

# Methodological and Analytical Aspects of Longitudinal Research

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**Educational content / Obrazovni sadržaj**

*Publication status / Verzija rada:* **Accepted version / Završna verzija rukopisa prihvaćena za objavljivanje (postprint)**

*Publication year / Godina izdavanja:* **2023**

*Permanent link / Trajna poveznica:* <https://urn.nsk.hr/urn:nbn:hr:131:972497>

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*Download date / Datum preuzimanja:* **2024-07-23**



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# Methodological and Analytical Aspects of Longitudinal Research

COORDINATE project

November 17, 2023



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# LECTURE CONTENT

1. Aspects of longitudinal design (a brief overview)
  - Longitudinal hypotheses
  - Sample size
  - Number of waves
  - Measures
2. Challenges and recommendations
  - Logistic
  - Methodological
    - Attrition
3. Choosing an analysis framework (a brief overview + example)

# WHAT IS LONGITUDINAL DESIGN?

Data collected using multiple measurement occasions across time nested within same entities (e.g., individuals – within-individual changes over time)



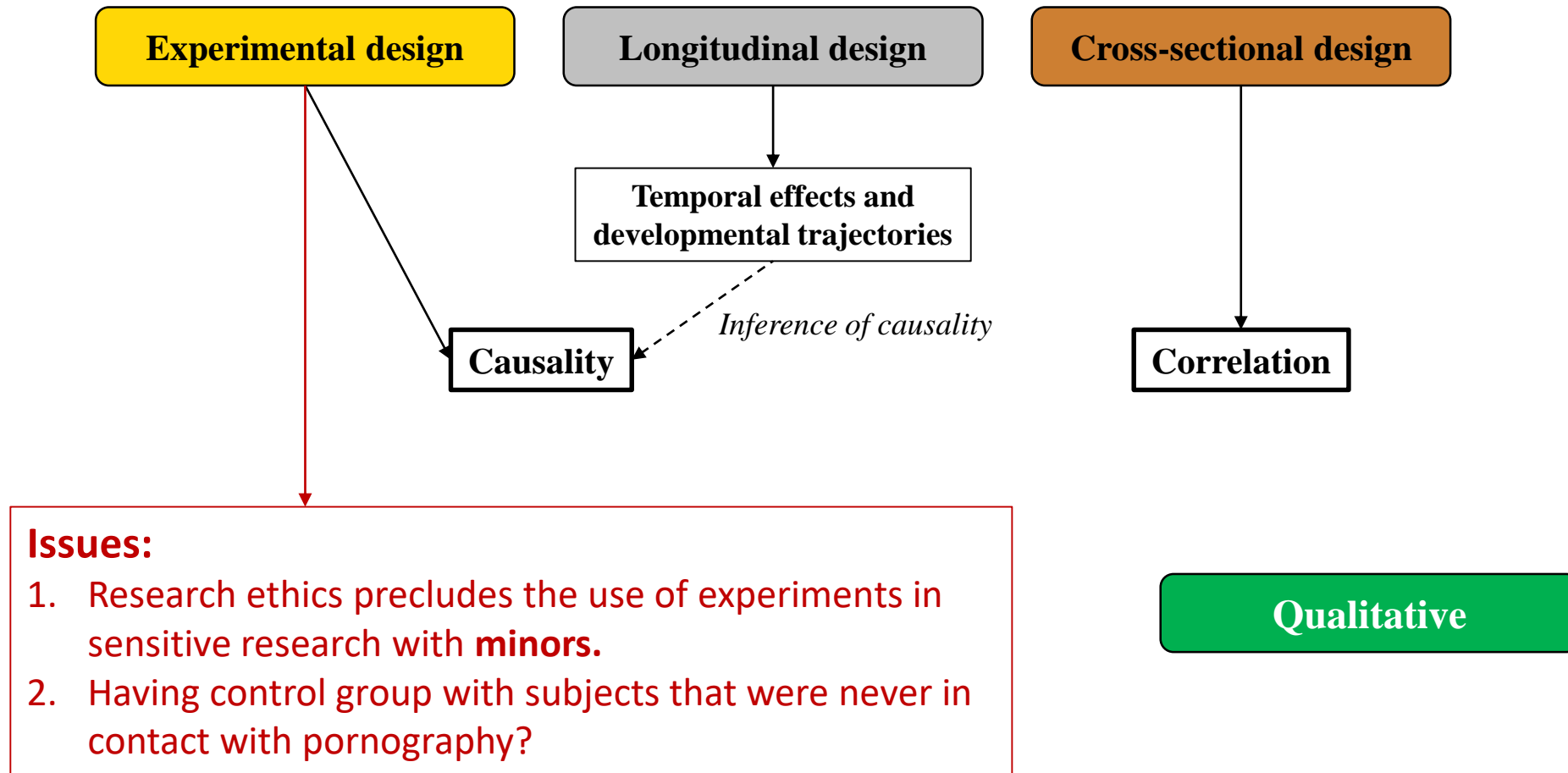
At least **three measurement occasions** (waves)

- With only two waves of data: a) difficult to disentangle true change from measurement error; b) impossible to model nonlinear forms of change.

Different from (econometric) time-series design.

# In some cases...THE BEST POSSIBLE DESIGN?

How to assess pornography use in adolescent population?

