CENTRO JUSTICIA EDUCACIONAL

ANID PIA CIE160007

# *Motivation profiles among teachers across 47 different countries*

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# Before we start …

The analyzes of this presentation were carried out for a team research project. Soon this work will be published under the name of:

*Teacher motivation in Chile: Motivational profiles and teaching quality in an incentive-based education system*

***Authors:*** Miguel Órdenes, Ernesto Treviño, Rosario Escribano and Diego Carrasco

***Journal:*** Research in Education (RIE)

# Goals

1. Discuss the difference between two latent class models, and ***why*** interpretability of the model is a priority over general model fit for country comparisons.

2. Show ***how*** we estimated the model. We will describe each step taken together to fit the proposed model while including the sample design of TALIS.

# INTRODUCTION

Teacher motivation has been studied in relationship to the intrinsic and prosocial and extrinsic factors that influence people to become and stay in the teaching profession

Brookhart and Freeman (1992), Watt and Richardson (2008).

One of our main research questions was understand the potential different arrays of teacher motivation with empirical data

*Why don't we choose the model with the best statistical fit?*

# Sample specifications

- We use data from the Teaching and Learning International Survey 2018 (TALIS 2018) to understand the potential different arrays of teacher motivation.

- The sampling design consists of a two-stage probability sample design

- We use all the participating countries and region from lower secondary levels
  - 47 educational systems
  - + 150.000 teachers

# Variables

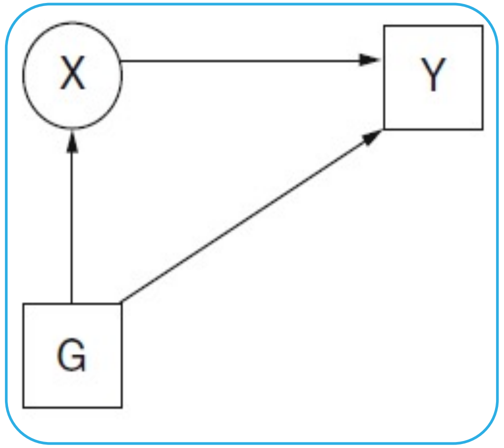
Teaching offered a steady career path
Teaching provided a reliable income
Teaching was a secure job
The teaching schedule fit with responsibilities in my personal life*
Teaching allowed me to influence the development of young people**
Teaching allowed me to benefit the socially disadvantaged
Teaching allowed me to provide a contribution to society

| ***Original:***<br>Ordinal 4-level scale | ***Recode:***<br>Dichotomic variable |
| --- | --- |
| “Not important at all”<br>“Of low importance” | 0 |
| ”Of moderate importance”<br>“Of high importance” | 1 |

# 1. WHY?

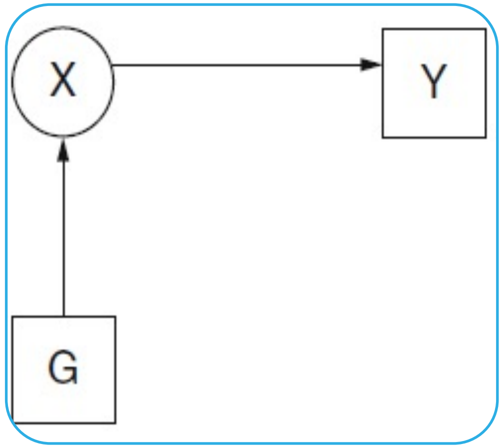
Discuss the difference between two latent class models, and ***why*** interpretability of the model is a priority over general model fit for country comparisons.

# Latent Class Analysis with Large Scale Data




## Partial homogeneous model

- Allows the intercept variations for different countries and have better fit




## Structurally homogeneous model

- Keep the response patterns of each class fixed between countries



*Image Source*: Simultaneous Latent-Class Analysis Across Groups ( Kankaras and Vermunt, 2015)

# 2. HOW?

Show ***how*** we estimated the model. We will describe each step taken together to fit the proposed model while including the sample design of TALIS.

