Mixed-Design ANOVA

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CPSY501
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Please download:
- ***treatment5.sav***

Outline: Mixed-Design ANOVA

- Mixed-Design ANOVA: concept, SPSS, output
- Interactions: finding significant effects
  - Graphing, estimated marginal means
  - Using simple effects to aid interpretation
  - Extra main effects beyond the interactions
- Exploring gender as a moderator
- Misc: APA style
- Misc: Practise mixed-design ANOVA
- Misc: Covariates: Mixed-design ANCOVA

TREATMENT RESEARCH DESIGN	Pre-Test	Post-Test	Follow-up
Cognitive-Behavioural Therapy			
Church-Based Support Group			
Wait List control group			

Factorial ANOVA

Repeated Measures ANOVA

Assumptions of RM ANOVA

- Parametricity: (a) interval-level DV, (b) normal DV, (c) homogeneity of variances.
  - But not independence of scores!
- Sphericity: homogeneity of variances of pairwise differences between levels of the within-subjects factor
  - Test: if Mauchly's $W \approx 1$, we are okay
  - If the within-subjects factors has only 2 cells, then $W=1$, so no significance test is needed.

Follow-up analysis: post-hoc

- If the overall RM ANOVA is significant, explore differences between specific cells/times:
  - Analyze → GLM → Repeated Measures: Define → Options:
  - Estimated Marginal Means: move RM factor to "Display means for"
  - Select "Compare Main Effects", use "Confidence interval adjust.": Bonferroni
- Plot the effects over time:
  - Plots → IV in "Horizontal axis" → Add
  - Or try error bar plots

Post hoc comparisons, cont.

- Note: the Post-Hoc button applies only to between-subjects factors
  - Hence not applicable here: we only have one IV (Time) and it is within-subjects
- Interpret the output:
  - Bonferroni results show that the mean Pre-test scores are significantly higher than the mean Post-test & Follow-up scores
  - But the Post-test & Follow-up scores are not significantly different
  - (see "Pairwise Comparisons", "Estimates")

Mixed-Design ANOVA

- Advantages: More complete model
  - Moderators!
  - Treatment effects of interventions: Treatment groups (between-subjects) X Time (pre-/post-) (within-subjects)
  - Any therapy study would use this!!
- Disadvantages: “More work…”
  - Tracking, interpreting interactions
  - Can we trust complex results?
  - May need larger sample sizes

Treatment5 Example

- DV: Depressive symptoms
  - (healing = decrease in reported symptoms)
- IV1: Treatment group (between-subjects)
  - CBT: Cognitive-behavioural therapy
  - CSG: Church-based support group
  - WL: Wait-list control
- IV2: Time (pre-, post-, follow-up) (within-subj)
- We will now do a full mixed-design study using both Treatment group and Time

