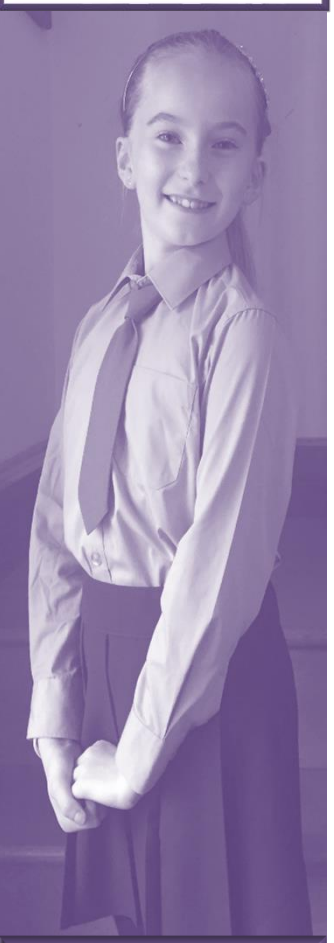

10th Annual Research Conference 2018

A Latent Growth Curve Model of the Relationship Between Computer Usage and Academic Performance in a Longitudinal Sample of Irish Children

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Technology in the Home

- Multi-centre study “EU – Kids online” (2004 to 2014) – presence of computers and other internet enabled devices approaching saturation Europe wide
- Many homes now have multiple devices making supervision and monitoring difficult
- Children using computers at earlier ages and for longer than ever before with important consequences for habit formation and for developmental trajectories in many domains
- Evidence for low overall digital literacy
  - (European commission 2013)

Computer Usage, Applications and Educational Outcomes

- Computer use has varied effects on academic performance. Mixed effects reported varying by **usage** intensity and **application** types.
- Some evidence for Impaired memory and concentration
  - Johnson (2006)
- Academic advantages have been seen in several large scale studies:
  - Programme for International Student Assessment (PISA) (OECD,2005)
  - Longitudinal Study of Australian Children (Fiorini, 2010)
- Previous Research using GUI data at 9 years shows both positive and negative effects of computer use (Casey et al. 2012)

Summary - Casey et al (2012)

Summary of Casey et al (2012)

- Importance of controlling for social gradient in test outcomes
  - (Williams et al 2009)

- Better test outcomes at 9 years
  - Moderate computer usage
  - Unsupervised computer usage
  - Informational computer applications

- Worse test outcomes at 9 years
  - Social media use

Aims of current study

- Replicate and extend initial findings of Casey et al (2012)
- Move from cross sectional to a longitudinal view

Data Source for the Current Study

- Child Cohort GUI Anonymised Microdata File (AMF)

- **Sample size**
- Wave 1 9yrs Unweighted sample of - 8,568
- Wave 2 13yrs Unweighted sample of - 7,525
- Wave 3 17yrs Unweighted sample of - 6,210

- Pure fixed panel design

- Evidence of differential attrition across waves (Williams, 2009). Re-weighted using census information

Educational Performance Variables

- **9 Year Data**
  - Drumcondra Primary Maths Test
  - Drumcondra Primary Reading Test
- **13 Year Data**
  - Drumcondra Numerical Ability Test
  - Drumcondra Verbal Reasoning Test
- **17 Year Data**
  - Junior Certificate Mathematics
  - Junior Certificate English

- **Scoring Junior Certificate**
  - Junior Certificate (Grade A-E)
  - Junior Certificate level (Higher, Ordinary, Foundation)
  - Scale constructed following a coding scheme producing a Leaving Certificate points total equivalent range 10-100

