Dissertation

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Contents

Introduction

Mention the context of the research topic and why it is important. Mention what is the research gap and why it matters. Discuss how you will answer the research question.

Nearly one third of global population suffer from insuffcent physical activity, a 9% increase from 20 years ago (Strain et al, 2024). Understanding the factors that influence engagement in PA is critical, as regular activity supports cardiovascular health, metabolic function, mental well-being, and overall quality of life. Identifying the underlying determinants of PA can inform interventions, policies, and educational strategies aimed at improving health outcomes in both youths and adults.

Motives for physical activity have been studied extensively, with frameworks such as Self-Determination Theory and the Theory of Planned Behaviour providing evidence for both intrinsic and extrinsic drivers. However, most existing studies investigate age-related differences within youths or within adults, but rarely compare the two populations directly. This leaves unclear whether the same motives operate similarly across life stages, or whether different developmental contexts shape the salience of specific motives. To address this, the present study explores how different motives for PA manifest across youths and adults, using both observed differences and latent class analysis to identify distinct motivational profiles.

- Research Questions

1. Do perceived exercise motives influence physical activity differently in youths and adults?
2. How do age differences shape dominant exercise motives within youth and adult groups?

To test whether motives predict PA differently across youths and adults, multigroup structural equation modelling was used to examine associations between key motives and self-reported PA. Latent class analysis was used to identify motivational profiles within each group, enabling age-based comparisons.

All analyses were based on self-reported perceptions of motives, reflecting subjective experiences rather than externally imposed classifications.

Literature Review

- Discuss the main papers in your research area. • Try to summarise the current knowledge but also be critical of the limitations that you see and highlight gaps.

ADD MORE YOUTHS PAPERS BE MORE CRITICAL OF PAPER METHODS (like social cognitive)

Nascimento 2023 Only the well-being factor is affected by age.

Physical activity motivation varies across the lifespan, and understanding these differences is essential for designing effective interventions. Although prior work shows age-linked motivational patterns within either youths or adults, few studies directly compare these groups in the same framework. This limits our understanding of whether similar motives carry the same weight across developmental stages, or whether distinct clusters of motives emerge that reflect age-specific priorities. Among adults, research using Self-Determination Theory (SDT) indicates that along with geenral PA levels (Geller), intrinsic and identified motivation tend to decline with age, while middle-aged and older adults are more likely to exercise for fitness and health reasons rather than for appearance or social recognition (Brunet & Sabiston, 2011; Davis et al., 1995). Autonomy support and enjoyment are higher in individuals with strong motivational profiles, suggesting that quality of motivation may interact with age-related patterns (Heredia-León et al., 2023). Social Cognitive Theory (SCT) research shows that self-efficacy and social support are key determinants of exercise behavior, with gender differences observed in adults (Oyibo, 2018). Similarly, the Theory of Planned Behavior (TPB) highlights perceived behavioral control as the strongest predictor of exercise intention, emphasizing the role of perceived capability in promoting activity across adulthood (Neipp et al., 2013).

In youths, SDT-based studies demonstrate that overall motivation tends to be higher than in adults, with social and relational contexts playing a central role. Children often link physical activity to interactions with friends or siblings, reflecting the importance of relatedness needs (Sebire et al., 2013). Motivation also varies by sex, age, school, and socioeconomic background, with students who exhibit high-quality motivation showing greater autonomy support, intention to be active, enjoyment, and lower boredom (Heredia-León et al., 2023; Tapia Serrano).

Most research on motivational influences in physical activity examines youths and adults separately, and often with distinct measurement tools tailored to each population. This makes it difficult to determine whether differences reflect true developmental patterns or simply methodological artifacts. By applying the same motive items across both groups, this study enables a more valid comparison of how motives relate to physical activity in youths versus adults (H1), while also identifying distinct motivational profiles within each group and examining how age predicts profile membership (H2).

Given that enjoyment, social interaction, and guilt have been shown to play larger roles in youths, while fitness motives become more salient in adults, it is plausible that the strength of associations between motives and PA differs systematically between the groups. Testing this directly allows us to determine whether motivational influences are developmentally specific or broadly consistent. The influence of specific exercise motives may differ between youths and adults. Enjoyment, guilt, and social motives appear more salient in youths, whereas fitness-related motives gain prominence in middle-aged adults. Some factors, such as access to opportunities for activity, may operate similarly across age groups.

- H1: The influence of exercise motives on physical activity differs between youths and adults.

** H1a: Enjoyment, guilt, and social motives have a stronger influence in youths than in adults.

** H1b: Fitness motives have a stronger influence in adults than in youths.

** H1c: The influence of opportunity on physical activity is similar across age groups.

Evidence for motivational profiles in both populations indicates the existence of distinct clusters of individuals characterized by differing motive dominance, with age-related patterns suggesting that younger youths tend toward enjoyment-dominant profiles, while middle-aged and older adults are more likely to be fitness-dominant.

- H2: Distinct motivational profiles exist within youths and within adults.

** H2a: Middle-aged and older adults are more likely than younger adults to belong to fitness-dominant profiles or score highly in fitness motives.

** H2b: Younger youths are more likely than older youths to belong to enjoyment-dominant profiles.

Data and Methods

- Discuss what variables you will use, how they are coded, the amount of missing data they have and present descriptive statistics.
- Discuss the statistical models that you will use. Explain how the models will answer your research questions. Discuss what sequence of models you will run.

Data

The study uses survey responses from datasets collected by Ipsos on behalf of Sport England (2024, 2025). These datasets were selected because the youth and adult surveys share a parallel structure, and several items are worded identically, providing a strong baseline for direct comparison between age groups. All motivational measures were captured using single-item survey questions. A list of relevant survey questions is provided in Appendix A. For motive variables, descriptive statistics, bivariate correlations, and variance inflation factors (VIF) were calculated to assess distributional properties, relationships among variables. Challenge and relaxation are only included in the LCA models due to different wording in the survey questions for adults and youths. A total of 117,247 adult and 30,670 youth observations were used in the SEM analyses, whereas 110,378 adult and 28,886 youth observations were included in the LCA. Only cisgender adults without disabilities were included in the analyses to maintain comparability and avoid skewed results due to small subgroup sizes. As ethnicity, education, and gender were included as control variables, these factors were retained alongside the analyzed items. Participants with missing responses on any relevant items were also excluded.

- Enjoyment – whether the individual finds exercise satisfying.
- Social engagement – exercising for fun with friends.
- Health and fitness – exercising to maintain physical well-being.
- Opportunity – having the chance to exercise.

- Guilt – sense of personal obligation to exercise.
- Challenge – exercising to push oneself or compete with others.
- Relaxation – exercising to reduce stress and worry.
- Minutes Exercised - weekly minutes of moderate-to-vigorous PA; see appendix for specific activities.

Adult Dataset

The adult dataset was drawn from households sampled via the Postcode Address File (PAF), with up to two residents aged 16 or older invited to participate through either an online survey or a paper questionnaire. Data were gathered in successive waves, aiming for approximately 500 responses per local authority, and were distributed as evenly as possible across the period from November 2022 to November 2023 to reduce seasonal bias. In total, 173,950 surveys were completed.

Each item was rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher values reflecting stronger endorsement of the statement.

Several items, such as importance of exercise, were removed for adults due to its high correlation with enjoyment and fitness (>0.5).

Variable	Mean	Median	SD	PercentNA
Enjoyment	2.125675	2.0	1.0248819	4.344232
Social	2.886690	3.0	1.1603390	6.383262
Fitness	1.862708	2.0	0.8631442	3.942348
Guilt	2.553219	2.0	1.1044993	5.035701
Opportunity	2.010306	2.0	0.9913168	4.017506
Importance	1.979520	2.0	0.9118422	4.214147
Challenge	2.757458	3.0	1.1511982	6.142755
Relaxation	2.262504	2.0	1.0124889	5.331622
Minutes.Exercised	493.496059	337.5	475.1089002	0.000000

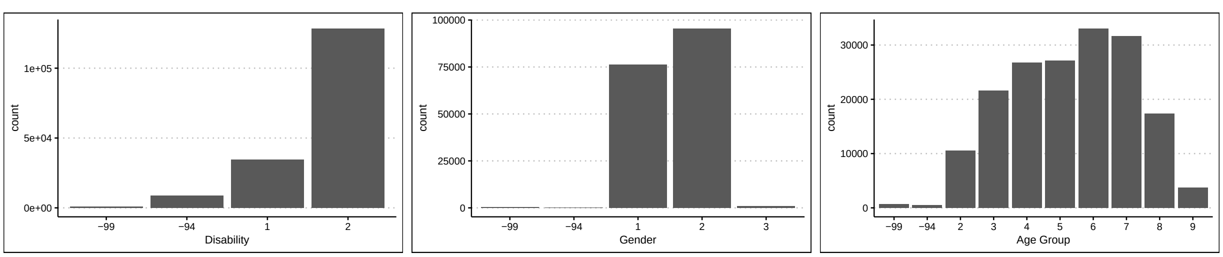
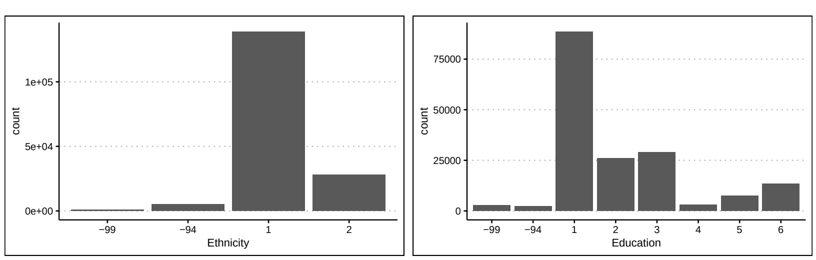


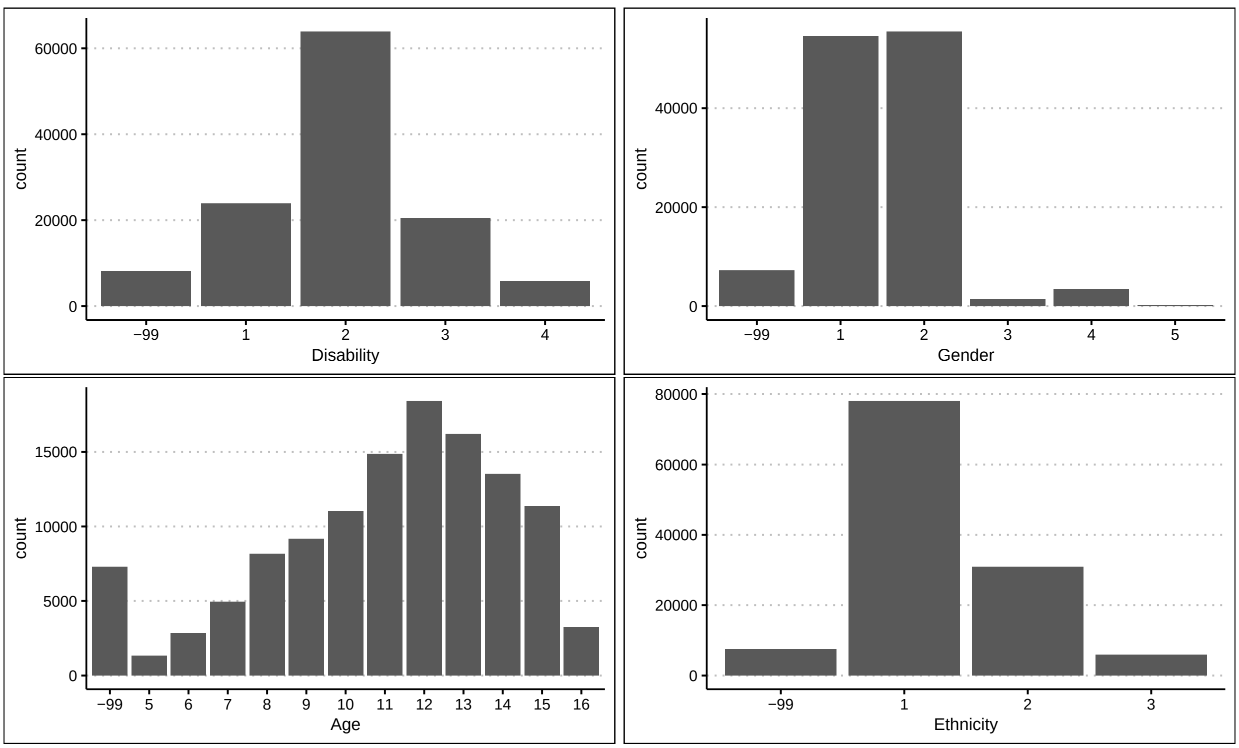
Figure 1: Negative values are mising responses.



