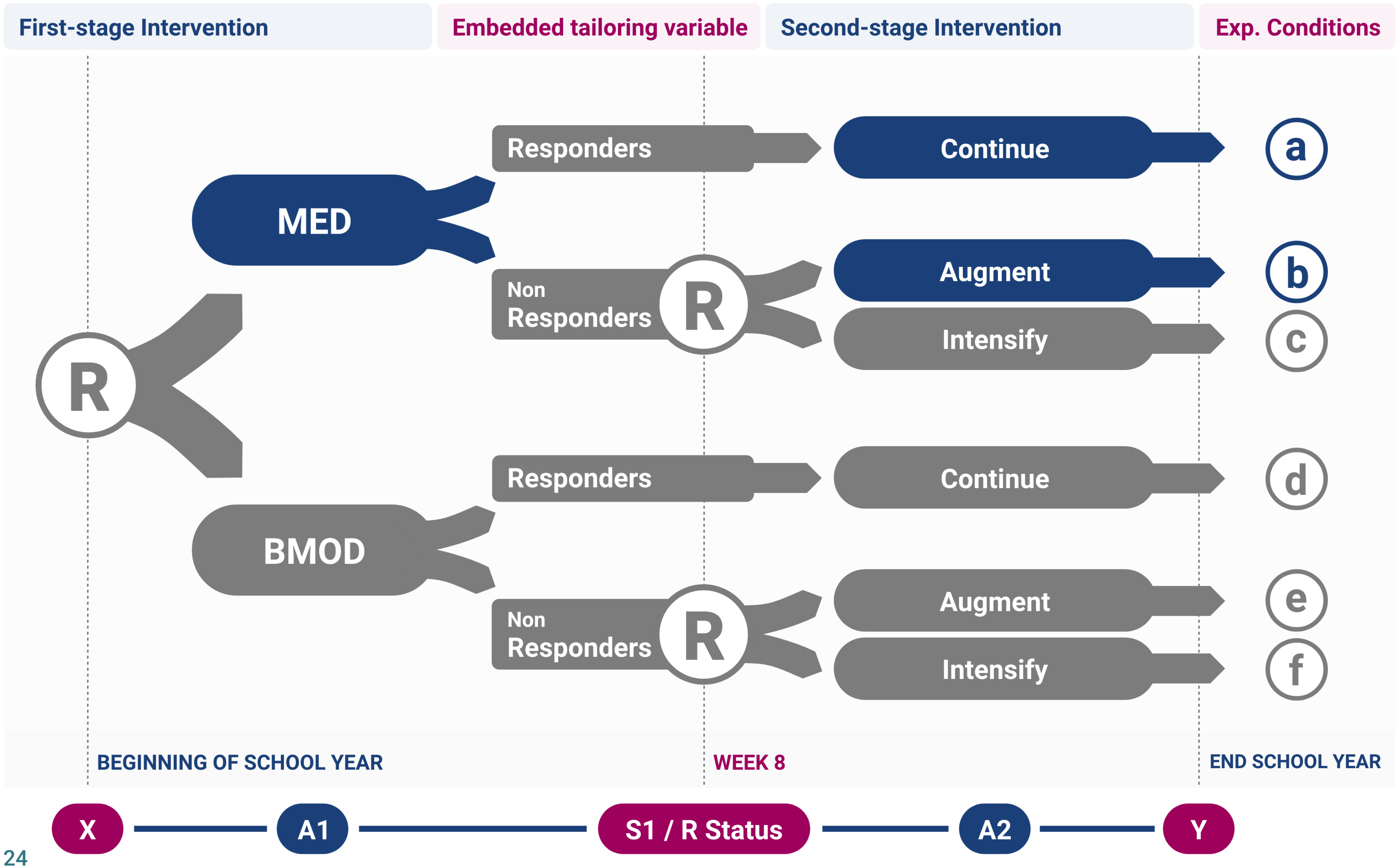
Outline

Illustrative Example: ADHD SMART Study (PI: Pelham)