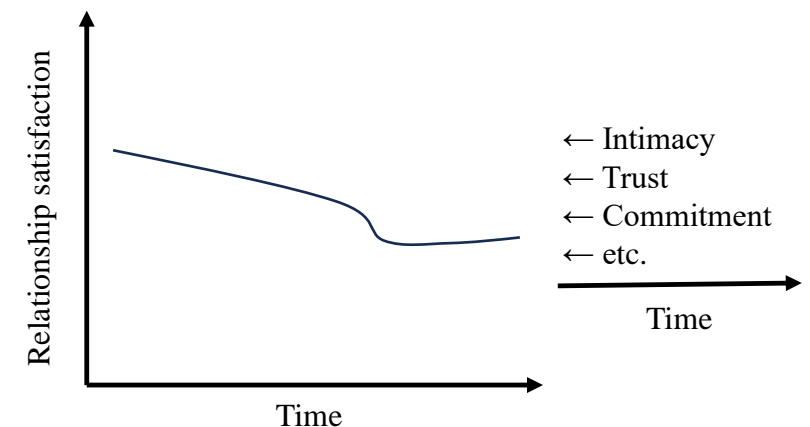


# NEED FOR LONGITUDINAL DESIGN

1. Assess temporal effects and developmental trajectories.
2. Test existing (cross-sectional) theory from a longitudinal perspective.
3. While cross-sectional studies render causal inference unwarranted, well-conducted longitudinal study will provide an inference of causality.
  - For example, should we pursue experimental design for a target topic or not?
4. Do conclusions differ between cross-sectional and longitudinal designs?
  - Compare longitudinal effect sizes to the cross-sectional effect sizes.
  - If a longitudinal study makes the same predictions and leads to the same conclusions as a cross-sectional study, is there a unique theoretical contribution?

# CONSTRUCTING LONGITUDINAL HYPOTHESES

- Not uncommon that theories (or research-related conclusions) overlook **when** an effect is likely to occur or for what **duration**.
  - Longitudinal versions of cross-sectional hypotheses
    - „A is associated with B” → „A is associated with B *over time*”
- **Focus on unique change in a construct (vs. its static representation):**
  1. When does the change occur?
  2. For how long it lasts and how it changes?
  3. Why it changes?
  4. What is associated with the change?
  5. What is the nature of the association?
    - Decreasing/increasing trend
      - Less or more substantial change



# SAMPLE SIZE

As large as possible! (**attrition**)

**Keep in mind that:**

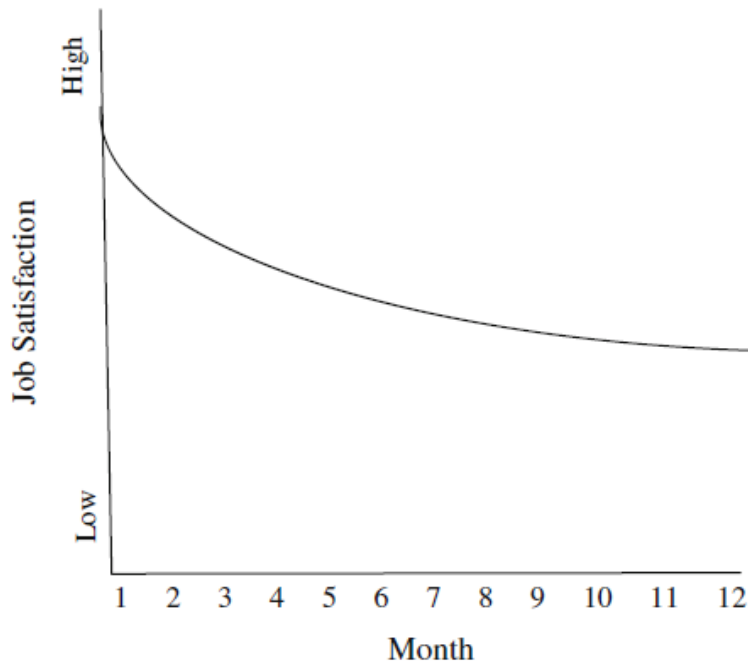
1. Total sample size (observations) = subjects x measurement occasions
2. Within-subject designs have smaller error terms (compared to cross-sectional designs)
3. Power analysis is complex (subjects, measurement occasions, linear or nonlinear change, variability in change over time)
  - Adding more subjects should reflect on between-person effects
  - Adding more measurement occasions should reflect on within-person effects



# NUMBER OF MEASUREMENT OCCASIONS

## Exactly equal spacing (less important) vs. number of time points (more important)

- Frequent enough to detect hypothesized kind of change and that the occasions cover a reasonable duration of time



(Ployhart & Ward, 2011)

### Possible assessments:

**T1, T12:** detecting linear decline

**T1, T6, T12:** detecting nonlinearity

**T1, T2, T3:** overestimating negative slope

**T10, T11, T12:** underestimating negative slope

### Guidelines for number measurement occasions (and time lags)

1. Review related literature.
2. When there is no „natural” measurement dynamic, conduct interviews or behavioral observations with relevant subjects to determine a measurement schedule.

# CHALLENGES

## LOGISTIC

- Time consuming (number of waves, time lags)
- Recruitment
  - Often requires larger baseline samples
- „Gatekeepers” (classroom-based)
  - School principals, etc.
- Motivating participants (online)
  - Incentives

## METHODOLOGICAL

- Attrition
  - Reasons for lost to follow-up participants
  - Potential bias
  - Online vs. classroom-based (on-site) vs. commercial panel
- Familiarity with research topic and measures
- (Re)contacting participants and linking surveys
- Assuring anonymity (online)
- Assuring privacy (classroom-based)

## FINANCIAL

- Requires a research team
- Expensive

# RECENT EXPERIANCE

## The PROBIOPS Study


→ Prospective Biopsychosocial Study of the Effects of Sexually Explicit Material on Young People's Sexual Socialization and Health (2015-2018)

ABOUT

RESEARCH TEAM

→ Project leader: Aleksandar Štulhofer, PhD  
Team: sociologists, psychologists and a medical biochemist

INTERNATIONAL COLLABORATION

→ 14 international collaborators  etc.