Youths Dataset

Data for youths were collected via a school-focused, stratified sampling approach. Only responses from Year 7 to Year 11 were utilized. Younger cohorts completed a simplified survey or had responses recorded on their behalf, and are thus excluded due to reduced comparability.

Variable	Mean	Median	SD	PercentNA
Enjoyment	1.653111	2	0.7188537	9.817977
Social	2.185073	2	0.8672623	42.211906
Fitness	1.780182	2	0.7032159	40.949921
Opportunity	1.612999	2	0.6290499	39.725535
Guilt	2.520805	3	0.9114734	42.623031
Importance	1.413660	1	0.5802182	6.787253
Challenge	1.870674	2	0.7527904	16.347765
Relaxation	2.223833	2	0.9051345	42.034541
Minutes.Exercised	426.587188	290	427.9877225	1.043753



Multigroup Structural Equation Modeling (SEM)

Differences in the relationships between self-reported motives and PA levels across youths and adults were examined while controlling for demographic factors (see appendix for code and model specs).

Motivation variables included enjoyment, social, fitness, guilt, and opportunity. To account for differences in Likert scales between adults and youths, all motivation variables were dichotomized into "strongly agree" and "not strongly agree." Demographic covariates included gender, age, and ethnicity. Gender was limited to female and male due to small sample sizes of other categories. Ethnicity was collapsed into White British and Non-White British for similar reasons. Youth participants included only those aged 11 and older who responded to the relevant items. Adult participants were grouped by age ranges (16–34, 35–44, 45–54, 55–64, 65–74, 75+) because exact ages were unavailable. The youngest and oldest two groups were further collapsed to reduce skew and ensure balanced distributions. A cap of 1680 minutes per week was applied to reported PA to minimize the impact of potential data entry errors and extreme values.

Multigroup SEM was used to assess how each motive predicts PA levels, allowing direct comparison of pathway strengths between youths and adults. A freely estimated model was compared to constrained models in which individual or all motive pathways were fixed to equality, enabling evaluation of whether the effects of motives differ across age groups. Differences in the predictive strength of each motive on physical activity minutes were also calculated.

Latent Profile Analysis (LCA)

Latent class analysis (LCA) was conducted separately within the youths and adults groups to explore age-related differences in motivational profiles.

The original Likert-scale responses were retained. Additional predictors capturing similar motivational constructs but worded differently were included (see Appendix B). Motives served as predictors, while ethnicity, gender, age, and education (for adults only) were included as covariates. Ten random starts were used per class model to ensure stable solutions.

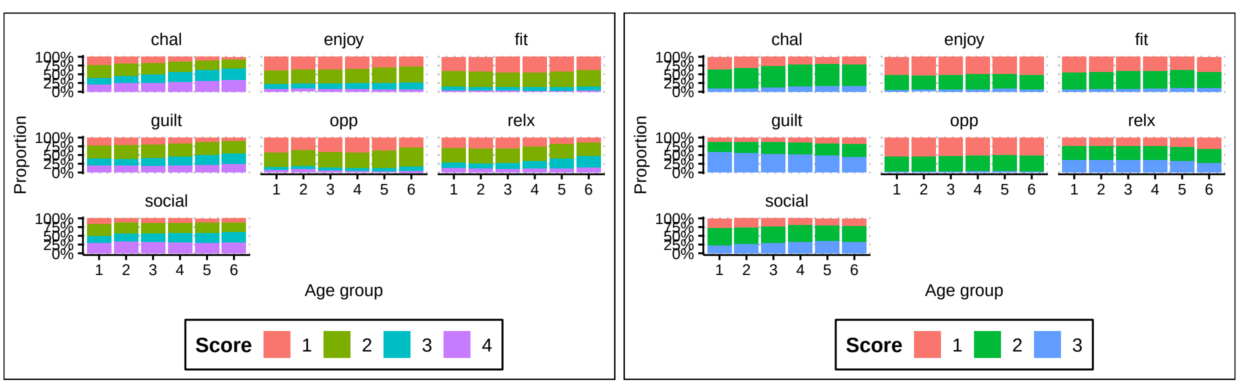
The optimal number of classes was determined by evaluating BIC elbow plots, relative entropy, bootstrap Vuong-Lo-Mendell-Rubin likelihood ratio tests (BLRT), class proportions, and substantive interpretability. Class-specific statistics were calculated, and multinomial logistic regression was performed with age predicting class membership. Odds ratios and 95% confidence intervals were derived by exponentiating the estimated coefficients and their standard errors (

$$\mathrm{OR} = \exp(\hat{\beta}), \quad 95\%\, CI = \exp\left(\hat{\beta} \pm 1.96 \times SE\right)$$

)

This procedure allows assessment of both the magnitude and statistical significance of age effects on class membership and, consequently, on PA-related motivational profiles.

There exist clear patterns in the response distrbution by age group in both adults and youths.



Results

• Present the results of the analysis. • Try to focus on how the results answer your research questions and hypotheses. • Try to focus on substantive interpretation of the results (and not just if something is significant or not). Are the effects large? Are they substantively important?

SEM

There are minor yet significant differences in the impact of every motive.

var	est.youth	est.adult	diff
enjoyb	144.740986	121.689184	23.051801
guiltb	40.697682	17.917790	22.779893
oppb	38.888023	97.339970	-58.451947
fitb	79.114739	106.118565	-27.003825
socialb	43.155354	66.484899	-23.329545
age	-2.305814	-9.475518	7.169704

Summary and spec of model in appendix. Motivational mediators contribute meaningfully to activity levels in both groups, with enjoyment and fitness motives being the strongest predictors.

Youth show stronger effects of enjoyment and guilt on exercise minutes, with slopes about 23 minutes higher than adults. Adults show stronger effects of opportunity, fitness, and social motives, with differences ranging from 23 to 58 minutes. Age shows a smaller difference (~7 minutes), with exercise minutes decreasing slightly more with age among adults.

Opportunity has a bigger effect on adults, this makes sense since children have more free time and more access to facilities like parks school gym etc.

Youths are more likely to feel guilty, also makes sense as adults (especially older) do not exercise as much for social recognition and appearnace goals. consistent with H1a. However, while social motive has a positive effect, it has a bigger impact on adults. Not sure why. fitness makes sense to matter more to adults.

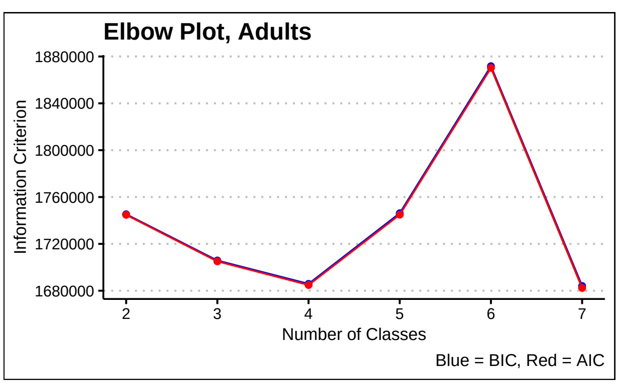
Age has a small but significant negative total effect on activity, more pronounced in adults than youths.

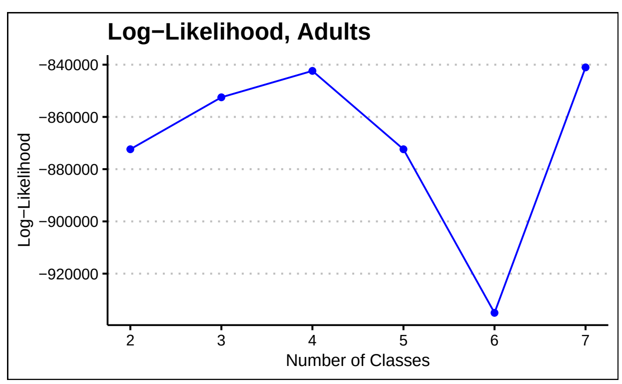
ADD IMPLICATIONS OF SUBSTANTIVE INTERPRETATION

LCA

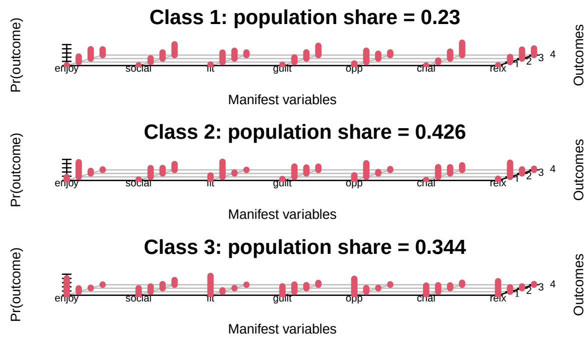
Median mins per class, rather than mean due to skew in distribution of minutes exercised (right skew), is calculated.

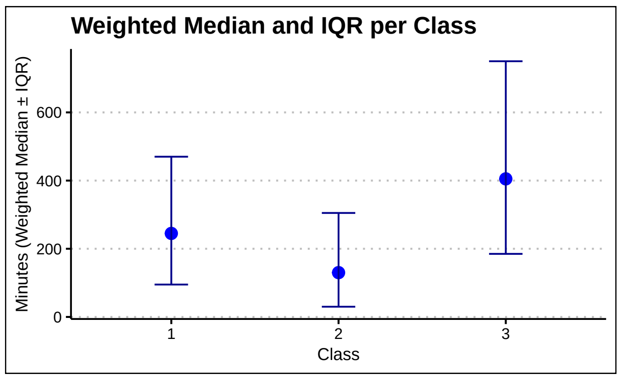
Adults



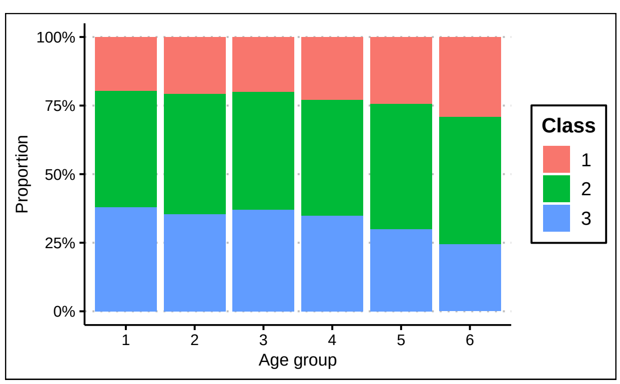


3 and 4 classes both seem ok at first glance, with simlar relative entropy, BIC, and max posterior entropy per class. While BLRT recommends the 4-class model, upon closer inspection, 3 classes has the best substantive interpretation, 4- and 5- class models contain very similar classes with minor distribution differences in their responses.





