Dissertation

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rmdwc::rmdcount('Paper.rmd')

add that social cognitive theory is outdated (if time)

Contents

Introduction

Physical inactivity remains widespread across different age groups and is considered a major public health issue (Mitchell, 2019). 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. Motivation has consistently been identified as a central determinant of behaviour, including participation in physical activity (Daley & Duda, 2006; Deci & Ryan, 2008; Duncan et al., 2010; Falk et al., 2015; Flannery, 2017). 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.

Literature Review

While other frameworks, such as Social Cognitive Theory, are widely cited, this dissertation focuses on Self-Determination Theory and the Theory of Planned Behaviour, which provide useful conceptual perspectives for understanding and interpreting motivational patterns.

Self-Determination Theory (SDT)

Self-Determination Theory (SDT) is a popular framework that has gained popularity in the past two decades. Developed by Deci & Ryan, it has shed light on the understanding of human motivation, emphasizing the degree to which behavior is self-determined versus controlled. Motivation is distinguished in terms of autonomy, with autonomous forms associated with volition and self-endorsement of behavior, and controlled forms reflecting pressure from external contingencies or internalized demands such as guilt or ego involvement. Within SDT, extrinsic motivation is subdivided into external regulation, introjected regulation, identified regulation, and integrated regulation, representing increasing internalization of instrumental behaviors. Intrinsic motivation, by contrast, arises from interest, enjoyment, or inherent satisfaction in the activity itself. These motivational types have implications for physical activity, as more autonomous motives are linked to sustained engagement, positive psychological outcomes, and long-term health (CITE).

In physical activity and health behaviour research, this framework is especially influential because it links the quality of motivation, rather than its quantity, to long-term adherence and wellbeing. Empirical studies confirm that need-supportive interventions can improve exercise uptake, reduce dropout, and enhance both physical and psychological wellbeing (Teixeira et al., 2012; Ng et al., 2012). Consequently, SDT provides not just a descriptive model of motivation but also a prescriptive guide for designing effective physical activity and health promotion programmes.

Theory of Planned Behaviour (TPB)

The Theory of Planned Behavior (TPB), proposed by Ajzen in 1991, is a widely used framework for predicting and understanding human behavior, emphasizing the role of intention as the proximal determinant of action. According to TPB, behavioral intentions are influenced by three key factors: attitudes toward the behavior, subjective norms, and perceived behavioral control. Attitudes reflect an individual's positive or negative evaluation of performing the behavior, subjective norms capture perceived social pressure from significant others to engage or not engage, and perceived behavioral control represents the perceived ease or difficulty of performing the behavior, akin to self-efficacy. These factors interact to shape intention, which in turn predicts behavior, although perceived behavioral control can also have a direct effect on behavior. In the context of physical activity, TPB has been used to explain variations in exercise participation across age groups, demonstrating that stronger intentions—supported by favorable attitudes, positive social norms, and higher perceived control—are associated with higher levels of activity. However, the framework also recognizes that intentions do not always translate into behavior, highlighting the importance of situational constraints and individual capabilities.

Age Differences

Across the lifespan, intrinsic and personally meaningful motivations are consistently associated with higher levels of physical activity. However, intrinsic motivation tends to decline with age (Brunet & Sabiston, 2011; Dishman et al., 2018; de Maio Nascimento, 2023), suggesting that the factors driving engagement shift across developmental stages. Environmental opportunities, such as access to facilities or structured programs, appear to facilitate activity regardless of age, providing a common context that supports engagement across populations.

In youths, intrinsic motivation, enjoyment, and social support are strong predictors of habitual physical activity. Longitudinal evidence indicates that adolescents who maintain higher intrinsic motivation and personally meaningful goals—particularly those emphasizing enjoyment—remain more active over time, whereas declines in social, competence, or appearance goals can weaken engagement (Dishman et al., 2018). Cross-sectional studies further show that higher motivation profiles in adolescents are associated with adaptive outcomes such as responsibility, resilience, and social support (Manzano-Sánchez et al., 2019; Heredia-León et al., 2021). Collectively, these findings suggest that enjoyment- and social-oriented motives play a particularly salient role in sustaining physical activity in younger populations.

