Longitudinal Data Analysis Contest, LaCOSA II Conference (Lausanne, June 2016)

Katharina Loter & Oliver Arránz Becker

Internet Addiction among Adolescents at Age 13-15: An Example for Latent Class Growth Analysis with Nonignorable Dropout

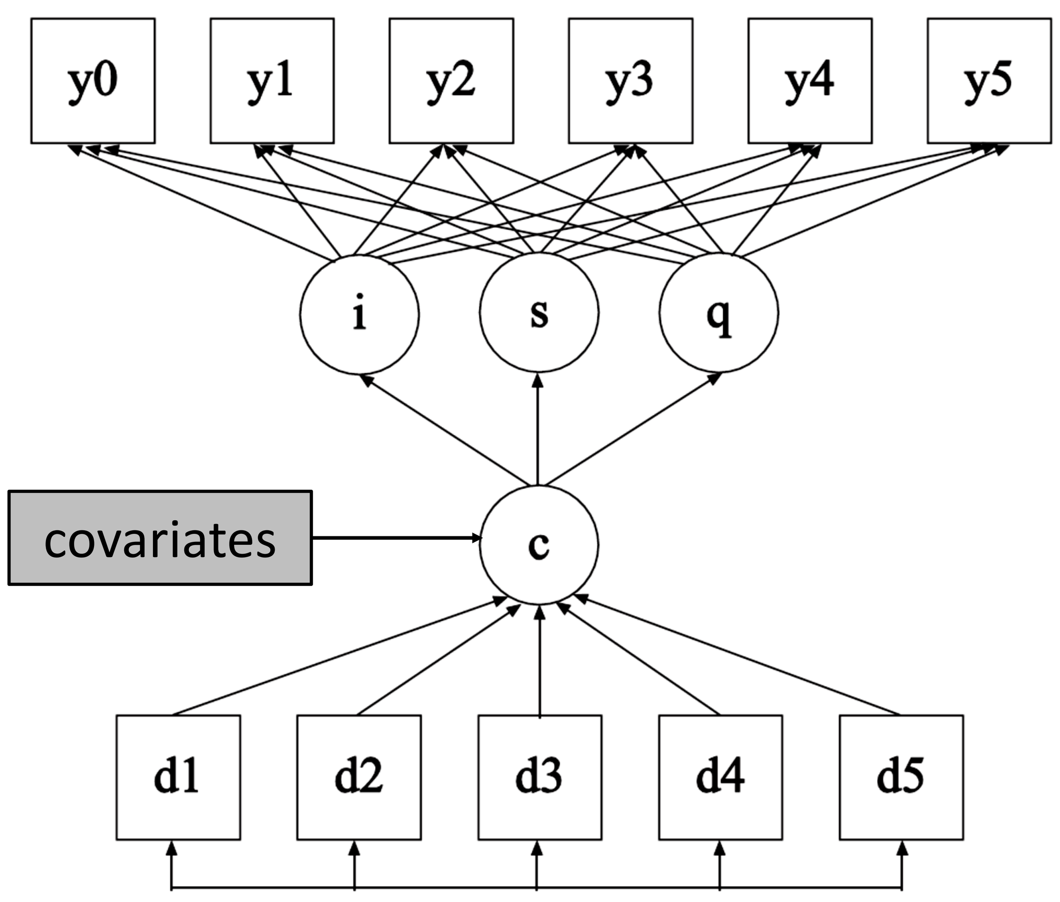
Introduction

In modern societies, youth grows up with a new type of mass communication media. New media entail rich opportunities for seeking information and allow adolescents to engage in highly effective and flexible online communication (e.g., through online social media networks). These new technological opportunities also foster overly dependency from "staying connected" and Internet overuse, including – in extreme cases – the emergence of Internet addiction, a phenomenon that has recently received increasing attention among psychiatrists and social scientists (Kuss et al. 2014). However, longitudinal research on trajectories of Internet addiction among adolescents over time and its determinants is still scarce. We employ a growth mixture model (GMM) approach on five-wave panel data from from a longitudinal study of adolescents in the Swiss canton of Vaud to model inter-individual heterogeneity in Internet addiction trajectories.

Method

Latent growth curve (LGC) modelling (e.g., Hox & Stoel 2005) has become a well-known and powerful tool for modelling and illustrating inter-individual differences in intra-individual change over time. However, one limitation is the assumption that individuals come from one single population. In order to capture unobserved heterogeneity in trajectories, LGC modelling can be combined with latent class (LC) modelling, where latent classes are defined by random growth parameters from LGC (Muthén et al. 2011). The goal of the resulting growth mixture models (GMM) is to determine subpopulations (classes) of individuals who share characteristic trajectories of the studied outcome (i.e., Internet addiction) and to estimate the prevalence and determinants of these classes.
The study for this contest is an unbalanced panel with five waves. We analyze a subset of 359 adolescents at age 13-15. One of the main analytical challenges is that the sample is not representative and thus should be weighted. Moreover, some respondents (around 17%) drop out of the panel. Since it can be expected that dropout is related to the dependent variable, a "missing not at random" (MNAR) Roy latent class dropout model was employed to correct bias in the GMM parameters (see Fig. 1).