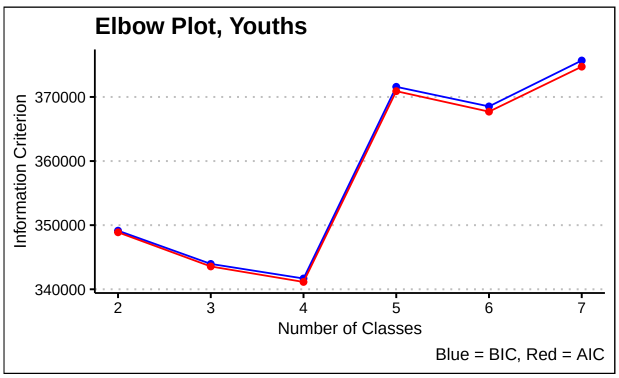
- Class 1: this class strongly endorses intrinsic motives (enjoyment, ability, importance) and is confident in their capability. They are highly consistent in responses across items. With low levels of guilt
- Class 2: Most items have higher probabilities on 3–4 (neutral to disagree) except moderate on opportunity and ability. Low on guilt and eagerness for challenges. They do not exercise to relax.
- Class 3: This class displays ocnsistently moderately positive attitudes toward PA, with the exception of social.
- Age: odds of being in the low motivation class increase with age, especially in the oldest group. odds of being in the moderate motivation class also increase with age, but not as strongly as the low motivation class.

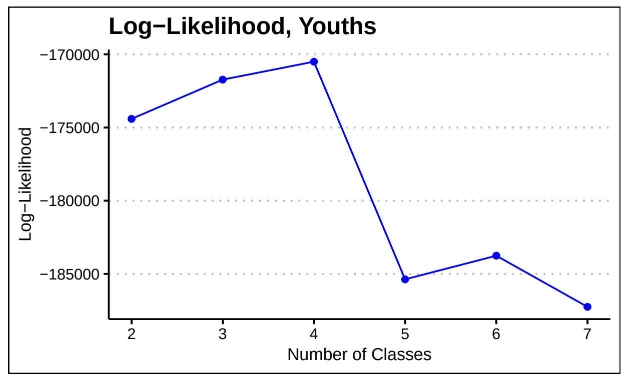


Multinomial logistic regression examined the association between age and motivation profile, with the highly motivated class (Class 1) as the reference. Compared with the youngest adults (age1), older age groups had higher odds of being in the moderate (Class 3) or low motivation (Class 2) classes. The effect was strongest in the oldest group (age6), who were about twice as likely to belong to the low motivation class (OR = 2.06) and 1.84 times more likely to belong to the moderate motivation class, relative to the highly motivated class. These results indicate that motivation tends to decline with age, with fewer older adults exhibiting the highly positive/intrinsic profile.

Youths

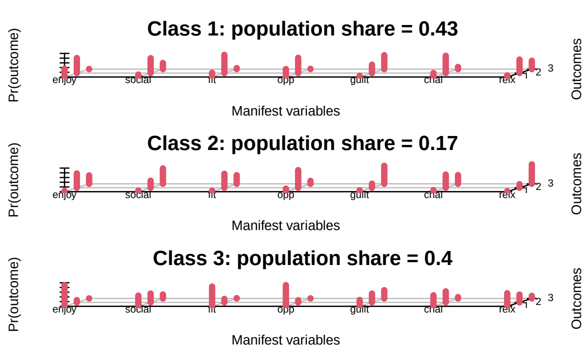
BIC plot indicates 3 or four 4 to reduce BIC the most. BLRT preferred 4 classes. Relative entropy values are 0.7157817 and 0.6847339 for 3 and 4 classes, respectively, which shows 3 to have slightly better separation between classes. The likelihood is similar between 3 and 4 classes. Average posterior probabilities are better in the 3-class model, as all classes have a >.80 pp.

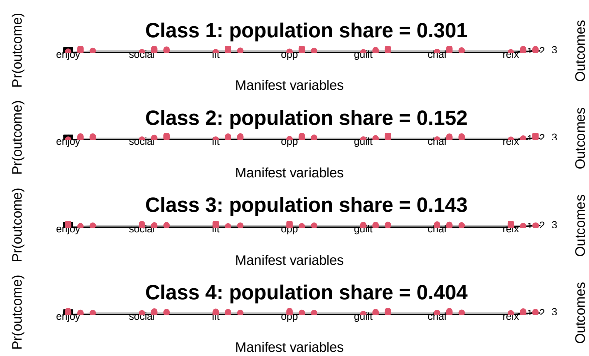




See appendix for elbow plot avereage pp etc Both 3 and 4- class models show promise. BIC plot does not show a typical elbow shape, as adding more classes beyond 4 actually diminished the fit. This is possibly due to the log-likelihood not increasing significantly with more classes, and BIC's penalty for higher complexity outweighs the improvement

However, the 4-class model contains 2 very similar classes. Hence the 3-class model was chosen.

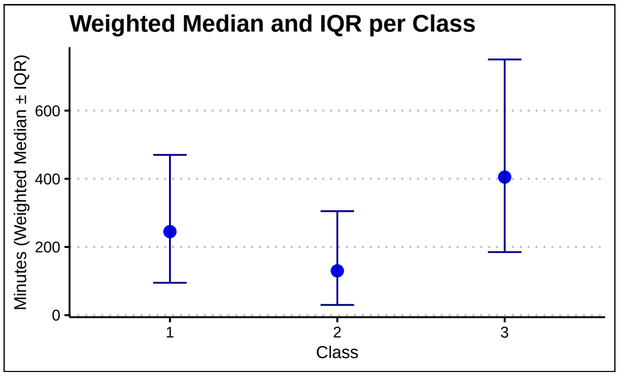




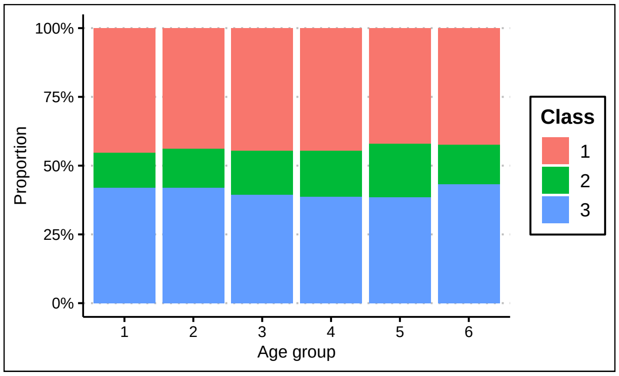
Class 1: A highly engaged group exercising for intrinsic (enjoyment, competence) and extrinsic (importance, fitness, social) reasons. (High across core motives: enjoyment, fitness, importance, ability → strong positive orientation to exercise. Moderate-to-high secondary motives: social, challenge, relaxation. Mixed guilt: not central.)

Class 2: they agree exercise is valuable, but don't strongly enjoy it. Low guilt and relaxation. They see exercise as important and somewhat social, but motivation is not driven by strong enjoyment or self-competence. This group might exercise out of social reinforcement or external values rather than intrinsic enjoyment. (Moderate enjoyment, social, fitness, opportunity, challenge, ability.)

Class 3: They believe exercise is important (cognitive endorsement), but lack enjoyment, confidence, or social drive. Likely lower actual participation; motivation here is more abstract belief than emotional or social



engagement. (Low enjoyment, fitness, challenge, social, guilt, ability, relaxation. Moderate opportunity and high importance.)



Age: The youngest group is most likely to be in class 1. However, class 2 have only minor (<20%) deviations in each age group, indicating that age has little systematic effect. However, the youngest age group is only 20% as likely to belong in class 3, and the trend increases as age goes up. Ie. the older the youths are the more likely they are to be in class 3. This makes sense as youths become more e.g. self-conscious, entangled with other responsibilities, more autonomy and more ways to entertain themselves.

This supports hypothesis 2b, that younger youths are more likely to belong to enjoyment-dominant profiles.

Conclusions

- Summarise what you have found. Restate your questions and hypotheses and show how you answer them. • Discuss possible limitations and implications they might have for the results. • Discuss implications for theory and/or policy based on what you found.

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Appendix A - Survey Questions