# How we run the analysis

- An exploratory sample and a validation sample were used for this study

All analyses were carried using the software Latent Gold v5.1

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- Structurally homogeneous latent class analyses models were performed with the exploratory sample varying the number of classes from one to 10.

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| Classes | BIC | AIC | Param | $L^2$ | % change $L^2$ | Class.Err |
|---|---|---|---|---|---|---|
| 1 | 160816.20 | 160759.73 | 7 | 44411.43 | 0.00 | 0.00 |
| 2 | 135736.06 | 135243.99 | 61 | 18787.70 | 0.58 | 0.04 |
| 3 | 129933.40 | 129005.74 | 115 | 12441.44 | 0.72 | 0.07 |
| 4 | 128326.17 | 126962.91 | 169 | 10290.61 | 0.77 | 0.07 |
| 5 | 126616.92 | 124818.06 | 223 | 8037.77 | 0.82 | 0.10 |
| 6 | 126214.94 | 123980.48 | 277 | 7092.18 | 0.84 | 0.14 |
| 7 | 125850.83 | 123180.77 | 331 | 6184.48 | 0.86 | 0.16 |
| 8 | 125989.89 | 122884.24 | 385 | 5779.94 | 0.87 | 0.17 |
| 9 | 126177.02 | 122635.77 | 439 | 5423.48 | 0.88 | 0.18 |
| 10 | 126445.50 | 122468.65 | 493 | 5148.35 | 0.88 | 0.16 |

BIC= Bayesian Information Criteria, AIC= Akaike´s Information Criterion, Param. = number of parameters in the model, $L^2$ = likelihood ratio chi-square statistic, % change $L^2$ = percentage of change of $L^2$ between k and k+n.

- An exploratory sample and a validation sample were used for this study
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- Selection criteria based on relative adjustment indexes (AIC, BIC), classification error, and interpretability

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- Partially homogeneous latent class model was performed with the number of classes of the previously chosen model, an the both wee compared

All analyses were carried using the software Latent Gold v5.1

Homogeneous

| | LL | BIC(LL) | AIC(LL) | Npar | $L^2$ | df | Class.Err. |
|---|---|---|---|---|---|---|---|
| Model1 | -80372,87 | 160816,20 | 160759,73 | 7,00 | 44411,43 | 23537,00 | 0,00 |
| Model2 | -67561,00 | 135736,06 | 135243,99 | 61,00 | 18787,70 | 23483,00 | 0,04 |
| ***Model3*** | ***-64387,87*** | ***129933,40*** | ***129005,74*** | ***115,00*** | ***12441,44*** | ***23429,00*** | ***0,07*** |
| Model4 | -63312,45 | 128326,17 | 126962,91 | 169,00 | 10290,61 | 23375,00 | 0,07 |
| Model5 | -62186,03 | 126616,92 | 124818,06 | 223,00 | 8037,77 | 23321,00 | 0,10 |
| Model6 | -61713,24 | 126214,94 | 123980,48 | 277,00 | 7092,18 | 23267,00 | 0,14 |
| Model7 | -61259,39 | 125850,83 | 123180,77 | 331,00 | 6184,48 | 23213,00 | 0,16 |

Heterogeneous

| | LL | BIC(LL) | AIC(LL) | Npar | $L^2$ | df | Class.Err. |
|---|---|---|---|---|---|---|---|
| Model1 | -72766,96 | 148845,84 | 146191,92 | 329,00 | 29199,62 | 23215,00 | 0,00 |
| Model2 | -63576,84 | 131009,21 | 127919,69 | 383,00 | 10819,39 | 23161,00 | 0,04 |
| ***Model3*** | ***-61274,34*** | ***126947,79*** | ***123422,68*** | ***437,00*** | ***6214,38*** | ***23107,00*** | ***0,06*** |
| Model4 | -60369,21 | 125681,14 | 121720,43 | 491,00 | 4404,13 | 23053,00 | 0,07 |
| Model5 | -60059,11 | 125604,53 | 121208,22 | 545,00 | 3783,92 | 22999,00 | 0,18 |
| Model6 | -59982,71 | 125995,34 | 121163,43 | 599,00 | 3631,13 | 22945,00 | 0,22 |
| Model7 | -59836,35 | 126246,22 | 120978,71 | 653,00 | 3338,41 | 22891,00 | 0,25 |