PAPERS PUBLISHED

→ 40 published papers

MANUSCRIPTS UNDER REVIEW

CONFERENCES

BRIEF SUMMARY OF FINDINGS

**Topics:** question-behavior effect, parental monitoring, body-surveillance, internalization of appearance ideals, sexism, the role of religiosity, compulsive pornography use, communication about sexuality, well-being, sexual risk taking, sexual victimization, sexual permissiveness, perceived pornography realism, academic achievement, content progression thesis, sexual satisfaction, sexting, sexual aggressiveness, sexual agency, selective dropout, the role of testosterone, etc.

AWARDS

CONTACT US

SAŽETAK

Informacija za roditelje

Preliminarni izvještaj

<http://probiops.ffzg.hr>

Funded by Croatian Science Foundation

# PROBIOPS: Participants and procedures

## ZAGREB

- Spring 2015.
- 59/90 high-schools
- 6 waves
- 6 month between waves
- Leaflet recruitment
- Online questionnaires
- N (T1<sub>baseline</sub>) = 2,235
- Lottery based incentives

## RIJEKA (population wise, 3<sup>rd</sup> Croatian city)

- Winter 2015.
- 14/23 high-schools
- 6 waves
- 5-6 month between waves
- Classroom based
- Paper-pen questionnaires
- N (T1<sub>baseline</sub>) = 1,287
- No incentives

ZAGREB		
Wave	Year	N
1	2015	2235
2		636
3	2016	711
4		683
5	2017	686
6		511

Mean age (T1) = 16.2  
41% **M** / 59% **F**

All 6 waves = 307

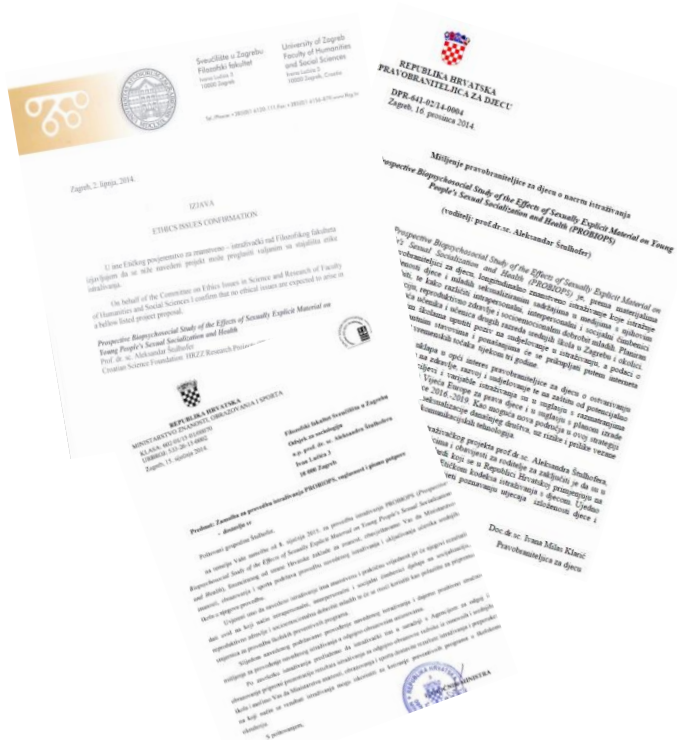
RIJEKA		
Wave	Year	N
1	2015	1287
2	2016	1281
3		1232
4	2017	1176
5		931
6	2018	892

Mean age (T1) = 15.9  
44% **M** / 56% **F**

All 6 waves = 430

# RECOMMENDATIONS (long before data collection)

Obtaining approvals (e.g., relevant „gatekeepers”)



Developing a catchy public name and an attractive visual identity + feedback (e.g., focus groups)



Developing a „recruitment” leaflet and video tutorial



# RECOMMENDATIONS (long before data collection)

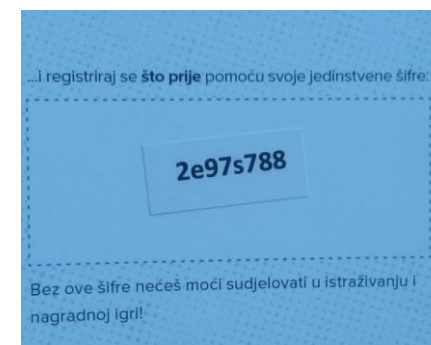
## Setting up a registration website and social media sites



## Deciding on incentives model (e.g., lottery based) + feedback

ZAGREB	
Wave	Collected
1	27%
2	57%
3	63%
4	61%
5	67%
6	62%

## System for assuring confidentiality (separate database for contact information and questionnaire data + linking database)



	A	B	C	D	E	F
1	ID	full_resp	pages	Token	token_group	school
2	13	1	13	rdkxkcm7	14	1
3	18	1	13	ckxrsrnc	8	1
4	20	1	13	p6kvq2pr	14	1
5	22	1	13	7r6z7sz4	1	3
6	24	1	13	dppzcvny	80	3
7	38	1	13	bruzuiva	4	3

# A brief detour..INCENTIVES

## Types of incentives

- An incentive which shows respect for participants' time and effort
- Money, gift cards, food vouchers, school supplies, telephone cards, etc.