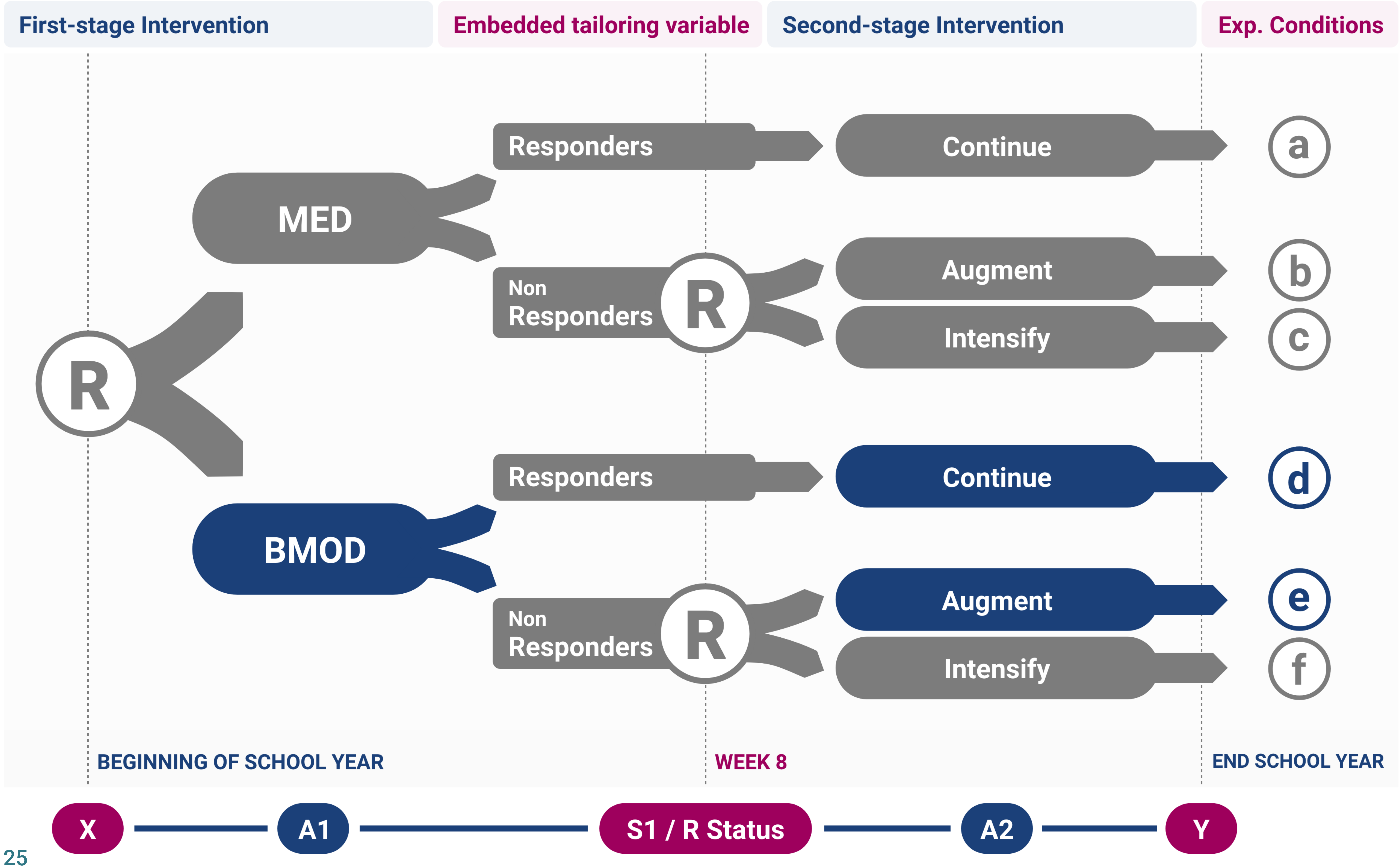
Prepare (again) for a third primary aim analysis by
(d): Estimate and compare the mean outcome under two of the embedded AIs using weighted least squares

Use a single weighted-and-replicated least squares regression approach capable of address any/all three primary aims in a SMART

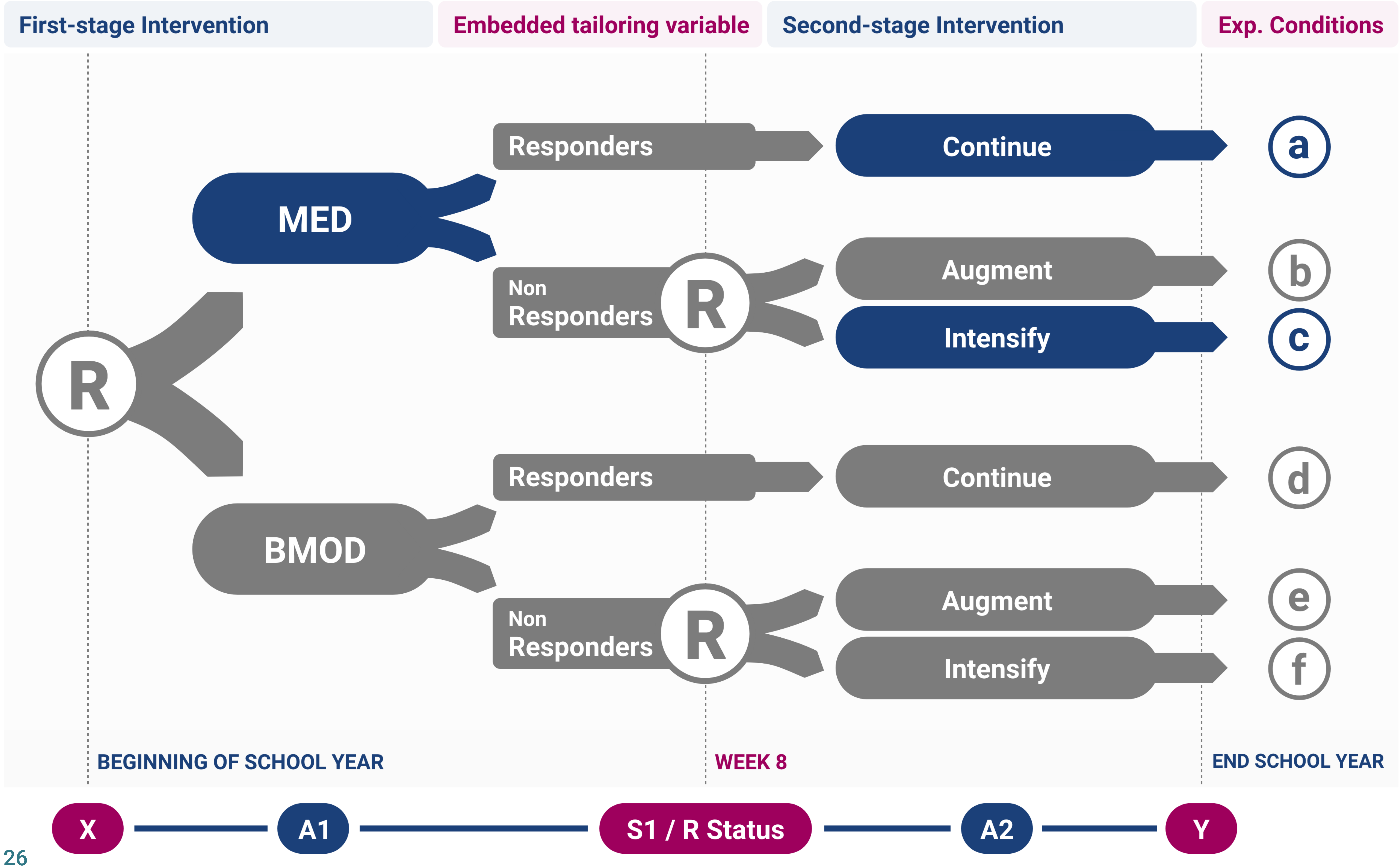
What about a regression to compare AI#1 (MED, add BMOD) vs…