- An exploratory sample and a validation sample were used for this study
- Structurally homogeneous latent class analyses models  were performed with the exploratory sample varying the number of classes from one to 10.
- Selection criteria based on relative adjustment indexes (AIC, BIC), classification error, and interpretability
- Partially homogeneous latent class model was performed with the number of classes of the previously chosen model, an the both wee compared
- Structurally homogeneous latent class analysis model was performed with the validation sample. Chilean sample is extracted

All analyses were carried using the software Latent Gold v5.1

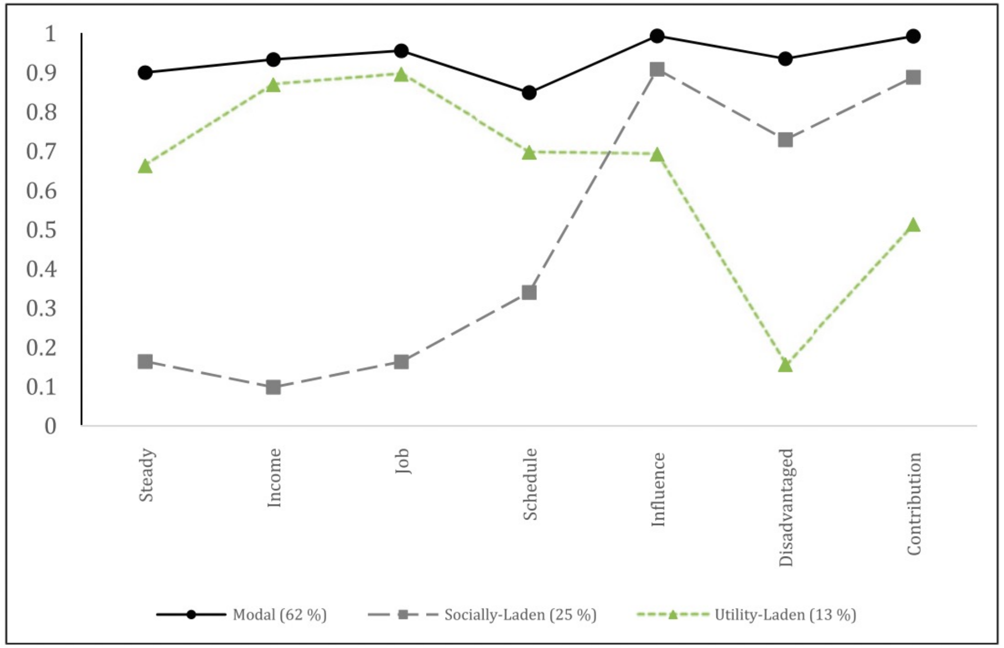



**Figure 1.** Patterns of mean response probabilities for the three-class solution on the exploratory sample. Note: In the x-axis, the seven indicators are included. In the y-axis are the expected mean probability for each class.