Mixed-Design: SPSS

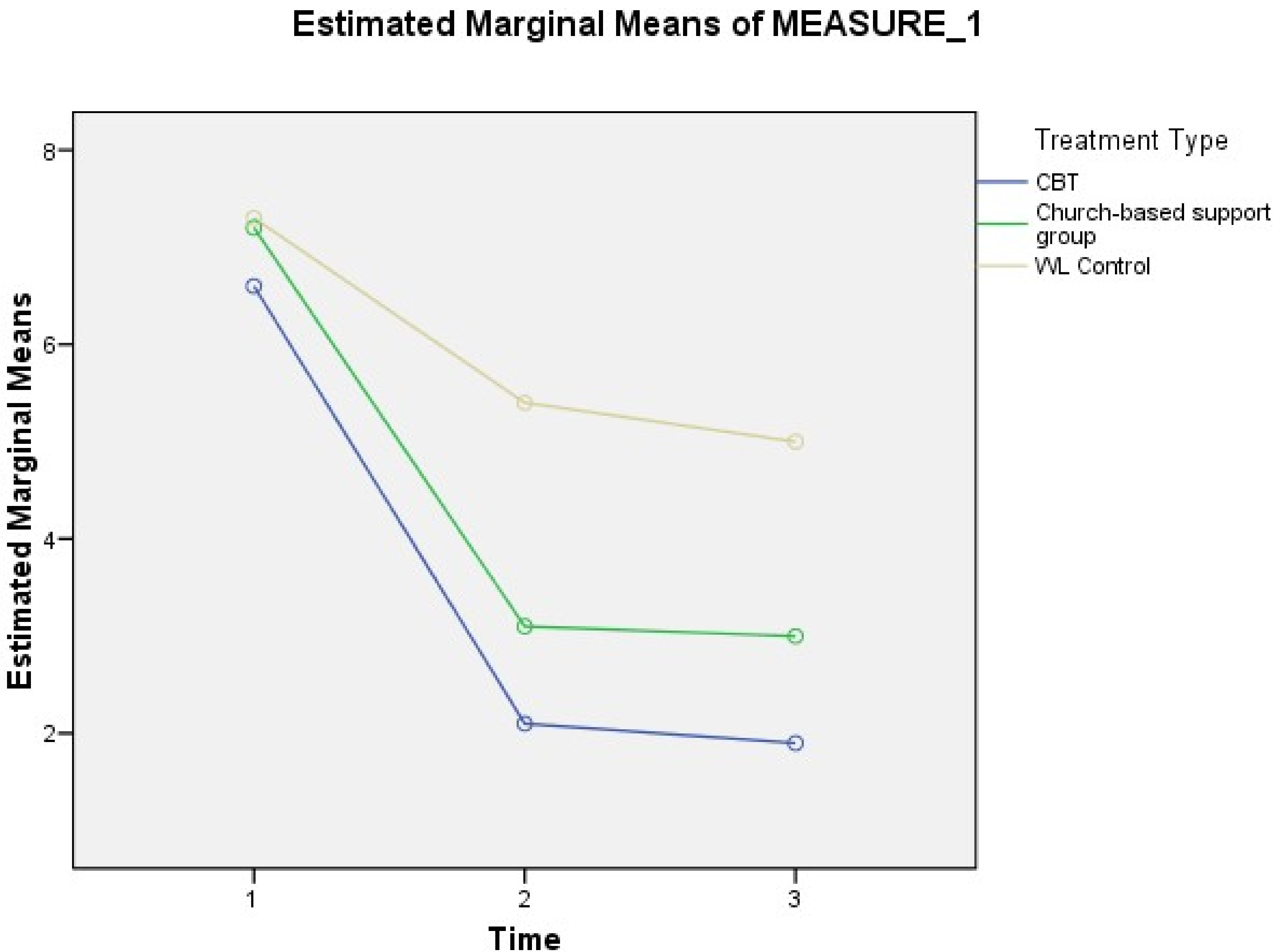
- Analyze → GLM → Repeated measures → Define: Add IVs to "Between Subjects Factor(s)"
- Options: Effect size, Homogeneity tests, etc.
- Check assumptions: Parametricity, sphericity
  - Note: sphericity holds for treatment5 if we include the treatment groups in the design!

Output: ANOVA Tables

- Output: first purely between-subjects effects
  - Then within-subjects effects and interactions involving within-subjects factors
- Main effects and interaction effects: check *F*-ratios, significance level, and effect size
  - Highest-order significant interactions first
- For all significant effects, do follow-up:
  - Graph interactions
  - Post-hoc cell-by-cell comparisons
  - See if main effects have an interpretation beyond the higher-order interactions

Examining Interactions

- Graph significant interactions to understand
  - Graphs plot the estimated marginal means
- Confirm with the numbers behind the plots:
  - Options: Estimated Marginal Means
  - Examine confidence intervals
- Treatment5: "The interaction of treatment group by time is significant, $F(4, 54) = 7.28$, $p < .001$, $\eta^2 = .350$, demonstrating that …"



Estimated Marginal Means of MEASURE_1
Treatment Type
CBT
Church-based support group
WL Control
Estimated Marginal Means
8
6
4
2
1
2
3
Time

Interactions: Simple Effects

- Follow-up on significant interaction:
- Use simple effects to describe precisely which treatment groups differ significantly
    - E.g., focus on just post-treatment time and do one-way ANOVA with Bonferroni post-hoc
    - Confirm with estimated marginal means
- The effect here is strong and clear, so even this conservative strategy shows that both treatment groups are lower than WL group, at post-treatment and follow-up times.