Educational Variable Parameterisation

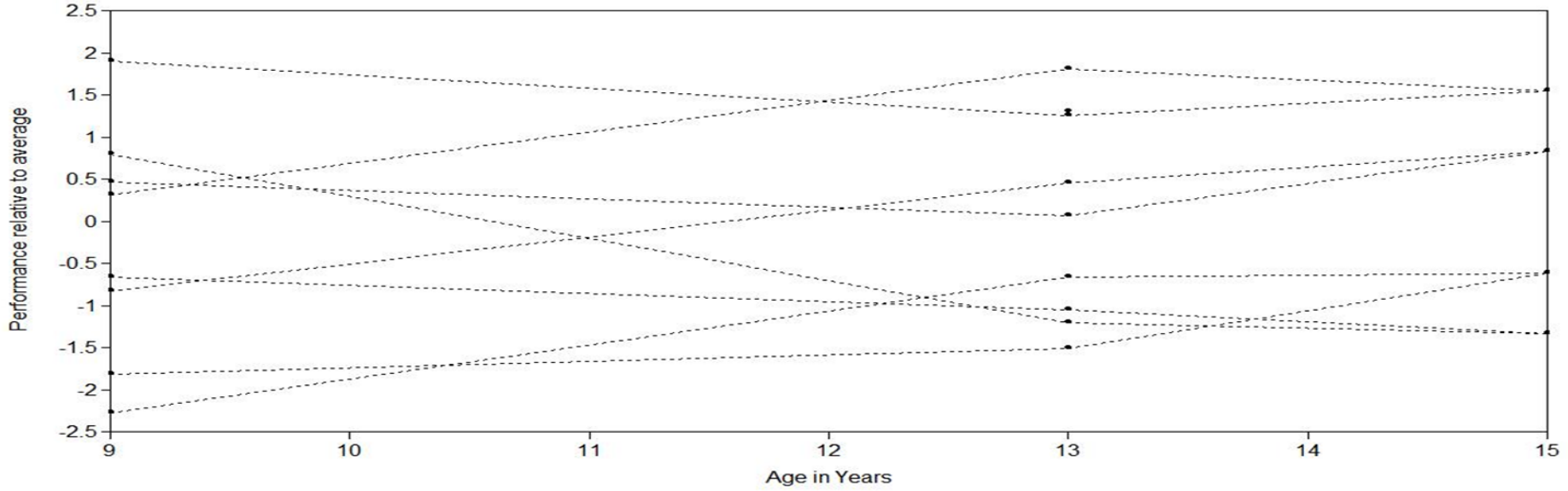
- **Parameterisation across variables problematic:** An assumption of growth modelling requires variables to be on the same scale.

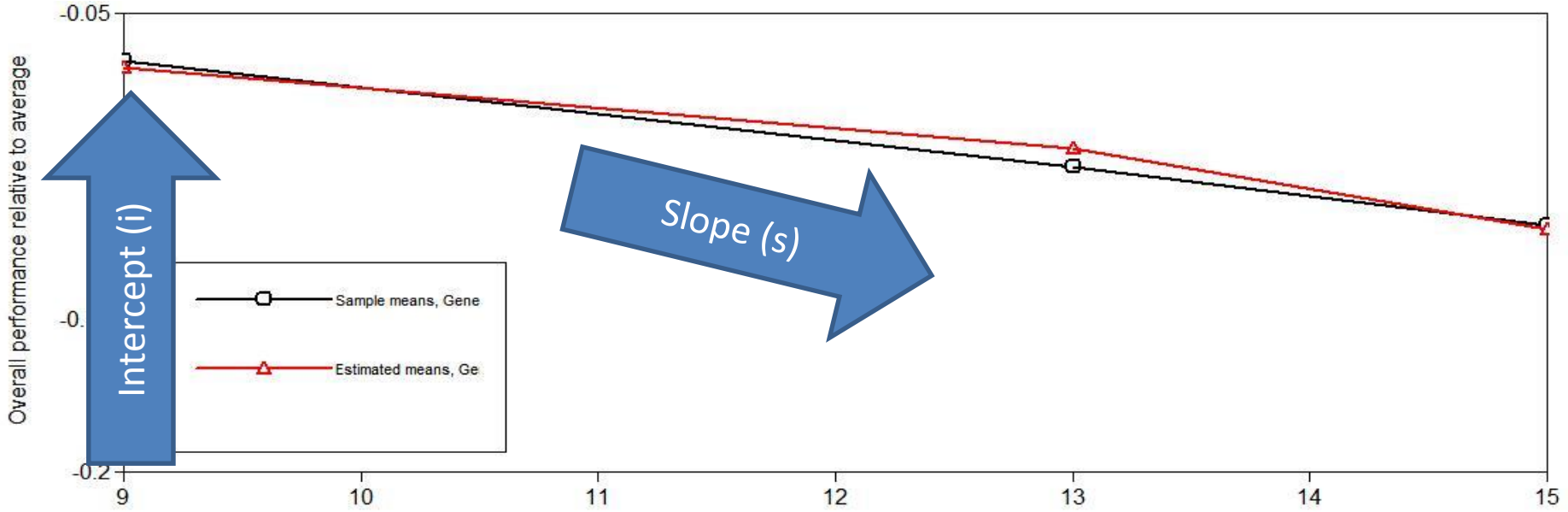
- **Current solution:** All educational variables re-scaled as z-scores such that an average performance has a mean score of zero and SD of one.