Appendix B - R Code

```
> # Library --------------------------------------------------------------
> set.seed(2025)

> library(tidyverse)

> library(car)

> # Read Data ------------------------------------------------------------
> #
> # data.child <- read.csv('data/child_main.tab', header=T, sep='\t')
> # data.adult <- read.csv('data/adult.tab', header=T, sep='\t')
> #
> # # Read relevant fields
> # child.var <- data.child %>% select(# likert predictors
> #                                    'PL_Enjoy_bc_ans', 'PL_Conf_bc_ans',
> #                                    'PL_Easy_bc_ans', 'PL_GdMe_bc_ans',
> #                                    'PL_Know_c_ans', 'MO_Opp_c',
> #                                    'MO_Fit_c', 'MO_Relax_c', 'MO_Fun_c',
> #                                    'MO_Guilt_c', 'MO_Haveto_b_36',
> #                                    'MO_Haveto_c_711', 'PR_Fam_c', 'PR_Oth_c',
> #                                    'Try_bc', 'outdoor_bcd_Overall',
> #                                    'Exeramt_bc', 'ExeramtMore_bc1_2',
> #                                    'ExeramtMore_bc2_2', 'ExeramtMore_bc3_2',
> #                                    'mins_modplus_outschool_Week_ALL',
> #
> #                                    # demographic
> #                                    'age_11', 'eth2', 'gend3', 'eth6',
> #                                    'Disab_All_POP',
> #
> #                                    # binary predictors
> #                                    'PL_Enjoy_bc_SA_gr2', 'MO_Fun_c_SA',
> #                                    'MO_Fit_c_SA',
> #                                    'MO_Guilt_c_SA', 'MO_Opp_c_SA'
> # )
> #
> # # Save to save computation time
> # save(child.var, file = "child.var.RData")
> #
> #
> # # Same process for adults, different variables
> # adult.var <- data.adult %>% dplyr::select('Motiva_POP','motivb_POP',
> #                                           'motivc_POP','motivd_POP',
> #                                           'motive_POP','READYAB1_POP',
> #                                           'READYOP1_POP','motivex2a',
> #                                           'motivex2b','motivex2c',
> #                                           'motivex2d','inclus_a',
> #                                           'inclus_b','inclus_c',
> #                                           'indev','indevtry',
> #                                           'workactlvl',
> #                                           'DUR_HVY_CAPPED_SPORTCOUNT_A01',
> #                                           'DUR_MOD_CAPPED_SPORTCOUNT_A01',
```

```
> #
> #                                           # demographic
> #                                           'Age17','Age3','AgeTGC',
> #                                           'Age4','Age5','Age5_2',
> #                                           'Age9','Disab2_POP',
> #                                           'Gend3','Eth2','Eth7',
> #                                           'Educ6',
> #
> #                                           # binary predictors
> #                                           'Motiva_POP_GR2', 'motivex2c_GR2',
> #                                           'motivex2a_GR2', 'motivc_POP_GR2',
> #                                           'READYOP1_POP_GR2')
> #
> # save(adult.var, file = "adult.var.RData")
>
> # Basic Distributions and Stats -------------------------------------------
>
> load("child.var.RData")

> load("adult.var.RData")

> glimpse(child.var)
Rows: 122,347
Columns: 31
$ PL_Enjoy_bc_ans                 <int> 4, 1, 2, 2, 1, 5, 1, 4, 2, 1, 2, 1, 1,~
$ PL_Conf_bc_ans                  <int> 4, 1, 2, 3, 1, 2, 1, 2, 1, 1, 2, 2, 2,~
$ PL_Easy_bc_ans                  <int> 4, 2, 2, 3, 2, 3, 2, 2, 2, 1, 5, 3, 3,~
$ PL_GdMe_bc_ans                  <int> 1, 1, 2, 2, 1, 1, 1, 2, 5, 1, 2, 1, 2,~
$ PL_Know_c_ans                   <int> 2, 2, 2, 2, 1, 2, 1, -98, -98, -98, -9~
$ MO_Opp_c                        <int> 1, 2, 2, 2, 1, 2, 1, -98, -98, -98, -9~
$ MO_Fit_c                        <int> 99, 1, 2, 3, 2, 2, 1, -98, -98, -98, -~
$ MO_Relax_c                      <int> 3, 1, 3, 3, 2, 3, 1, -98, -98, -98, -9~
$ MO_Fun_c                        <int> 4, 2, 3, 2, 3, 3, 3, -98, -98, -98, -9~
$ MO_Guilt_c                      <int> 4, 1, 2, 3, 1, 4, 2, -98, -98, -98, -9~
$ MO_Haveto_b_36                  <int> -98, -98, -98, -98, -98, -98, -98, 1, ~
$ MO_Haveto_c_711                 <int> 2, 4, 3, 3, 3, 2, 4, -98, -98, -98, -9~
$ PR_Fam_c                        <int> 4, 3, 2, 3, 3, 2, 3, -91, -91, -91, -9~
$ PR_Oth_c                        <int> 2, 5, 2, 2, 3, 2, 3, -91, -91, -91, -9~
$ Try_bc                          <int> 5, 1, 2, 3, 2, 1, 1, 2, 2, 2, 2, 1, 2,~
$ outdoor_bcd_Overall             <int> 3, 3, 3, 2, 3, 3, 3, -98, -98, -98, -9~
$ Exeramt_bc                      <int> 1, 2, 1, 1, 1, 1, 1, 3, 1, 1, 3, 1, 1,~
$ ExeramtMore_bc1_2               <int> 1, -98, 0, 1, 0, 0, 0, -98, 1, 1, -98,~
$ ExeramtMore_bc2_2               <int> 0, -98, 0, 0, 0, 1, 1, -98, 1, 1, -98,~
$ ExeramtMore_bc3_2               <int> 0, -98, 1, 0, 1, 0, 0, -98, 0, 0, -98,~
$ mins_modplus_outschool_Week_ALL <int> 330, -96, 90, 60, 0, 95, 490, 0, 840, ~
$ age_11                          <int> 12, 12, 12, 13, 12, 13, 13, 10, 10, 9,~
$ eth2                            <int> 2, 2, 2, 1, 2, 3, 1, 2, 2, 2, 1, 3, 3,~
$ gend3                           <int> 2, 2, 2, 2, 2, 2, 2, 1, 1, 1, 3, 1, 2,~
$ eth6                            <int> 3, 3, 3, 1, 2, 7, 1, 5, 3, 4, 1, 7, 7,~
$ Disab_All_POP                   <int> 2, 3, 3, 2, 2, 2, 2, 1, 1, 2, 4, 2, 2,~
$ PL_Enjoy_bc_SA_gr2              <int> 2, 1, 2, 2, 1, 99, 1, 2, 2, 1, 2, 1, 1~
$ MO_Fun_c_SA                     <int> 2, 2, 2, 2, 2, 2, 2, -98, -98, -98, -9~
$ MO_Fit_c_SA                     <int> 99, 1, 2, 2, 2, 2, 1, -98, -98, -98, -~
$ MO_Guilt_c_SA                   <int> 2, 1, 2, 2, 1, 2, 2, -98, -98, -98, -9~
```

```
$ MO_Opp_c_SA                     <int> 1, 2, 2, 2, 1, 2, 1, -98, -98, -98, -9~

> glimpse(adult.var)
Rows: 172,968
Columns: 36
$ Motiva_POP                    <int> 1, 3, 2, 1, -95, -98, 2, 5, 2, 2, 1, 2, ~
$ motivb_POP                    <int> 1, 2, 2, 2, 3, 2, 2, 3, 2, 3, 2, 3, 1, 1~
$ motivc_POP                    <int> 2, -95, -98, 2, 3, 2, 2, -99, 3, 4, 3, 3~
$ motivd_POP                    <int> 3, 5, 4, 2, 3, -98, 5, -99, 3, 3, 5, 3, ~
$ motive_POP                    <int> -98, -99, -98, -98, -99, -98, -99, -99, ~
$ READYAB1_POP                  <int> 1, -95, 2, 2, 3, -95, 2, 2, 1, 2, 1, 2, ~
$ READYOP1_POP                  <int> 1, 5, 2, 2, 3, -95, 2, 2, 2, 2, 1, 2, 1,~
$ motivex2a                     <int> 1, 2, 2, 2, 3, 1, 2, 2, 3, 2, 1, 3, 1, 1~
$ motivex2b                     <int> 1, 3, 2, 2, 3, 2, 2, 2, 3, 3, 2, 3, 1, 2~
$ motivex2c                     <int> 2, 3, -95, 2, 3, 4, 2, 3, 3, 2, 1, 2, 3,~
$ motivex2d                     <int> 2, 3, 2, 2, 3, -95, 4, 2, 3, 3, 3, 3, 2,~
$ inclus_a                      <int> 1, -98, -95, 2, -98, 4, -98, -98, 3, 2, ~
$ inclus_b                      <int> 2, -98, 2, 2, -98, -98, -98, -98, 4, 2, ~
$ inclus_c                      <int> 2, -98, -95, 2, -98, -95, -98, -98, 4, 2~
$ indev                         <int> 5, -98, 4, 1, -98, 4, -98, -98, -98, -98~
$ indevtry                      <int> 4, -98, 3, 4, -98, 4, -98, -98, -98, -98~
$ workactlvl                    <int> -98, -98, 1, 2, -98, 2, -98, -98, -98, 2~
$ DUR_HVY_CAPPED_SPORTCOUNT_A01 <dbl> 0, 0, 0, 0, 0, 210, 0, 0, 0, 0, 0, 180, ~
$ DUR_MOD_CAPPED_SPORTCOUNT_A01 <dbl> 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00~
$ Age17                         <int> 10, 11, 2, 3, 9, 6, 10, 15, 12, 10, 7, 4~
$ Age3                          <int> 3, 3, 1, 1, 3, 2, 3, 3, 3, 3, 2, 1, 3, 2~
$ AgeTGC                        <int> 3, 3, 1, 1, 2, 2, 3, 3, 3, 2, 2, 1, 2, 2~
$ Age4                          <int> 3, 3, 1, 1, 3, 2, 3, 4, 3, 3, 2, 1, 3, 2~
$ Age5                          <int> 4, 5, 2, 3, 4, 3, 4, 5, 5, 4, 4, 3, 4, 4~
$ Age5_2                        <int> 5, 5, 1, 2, 5, 3, 5, 5, 5, 5, 4, 2, 5, 4~
$ Age9                          <int> 6, 7, 2, 3, 6, 4, 6, 9, 7, 6, 5, 3, 6, 5~
$ Disab2_POP                    <int> 2, 1, 2, 2, 1, -94, 2, 1, 2, 2, 2, 2, 2,~
$ Gend3                         <int> 1, 1, 2, 1, 2, 2, 1, 1, 2, 1, 2, 2, 1, 1~
$ Eth2                          <int> 2, 1, 2, -94, 1, 2, 1, 2, 2, 1, 1, 1, 1,~
$ Eth7                          <int> 2, 1, 3, -94, 1, 2, 1, 4, 3, 1, 1, 1, 1,~
$ Educ6                         <int> 1, 6, 3, 3, 6, 1, 1, 6, 6, 1, 1, 2, 1, 2~
$ Motiva_POP_GR2                <int> 1, 0, 0, 1, -95, -98, 0, 0, 0, 0, 1, 0, ~
$ motivex2c_GR2                 <int> 0, 0, -95, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,~
$ motivex2a_GR2                 <int> 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1~
$ motivc_POP_GR2                <int> 0, -95, -98, 0, 0, 0, 0, -99, 0, 0, 0, 0~
$ READYOP1_POP_GR2              <int> 1, 0, 0, 0, 0, -95, 0, 0, 0, 0, 1, 0, 1,~

> # ethnicity
> prop.table(table(adult.var$Eth7))

> prop.table(table(child.var$eth6))

> # 2 is no disa
> table(child.var$Disab_All_POP)

> table(adult.var$Disab2_POP)

> # adult in bands of 5 years, child just in years
> table(child.var$age_11)
```

```
> table(adult.var$Age19plus)

> # too few transgendered adults, filter out
> table(adult.var$gend2_GR6)

> table(adult.var$indevtry)

> table(adult.var$motive_POP)

> # Clean Data for SEM ------------------------------------------------------
>
>
> child.bi <- child.var %>%
+   filter(Disab_All_POP == 2, # remove disabled and no answer
+          gend3 %in% c(1,2),
+          eth2 %in% c(1,2),
+
+          if_all(c(age_11, mins_modplus_outschool_Week_ALL), ~ .x > -1),
+
+          if_all(c(PL_Enjoy_bc_SA_gr2, MO_Fun_c_SA, MO_Fit_c_SA,
+                   MO_Guilt_c_SA, MO_Opp_c_SA), ~ .x > -1 & .x < 3)) %>%
+
+   dplyr::select(enjoyb=PL_Enjoy_bc_SA_gr2,
+                 socialb=MO_Fun_c_SA,
+                 fitb=MO_Fit_c_SA,
+                 guiltb=MO_Guilt_c_SA,
+                 oppb=MO_Opp_c_SA,
+
+                 gender=gend3,
+                 age=age_11,
+                 eth=eth2,
+                 mins=mins_modplus_outschool_Week_ALL
+
+   ) %>%
+
+
+   # change 2 (not strongly agree) to 0, consistent with adult
+   mutate(across(c(enjoyb,socialb,fitb,guiltb,oppb), ~ ifelse(.x==2, 0, .x)),
+          gender = gender-1,
+          eth = eth-1,
+          age = age-11)

> adult.bi <- adult.var %>% filter(Disab2_POP==2,
+                                  Gend3 %in% c(1,2),
+                                  Eth2 %in% c(1,2),
+                                  if_all(c(AgeTGC,
+                                           DUR_MOD_CAPPED_SPORTCOUNT_A01,
+                                           DUR_HVY_CAPPED_SPORTCOUNT_A01),
+                                         ~ .x > -1),
+                                  if_all(c(Motiva_POP_GR2, motivex2c_GR2,
+                                           motivex2a_GR2, motivc_POP_GR2,
+                                           READYOP1_POP_GR2),
+                                         ~ .x %in% c(0,1))) %>%
```

```
+
+
+   mutate(mins=DUR_MOD_CAPPED_SPORTCOUNT_A01 +
+            DUR_HVY_CAPPED_SPORTCOUNT_A01,
+          Gend3 = Gend3-1,
+          Eth2 = Eth2-1,
+          age = case_when(Age9==2~3L,
+                          Age9==9~8L,
+                          TRUE~as.integer(Age9)),
+          age=as.integer(age-3)
+   ) %>%
+
+
+   dplyr::select(enjoyb=Motiva_POP_GR2,
+                 socialb=motivex2c_GR2,
+                 fitb=motivex2a_GR2,
+                 guiltb=motivc_POP_GR2,
+                 oppb=READYOP1_POP_GR2,
+                 gender=Gend3,
+                 age,
+                 eth=Eth2,
+                 mins
+   )

> dallb <- bind_rows(
+   adult.bi %>% mutate(group = "adult"),
+   child.bi %>% mutate(group = "youth")
+ ) %>%
+   mutate(mins = ifelse(mins > 1680, 1680, mins))

> dallb$gender <- relevel(factor(dallb$gender), ref = "0")

> dallb$eth <- relevel(factor(dallb$eth), ref = "0")

> # Clean Data for PCA -----------------------------------------------------
>
> # # Check if collapsing is necessary
> # child.lik %>% dplyr::select(-max_post,-mins,-age,-eth) %>%
> #   pivot_longer(
> #     cols = everything(),   # or specify your Likert vars if df has other columns
> #     names_to = "Variable",
> #     values_to = "Response"
> #   ) %>%
> #   group_by(Variable, Response) %>%
> #   summarise(n = n(), .groups = "drop_last") %>%
> #   #"drop_last" drops the response variable,
> #   #so that the next part (proportion) does not calculate within each response
> #
> #   mutate(prop = n / sum(n)) %>%
> #   arrange(Variable, Response) %>% filter(prop < 0.05)
>
>
> child.lik <- child.var %>%
+
```

```
+   # 1-4, 1=strong agree, 4=strong disagree, 5=can't say
+   dplyr::select(enjoy=PL_Enjoy_bc_ans,
+                 social=MO_Fun_c,
+                 fit=MO_Fit_c,
+                 opp=MO_Opp_c,
+                 guilt=MO_Guilt_c, #99 instead of 5 for "can't say"
+
+                 imp=PL_GdMe_bc_ans,
+                 chal=Try_bc,
+                 relx=MO_Relax_c,
+
+                 dsbl=Disab_All_POP,
+                 gender=gend3,
+                 age=age_11,
+                 eth=eth2,
+                 mins=mins_modplus_outschool_Week_ALL
+   ) %>%
+
+   filter(dsbl == 2,
+          gender %in% c(1,2),
+          eth %in% c(1,2),
+          mins > -1,
+          if_all(c(enjoy,social,fit,guilt,opp,imp,chal,relx),
+                 ~ .x > -1 & .x < 5)) %>%
+   mutate(
+     mins = ifelse(mins > 1680, 1680, mins),
+     across(c(enjoy,social,fit,guilt,imp,chal,opp,relx),
+            ~ case_when(.x==4~3L, TRUE ~ as.integer(.x))),
+     age=age-10
+
+
+   ) %>%
+   dplyr::select(-dsbl)

> child.lik.back0 <- child.lik

> adult.lik <- adult.var %>%
+   mutate(mins=DUR_HVY_CAPPED_SPORTCOUNT_A01+DUR_MOD_CAPPED_SPORTCOUNT_A01) %>%
+
+   # 1=strong agree, 5=strong disagree
+   dplyr::select(enjoy=Motiva_POP,
+                 social=motivex2c,
+                 fit=motivex2a,
+                 guilt=motivc_POP,
+                 opp=READYOP1_POP,
+
+                 imp=motivb_POP,
+                 chal=motivex2d,
+                 relx=motivex2b,
+
+                 dsbl=Disab2_POP,
+                 gender=Gend3,
+                 age=Age9,
+                 eth=Eth2,
```

```
+                  edu=Educ6,
+                  mins
+   ) %>%
+
+   filter(dsbl==2,
+          if_all(c(gender,eth), ~ .x %in% c(1,2)),
+          if_all(everything(), ~ .x > -1),
+          edu != 5
+   ) %>%
+
+   mutate(across(c(enjoy,social,fit,guilt,opp,imp,chal,relx),
+                  ~ case_when(.x==5~4L, TRUE ~ as.integer(.x))),
+          edu = case_when(edu==6~5L, TRUE~edu),
+          age = as.integer(case_when(age==2~3L,
+                         age==9~8L,
+                         TRUE~as.integer(age)))-2
+
+   ) %>%
+
+
+   dplyr::select(-dsbl)

> adult.lik.back0 <- adult.lik

> # Checks ------------------------------------------------------------------
> # Collinearity
> dallb1 <- dallb %>% dplyr::select(-gender,-eth,-group)