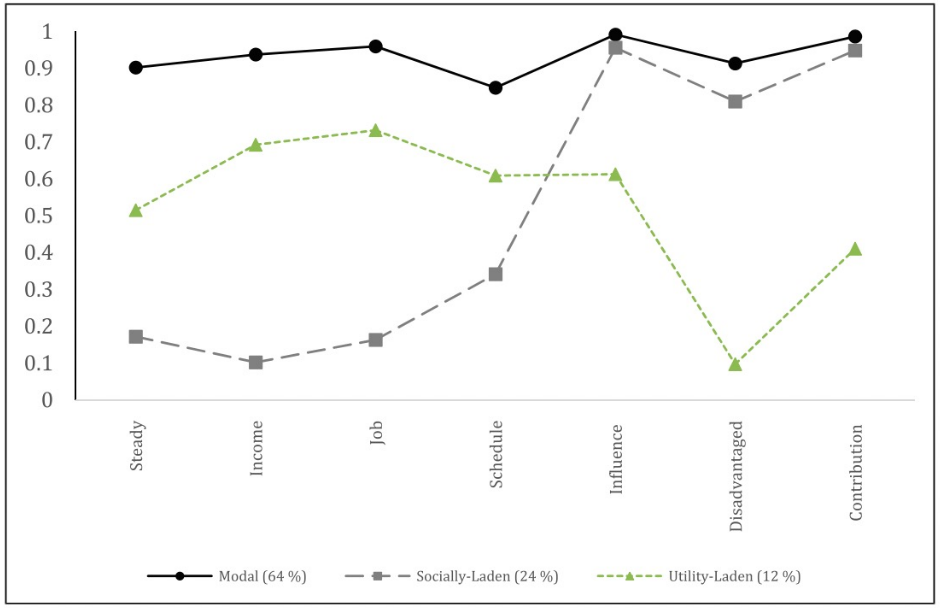



**Figure 2.** Patterns of mean response probabilities for the three-class solution on the validation sample. Note: In the x-axis, the seven indicators are included. In the y-axis are the expected mean probability for each class.

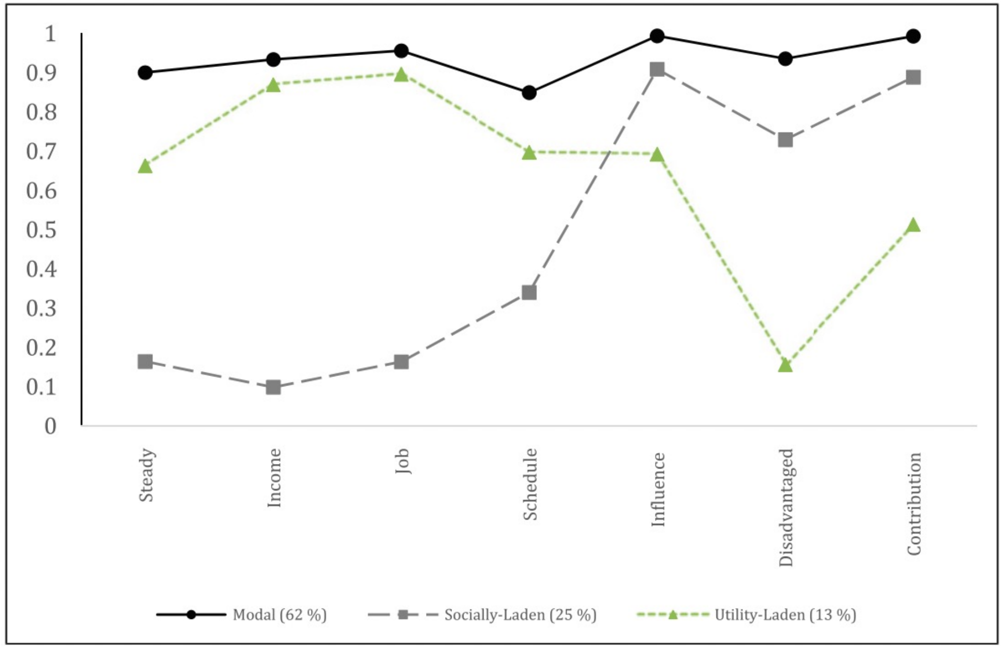
- An exploratory sample and a validation sample were used for this study
- Structurally homogeneous latent class analyses models  were performed with the exploratory sample varying the number of classes from one to 10.
- Selection criteria based on relative adjustment indexes (AIC, BIC), classification error, and interpretability
- Partially homogeneous latent class model was performed with the number of classes of the previously chosen model, an the both wee compared
- Structurally homogeneous latent class analysis model was performed with the validation sample.
- Interpret and label the response probability patters for each class.