- **Useful effects of parameterization strategy:**
  - Flattening of growth curve.
  - Intercept is free to vary across participants.
  - The average slope for the whole sample is close to zero.
  - Primary interest is in explaining variability in intercept and slope at an individual level

Growth Model example

(Mathematics scores at 9, 13 and 17)





Statistical models developed

Set up initial growth curve models

- Model 1: Baseline model
- Model 2: Household Level covariates
- Model 3: Child level covariates

Computer Usage and Applications Models

- Model 4: Computer usage and monitoring variables
- Model 5: Specific applications used at 9 and 13

Summary of Model Fit Statistics

Baseline models 1-3

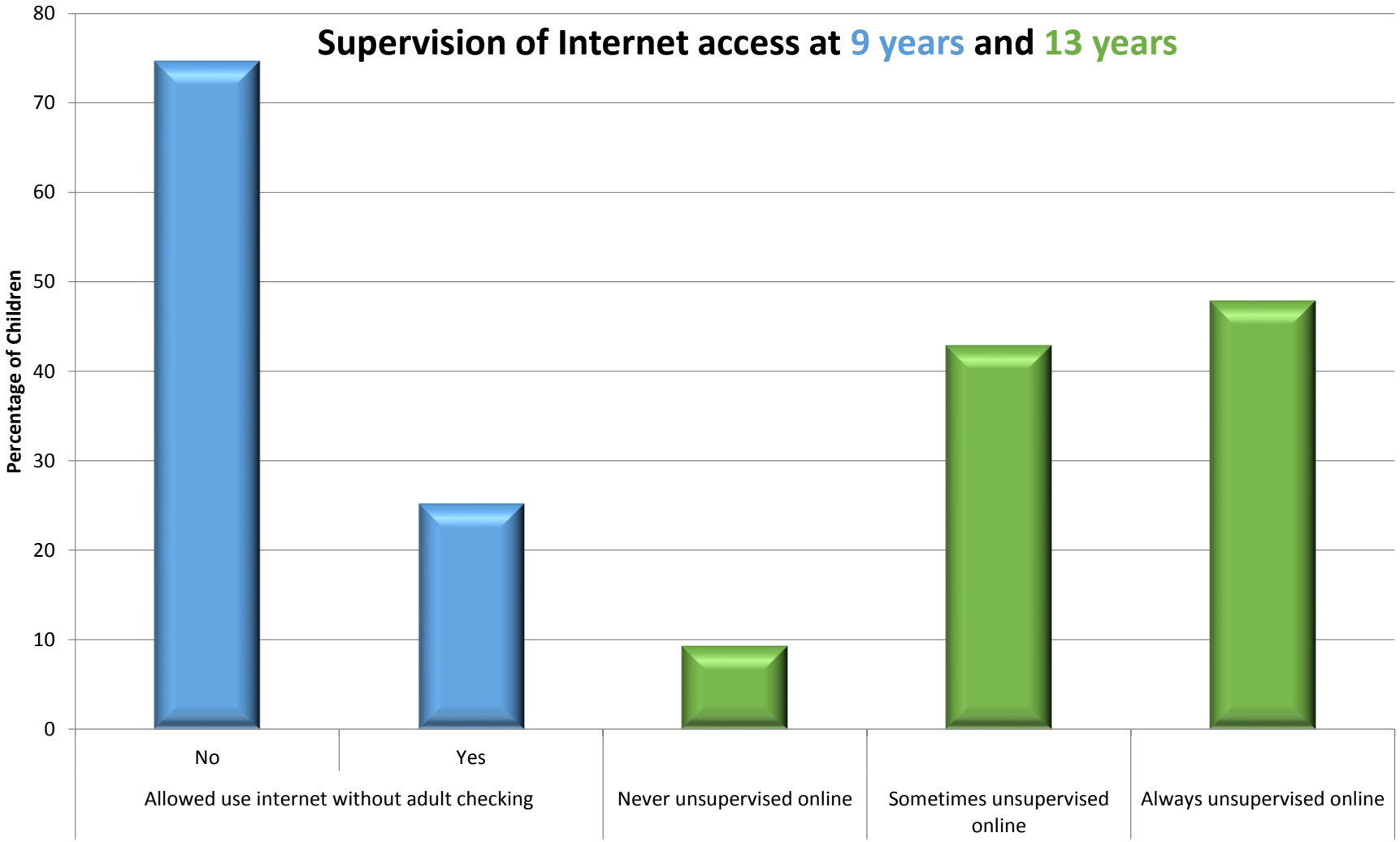
Covariates (Casey et al. 2012)