## Determining adequate incentive

- Incentive amounts vary depending on many factors, including:
  - Study budget
  - Standard of living in the study country
  - Population of interest
  - Institutional or governmental policies (monetary incentives not allowed, pre-established cap amount for incentives)

## Models

1. Each participant
2. Each participant + extra for participating in each subsequent wave
3. One-price lottery
4. Horizontal lottery (a number of awards, same incentive amount)
5. Pyramidal lottery (a number of awards, increasing incentive amount)
6. Combining previous models

**Acquire feedback!**

# RECOMMENDATIONS (before data collection)

Training a fieldwork force

Developing necessary planning/tracking sheets  
(coordinating, contacting, and **measures!**)



	C	D	E	F	G	H	
	<b>RIJEKA</b>	<b>Study waves</b>			<b>a</b>	<b>b</b>	<b>c</b>
<b>Modul / topics / indicators</b>	<b>planned</b>	<b>I.</b>	<b>II.</b>	<b>III.</b>			
	<b>missing</b>	<b>TOTAL=</b>	<b>111</b>	<b>113</b>	<b>110</b>		
<b>SOCIODEMOGRAPHIC MODULE</b>							
<b>Participant related (0-10)</b>			<b>8</b>	<b>3</b>	<b>12</b>		
Gender (filter)		<b>1</b>	<b>X</b>	<b>X</b>	<b>X</b>		
Age (month)		<b>1</b>					
Age (year)		<b>1</b>	<b>X</b>				
Academic achievement		<b>1</b>	<b>X</b>		<b>X</b>		
Average grade (HR, ENG, PSJ)		<b>3</b>			<b>X</b>		
Educational aspiration		<b>1</b>					
Religious practice		<b>1</b>	<b>X</b>		<b>X</b>		
Faith in god		<b>4</b>	<b>X</b>		<b>X</b>		
Relationship status		<b>1</b>			<b>X</b>	<b>X</b>	
Relationship duration		<b>1</b>			<b>X</b>	<b>X</b>	
Edge centered network characteristics		<b>15</b>					

datum	škola	predmet	učenik	status
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10.4.2016.	Škola 100	Matematika	111	ok



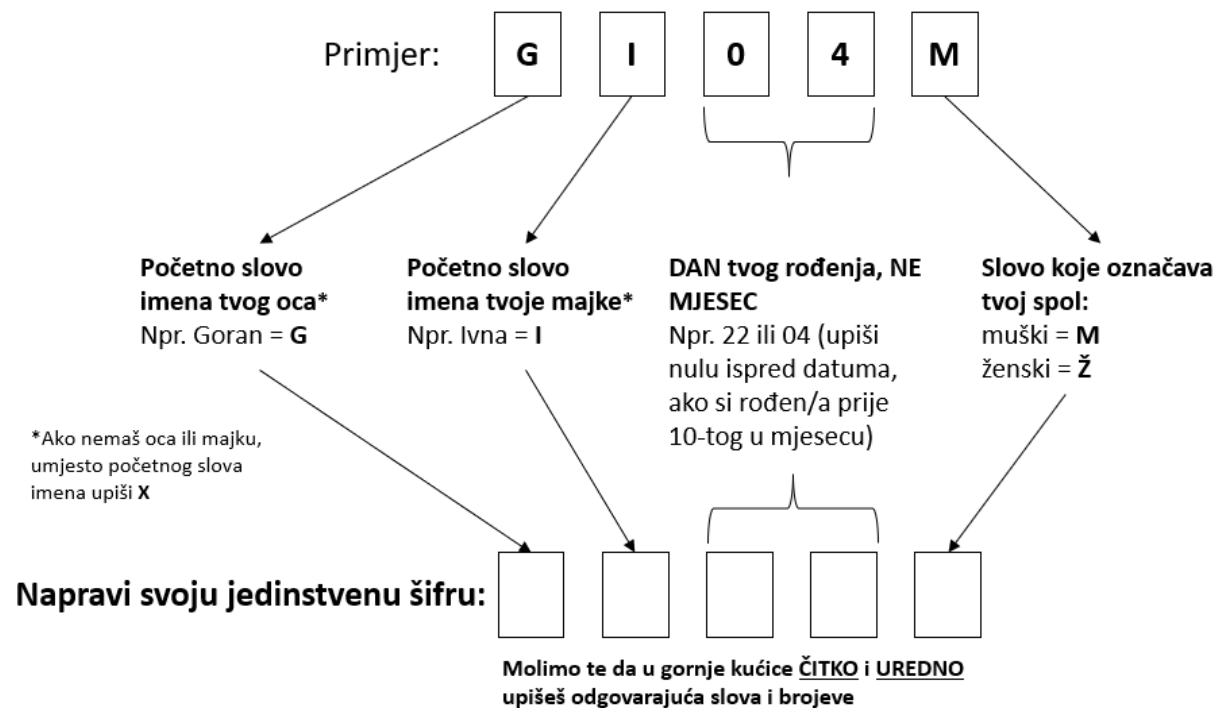
# RECOMMENDATIONS (during data collection)