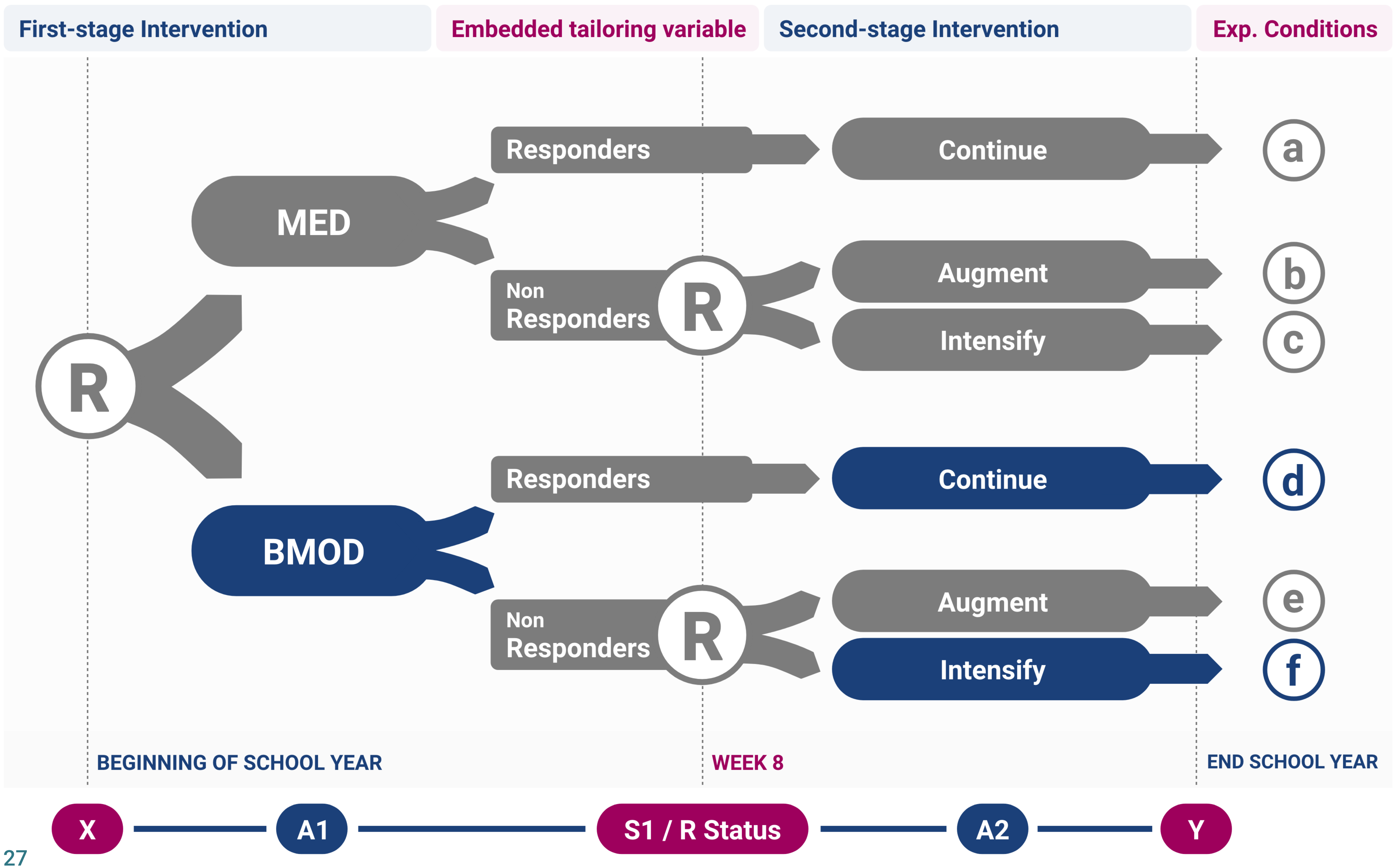
…AI #2 (BMOD, Add MED) vs…



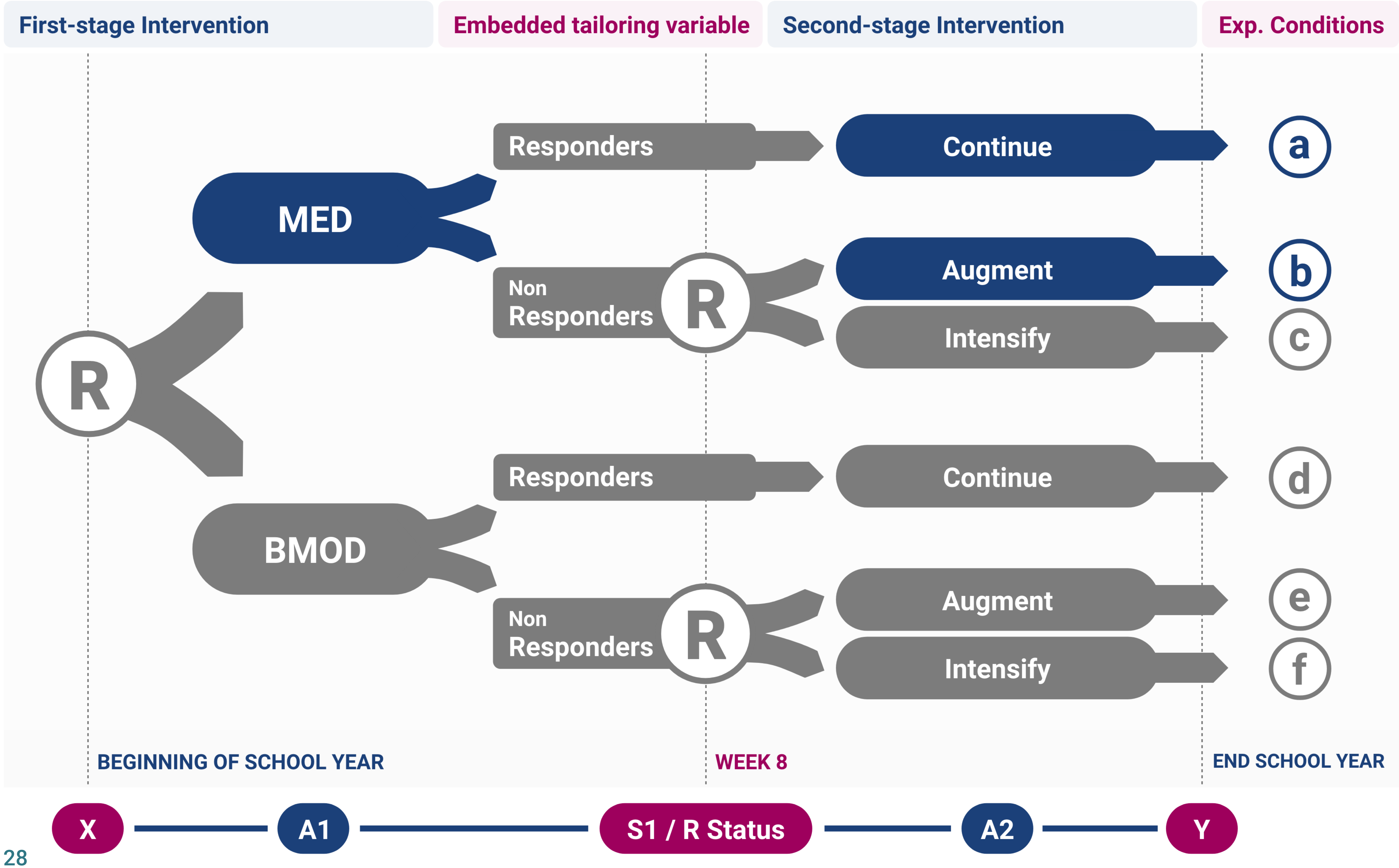