Among adults, motivation tends to shift toward health- and fitness-related goals. Adults frequently report exercising for reasons aligned with personal health, fitness, and psychological well-being rather than external rewards (Brunet & Sabiston, 2011; Nascimento et al., 2023). Relaxation and stress relief have also been highlighted as important motivating factors, contributing to voluntary adherence and psychological benefits (de Maio Nascimento, 2021; Vuckovic, 2015; Kilgour, 2005). Evidence suggests that these motives remain relatively stable across younger and older adults, with comparable importance reported by women over 50 (Kilgour, 2005; Vuckovic, 2015). Overall, fitness- and relaxation-related motives appear more prominent in adults than in youths.

While specific motives vary by age, some contextual factors influence physical activity similarly across groups. Access to facilities, opportunities to participate, and supportive environments facilitate engagement across the lifespan, providing a baseline influence independent of age-specific motivational differences (Brunet & Sabiston, 2011; Dishman et al., 2018).

These patterns suggest clear age-related differences in the influence of specific motives. Enjoyment, social, and guilt motives are especially relevant for youths, whereas fitness- and relaxation-related motives are more salient in adults. Environmental opportunities appear to exert a similar influence across age groups.

Hypothesis 1: The influence of exercise motives on physical activity differs between youths and adults.

- H1(a). Enjoyment, social, and guilt motives are more influential in youths than in adults.

- H1(b). Fitness and relaxation motives are more influential motives in adults than in youths.

- H1(c). Environmental opportunities influence physical activity similarly across age groups.

Motivational Profiles

Hypothesis 2: Distinct motivational profiles exist within youths and within adults.

In adults, Ostendorf et al. (2021) identified three primary motivational profiles among individuals with overweight or obesity: high autonomous, high combined, and moderate combined. The high autonomous profile was characterized by strong intrinsic and identified motivations, with minimal influence of external or introjected regulation. The high combined profile reflected elevated levels across all regulatory types, while the moderate combined profile exhibited intermediate levels on all regulations. Longitudinally, the high autonomous profile demonstrated the least decline in moderate-to-vigorous physical activity during transitions from supervised to unsupervised exercise, suggesting that intrinsic and identified motivations support sustained behavior, whereas moderate-to-high external regulation may require additional support for continued engagement. Nuss et al. (2023) further identified four motivational profiles in Canadian adults,

showing that combinations of controlled and autonomous motivation may synergistically support activity, with low overall motivation corresponding to minimal engagement. Collectively, these findings highlight that adult populations are not homogeneous in their motivational profiles, and that the prevalence of lower-engagement profiles increases with age. This supports the hypothesis that, with increasing age, adults are progressively more likely to belong to classes characterized by lower overall agreement across motivational items, with the oldest adults showing the sharpest decline.

In adolescents, Moreno-Murcia et al. (2011) found two primary motivational profiles in physical education students: a self-determined profile, with high intrinsic and identified motivation, and a non-self-determined profile, with elevated external, introjected, and amotivated scores. The self-determined profile was positively associated with Theory of Planned Behavior constructs such as intention, subjective norm, perceived behavioral control, and attitude, indicating that higher autonomous motivation supports favorable cognitions and participation behaviors. Cross-sectional studies further corroborate these trends. Manzano-Sánchez et al. (2019) identified higher motivation profiles among adolescents aged 12–16, which were associated with adaptive outcomes such as responsibility, resilience, and perceived social support. Heredia-León et al. (2021) reported that students with high-quality and high-quantity motivational profiles demonstrated greater intention to be physically active and enjoyment in PE classes, whereas low-quality profiles corresponded to higher boredom and lower engagement. Tapia-Serrano et al. (2022) identified five profiles in children, ranging from highly amotivated to autonomously motivated, showing that even controlled motivation can promote short-term engagement, though autonomy supports more sustained activity. Collectively, these studies suggest that younger populations exhibit a range of motivational profiles, and the likelihood of belonging to profiles with lower motivation increases with age. This aligns with the hypothesis that, as age increases, youths are progressively more likely to belong to classes characterized by lower overall agreement across motivational items.

- H2(a). With increasing age, the likelihood of adults belonging to classes with lower overall agreement across motivational items increases, reflecting a gradual decline in motivation, with the oldest adults showing the steepest decrease.