## Classroom-based data collection

Use privacy panels



Develop coding system for linking participants across multiple study waves



# RECOMMENDATIONS (during data collection)

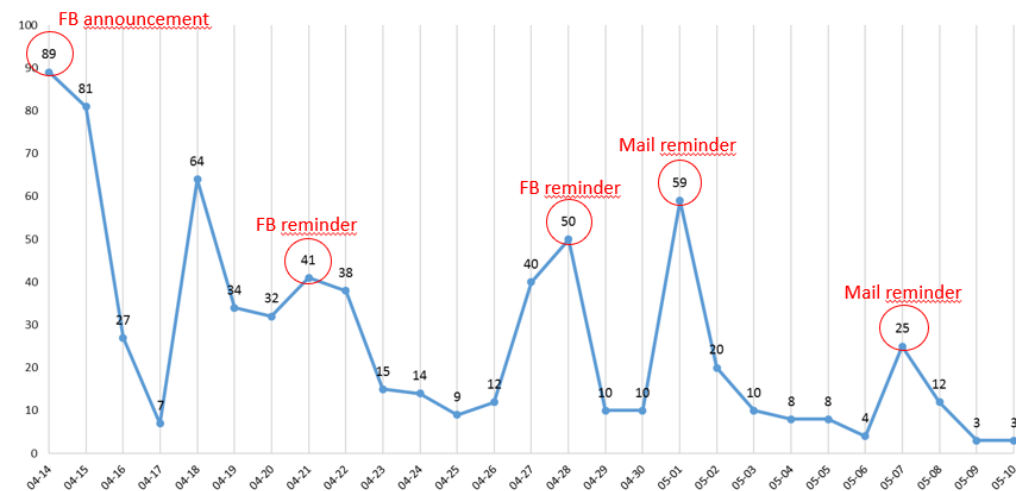
## Response tracking

**Issues:** rarely checking email, changing email address, using „secondary” email for the initial registration

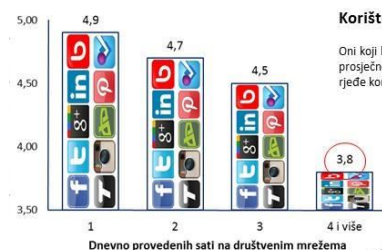
## Maintaining communication before/during/after data collection periods

- Repeated in-person visits
- Social media posts with interesting results
- Social media and e-mail announcements
- Social media and e-mail reminders

### 3. wave response flow



Fieldwork: 14.04. - 06.05. (13 work days)



### Korištenje društvenih mreža i seksualna iskustva

Oni koji koriste društvene mreže 4 ili više sati dnevno imaju prosječno gledano manje seksualnih iskustava – od onih koji rjeđe koriste društvene mreže.



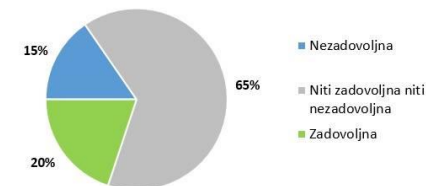
Djevojke koje su prekomjerne tjelesne težine su manje zadovoljne svojim izgledom od onih koje su normalne tjelesne težine. Međutim, djevojke koje imaju izrazito nisku tjelesnu težinu s obzirom na visinu (u medicinskom smislu - pothranjene) su podjednako zadovoljne svojim izgledom kao djevojke normalne težine!

### Zadovoljstvo izgledom i seksualna iskustva (samo djevojke)

Među djevojkama su veći broj seksualnih ponašanja (kao što su ljubljenje, dodirivanje intimnih dijelova tijela, seksualni odnos...) isprobale one djevojke koje su manje zadovoljne svojim izgledom nego one koje su osrednje ili jako zadovoljne svojim izgledom.

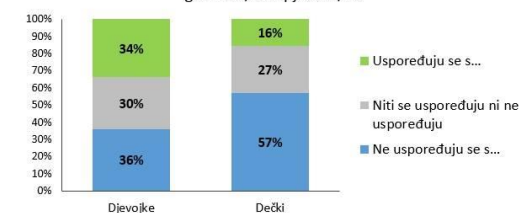


### Zadovoljstvo vlastitim izgledom (samo djevojke)



Rezultati analize pokazuju da je 15% djevojkama nezadovoljno svojim fizičkim izgledom.

### Uspoređivanje vlastitog izgleda s izgledom popularnih glumaca/ica i pjevača/ica



Djevojke više uspoređuju svoj izgled s izgledom popularnih glumica, pjevačica i plesačica od svojih muških vršnjaka. Zanimljivo je da od 34% posto djevojkama koje su sklone uspoređivanju, najveći broj njih (41%) provodi 6 ili više sati dnevno na društvenim mrežama i gledajući razne serije i filmove. Istovremeno, među djevojkama koje ne uspoređuju svoj izgled s izgledom raznih popularnih osoba najveći broj ih je zadovoljno svojim fizičkim izgledom.

# RECOMMENDATIONS (during data collection)

Maintaining communication before/during/after data collection periods

- Repeated in-person visits

1. wave		2. wave		3. Wave	
Schools	Respondents	Visited	Respondents	Visited	Respondents
59	2210	35	542 (M* = 32%)	31	601 (M* = 39%)
		Not visited	Respondents	Not visited	Respondents
		24	68 (M* = 15%)	28	124 (M* = 21%)
		Schools	Respondents	Schools	Respondents
		59	610	59	725
			„in-person effect”		„in-person effect”
			+17%		+18%

\*M = average response rate in (not)visited schools based on the number of baseline respondents

# RECOMMENDATIONS (during data collection)

**Qualitative feedback** (intention to drop-out, satisfaction with incentives, etc.)

BARRIERS	IVANIĆ GRAD	SESVETE	ZAGREB
Long time Intervals and forgetfulness	✓		
Rare communication with participants, lack of reminders	✓	✓	
Image research too laid back. Unrecognized seriousness and importance of research	✓		
Prizes are not particularly motivating			✓
Use of e-mail compared to Facebook, WhatsApp or similar		✓	✓
Immaturity (boys)			✓

RECOMMENDATIONS AND SUGGESTIONS:	IVANIĆ GRAD	SESVETE	ZAGREB
Joining the Facebook group	✓		
Frequent e-mails (though rarely checked)	✓	✓	
More content on the Facebook group	✓		
Be sure to visit schools	✓		✓
Completing the questionnaire during class	✓	✓	✓
emphasize prizes		✓	
Create an impression of obligation to an adult at school (teacher, psychologist ...)			✓
Some will be more interested if you have „dirty” questions		✓	



# RECOMMENDATIONS (**during/after** data collection)

## Are we losing the most relevant cases first? (**attrition**)

- In longitudinal research, losing particular types of participants over the course of the study may become a serious analytical issue (e.g., identifying moderating effects, diminishing or inflating links between predictors and outcomes of interest).
  - *Štulhofer et al. (2021). Selective Dropout in Longitudinal Studies of Adolescent Pornography. Archives of sexual behavior, 50, 2215–2226.*
- **Using two independent panel samples, we examined:**
  1. Was attrition substantially different among adolescents who may be particularly vulnerable to pornography use compared to other participants?
    - Vulnerability indicators (measured at the baseline): adverse family situation, lower academic achievement, early biological maturation, lower self-esteem, sexual aggressiveness, earlier sexual debut.
  2. Did panel type (online vs. classroom-based) moderate associations between attrition and the vulnerable group membership?