- PCG/SCG Education
- HSD Structure
- HSD Social class
- Equivalised Income
- Child gender
- Child early reading

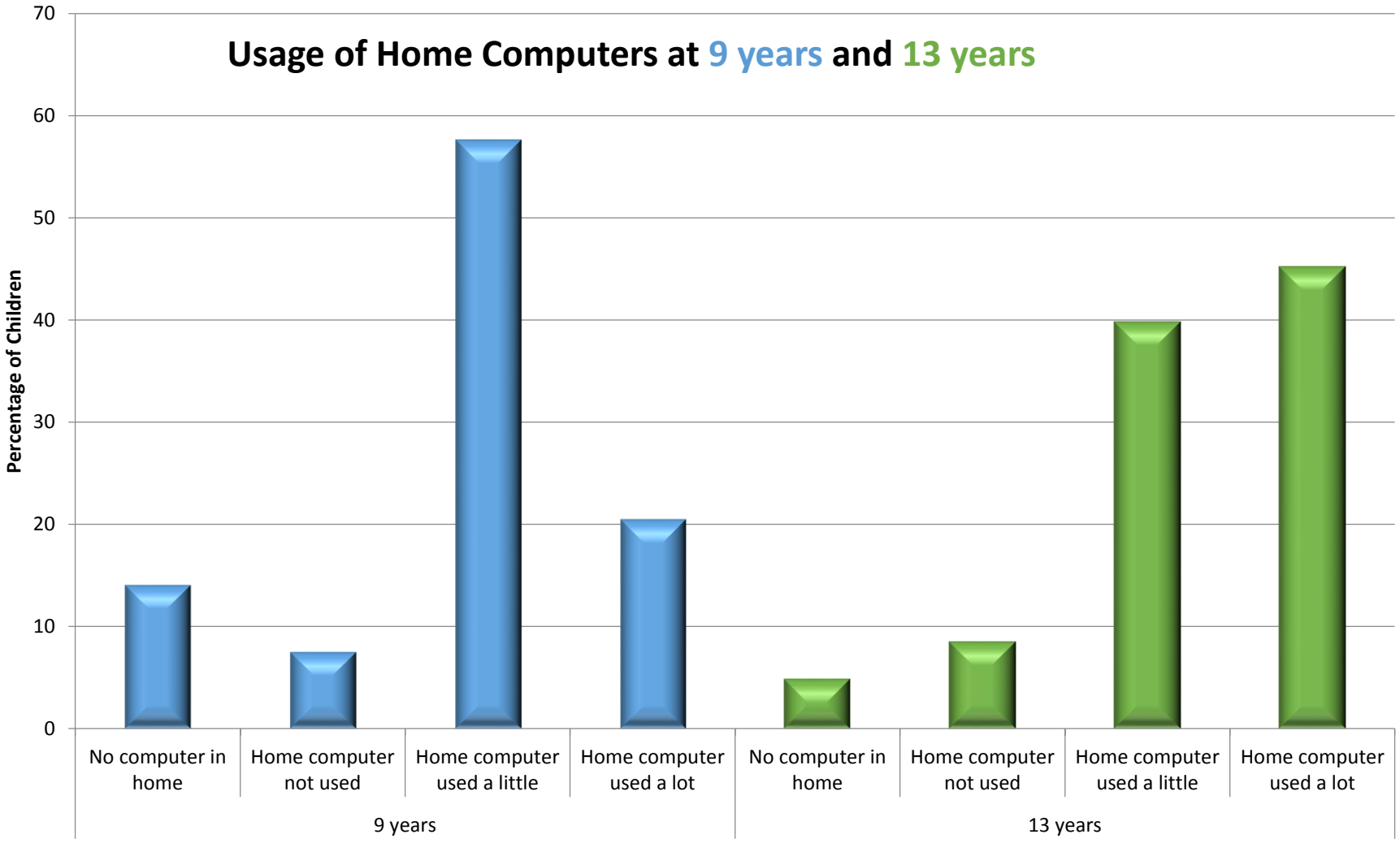
Model Fit Statistics support all models

- Chi-sq to df ratio ✓
- CFI values above 0.9 ✓
- RMSEA values below 0.10 ✓
- SRMR values below 0.10 ✓