…AI #3 (MED, INTENSIFY) vs…



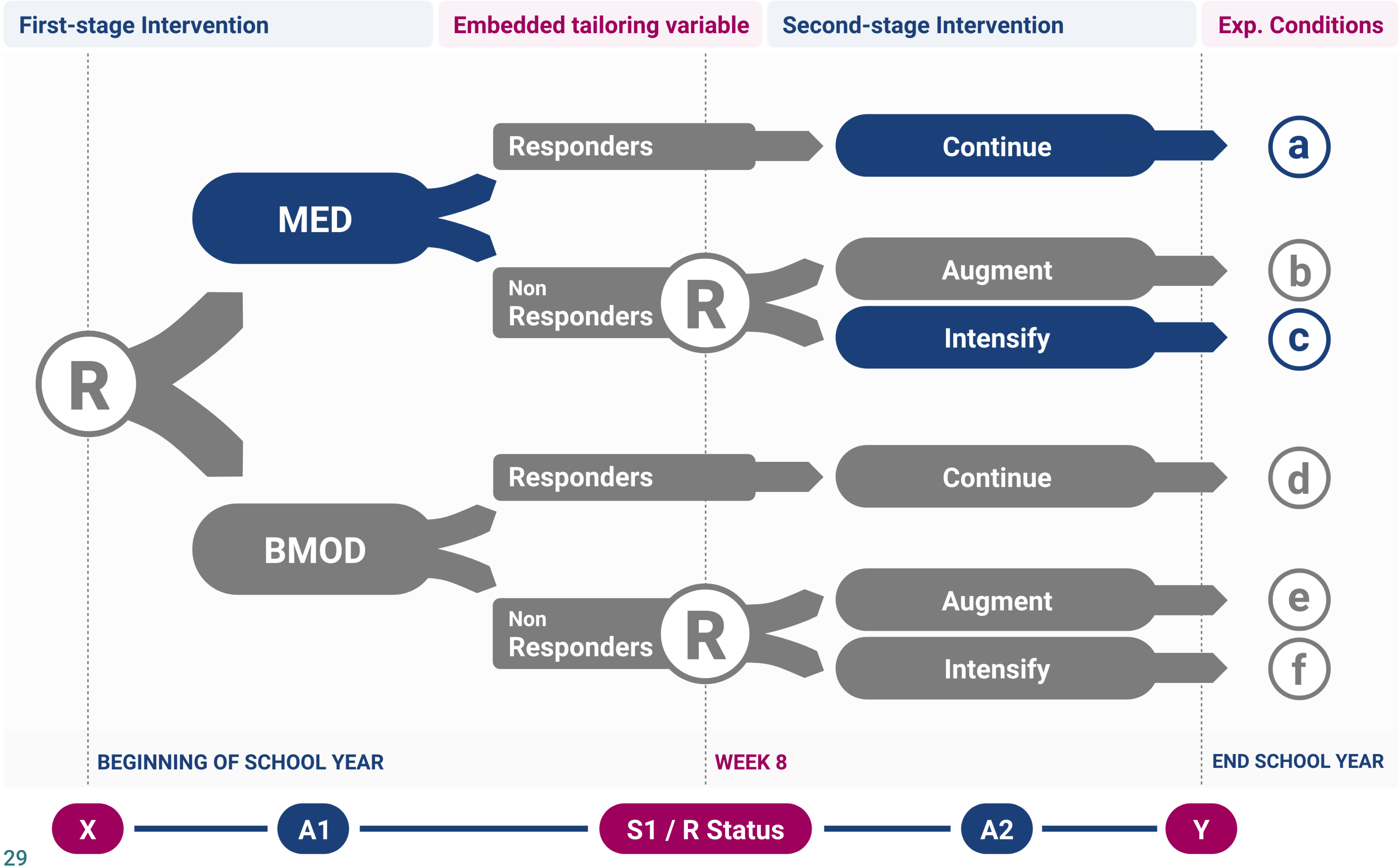
...AI#4 (BMOD, INTENSIFY), all in one swoop!