# RECOMMENDATIONS (**during/after** data collection)

Are we losing the most relevant cases first? (**attrition**)

- Based on attrition patterns in two panels, we distinguished: **early attrition, later attrition, and participation gaps.**

## RESULTS

1. Only early attrition was substantially higher among more vulnerable adolescents, compared with other participants.
2. Panel type moderated the associations between adolescent vulnerability and participation gaps, which was significant for the classroom-based but not the online panel.

Adolescents who are believed to be under increased risk of adverse outcomes associated with pornography use are less likely to complete longitudinal studies.

# RECOMMENDATIONS (**during/after** data collection)

## Are we losing the most relevant cases first? (**attrition**)

### Pre-designed attrition reducing strategies (examples)

#### Modality of data collection

- Resources and required baseline sample
- Online data collections platforms vs. cell phone app

#### Preparations for attrition

- Short questionnaires (and planned missing)
- Study's visual identity and presence
- Desirable incentives
- Focus groups (before and during data collection)

#### Delaying selective dropout

- Notifying participants about an upcoming study wave
- Communicating simple but interesting findings
- Adding or modifying incentives (e.g., adding bonus incentives tied to the number of waves completed)
- Seeding the panel with specially incentivized and committed peer leaders



# RECOMMENDATIONS (**during/after** data collection)

## Are we losing the most relevant cases first? (**attrition**)

A simple analytic approach to assess attrition

### For example, assessing attrition from T1 to T2

- N (T1, baseline) = 100
- N (T2) = 75

### Binary logistic regression analysis

- Which participants have higher odds for dropping out?
- **Use T1 data**
- **DV**
  - 0 = Participants in T2 (75)
  - 1 = Lost to follow-up (25)
- **IV**
  - Relevant predictors of attrition (age, gender, etc.)

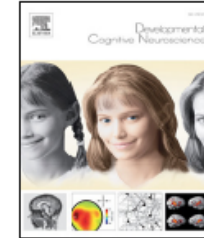
# CHOOSING AN ANALYSIS FRAMEWORK



Contents lists available at [ScienceDirect](#)

## Developmental Cognitive Neuroscience

journal homepage: [www.elsevier.com/locate/dcn](http://www.elsevier.com/locate/dcn)



### The Hitchhiker's guide to longitudinal models: A primer on model selection for repeated-measures methods

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# CHOOSING AN ANALYSIS FRAMEWORK

## Two general modeling frameworks

```
graph TD; A[Two general modeling frameworks] --> B[Multilevel (mixed-effect / hierarchical) modeling]; A --> C[Structural equation modeling (SEM)]; B --> D[Similarities between the multilevel and SEM frameworks often outweigh the differences.]; C --> D;
```

### Multilevel (mixed-effect / hierarchical) modeling

- Estimating higher levels of nesting (e.g., beyond individual)
- Limited with respect to measurement error in predictors or outcomes
- Simple inclusion of multiple time-variant covariates (e.g., relation satisfaction) and time-invariant covariates (e.g., gender)
- Relative model fit indices (AIC/BIC and likelihood ratio test) [model comparison]

### Structural equation modeling (SEM)

- Repeated measures as multiple indicators on one or more latent factors
- Estimating and removing the effect measurement error in predictors or outcomes
- Absolute model fit indices (CFI, TLI, RMSEA)
- Mediated relationships between constructs

Similarities between the multilevel and SEM frameworks often outweigh the differences.