Figure 1: Roy latent class dropout model (Muthén et al. 2011)

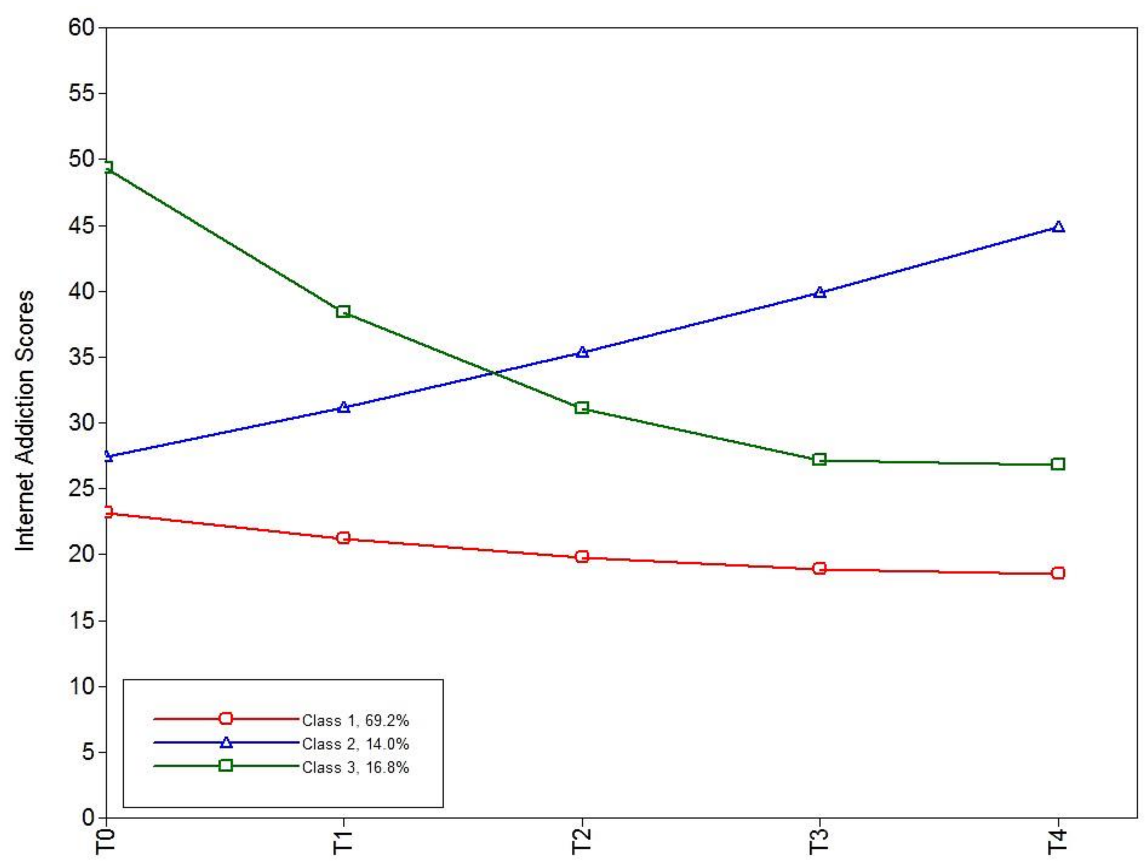


After careful exploration of goodness-of-fit measures from a series of conditioned and unconditioned quadratic LC-LGC models (see Table 1), we arrived at a parsimonious and sound 3-class solution, with a Roy dropout model part for waves 4 and 5.

Table 1: Goodness-of-fit measures for a 3-class solution

Model	BIC	Bootstrap-LLRT	LRT test
Roy Model: free intercept variances (unequal in LC)	**11.821.433**	**0.0000**	**0.0405**
Roy Model: free intercept variances (equal in LC)	11.823.247	0.0000	0.1673