Interactions: Interpretation

- We found a significant interaction:
  - "The interaction of treatment group by time is significant, $F(4, 54) = 7.28$, $p < .001$, $\eta^2 = .350$, demonstrating that …"
- Graphing + simple effects + est. marg. means give us the interpretation of the interaction:
  - "…the decrease in symptoms of depression from pre-test to post-test and follow-up was greater for the treatment groups than it was for the WL control group."

Main Effects with Interactions

- Main effects are only meaningful if they tell us something beyond what the interaction tells us.
- In Treatment5, both Treatment and Time main effects merely reflect the interaction effect.
  - Only report the interaction with follow-up

Follow-up for Main Effects

- To look for main effects beyond the interaction:
- If there are only 2 levels of a repeated measure, no post-hoc is needed; the main effect is simply the pairwise difference between the two levels.
- If there are more than 2 levels:
- For between-subjects factors: "Post Hoc" button
  - Select appropriate post-hoc test
- For within-subjects factors: Options: "Compare means"
  - Remember to use Bonferroni correction

Treatment5: Interpretation

- Last time, we ran a simple RM ANOVA on treatment5 and found a significant main effect for Time
- But that is not the best model to explain the data, as we found today with Mixed-Design:
- What's really going on is the interaction between Treatment Group and Time:
  - Treatment effect over time

Other Moderators: Gender?

- We found a clear treatment effect, but are there other potential moderators to add to the model?
- In counselling psychology, gender often is an important variable in many analyses
- RQ: Do the treatments seem to work “the same” for both women and men?
  - Look for 3-way: Gender * Time * Treatment
  - 2-way interaction may also be useful: Gender * Time or Gender * Treatment
  - Main effect for gender not useful here

Gender as Moderator: SPSS

- Clean and check assumptions on Gender
  - We actually have missing data for gender
- Analyze → GLM → Repeated measures → Define:
  - "Between Subjects Factor(s)":
    now add both Treatment Group and Gender
- Interpret output tables for interactions:
  - Remember that SPSS prints
    pure between-subjects effects separately
    from within-subjects effects and interactions

Output: Gender effects

- Between-subjects effects:
  - Gender * Group effect is not significant
- Within-subjects effects:
  - No 3-way interaction
  - Time * Gender effect is significant (21% effect size)
- Follow-up on Time * Gender:
  - Graph and get estimated marginal means to try to understand the interaction

Summary: Moderation analysis

- Women showed less improvement on average than did the men,
  but that did not depend on treatment group.
- So gender moderates response to treatment (but also to Waitlist!)
  - Doesn't change our interpretation of the treatment effect – it still seems to “fit” both women and men
  - For research publications, this “check” might not even be reported for the journal.

APA style notes

- Provide evidence for your interpretations!
  - Explain why you think something is true and report the statistics …
- No space between F and (): "$F(2, 332) = \ldots$"
- R^2 is NOT the same as r^2
- Kolmogorov-Smirnov test: "$D(105) = \ldots$"
- Round to 2 decimal places for most stats
  - Round to 3 for p and η^2
- Italicize Latin letters (p), not Greek letters (η^2)

Practise: Mixed ANOVA

- Treatment5: try a Mixed ANOVA with:
  - Within-subjects: "outcome" and "follow-up"
  - Between-subjects: "relationship status"
- Check assumptions
- Is there a significant interaction effect between pre/post treatment and relationship status?
  - If so, interpret the interaction.

FYI: Covariates in Mixed-Design

- ANCOVA + RM + Factorial:
  - Enter "Covariates" in GLM → RM dialog
- Covariates must remain constant across all levels of the within-subjects (RM) factor
  - "Varying" covariates: enter as second RM IV in the model (or use multi-level modelling)
- Covariates should not be related to predictors
  - Should have no significant interactions
  - Need for homogeneity of regression slopes