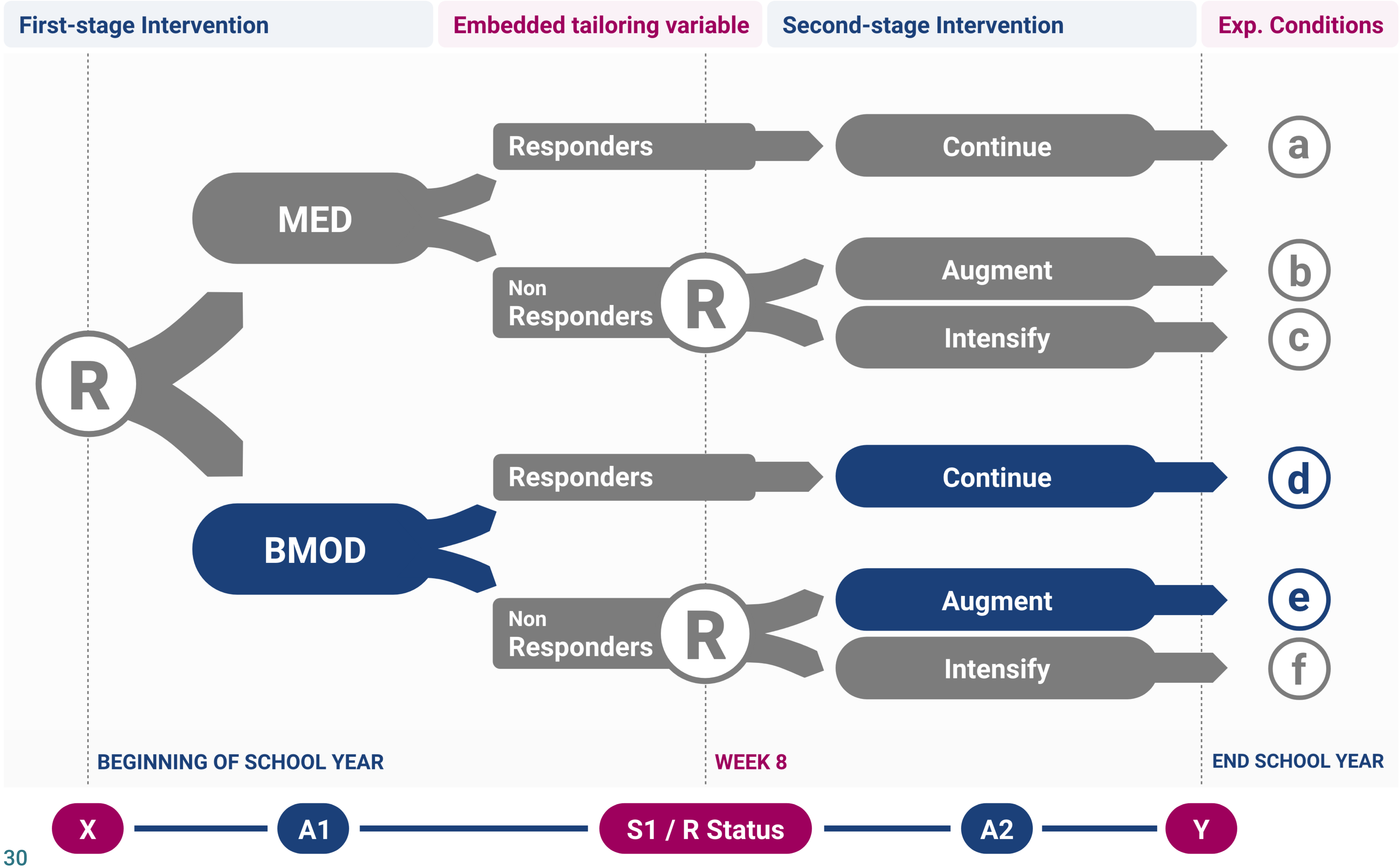
Notice that AI#1 and AI#3 (start MED) share responders (box A)