- H2(b). With increasing age, the likelihood of youths belonging to classes with lower overall agreement across motivational items increases, reflecting a gradual decline in motivation.

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 116,873 adult and 29,798 youth observations were used in the SEM analyses, whereas 116,018 adult and 28,269 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 – exercising for fun with friends.

- Fitness – exercising to maintain physical well-being.

- Guilt – sense of personal obligation to exercise.

- Opportunity – having the chance to exercise.

- Relaxation – exercising to reduce stress and worry.

- Ability - self-perceived competence and confidence in engaging in PA.

- Importance - perceived personal importance and understanding of the value of PA.

- Challenge – tendency to pursue and persist through challenges.

- Minutes - weekly minutes of moderate-to-vigorous PA; see Appendix B for specific activities included.

Adult Dataset

The adult dataset analysed in this dissertation is derived from the Active Lives Adult Survey (Year 8: 2022–2023), conducted by Ipsos on behalf of Sport England with additional funding from the Office for Health Improvement and Disparities (OHID). The survey is designed as a large-scale, nationally representative measure of adult participation in sport and physical activity in England. It follows a push-to-web methodology, whereby sampled households received up to four postal mailings inviting participation. The first two mailings provided instructions and passcodes to complete the survey online, while the third included a paper self-completion questionnaire to maximise response rates. A final reminder letter encouraged online participation. Data were collected between November 2022 and November 2023, with responses obtained from 172,968 adults aged 16 and above across England.

The questionnaire focused on a wide range of topics related to sport and physical activity, including frequency, duration, and location of participation, alongside attendance at sporting events, volunteering, club membership, and motivational and attitudinal measures. Standard demographic questions were also included, covering age, gender, socio-economic status, education, household composition, sexual identity, and religion. To balance questionnaire length and data breadth, some modules were administered only to subsamples of respondents, particularly in the online version.

The sample was drawn using random probability sampling from the Postcode Address File (PAF). A total of 562,644 addresses were invited, with up to two adults per household eligible to respond. Multiple reminders ensured greater response coverage, helping mitigate nonresponse bias. The combination of online and postal modes, alongside stratified sampling and weighting, was intended to enhance representativeness of the adult population in England.

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.
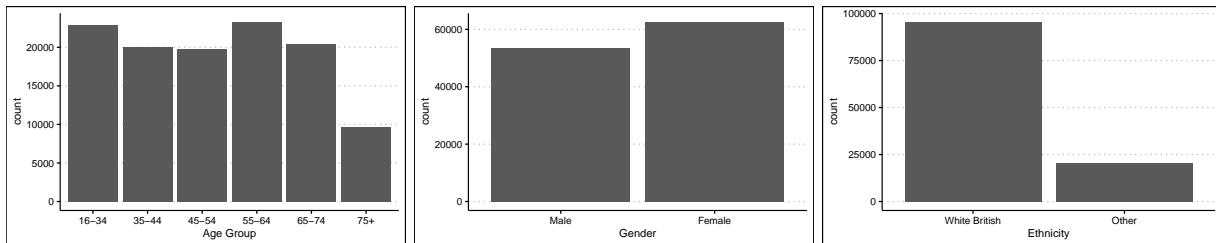

Figure 1: Distribution of age, gender, and ethnicity in adults.

Proportions of gender and ethnicity are extremely similar in the subsamples used for SEM and LCA models. Females constitute 54% of the sample, while white British constitute 82% of the total sample. The youngest and oldest two age groups were collapsed together due to the small size of most extreme groups. The decision to collapse the oldest adult categories (64–75 and 76+) was made because motivational profiles in these two groups did not differ meaningfully in preliminary analyses, and because the very small number of 76+ respondents would have produced unstable estimates if analyzed independently. Combining them ensured more robust model performance without obscuring theoretically important distinctions, which were not expected to be as pronounced at that stage of life. After collapsing, there are only some skewness. Responses with missing value in any of the motives are removed.

There's a general left skew in responses, indicating most did not answer strongly agree to most items.