Model 4: Computer usage and monitoring
Descriptives: Supervision



Model 4: Computer usage and monitoring
Descriptives: Computer usage



Model 4 Summaries
Supervision and Usage

	Initial effects at 9 (Intercept)	Mathematics β	p-value	Reading β	p-value
9 years	No computer in home	-0.26	***	-0.29	***
	Never uses computer	-0.05	ns	-0.09	*
	Uses computer a lot	-0.04	ns	-0.11	***
	Independent access	0.09	**	0.09	**
	Change over time (Slope)	**Mathematics β**	**p-value**	**Reading β**	**p-value**
13 years	No computer in home	-0.12	**	-0.10	*
	Never uses computer	-0.03	ns	-0.06	*
	Uses computer a lot	-0.14	***	-0.07	***
	Always supervised	-0.02	ns	-0.01	ns
	Never supervised	-0.03	ns	0.02	ns

* P < .1, ** p < .05, *** p < .001

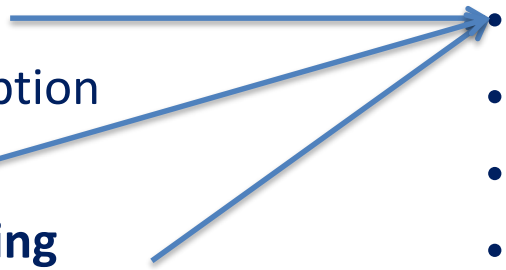
Reference categories:

- Moderate computer usage at 9 and 13
- Sometimes supervised at 13
- **Findings of Casey et al 2012 are replicated**
- Early independence related to better early outcomes
- Longitudinally, relative to moderate computer users, both high intensity and non-users show negative developmental trajectories

Computer Applications

- **Applications used at 9**

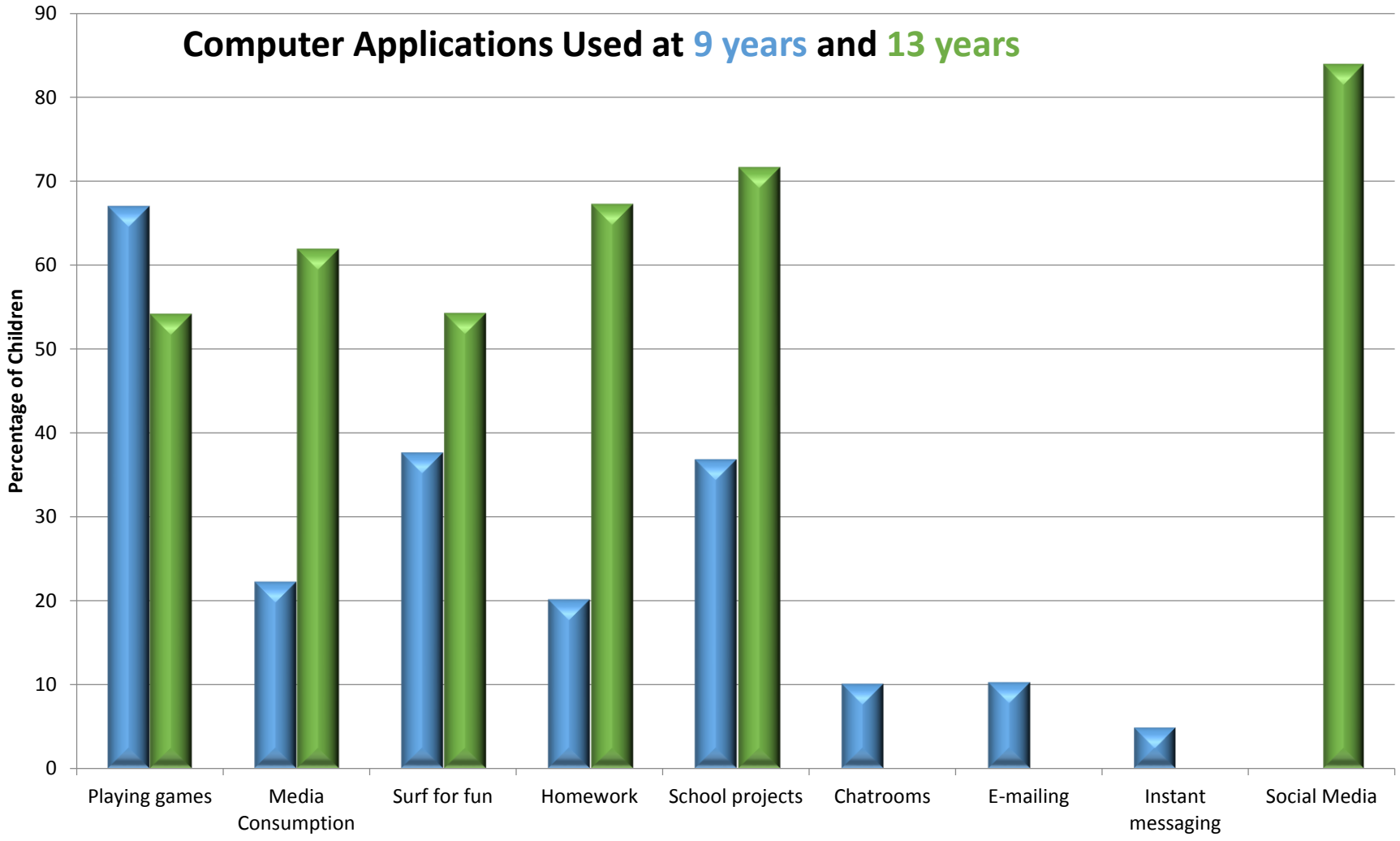
- Playing games
- **Chatrooms**
- Media Consumption
- **E-mailing**
- **Instant messaging**
- Surf for fun
- Homework
- School projects