> cor(dallb1, method = "pearson") # opp, fit and enjoy have mod corr with each other, others ok

> cor(child.lik.back0 %>% dplyr::select(-gender,-eth, -age), method = "pearson")

> # # remove easy, corrleation too high with confidence, which makes sense
> # child.lik <- child.lik.back %>% dplyr::select(-easy)
>
> # Check adult lik corr
> adult.lik <- adult.lik.back0

> cor(adult.lik.back0 %>% dplyr::select(-gender,-eth), method = "pearson")

> adult.lik1 <- adult.lik %>% dplyr::select(-gender,-eth, -imp)

> cor(adult.lik1, method = "pearson")

> # corrleation too high
> child.lik <- child.lik.back0 %>% dplyr::select(-imp)

> adult.lik <- adult.lik.back0 %>% dplyr::select(-imp)

> child.lik.back <- child.lik

> adult.lik.back <- adult.lik

> # VIF
```

```
> vif_model <- lm(mins ~ enjoyb + socialb + fitb + guiltb + oppb, data = dallb1)

> vif(vif_model)

> # Proportions of each motive by group
> dallb2 <- dallb %>% dplyr::select(-gender,-eth)

> # # Mean
> # dallb2 %>% group_by(group) %>%
> #   summarize(across(
> #     .cols = all_of(setdiff(names(dallb2), "group")),
> #     .fns = list(mean = mean, sd = sd)
> #   ))
>
>
```

```
> # Libraries ------------------------------------------------------------
> set.seed(2025)

> library(tidyverse)

> library(lavaan)

> # SEM ------------------------------------------------------------------
>
> # Free model
> m0 <- '
+   # Mediators: controlling for age, gender, and ethnicity (group-specific coefficients)
+   enjoyb ~ c(a1_adult, a1_youth)*age + c(g1_adult, g1_youth)*gender + c(e1_adult, e1_youth)*eth
+   guiltb ~ c(a2_adult, a2_youth)*age + c(g2_adult, g2_youth)*gender + c(e2_adult, e2_youth)*eth
+   oppb   ~ c(a3_adult, a3_youth)*age + c(g3_adult, g3_youth)*gender + c(e3_adult, e3_youth)*eth
+   fitb   ~ c(a4_adult, a4_youth)*age + c(g4_adult, g4_youth)*gender + c(e4_adult, e4_youth)*eth
+   socialb~ c(a5_adult, a5_youth)*age + c(g5_adult, g5_youth)*gender + c(e5_adult, e5_youth)*eth
+
+   # Main outcome: motives predicting mins, controlling for demographics (group-specific coefficients)
+   mins ~ c(b1_adult, b1_youth)*enjoyb + c(b2_adult, b2_youth)*guiltb + c(b3_adult, b3_youth)*oppb +
+           c(b4_adult, b4_youth)*fitb + c(b5_adult, b5_youth)*socialb + c(c_adult, c_youth)*age +
+           c(g6_adult, g6_youth)*gender + c(e6_adult, e6_youth)*eth
+
+ # For Adults
+ indirect_age_enjoyb_adult  := a1_adult * b1_adult
+ indirect_age_guiltb_adult  := a2_adult * b2_adult
+ indirect_age_oppb_adult    := a3_adult * b3_adult
+ indirect_age_fitb_adult    := a4_adult * b4_adult
+ indirect_age_socialb_adult := a5_adult * b5_adult
+ total_age_adult := c_adult + indirect_age_enjoyb_adult + indirect_age_guiltb_adult +
+                    indirect_age_oppb_adult + indirect_age_fitb_adult + indirect_age_socialb_adult
+
+ # For Youth
+ indirect_age_enjoyb_youth  := a1_youth * b1_youth
+ indirect_age_guiltb_youth  := a2_youth * b2_youth
+ indirect_age_oppb_youth    := a3_youth * b3_youth
+ indirect_age_fitb_youth    := a4_youth * b4_youth
+ indirect_age_socialb_youth := a5_youth * b5_youth
+ total_age_youth := c_youth + indirect_age_enjoyb_youth + indirect_age_guiltb_youth +
+                   indirect_age_oppb_youth + indirect_age_fitb_youth + indirect_age_socialb_youth
+ '

> f0 <- sem(m0, data = dallb, group = "group")


> sem.free <- summary(f0, fit.measures = TRUE, standardized = TRUE)

> # Constrain all to be equal
> f.con <- sem(m0, dallb, group = "group",
+              group.equal = c("intercepts", "regressions"))


> # Check if significantly different
```

```
> f0fcon <- anova(f0, f.con)

> f0fcon

> # Spec one constraint at a time
> m1 <- '
+   # Mediators
+   enjoyb ~ age + gender + eth
+   guiltb ~ age + gender + eth
+   oppb ~ age + gender + eth
+   fitb ~ age + gender + eth
+   socialb ~ age + gender + eth
+
+   # Main outcome
+   mins ~ c("a1","a1")*enjoyb + guiltb + oppb + fitb + socialb + age + gender + eth
+ '

> m2 <- '
+   # Mediators
+   enjoyb ~ age + gender + eth
+   guiltb ~ age + gender + eth
+   oppb ~ age + gender + eth
+   fitb ~ age + gender + eth
+   socialb ~ age + gender + eth
+
+   # Main outcome
+   mins ~ enjoyb + c(a,a)*guiltb + oppb + fitb + socialb + age + gender + eth
+ '

> m3 <- '
+   # Mediators
+   enjoyb ~ age + gender + eth
+   guiltb ~ age + gender + eth
+   oppb ~ age + gender + eth
+   fitb ~ age + gender + eth
+   socialb ~ age + gender + eth
+
+   # Main outcome
+   mins ~ enjoyb + guiltb + c(a,a)*oppb + fitb + socialb + age + gender + eth
+ '

> m4 <- '
+   # Mediators
+   enjoyb ~ age + gender + eth
+   guiltb ~ age + gender + eth
+   oppb ~ age + gender + eth
+   fitb ~ age + gender + eth
+   socialb ~ age + gender + eth
+
+   # Main outcome
+   mins ~ enjoyb + guiltb + oppb + c(a,a)*fitb + socialb + age + gender + eth
+ '

> m5 <- '
```

```
+   # Mediators
+   enjoyb ~ age + gender + eth
+   guiltb ~ age + gender + eth
+   oppb ~ age + gender + eth
+   fitb ~ age + gender + eth
+   socialb ~ age + gender + eth
+
+   # Main outcome
+   mins ~ enjoyb + guiltb + oppb + fitb + c(a,a)*socialb + age + gender + eth
+ '

> # Small eigenvalue close to 0, does not matter
> f1 <- sem(m1, data = dallb, group = "group", meanstructure = TRUE)


> f2 <- sem(m2, data = dallb, group = "group", meanstructure = TRUE)


> f3 <- sem(m3, data = dallb, group = "group", meanstructure = TRUE)


> f4 <- sem(m4, data = dallb, group = "group", meanstructure = TRUE)


> f5 <- sem(m5, data = dallb, group = "group", meanstructure = TRUE)


> # Check all models are significantly different from m0
> anova(f0, f1)

> anova(f0, f2)

> anova(f0, f3)

> anova(f0, f4)

> anova(f0, f5)

> # Put slope diff. in a table
> params <- parameterEstimates(f0, standardized = T)

> # filter
> slopes <- params %>%
+   filter(lhs == "mins", op == "~") %>%
+   dplyr::select(var=rhs, group, est, se)

> # filtre more
> slopes.ad <- slopes %>% filter(group == 1) %>%
+   dplyr::select(var, est.adult = est, se.adult = se)

> slopes.ch <- slopes %>% filter(group == 2) %>%
+   dplyr::select(var, est.youth = est, se.youth = se)
```

```
> # join!
> slopes.diff <- data.frame()

> slopes.diff <- left_join(slopes.ch, slopes.ad, by = "var")

> # calculate
> slopes.diff <- slopes.diff %>%
+   mutate(
+     diff = est.youth - est.adult
+     # se.diff = sqrt(se.adult^2 + se.youth^2),
+     # z = diff / se.diff,
+     # p = 2 * (1 - pnorm(abs(z)))
+   ) %>%
+   filter(!var %in% c("gender","eth")) %>%
+   dplyr::select(-se.youth, -se.adult)

> slopes.diff
```

```
> # Libraries ---------------------------------------------------------------
> set.seed(2025)

> library(tidyverse)

> library(Hmisc)

> library(ggplot2)

> library(nnet)

> library(tidyLPA)

> library(poLCA)

> library(poLCAExtra)

> # LCA, Youths -------------------------------------------------------------
> child.lik <- child.lik.back

> # Predictors (motives)
> child.lik.y <- (child.lik %>%
+                           dplyr::select(-mins,-age,-gender,-eth))

> child.lik.y <- as.matrix(child.lik.y %>% mutate(across(everything(), as.integer)))

> # Spec formula for LCA
> lca.f.child <- child.lik.y ~ gender + eth

> # Run LCA with 2-7 classes
> # LCAE.ch <- poLCA(lca.f.child, data = child.lik, nclass = 2:7)
> # save(LCAE.ch, file="LCAE.ch.RData")
> load("LCAE.ch.RData")

> # bootstrapped Vuong-Lo-Mendell-Rubin likelihood ratio test
> # blrt.ch <- poLCA.blrt(LCAE.ch,quick = T, nrep=10)
> # save(blrt.ch,file="blrt.ch.RData")
> # load("blrt.ch.RData")
>
>
> # Output
> ch.lca.output <- LCAE.ch$output %>% dplyr::select(nclass,llike,AIC,BIC,
+                                                   Rel.Entropy,LMR,p)

> ch.lca.output

> # check max posterior
> # for(k in 2:4){
> #
> #   child.lik$post <- apply(LCAE.ch$LCA[[k]]$posterior, 1, max)
> #
> #   child.lik$class <- LCAE.ch$LCA[[k]]$predclass
> #
```

```
> #   print(
> #     ggplot(child.lik, aes(x = post, fill = factor(class))) +
> #     geom_histogram(binwidth = 0.05, alpha = 0.7, position = "identity") +
> #     labs(x = "Max Posterior Probability", y = "Count", fill = "Class",
> #          title = paste0(k+1," Classes, Youths")) +
> #     theme_minimal()
> #   )
> #
> #   print(ggplot(child.lik, aes(x = factor(class), y = post)) +
> #     geom_boxplot(fill = "skyblue") +
> #     labs(x = "Class", y = "Max Posterior Probability",
> #          title = paste0(k+1," Classes, Youths")) +
> #     theme_minimal()
> #   )
> # }
>
> # Compare 3 and 4 class average posterior and class prop
> post4.ch <- LCAE.ch$LCA[[3]]$posterior

> class4.ch <- apply(post4.ch, 1, which.max)

> class.size4.ch <- prop.table(table(class4.ch))

> ave.pp4.ch <- sapply(1:ncol(post4.ch), function(k) {
+   inds <- which(class4.ch == k)
+   mean(post4.ch[inds, k])
+ })

> post3.ch <- LCAE.ch$LCA[[2]]$posterior

> class3.ch <- apply(post3.ch, 1, which.max)

> class.size3.ch <- prop.table(table(class3.ch))

> ave.pp3.ch <- sapply(1:ncol(post3.ch), function(k) {
+   inds <- which(class3.ch == k)
+   mean(post3.ch[inds, k])
+ })

> # BEST CLASS decided
> # 3 classes is best
> lca.best.ch <- LCAE.ch$LCA[[2]]

> child.lik$class <- lca.best.ch$predclass

> # child.lik$post <- apply(lca.best.ch$posterior, 1, max)
>
> # Calculate median minutes
> n.classes <- 3

> wmed.ch <- numeric(n.classes)

> wq25.ch <- numeric(n.classes)
```

```
> wq75.ch <- numeric(n.classes)

> for (k in 1:n.classes) {
+
+   q <- wtd.quantile(child.lik$mins,
+                     weights = lca.best.ch$posterior[,k],
+                     probs = c(0.25, 0.5, 0.75))
+   wq25.ch[k] <- q[1]
+   wmed.ch[k] <- q[2]
+   wq75.ch[k] <- q[3]
+ }

> # Regressions
> child.lik$age <- child.lik.back$age

> child.lik$class <- relevel(factor(child.lik$class), ref = "1")

> child.lik$age <- relevel(factor(child.lik$age), ref = "1")

> fit.ch <- multinom(class ~ age,
+                    data = child.lik)
# weights:  21 (12 variable)
initial  value 31734.514570
iter  10 value 29831.498758
final  value 29364.954492
converged

> # odds ratio
> or.ch <- exp(coef(fit.ch))

> or.ch

> sum.fit.ch <- summary(fit.ch)

> se <- sum.fit.ch$standard.errors

> # Coefficients
> coefs.ch <- coef(fit.ch)

> # 95% CI for odds ratios
> ci.l.ch <- exp(coefs.ch - 1.96 * se)

> ci.u.ch <- exp(coefs.ch + 1.96 * se)

> # Odds ratios themselves
> or <- exp(coefs.ch)

> # Combine into a table
> or.ci.ch <- data.frame(
+   CI.lower = round(ci.l.ch, 3),
+   CI.upper = round(ci.u.ch, 3)
+ )

> colnames(or.ci.ch) <- c("Intercept.L", "Age2.L", "Age3.L", "Age4.L",
```

```
+                          "Age5.L","Age6.L","Intercept.U","Age2.U", "Age3.U", "Age4.U",
+                          "Age5.U","Age6.U")

> # Check class distribution per age
>
> tb.byage.ch <- child.lik %>%
+ count(age, class) %>%
+   pivot_wider(names_from = class, values_from = n, values_fill = 0)

> # LCA, Adults -------------------------------------------------------------
> ## almost exactly the same as youths,
> ## with the addition of Education as a covariate
>
> adult.lik <- adult.lik.back

> # Predictors (motives)
> adult.lik.y <- as.matrix(adult.lik %>%
+                             dplyr::select(-mins,-age,-gender,-eth,-edu))

> # Spec formula for LCA
> lca.f.adult <- adult.lik.y ~ gender + eth + edu

> # LCAE.ad <- poLCA(lca.f.adult, data = adult.lik, nclass = 2:7)
> # save(LCAE.ad, file="LCAE.ad.RData")
> load(file="LCAE.ad.RData")

> # bootstrapped Vuong-Lo-Mendell-Rubin likelihood ratio test
> # blrt.ad <- poLCA.blrt(LCAE.ad, quick = T,nreps = 10)
> # save(blrt.ad,file="blrt.ad.RData")
> # load(file="blrt.ad.RData")
>
>
> # Take relevant stats
> ad.lca.output <- LCAE.ad$output %>% dplyr::select(nclass,llike,AIC,BIC,
+                                                    Rel.Entropy,LMR,p)

> ad.lca.output

> # adeck posterior and boxplots
> # for(k in 2:5){
> #
> #   adult.lik$post <- apply(LCAE.ad$LCA[[k]]$posterior, 1, max)
> #   adult.lik$class <- LCAE.ad$LCA[[k]]$predclass
> #
> #   print(
> #     ggplot(adult.lik, aes(x = post, fill = factor(class))) +
> #       geom_histogram(binwidth = 0.05, alpha = 0.7, position = "identity") +
> #       labs(x = "Max Posterior Probability", y = "Count", fill = "Class",
> #            title = paste0(k+1," Classes, Adults")) +
> #       theme_minimal()
> #   )
> #
> #   print(ggplot(adult.lik, aes(x = factor(class), y = post)) +
> #           geom_boxplot(fill = "skyblue") +
```

```
> #           labs(x = "Class", y = "Max Posterior Probability",
> #                title = paste0(k+1," Classes, Adults")) +
> #           theme_minimal()
> #   )
> # }
>
> # Compare class average posteriors and class prop
>
> post5.ad <- LCAE.ad$LCA[[4]]$posterior

> class5.ad <- apply(post5.ad, 1, which.max)

> class.size5.ad <- prop.table(table(class5.ad))

> ave.pp5.ad <- sapply(1:ncol(post5.ad), function(k) {
+   inds <- which(class5.ad == k)
+   mean(post5.ad[inds, k])
+ })

> ave.pp5.ad

> post4.ad <- LCAE.ad$LCA[[3]]$posterior

> class4.ad <- apply(post4.ad, 1, which.max)

> class.size4.ad <- prop.table(table(class4.ad))

> ave.pp4.ad <- sapply(1:ncol(post4.ad), function(k) {
+   inds <- which(class4.ad == k)
+   mean(post4.ad[inds, k])
+ })

> ave.pp4.ad

> post3.ad <- LCAE.ad$LCA[[2]]$posterior

> class3.ad <- apply(post3.ad, 1, which.max)

> class.size3.ad <- prop.table(table(class3.ad))

> ave.pp3.ad <- sapply(1:ncol(post3.ad), function(k) {
+   inds <- which(class3.ad == k)
+   mean(post3.ad[inds, k])
+ })

> ave.pp3.ad

> # BEST CLASS decided
> # 3 classes is best
> lca.best.ad <- LCAE.ad$LCA[[2]]

> adult.lik$class <- lca.best.ad$predclass

> adult.lik$post <- apply(lca.best.ad$posterior, 1, max)
```

```
> # Calculate median minutes
> n.classes <- 3

> wmed.ad <- numeric(n.classes)

> wq25.ad <- numeric(n.classes)

> wq75.ad <- numeric(n.classes)

> for (k in 1:n.classes) {
+
+   q <- wtd.quantile(adult.lik$mins,
+                     weights = lca.best.ad$posterior[,k],
+                     probs = c(0.25, 0.5, 0.75))
+   wq25.ad[k] <- q[1]
+   wmed.ad[k] <- q[2]
+   wq75.ad[k] <- q[3]
+ }

> # Regressions
> adult.lik$age <- adult.lik.back$age

> adult.lik$class <- relevel(factor(adult.lik$class), ref = "1")

> adult.lik$age <- relevel(factor(adult.lik$age), ref = "1")

> fit.ad <- multinom(class ~ age,
+                    data = adult.lik)
# weights:  21 (12 variable)
initial  value 121262.627199
iter  10 value 118080.783140
final  value 116887.053981
converged

> # odds ratio
> or.ad <- exp(coef(fit.ad))

> or.ad

> sum.fit.ad <- summary(fit.ad)

> se.ad <- sum.fit.ad$standard.errors

> # Coefficients
> coefs.ad <- coef(fit.ad)

> # 95% CI for odds ratios
> ci.l.ad <- exp(coefs.ad - 1.96 * se.ad)

> ci.u.ad <- exp(coefs.ad + 1.96 * se.ad)

> # Combine into a table
> or.ci.ad <- data.frame(
```

```
+   CI.lower = round(ci.l.ad, 3),
+   CI.upper = round(ci.u.ad, 3)
+ )

> colnames(or.ci.ad) <- c("Intercept.L", "Age2.L", "Age3.L", "Age4.L",
+                         "Age5.L","Age6.L","Intercept.U","Age2.U", "Age3.U", "Age4.U",
+                         "Age5.U","Age6.U")

> # adeck class distribution per age
>
> tb.byage.ad <- adult.lik %>%
+   count(age, class) %>%
+   pivot_wider(names_from = class, values_from = n, values_fill = 0)
```