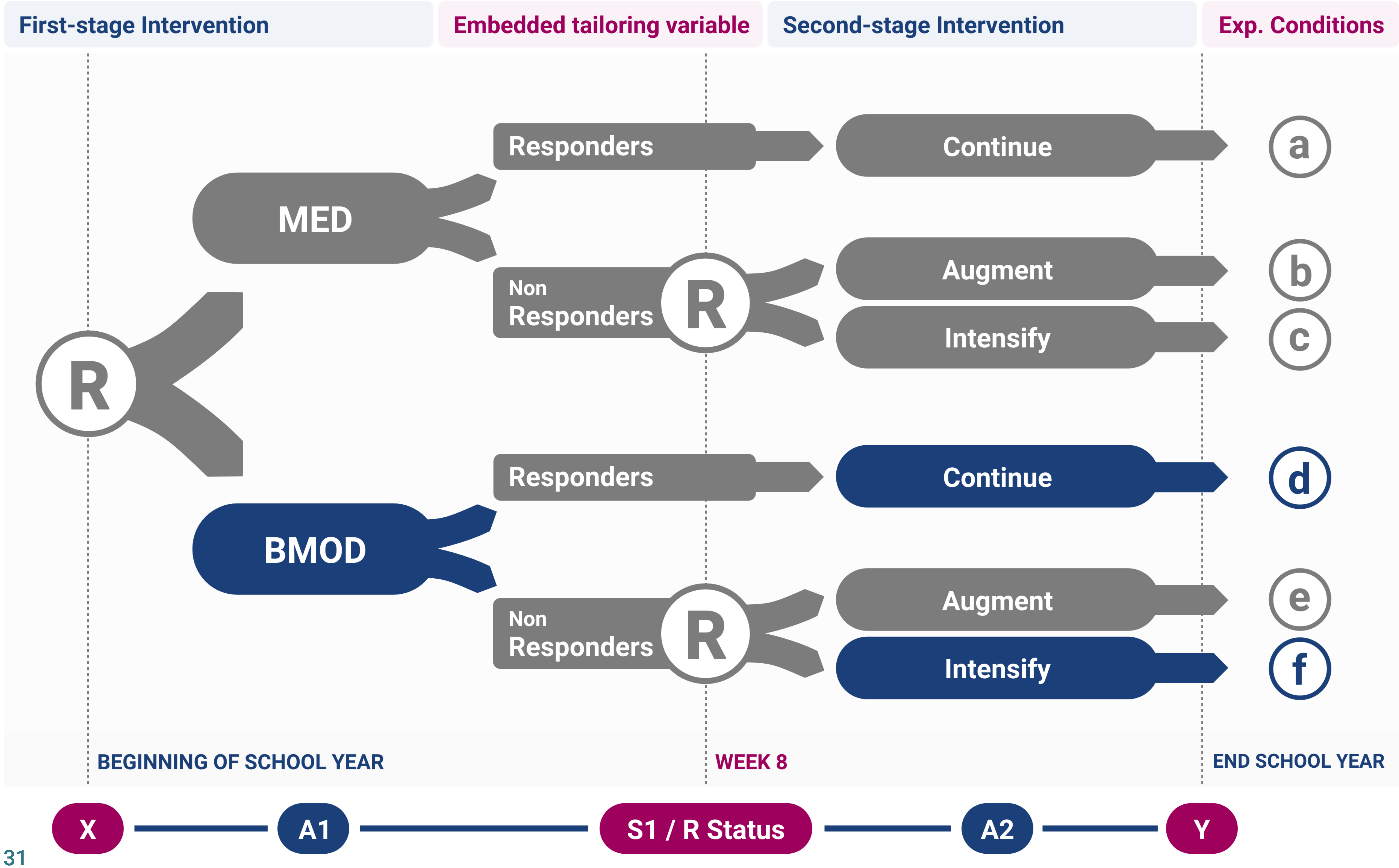
Notice that AI#1 and AI#3 (start MED) share responders (box A)



Similarly: Notice that AI#2 and AI#4 (start BMOD) share responders (box D)



Similarly: Notice that AI#2 and AI#4 (start BMOD) share responders (box D)



So, what’s going on?

In the ADHD SMART, all responders are consistent with two AIs

- Responders to MED are part of AI#1 and AI#3
- Responders to BMOD are part of AI#2 and AI#4

If our goal is to estimate the mean outcome under all AIs simultaneously, we must share responders somehow.

- But how?

What do we do?

- We "trick" the software into using the responders twice
- We do this by replicating responders:
    - Create 2 observations for each responder
    - We assign ½ of them A2 = 1, the other ½ A2 = -1
- W=2 to responders and W=4 to non-responders
- Robust standard errors account for weighting and the fact that responders are "re-used". No cheating here!

Weighting and Replicating Serve Different Purposes

Weighting

- Accounts for over/underrepresentation of responders or non-responders
- Because of the randomization scheme

Replicating

- Allows us to use standard software to do simultaneous estimation and comparison
- Because participants are consistent with more than one AI

SAS code for Replication-and-Weighting to Compare Means Under All Four AIs

```
data dat9; set dat1;
 if R=1 then do;
   ob = 1; A2 =-1; weight = 2; output;
   ob = 2; A2 = 1; weight = 2; output;
   end;
  else if R=0 then do;
   ob = 1; weight = 4; output;
   end;
run;
```

Replicated Data

Obs	ID	A1	R	A2	Y	o11c	o12c	o13c	o14c	ob	weight
45	32	1	1	−1	5	−0.35333	−2.73889	−0.31333	0.19333	1	2
46	32	1	1	1	5	−0.35333	−2.73889	−0.31333	0.19333	2	2
47	33	1	0	1	3	0.64667	−1.07820	0.68667	0.19333	1	4
48	34	1	0	1	2	[illegible]	[illegible]	−0.31333	0.19333	1	4
49	35	1	0	−1	5	[illegible]	[illegible]	−0.31333	0.19333	1	4
50	36	−1	0	1	1	[illegible]	[illegible]	−0.31333	0.19333	1	4
51	37	−1	1	−1	1	−0.35333	0.99556	−0.31333	0.19333	1	2
52	37	−1	1	1	1	−0.35333	0.99556	−0.31333	0.19333	2	2
53	38	−1	0	−1	3	−0.35333	0.14034	0.68667	−0.80667	1	4
54	39	−1	1	−1	3	0.64667	1.64983	0.68667	0.19333	1	2
55	39	−1	1	1	3	0.64667	1.64983	0.68667	0.19333	2	2

Responders are replicated!