- **Applications used at 13**

- Playing games
- **Social Media**
- Media Consumption
- Surfing for fun
- Homework
- School Projects

Model 5: Applications
Descriptives: Applications used



Model 5 Summaries
Specific applications

	Initial effects at 9 (Intercept)	Mathematics β	p-value	Reading β	p-value
9 year applications	**School projects**	**0.09**	**	**0.12**	***
	Homework	-0.01	ns	-0.04	ns
	Chatrooms	-0.01	ns	-0.04	ns
	Playing Games	**0.13**	***	**0.09**	**
	Surfing for fun	**0.07**	*	**0.08**	**
	Instant messaging	-0.20	**	-0.20	**
	E-mailing	**0.10**	*	**0.16**	***
	Movies/Music	-0.12	***	-0.17	***

	Change over time (Slope)	Mathematics β	p-value	Reading β	p-value
13 year applications	**School projects**	**0.08**	***	**0.08**	***
	Homework	**0.05**	**	**0.03**	*
	Social media	-0.11	***	-0.06	**
	Games	0.00	ns	-0.03	*
	Surfing for fun	0.00	ns	**0.03**	*
	Movies/Music	-0.03	**	-0.01	ns

* P < .1, ** p < .05, *** p < .001

- Findings of Casey et al 2012 are largely replicated.
- Early informational and fun uses of computer associated with better initial outcomes
- Longitudinally, there is support for consistent positive effects for informational patterns of usage
- Consistent negative effects are also seen for consumptive/ interruptive patterns computer usage

Implications

- Findings are supported both cross-sectionally and longitudinally
- Importance of overall moderation in hours of computer use
- Evidence that informational computer use supports better educational outcomes
- Evidence that Media consumption and Social Media use have negative effects on educational outcomes
- Support for “Ladder of opportunities” concept in technology
  - (Livingstone et al 2011)

Opportunites

- Structured guidelines on screen time could help parents know when to limit their children's activities
  - www.makeastart.ie (Safefood, 2018)
- Guidelines should also include information on beneficial types of activities on computers and mobile devices
- Endless potential to use access to media and games as a powerful behavioural motivator for success
  - Game based learning
  - Age appropriate reward charts / targets
  - Increased parental controls on systems

Future Research

- Challenges of parameterisation of educational outcomes
- Application by Usage interactions
- Possibilities of establishing classes of use and their consequences
- Develop useful guidelines for age appropriate activity cutoffs

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Questions, comments and suggestions are very welcome