# CHOOSING AN ANALYSIS FRAMEWORK: KEY CONSIDERATIONS

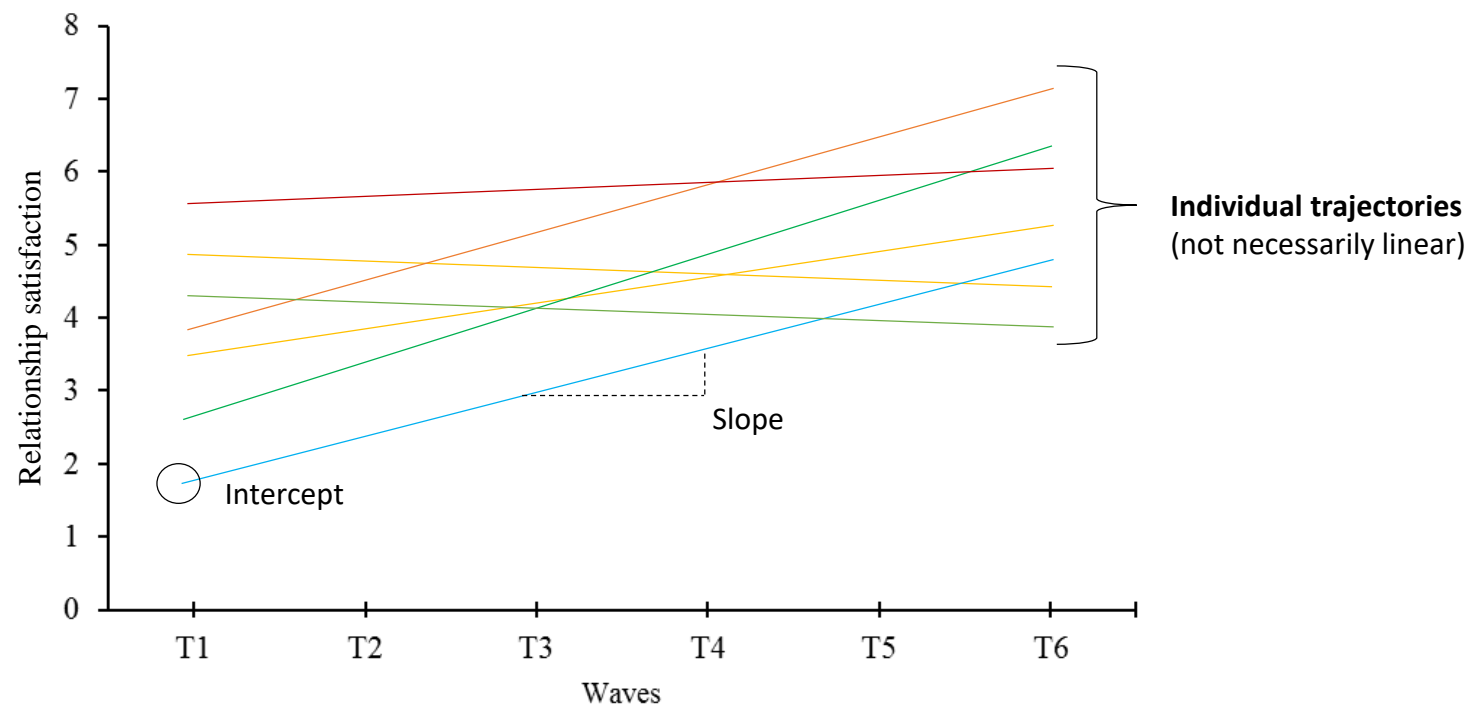
- Research question / hypothesis
- Variable type (categorical / quantitative) // (manifest / latent)
- Number of covariates
- Type of covariates (time-invariant / time-variant)
- (Un)balanced data (unequally spaced measurement occasions and/or missing data)
- Type of change (growth curve)
- Higher-order nesting
- Software

# SEM framework example: Latent Growth Curve Modeling

- Enables an assessment of between-person differences over time by estimating within-person latent trajectories of change
  - Observed repeated measures of a construct are represented by two latent factors (latent intercept and latent slope), and their means and variances
  - Latent intercept = initial level of a measured construct
  - Latent slope = measured construct's change over time

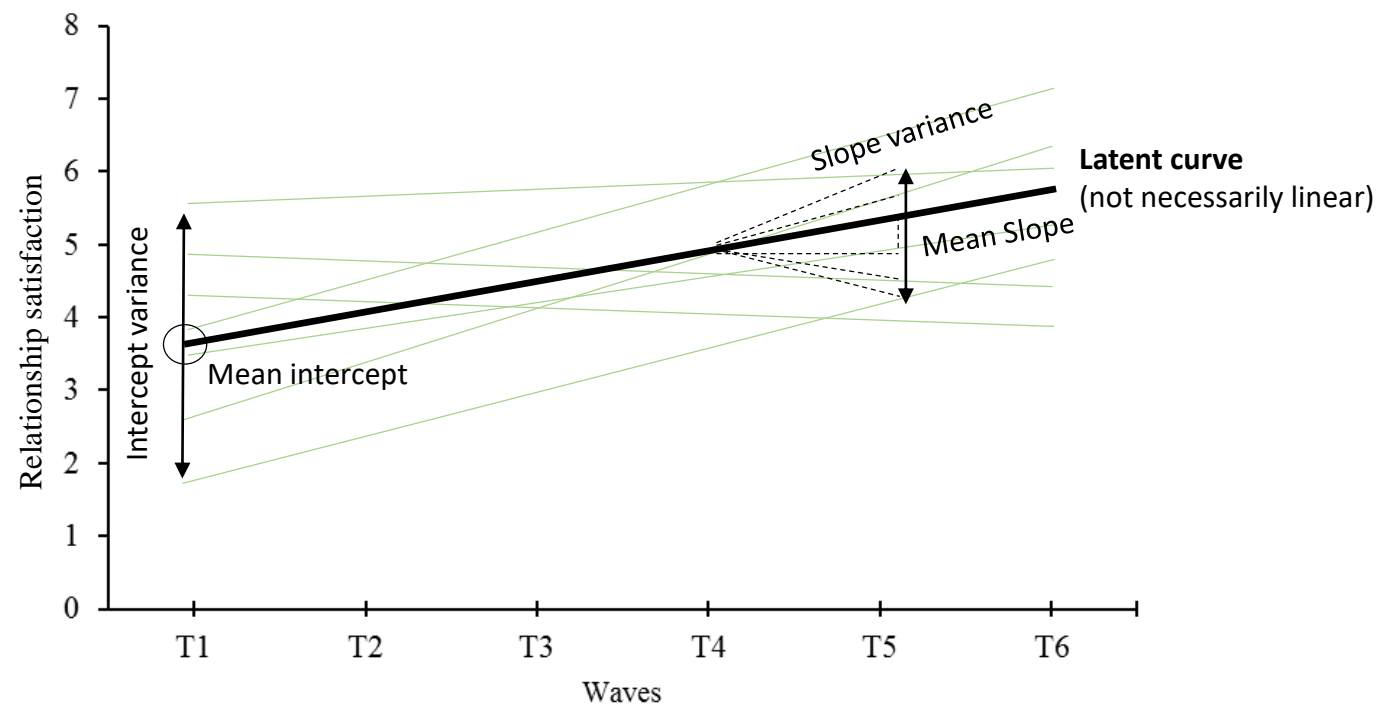
# SEM framework example: Latent Growth Curve Modeling