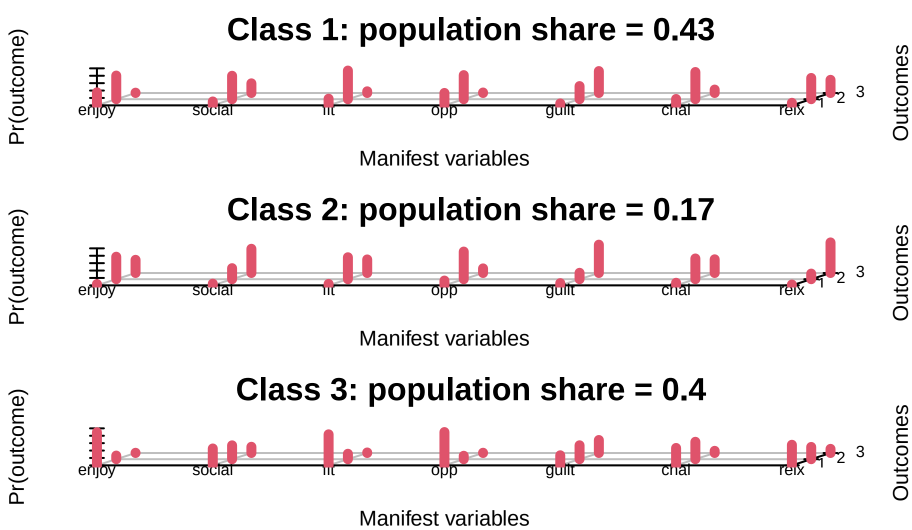
```
> set.seed(2025)

> library(tidyverse)

> library(ggplot2)

> library(poLCA)

> library(poLCAExtra)

> library(scales)

> library(ggthemes)

> # Descriptive ------------------------------------------------------------
> #
> cor.ie <- cor(adult.lik.back0 %>% dplyr::select(-gender,-eth), method = "pearson")[6,1]

> cor.if <- cor(adult.lik.back0 %>% dplyr::select(-gender,-eth), method = "pearson")[6,3]

> cor.imp <- data.frame("Imp,Enjoy"=cor.ie, "Imp,Fit"=cor.if)

> # get summary of all motives
> adult.summary <- adult.var %>%
+   mutate(mins = DUR_HVY_CAPPED_SPORTCOUNT_A01+
+                  DUR_MOD_CAPPED_SPORTCOUNT_A01) %>%
+   dplyr::select(
+     Enjoyment = Motiva_POP,
+     Social = motivex2c,
+     Fitness = motivex2a,
+     Guilt = motivc_POP,
+     Opportunity = READYOP1_POP,
+     Importance = motivb_POP,
+     Challenge = motivex2d,
+     Relaxation = motivex2b,
+     Minutes.Exercised = mins
+   ) %>%
+   summarise(
+     across(everything(),
+            list(
+              Mean = ~mean(.x[.x > 0], na.rm = TRUE),
+              Median = ~median(.x[.x > 0], na.rm = TRUE),
+              SD = ~sd(.x[.x > 0], na.rm = TRUE),
+              PercentNA = ~mean(.x < 0, na.rm = TRUE) * 100
+            ),
+            .names = "{.col}_{.fn}"
+     )
+   ) %>%
+   pivot_longer(everything(), names_to = c("Variable", "Stat"), names_sep = "_") %>%
+   pivot_wider(names_from = Stat, values_from = value)

> child.summary <- child.var %>%
+   dplyr::select(
```

```
+     Enjoyment = PL_Enjoy_bc_ans,
+     Social = MO_Fun_c,
+     Fitness = MO_Fit_c,
+     Opportunity = MO_Opp_c,
+     Guilt = MO_Guilt_c,
+     Importance = PL_GdMe_bc_ans,
+     Challenge = Try_bc,
+     Relaxation = MO_Relax_c
+   ) %>%
+   summarise(
+     across(everything(),
+            list(
+              Mean = ~mean(.x[.x > 0 & .x <= 4], na.rm = TRUE),
+              Median = ~median(.x[.x > 0 & .x <= 4], na.rm = TRUE),
+              SD = ~sd(.x[.x > 0 & .x <= 4], na.rm = TRUE),
+              PercentNA = ~mean(.x < 0 | .x > 4, na.rm = TRUE) * 100
+            ),
+            .names = "{.col}_{.fn}"
+     )
+   ) %>%
+   pivot_longer(everything(), names_to = c("Variable", "Stat"), names_sep = "_") %>%
+   pivot_wider(names_from = Stat, values_from = value)

> c.mins <- child.var %>%
+   summarise(Variable = "Minutes.Exercised",
+             Mean = mean(mins_modplus_outschool_Week_ALL[mins_modplus_outschool_Week_ALL > 0 ], na.rm =
+             Median = median(mins_modplus_outschool_Week_ALL[mins_modplus_outschool_Week_ALL > 0], na.r
+             SD = sd(mins_modplus_outschool_Week_ALL[mins_modplus_outschool_Week_ALL > 0], na.rm = TRUE
+             PercentNA = mean(mins_modplus_outschool_Week_ALL < 0, na.rm = TRUE) * 100)

> child.summary <- rbind(child.summary, c.mins)

> # get demographic overview (gender, edu, eth, mins)
> # adult
> #
> # Disability
> gg.ad.dsbl <- ggplot(adult.var, aes(x = as.factor(Disab2_POP))) +
+   geom_bar() +
+   labs(x = "Disability") +
+   theme_clean()

> # Gender
> gg.ad.gend <- ggplot(adult.var, aes(x = as.factor(Gend3))) +
+   geom_bar() +
+   labs(x = "Gender") +
+   theme_clean()

> # Age
> gg.ad.age <-ggplot(adult.var, aes(x = as.factor(Age9))) +
+   geom_bar() +
+   labs(x = "Age Group") +
+   theme_clean()

>   # Ethnicity
```

```
> gg.ad.eth <- ggplot(adult.var, aes(x = as.factor(Eth2))) +
+   geom_bar() +
+   labs(x = "Ethnicity") +
+   theme_clean()

> # Education
> gg.ad.edu <- ggplot(adult.var, aes(x = as.factor(Educ6))) +
+   geom_bar() +
+   labs(x = "Education") +
+   theme_clean()

> # YOuths
> #
> # Disability
> gg.ch.dsbl <- ggplot(child.var, aes(x = as.factor(Disab_All_POP))) +
+   geom_bar() +
+   labs(x = "Disability") +
+   theme_clean()

> # Gender
> gg.ch.gend <- ggplot(child.var, aes(x = as.factor(gend3))) +
+   geom_bar() +
+   labs(x = "Gender") +
+   theme_clean()

> # Age
> gg.ch.age <- ggplot(child.var, aes(x = as.factor(age_11))) +
+   geom_bar() +
+   labs(x = "Age") +
+   theme_clean()

> # Ethnicity
> gg.ch.eth <- ggplot(child.var, aes(x = as.factor(eth2))) +
+   geom_bar() +
+   labs(x = "Ethnicity") +
+   theme_clean()

> # SEM ---------------------------------------------------------------------
> # # slope_youth - slope_adult, pooled sd
> # cohen <- rbind(cohen.enj, cohen.soc, cohen.fit,cohen.glt,cohen.opp)
> # rownames(cohen) <- c("Enjoy", "Social", "Fit","Guilt","Opp")
> # colnames(cohen) <- c("Std Eff", "Min")
> # cohen
> # LCA Youths--------------------------------------------------------------
>
> # elbow plot
> gg.elbow.ch <- ggplot(ch.lca.output, aes(x = nclass)) +
+   geom_line(aes(y = BIC), color = "blue") +
+   geom_point(aes(y = BIC), color = "blue") +
+   geom_line(aes(y = AIC), color = "red") +
+   geom_point(aes(y = AIC), color = "red") +
+   labs(y = "Information Criterion", x = "Number of Classes",
+        title = "Elbow Plot, Youths",
+        caption = "Blue = BIC, Red = AIC") +
```

```
+   theme_clean()

> gg.elbow.ch

> gg.llik.ch <- ggplot(ch.lca.output, aes(x = nclass)) +
+   geom_line(aes(y = llike), color = "blue") +
+   geom_point(aes(y = llike), color = "blue") +
+   labs(y = "Log-Likelihood", x = "Number of Classes",
+        title = "Log-Likelihood, Youths") +
+   theme_clean()

> gg.llik.ch

> #
> # # Max posterior
> # gg.post.his.ch <- ggplot(child.lik, aes(x = post, fill = factor(class))) +
> #   geom_histogram(binwidth = 0.05, alpha = 0.7, position = "identity") +
> #   labs(x = "Max Posterior Probability", y = "Count", fill = "Class",
> #        title = paste0(k," Classes, Youths")) +
> #   theme_clean()
> # gg.post.his.ch
> #
> # # Boxplot
> # gg.post.box.ch <- ggplot(child.lik, aes(x = factor(class), y = post)) +
> #   geom_boxplot(fill = "skyblue") +
> #   labs(x = "Class", y = "Max Posterior Probability",
> #        title = paste0(k," Classes, Youths")) +
> #   theme_clean()
>
>
> # class,size/proportion, average pp,entropy
>
> tb.class3.ch <- data.frame(
+   Class = 1:ncol(post3.ch),
+   Proportion = as.numeric(class.size3.ch),
+   Avg_Posterior = round(ave.pp3.ch, 3)
+ )

> tb.class3.ch

> tb.class4.ch <- data.frame(
+   Class = 1:ncol(post4.ch),
+   Proportion = as.numeric(class.size4.ch),
+   Avg_Posterior = round(ave.pp4.ch, 3)
+ )

> # Weighted minutes, youths
> mins.child <- data.frame(
+   Class = 1:n.classes,
+   Weighted.Median = wmed.ch,
+   Weighted.Q25 = wq25.ch,
+   Weighted.Q75 = wq75.ch
+ )
```