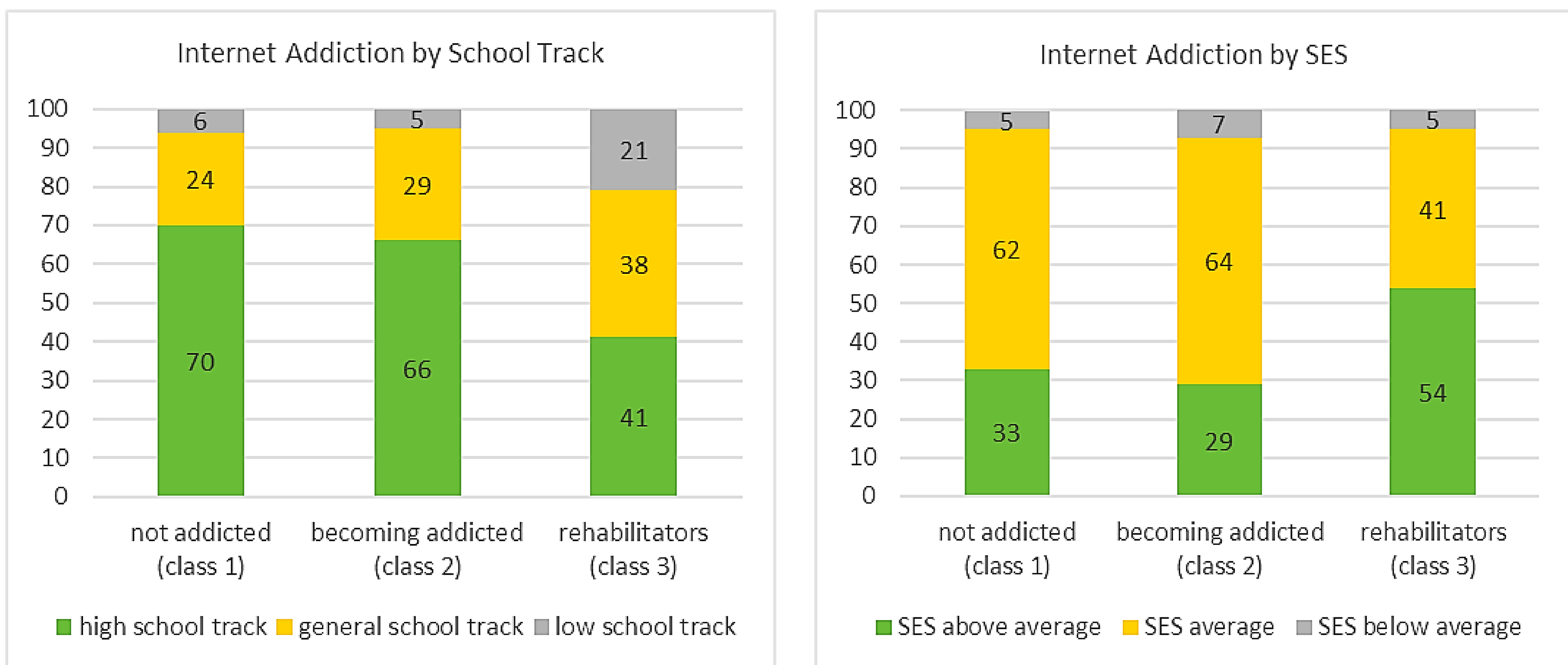
Figure 2: Three-class growth latent dropout model (weighted)



Results

The substantive interpretation of the three classes is as follows (see Fig. 2): The majority in the sample (class 1 "not Internet addicted", 69.2%) are characterized by consistently low IAT scores (mean: 20-25) throughout the observation period. The second class labelled "becoming Internet addicted" (14.0%) exhibited IAT scores that were initially low (mean around 27) but significantly increased over time (mean up to 45 at t4). The third class (called "rehabilitators", 16.8%) started out with high IAT scores (mean around 50) but then exhibited a decelerated decline to a mean IAT score of around 27 at t4.
In the second part of the analysis, most likely class membership was regressed (via multinomial logistic regressions within Roy latent class dropout model) on several demographic predictors at t0. We found out that adolescents being in a high (as opposed to general or low) school track are, in general, more likely not to suffer from Internet addiction (see Fig. 3) and rather belong to class 1 than to class 3 (b=1.49, p=0.003). Nevertheless, they are still at significantly higher risk to become Internet addicted (class 2 versus class 3) than their counterparts from lower school tracks (b=-1.63, p=0.01). Finally, an above-average family SES seems to protect from Internet addiction (b=1.17, p=0.027) with significantly more "rehabilitators" (see Fig. 3).

Figure 3: Internet Addiction by School Track and SES in % (n=359)



Summary and Conclusion

The study confirms previous findings that a considerable share of adolescents is at risk of being or becoming Internet addicted during their adolescent years. Our analyses suggest that apart from a stable non-addicted majority group, there is a considerable movement in the in the form of entry into and exit from Internet addiction.

References

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Kuss, D.J., Griffiths, M.D., Karila, L. & J. Billieux (2014). Internet addiction: a systematic review of epidemiological research for the last decade. Current pharmaceutical design, 20(25), 4026-4052.
Muthén B., Asparouhov T., Hunter A.M. & A.F. Leuchter (2011). Growth Modeling With Nonignorable Dropout: Alternative Analyses of the STAR*D Antidepressant Trial, Psychological Methods, 16(1): 17-33.