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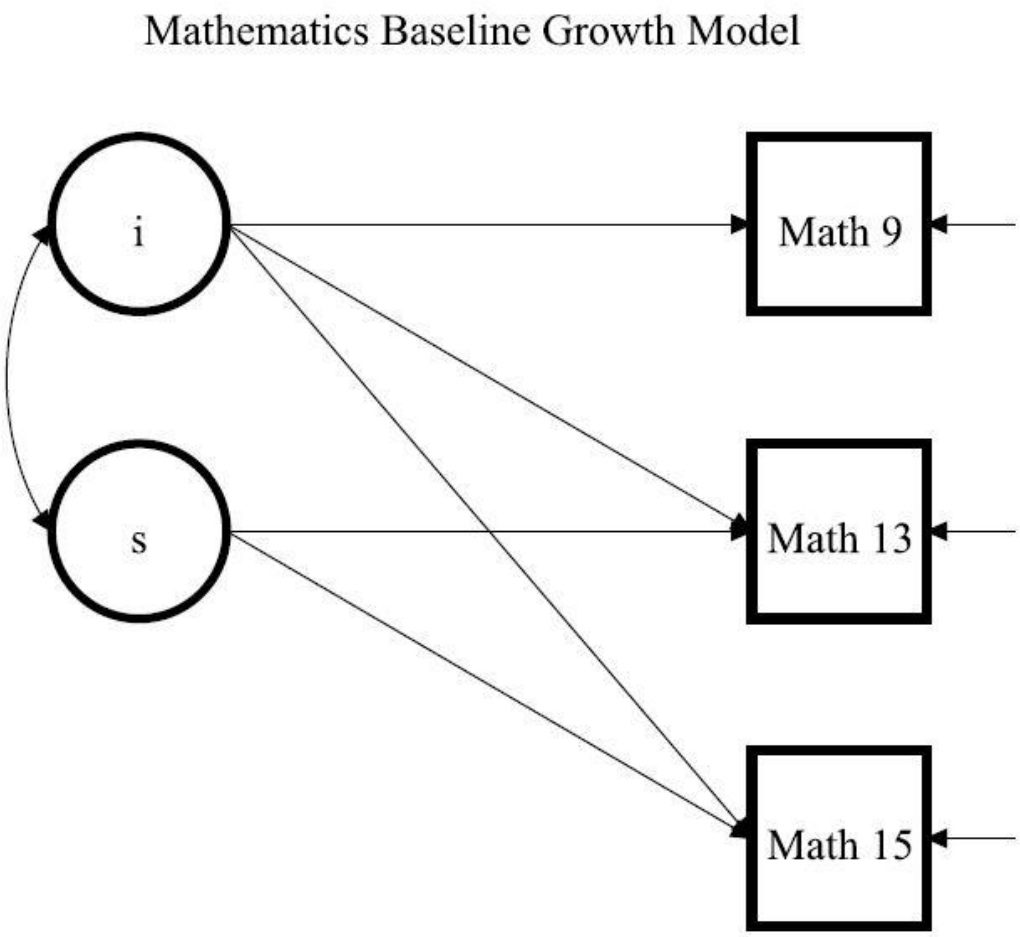
Growth Models



In this example, two "latent variables" are used to describe development over time based on your raw data

Intercept (i) estimates where you start.

Slope (s) shows your rate of change over time.

Model fit statistics (all models)

Mathematics

Model no.	Model name	Chi-sq	df	CFI	RMSEA	SRMR
1	Baseline	0.9	1	1	0	0.004
2	Household controls	75.9	31	0.988	0.015	0.008
3	Child level controls	146.5	33	0.971	0.024	0.01
4	Usage and Monitoring	221.8	47	0.957	0.024	0.01
5	Computer applications	231.4	61	0.960	0.021	0.008
6	Changes in behaviour	281.7	73	0.951	0.021	0.008

Reading

Model no.	Model name	Chi-sq	df	CFI	RMSEA	SRMR
1	Baseline	1.4	1	1	0.008	0.005
2	Household controls	62.6	31	0.991	0.013	0.009
3	Child level controls	288.6	33	0.936	0.035	0.014
4	Usage and Monitoring	336.7	47	0.929	0.031	0.012
5	Computer applications	386.9	61	0.924	0.029	0.011
6	Changes in behaviour	400.0	73	0.925	0.027	0.009

Summary

Chi-Sq changes with model complexity (df) and sample size. Ratio ideally below 5	✓ ✓ For all except final reading models
CFI values above 0.900	✓
RMSEA values below 0.10	✓
SRMR values below 0.10	✓