Each item was rated on a five-point Likert scale ranging from 1 (strongly agree) to 5 (strongly disagree). All motive items had responses 4 (disagree) and 5 (strongly disagree) collapsed into a single category due to the low proportion of responses to minimize distortion.

Table 1: Proportion of positive responses in adults.

	Proportion
enjoyb	0.3454
socialb	0.1354
fitb	0.4241
guiltb	0.1813
oppb	0.3909
relxb	0.2630
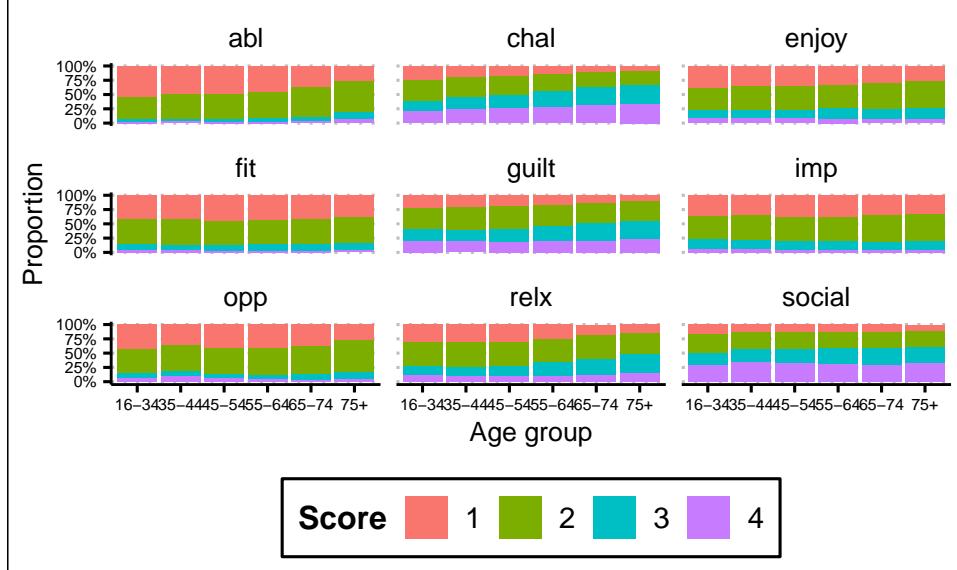
Figure 2: Distribution of adult responses for each motive on the Likert scale.

Across most motive items, the proportion of adults expressing strong positive agreement declines as age increases. In practical terms, older adults are less likely than their younger counterparts to strongly endorse beliefs such as feeling capable of engaging in physical activity, valuing it for the challenge, or pursuing it for enjoyment and fitness. They are also less likely to report strong feelings of guilt if they do not exercise, to believe they have sufficient opportunities to be active, or to view physical activity as an important way to relax. See Appendix C for additional information on the mean, median, standard deviation, and percentage of missing values (NAs), which were excluded from the final dataset.

Youth Dataset

The youth dataset used in this dissertation is drawn from the Active Lives Children and Young People Survey (Year 6: 2022–2023), conducted by Ipsos on behalf of Sport England. It is a large-scale, school-based online survey administered to pupils in Years 1–11, their parents (for Years 1–2 pupils), and teachers. Only pupil responses from year 6-11 (age 11-16) were used in this dissertation. The pupil questionnaire focused on participation in sport and physical activity over the previous week, alongside items on swimming, cycling, volunteering, wellbeing, and attitudes towards physical activity. It also included classification questions such as gender, disability, and long-term health conditions.