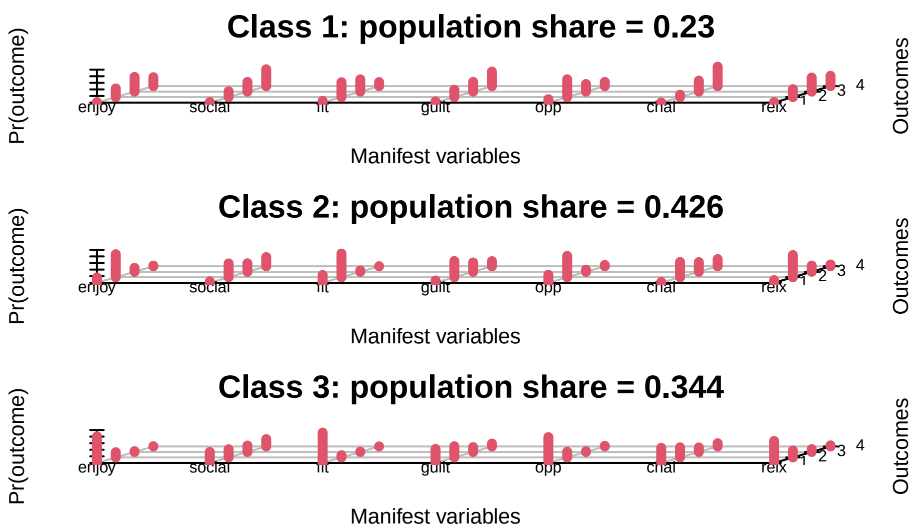
```
> mins.child

> gg.mins.ch <- ggplot(mins.child, aes(x = factor(Class), y = Weighted.Median)) +
+   geom_point(size = 3, color = "blue") +                 # median as a point
+   geom_errorbar(aes(ymin = Weighted.Q25, ymax = Weighted.Q75),
+                 width = 0.2, color = "darkblue") +      # IQR as error bars
+   labs(x = "Class", y = "Minutes (Weighted Median ± IQR)",
+        title = "Weighted Median and IQR per Class") +
+   theme_clean()

> gg.mins.ch

> gg.med.ch <- ggplot(mins.child, aes(x = Class, y = Weighted.Median)) +
+   geom_col() +
+   labs(x = "Latent Class", y = "Probability-Weighted Median Minutes")

> gg.med.ch

> # Predictor plot
> plot(LCAE.ch, nclass = 2)
```




```
> # Bootstrap Vuong-Lo-Mendell-Rubin Likelihood Ratio Test
> or.ch

> # Appendix
> or.ci.ch

> # Include actual coeffs in appendix
> lca.best.ch$probs

> tb.byage.ch

> gg.byage.ch <- child.lik %>%
```

```
+   dplyr::count(age, class) %>%
+   group_by(age) %>%
+   mutate(prop = n / sum(n)) %>%
+   ggplot(aes(x = factor(age), y = prop, fill = factor(class))) +
+   geom_col() +
+   labs(x = "Age group", y = "Proportion", fill = "Class") +
+   scale_y_continuous(labels = scales::percent_format()) +
+   theme_clean()

> gg.byage.ch

> vars.ch <- setdiff(names(child.lik), c("age","mins","post","class",
+                                        "gender","eth","edu"))

> child.lik_long <- child.lik %>%
+   pivot_longer(cols = all_of(vars.ch), names_to = "variable", values_to = "score") %>%
+   count(age, variable, score) %>%
+   group_by(age, variable) %>%
+   mutate(prop = n / sum(n))

> gg.vars.ch <- ggplot(child.lik_long, aes(x = factor(age), y = prop, fill = factor(score))) +
+   geom_col() +
+   facet_wrap(~variable, nrow = 3, ncol = 3) +
+   labs(x = "Age group", y = "Proportion", fill = "Score") +
+   scale_y_continuous(labels = percent_format()) +
+   theme_clean() +
+   theme(legend.position = "bottom")

> # LCA Adults --------------------------------------------------------------
>
>
> # elbow plot
> gg.elbow.ad <- ggplot(ad.lca.output, aes(x = nclass)) +
+   geom_line(aes(y = BIC), color = "blue") +
+   geom_point(aes(y = BIC), color = "blue") +
+   geom_line(aes(y = AIC), color = "red") +
+   geom_point(aes(y = AIC), color = "red") +
+   labs(y = "Information Criterion", x = "Number of Classes",
+        title = "Elbow Plot, Adults",
+        caption = "Blue = BIC, Red = AIC") +
+   theme_clean()

> gg.elbow.ad

> gg.llik.ad <- ggplot(ad.lca.output, aes(x = nclass)) +
+   geom_line(aes(y = llike), color = "blue") +
+   geom_point(aes(y = llike), color = "blue") +
+   labs(y = "Log-Likelihood", x = "Number of Classes",
+        title = "Log-Likelihood, Adults") +
+   theme_clean()

> gg.llik.ad

> # # Max posterior
```

```
> # gg.post.his.ad <- ggplot(adult.lik, aes(x = post, fill = factor(class))) +
> #   geom_histogram(binwidth = 0.05, alpha = 0.7, position = "identity") +
> #   labs(x = "Max Posterior Probability", y = "Count", fill = "Class",
> #        title = paste0(k," Classes, Adults")) +
> #   theme_clean()
> # gg.post.his.ad
> #
> # # Boxplot
> # gg.post.box.ad <- ggplot(adult.lik, aes(x = factor(class), y = post)) +
> #   geom_boxplot(fill = "skyblue") +
> #   labs(x = "Class", y = "Max Posterior Probability",
> #        title = paste0(k," Classes, Adults")) +
> #   theme_clean()
>
>
> # class,size/proportion, average pp,entropy
>
> tb.class3.ad <- data.frame(
+   Class = 1:ncol(post3.ad),
+   Proportion = as.numeric(class.size3.ad),
+   Avg_Posterior = round(ave.pp3.ad, 3)
+ )

> tb.class3.ad

> mins.adult <- data.frame(
+   Class = 1:n.classes,
+   Weighted.Median = wmed.ad,
+   Weighted.Q25 = wq25.ad,
+   Weighted.Q75 = wq75.ad
+ )

> mins.adult

> gg.mins.ad <- ggplot(mins.adult, aes(x = factor(Class), y = Weighted.Median)) +
+   geom_point(size = 3, color = "blue") +                 # median as a point
+   geom_errorbar(aes(ymin = Weighted.Q25, ymax = Weighted.Q75),
+                 width = 0.2, color = "darkblue") +      # IQR as error bars
+   labs(x = "Class", y = "Minutes (Weighted Median ± IQR)",
+        title = "Weighted Median and IQR per Class") +
+   theme_clean()

> gg.mins.ad

> #
> # # Weighted minutes, youths
> # gg.med.ad <- ggplot(mins.adult, aes(x = Class, y = Weighted.Median)) +
> #   geom_col() +
> #   labs(x = "Latent Class", y = "Probability-Weighted Median Minutes")
>
>
> # Predictor plot
> plot(LCAE.ad, nclass = 2)
```




```
> # plot(LCAE.ad, nclass = 3)
>
> # Bootstrap Vuong-Lo-Mendell-Rubin Likelihood Ratio Test
> # 100 reps
> # blrt.ad
> or.ad

> or.ci.ad

> # Include actual coeffs in appendix
> lca.best.ad$probs

> tb.byage.ad

> gg.byage.ad <- adult.lik %>%
+   dplyr::count(age, class) %>%
+   group_by(age) %>%
+   mutate(prop = n / sum(n)) %>%
+   ggplot(aes(x = factor(age), y = prop, fill = factor(class))) +
+   geom_col() +
+   labs(x = "Age group", y = "Proportion", fill = "Class") +
+   scale_y_continuous(labels = scales::percent_format()) +
+   theme_clean()

> gg.byage.ad

> vars.ad <- setdiff(names(adult.lik), c("age","mins","post","class",
+                                         "gender","eth","edu"))

> adult.lik_long <- adult.lik %>%
+   pivot_longer(cols = all_of(vars.ad), names_to = "variable", values_to = "score") %>%
+   count(age, variable, score) %>%
+   group_by(age, variable) %>%
+   mutate(prop = n / sum(n))
```

```
> gg.vars.ad <- ggplot(adult.lik_long, aes(x = factor(age), y = prop, fill = factor(score))) +
+   geom_col() +
+   facet_wrap(~variable, nrow = 3, ncol = 3) +
+   labs(x = "Age group", y = "Proportion", fill = "Score") +
+   scale_y_continuous(labels = percent_format()) +
+   theme_clean() +
+   theme(legend.position = "bottom")

> gg.vars.ad
```