Assessing group means and between-person differences over time



# SEM framework example: Latent Growth Curve Modeling

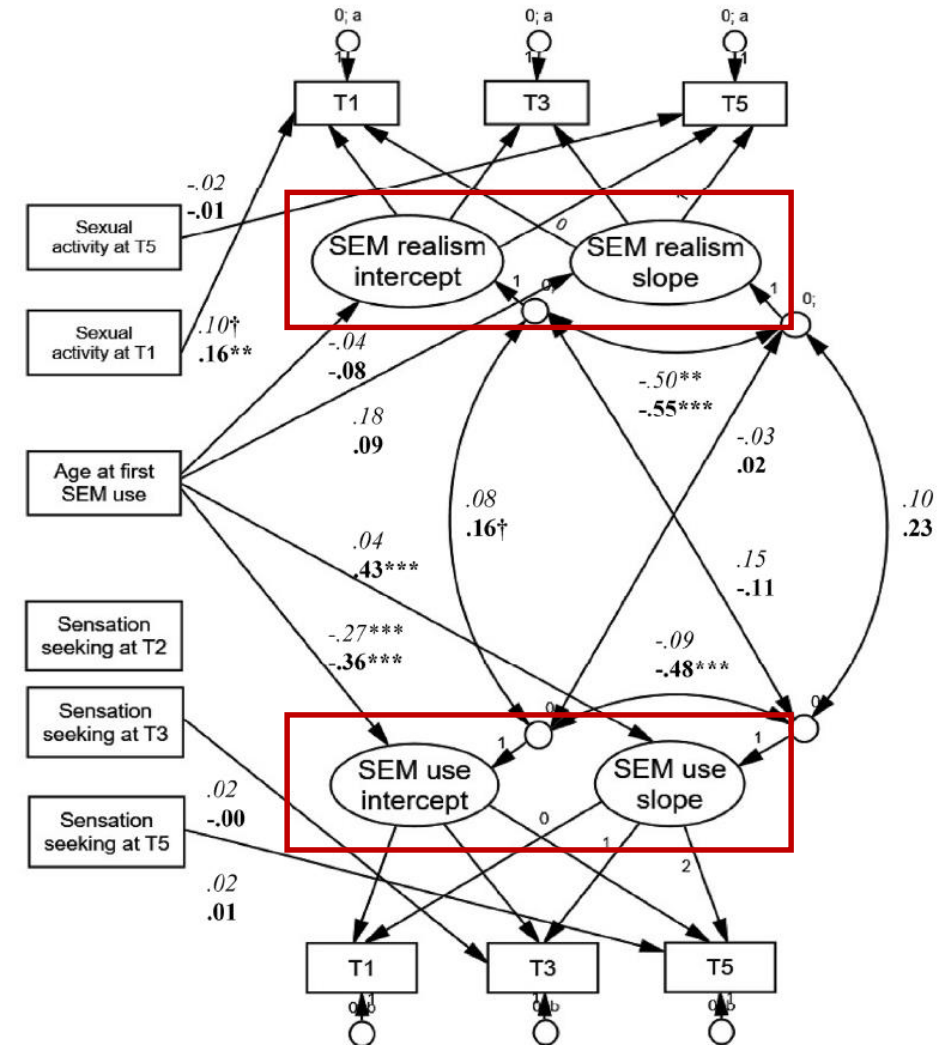
Estimating between-person differences in within-person change over time using **latent curve** and its **intercept** and **slope**



# SEM framework example: Latent Growth Curve Modeling

## Advantages

- Assessing multiple constructs simultaneously (parallel LGCM)
- Ability to handle unequally spaced measurement occasions, nonlinear trajectories, and partially missing data
- Flexibility of including both time-invariant and time-varying covariates





# SEM framework example: Latent Growth Curve Modeling

Interpretations of **positive** correlations between two latent constructs:

Construct B - SLOPE	Construct A - SLOPE		Construct A - INTERCEPT
	Increasing trend	Decreasing trend	
Increasing trend	The higher the increase in construct A, the more substantial the increase in construct B	The higher the increase in construct B, the less substantial the decrease in construct A	The higher the baseline assessment of construct A, the <b>more</b> substantial the increase in construct B over time
Decreasing trend	The higher the increase in construct A, the less substantial the decrease in construct B	The steeper the decrease in construct A, the more substantial the decrease in construct B (alternatively – both are decreasing less steeply)	The higher the baseline assessment of construct A, the <b>less</b> substantial the decrease in construct B over time

Interpretations of **negative** correlations between two latent constructs:

Construct B - SLOPE	Construct A - SLOPE		Construct A - INTERCEPT
	Increasing trend	Decreasing trend	
Increasing trend	The higher the increase in construct A, the less substantial the increase in construct B	The higher the increase in construct B, the more substantial the decrease in construct A	The higher the baseline assessment of construct A, the <b>less</b> substantial the increase in construct B
Decreasing trend	The higher the increase in construct A, the more substantial the decrease in construct B	The steeper the decrease in construct A, the less substantial the decrease in construct B	The higher the baseline assessment of construct A, the <b>more</b> substantial the decrease in construct B

# Final remark...

Common statement („mantra”) in research papers:  
*More longitudinal research is needed.*

Time/effort/costs vs. sound empirical/theoretical contribution

# LITERATURE

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