Non-Responders aren't!

After Replication-and-Weighting, the SAS code for the weighted regression

The Regression and Contrast Coding Logic:

Recall:

- Our goal is to compare all 4 embedded AIs
- We have 2 indicators: A_1, A_2

$A_1 = 1$ -> BMOD

$A_1 = -1$ -> MED

$A_2 = 1$ -> INTENSIFY

$A_2 = -1$ -> AUGMENT

To compare all 4 AIs, we can fit the following Model:

$$Y = \beta_0 + \beta_1 A_1 + \beta_2 A_2 + \beta_3 A_1 A_2 + e$$

After Replication-and-Weighting, the SAS code for the weighted regression

The Regression and Contrast Coding Logic:

$$Y = \beta_0 + \beta_1 A_1 + \beta_2 A_2 + \beta_3 A_1 A_2 + e$$

Mean Y under AI#1 (MED, AUGMENT) = $\boldsymbol{\beta_0 + \beta_1(-1) + \beta_2(-1) + \beta_3(-1)(-1)}$

Mean Y under AI#2 (BMOD, AUGMENT) = $\boldsymbol{\beta_0 + \beta_1(1) + \beta_2(-1) + \beta_3(1)(-1)}$

Mean Y under AI#3 (MED, INTENSIFY) = $\boldsymbol{\beta_0 + \beta_1(-1) + \beta_2(1) + \beta_3(-1)(1)}$

Mean Y under AI#4 (BMOD, INTENSIFY) = $\boldsymbol{\beta_0 + \beta_1(1) + \beta_2(1) + \beta_3(1)(1)}$

A_1 = 1 -> BMOD

A_1 = -1 -> MED

A_2 = 1 -> INTENSIFY

A_2 = -1 -> AUGMENT

After Replication-and-Weighting, the SAS code for the weighted regression

The Regression and Contrast Coding Logic:

$$Y = \beta_0 + \beta_1 A_1 + \beta_2 A_2 + \beta_3 A_1 A_2 + e$$

Mean Y under AI#1 (-1, -1) = $\boldsymbol{\beta_0 + \beta_1(-1) + \beta_2(-1) + \beta_3(-1)(-1)}$

Mean Y under AI#2 (1, -1) = $\boldsymbol{\beta_0 + \beta_1(1) + \beta_2(-1) + \beta_3(1)(-1)}$

Mean Y under AI#3 (-1, 1) = $\boldsymbol{\beta_0 + \beta_1(-1) + \beta_2(1) + \beta_3(-1)(1)}$

Mean Y under AI#4 (1, 1) = $\boldsymbol{\beta_0 + \beta_1(1) + \beta_2(1) + \beta_3(1)(1)}$

A_1 = 1 -> BMOD
A_1 = -1 -> MED

A_2 = 1 -> INTENSIFY
A_2 = -1 -> AUGMENT

After Replication-and-Weighting, the SAS code for the weighted regression

The Regression and Contrast Coding Logic:

$$Y = \beta_0 + \beta_1 A_1 + \beta_2 A_2 + \beta_3 A_1 A_2 + e$$

Mean Y under AI#1 (-1, -1) = $\boldsymbol{\beta_0 + \beta_1(-1) + \beta_2(-1) + \beta_3(-1)(-1)}$

Mean Y under AI#2 (1, -1) = $\boldsymbol{\beta_0 + \beta_1(1) + \beta_2(-1) + \beta_3(1)(-1)}$

Mean Y under AI#3 (-1, 1) = $\boldsymbol{\beta_0 + \beta_1(-1) + \beta_2(1) + \beta_3(-1)(1)}$

Mean Y under AI#4 (1, 1) = $\boldsymbol{\beta_0 + \beta_1(1) + \beta_2(1) + \beta_3(1)(1)}$

Diff AI#1 – AI#2 = $\boldsymbol{(\beta_0 - \beta_1 - \beta_2 + \beta_3) - (\beta_0 + \beta_1 - \beta_2 - \beta_3) = -2\beta_1 + 2\beta_3}$

After Replication-and-Weighting, the SAS code for the weighted regression

```
proc genmod data = dat9;
 class id;
 model Y = A1 A2 A1*A2;
 scwgt weight;
 repeated subject = id / type = ind;
 estimate 'MeanY:AI#1(MED,AUGMENT) ' int 1 A1 -1 A2 -1 A1*A2  1;
 estimate 'MeanY:AI#2(BMOD,AUGMENT)' int 1 A1  1 A2 -1 A1*A2 -1;
 estimate 'MeanY:AI#3(MED,INTENSFY)' int 1 A1 -1 A2  1 A1*A2 -1;
 estimate 'MeanY:AI#4(BMOD,INTNSFY)' int 1 A1  1 A2  1 A1*A2  1;
 estimate '  Diff: AI#1 - AI#2     ' int 0 A1 -2 A2  0 A1*A2  2;
 estimate '  Diff: AI#1 - AI#3     ' int 0 A1  0 A2 -2 A1*A2  2;
 estimate '  Diff: AI#1 - AI#4     ' int 0 A1 -2 A2 -2 A1*A2  0; *etc...;
run;
```