Appendix C - R code: rmarkdown chunks

```
source(file="data.R")
source(file="SEM.R")
source(file="LCA.R")
source(file="Visualization.R")
opts <- options(knitr.kable.NA = '')
kable(list(adult.summary),align='c',booktabs = T) %>%
  kable_styling(position = 'center', font_size = 10,
              latex_options = c('striped',
                                'hold_position'))

gg.ad.dsbl
gg.ad.gend
gg.ad.age

gg.ad.eth
gg.ad.edu

opts <- options(knitr.kable.NA = '')
kable(list(child.summary),align='c',booktabs = T) %>%
  kable_styling(position = 'center', font_size = 10,
              latex_options = c('striped',
                                'hold_position'))

gg.ch.dsbl
gg.ch.gend
gg.ch.age
gg.ch.eth


gg.vars.ad
gg.vars.ch

opts <- options(knitr.kable.NA = '')
kable(list(slopes.diff),align='c',booktabs = T) %>%
  kable_styling(position = 'center', font_size = 10,
              latex_options = c('striped',
                                'hold_position'))

gg.elbow.ad
gg.llik.ad


plot(LCAE.ad, nclass = 2)


gg.mins.ch


gg.byage.ad
```

```r
gg.elbow.ch
gg.llik.ch


plot(LCAE.ch, nclass = 2)
plot(LCAE.ch, nclass = 3)


gg.mins.ch


gg.byage.ch

source("data.R", echo = T, print.eval = F,
       max.deparse.length=Inf, keep.source=T)
source("SEM.R", echo = T, print.eval = F,
       max.deparse.length=Inf, keep.source=T)
source("LCA.R", echo = T, print.eval = F,
       max.deparse.length=Inf, keep.source=T)
source("Visualization.R", echo = T, print.eval = F,
       max.deparse.length=Inf, keep.source=T)
```