All analyses were carried using the software Latent Gold v5.1

**Table 3.** Response probability of considering each statement as "Important" for each teacher motivation profile, using TALIS 2018 data.

| Item | Teacher motivation profiles: Modal (64.13%) | Socially-laden (23.62%) | Utility-laden (12.25%) |
|---|---|---|---|
| Teaching offered a steady career path | 0.90 | 0.17 | 0.66 |
| Teaching provided a reliable income | 0.93 | 0.10 | 0.87 |
| Teaching was a secure job | 0.96 | 0.16 | 0.90 |
| The teaching schedule fit with responsibilities in my personal life* | 0.85 | 0.34 | 0.70 |
| Teaching allowed me to influence the development of young people** | 0.99 | 0.91 | 0.69 |
| Teaching allowed me to benefit the socially disadvantaged | 0.94 | 0.73 | 0.16 |
| Teaching allowed me to provide a contribution to society | 0.99 | 0.89 | 0.51 |

Notes: *This item was shortened in the table for presentation purposes. Its full version reads: "The teaching schedule (e.g., hours, holidays, part-time positions) fit with responsibilities in my personal life". ** This item was also shortened; its full version reads "Teaching allowed me to influence the development of children and young people".



# THANK YOU!

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# Latent Gold Syntax: Homogeneous model

```
model
options
      algorithm
         tolerance=1e-008 emtolerance=0.01 emiterations=250 nriterations=50;
      startvalues
         seed=0 sets=10 tolerance=1e-005 iterations=50;
      bayes
         categorical=1 variances=1 latent=1 poisson=1;
      montecarlo
         seed=0 replicates=500 tolerance=1e-008;
      quadrature  nodes=10;
      missing  includeall;
      output
         parameters=first
         standarderrors
         probmeans=posterior
         profile
         profile=posterior
         bivariateresiduals
         loadings
         writeparameters='m01_parameters.txt'
         estimatedvalues=model;
         outfile 'm01_classification.txt'
         classification;

   variables


      caseid id_i;
      psuid id_j;
      samplingweight ws;

      dependent
         b01 ordinal, b02 ordinal, b03 ordinal, b04 ordinal, b05 ordinal,
         b06 ordinal, b07 ordinal;

      independent
         id_k nominal;

      latent

         LatVariable nominal 3 ;

   equations

      LatVariable  <- 1 | id_k ;

      b01 <- 1 + LatVariable;
      b02 <- 1 + LatVariable;
      b03 <- 1 + LatVariable;
      b04 <- 1 + LatVariable;
      b05 <- 1 + LatVariable;
      b06 <- 1 + LatVariable;
      b07 <- 1 + LatVariable;

end model
```

# Latent Gold Syntax: Heterogeneous model

```
model
options
      algorithm
         tolerance=1e-008 emtolerance=0.01 emiterations=250 nriterations=50;
      startvalues
         seed=0 sets=10 tolerance=1e-005 iterations=50;
      bayes
         categorical=1 variances=1 latent=1 poisson=1;
      montecarlo
         seed=0 replicates=500 tolerance=1e-008;
      quadrature  nodes=10;
      missing  includeall;
      output
         parameters=first
         standarderrors
         probmeans=posterior
         profile
         profile=posterior
         bivariateresiduals
         loadings
         writeparameters='m02_parameters.txt'
         estimatedvalues=model;
         outfile 'm02_classification.txt'
         classification;

   variables


      caseid id_i;
      psuid id_j;
      samplingweight ws;

      dependent
         b01 ordinal, b02 ordinal, b03 ordinal, b04 ordinal, b05 ordinal,
         b06 ordinal, b07 ordinal;

      independent
         id_k nominal;

      latent

         LatVariable nominal 3 ;

   equations

      LatVariable  <- 1 | id_k ;

      b01 <- 1 | id_k + LatVariable;
      b02 <- 1 | id_k + LatVariable;
      b03 <- 1 | id_k + LatVariable;
      b04 <- 1 | id_k + LatVariable;
      b05 <- 1 | id_k + LatVariable;
      b06 <- 1 | id_k + LatVariable;
      b07 <- 1 | id_k + LatVariable;

end model
```

# References


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