After Replication-and-Weighting, the SAS code for the weighted regression

Diff AI#1 – AI#2 = $-2\beta_1 + 2\beta_3$

```
proc genmod data = dat9;
 class id;
 model Y = A1 A2 A1*A2;
 scwgt weight;
 repeated subject = id / type = ind;
 estimate 'MeanY:AI#1(MED,AUGMENT) ' int 1 A1 -1 A2 -1 A1*A2  1;
 estimate 'MeanY:AI#2(BMOD,AUGMENT)' int 1 A1  1 A2 -1 A1*A2 -1;
 estimate 'MeanY:AI#3(MED,INTENSFY)' int 1 A1 -1 A2  1 A1*A2 -1;
 estimate 'MeanY:AI#4(BMOD,INTNSFY)' int 1 A1  1 A2  1 A1*A2  1;
 estimate '  Diff: AI#1 - AI#2     ' int 0 A1 -2 A2  0 A1*A2  2;
 estimate '  Diff: AI#1 - AI#3     ' int 0 A1  0 A2 -2 A1*A2  2;
 estimate '  Diff: AI#1 - AI#4     ' int 0 A1 -2 A2 -2 A1*A2  0; *etc...;
run;
```

Comparing Mean Outcomes for All AIs Simultaneously

Contrast Estimate Results

Label	Mean Estimate	95% Confidence Limits Lower	95% Confidence Limits Upper	Standard Error
Mean Y under AI #1 (MED, AUGMENT)	2.643	2.5305	3.1992	0.1706
Mean Y under AI #2 (BMOD, AUGMENT)	3.798	3.1643	3.8490	0.1747
Mean Y under AI #3 (MED, INTENSIFY)	2.342	2.4644	3.1145	0.1658
Mean Y under AI #4 (BMOD, INTENSIFY)	3.208	2.2515	3.0552	0.2050
Diff: AI#1 – AI#2	-1.16	-1.799	-0.5347	0.323
Diff: AI#1 – AI#3	0.0754	-0.3106	0.4614	0.1969

<u>NOTE</u>: We get the exact same results as before when we compared AI#1 vs AI#2, but now we can simultaneously make inference for all the comparisons.

This analysis is with simulated data.

But wait, there’s more…

Weighted-and-replicated regression can improve statistical precision (power)!

Replicated-and-Weighted Regression is More Efficient Statistically

```
proc genmod data = dat9;
 class id;
 model Y = A1 A2 A1*A2   Y0c  oddc;
 scwgt weight;
 repeated subject = id / type = ind;
 estimate 'MeanY:AI#1(MED,AUGMENT) ' int 1 A1 -1 A2 -1 A1*A2  1;
 estimate 'MeanY:AI#2(BMOD,AUGMENT)' int 1 A1  1 A2 -1 A1*A2 -1;
 estimate 'MeanY:AI#3(MED,INTENSFY)' int 1 A1 -1 A2  1 A1*A2 -1;
 estimate 'MeanY:AI#4(BMOD,INTNSFY)' int 1 A1  1 A2  1 A1*A2  1;
 estimate '  Diff: AI#1 - AI#2     ' int 0 A1 -2 A2  0 A1*A2  2;
 estimate '  Diff: AI#1 - AI#3     ' int 0 A1  0 A2 -2 A1*A2  2;
 estimate '  Diff: AI#1 - AI#4     ' int 0 A1 -2 A2 -2 A1*A2  0; *etc...;
run;
```

Improve power: Adjusting for baseline covariates that are associated with outcome leads to more efficient estimates (lower standard error = more power = smaller p-value).

Results for Weighted-and-Replicated Regression: Comparing Mean Outcome for all AIs Simultaneously

<u>Improved efficiency</u>: Adjusting for baseline covariates resulted in lower standard error and tighter confidence intervals. Point estimates remained about the same, as expected.

Contrast Estimate Results

Label	Mean Estimate	95% Confidence Limits: Lower	95% Confidence Limits: Upper	Standard Error
Mean Y under AI #1 (MED, AUGMENT)	2.780	2.5869	3.1733	0.1496
Mean Y under AI #2 (BMOD, AUGMENT)	3.750	3.0689	3.7018	0.1614
Mean Y under AI #3 (MED, INTENSIFY)	2.311	2.5163	3.1135	0.1524
Mean Y under AI #4 (BMOD, INTENSIFY)	3.212	2.3596	3.1081	0.1909
Diff: AI#1 – AI#2	-0.97	-0.9401	-0.0704	0.2219

SE in unadjusted model was **0.323**

Results for Weighted-and-Replicated Regression: Comparing Mean Outcome for all AIs Simultaneously

<u>Improved efficiency</u>: Adjusting for baseline covariates resulted in lower standard error and tighter confidence intervals. Point estimates remained about the same, as expected.

Contrast Estimate Results

Label	Mean Estimate	95% Confidence Limits: Lower	95% Confidence Limits: Upper	Standard Error
Mean Y under AI #1 (MED, AUGMENT)	2.8801	2.5869	3.1733	0.1496
Mean Y under AI #2 (BMOD, AUGMENT)	3.3854	3.0689	3.7018	0.1614
Mean Y under AI #3 (MED, INTENSIFY)	2.8149	2.5163	3.1135	0.1524
Mean Y under AI #4 (BMOD, INTENSIFY)	2.7338	2.3596	3.1081	0.1909
Diff: AI#1 – AI#2	-0.5053	-0.9401	-0.0704	0.2219
[illegible]	[illegible]	[illegible]	0.4115	0.1767

SE in unadjusted model was **0.2442**

SE in adjusted model but including only data from participants in AI#1 and AI#2 was **0.2244**

This analysis is with simulated data.

Citations

- Murphy, S. A. (2005). An experimental design for the development of adaptive intervention. Statistics in Medicine, 24, 455-1481.

- Nahum-Shani, I., Qian, M., Almirall, D., Pelham, W. E., Gnagy, B., Fabiano, G. A., ... & Murphy, S. A. (2012). Experimental design and primary data analysis methods for comparing adaptive interventions. Psychological methods, 17(4), 457.

Q&A

10 min