The sampling strategy was designed to permit analysis at both national and local authority levels. A stratified three-stage sampling process was used: schools were first sampled from the January 2021 school census, then three year groups were randomly selected within each participating school, and finally, one mixed-ability class was chosen per selected year group. Fieldwork was carried out in three phases aligned with the academic terms (September 2022–July 2023). Pupils typically completed the survey at school under teacher supervision, although in some secondary schools it could also be set as homework. To encourage participation, schools received credits for sports equipment and, if response thresholds were met, school-level feedback reports.
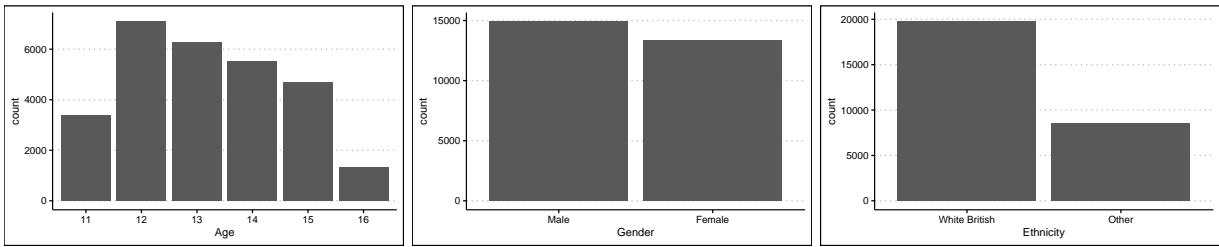
Figure 3: Distribution of age, gender, and ethnicity in youths.

47% are female. 70% are white British. Most youths are between 12-15 years old. There are only 4.63% of 16 year olds. Although 16-year-olds make up only about 5% of the youth sample, they were not collapsed with the 15-year-olds. This decision reflects a substantive rather than purely numerical consideration: the transition from 15 to 16 often marks a distinct developmental and social stage (e.g., legal thresholds, end of compulsory schooling, increased autonomy), which may correspond to meaningful differences in PA motives. Retaining this separation allows us to examine whether these turning points are reflected in motivational patterns, even with a relatively small subgroup.

Table 2: Proportion of positive responses in youths.

	Proportion
enjoyb	0.5094
socialb	0.2328
fitb	0.4145
guiltb	0.1411
oppb	0.5205
relxb	0.2529

There's a general left skew in responses, indicating most did not answer strongly agree to most items.

Each item was rated on a four-point Likert scale ranging from 1 (strongly agree) to 4 (strongly disagree). Similar to the adults dataset, the 3 (disagree) and 4 (stronlgy disagree) responses were collapsed into a single cateogry due to low proportions of those resopness. Missing responses and "I don't know" were removed from the dataset.
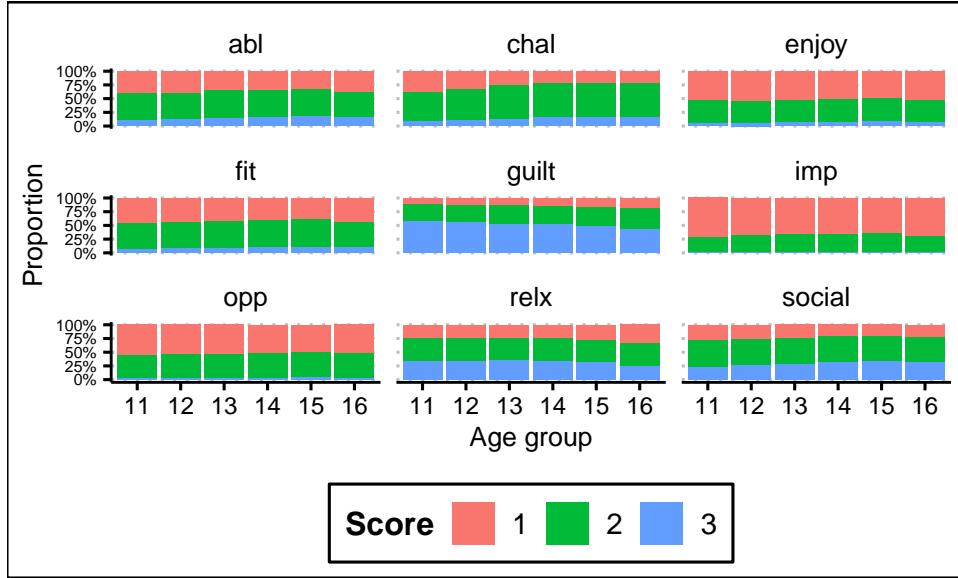
Figure 4: Distribution of youth responses for each motive on the Likert scale.

After collapsing, the items are fairly balanced with the exception of social, guilt, and relaxation. Responses with missing value in any of the motives are removed. The response patterns among youths are less consistent than those observed in adults. With increasing age, youths become less likely to report exercising for challenge or social reasons. A greater proportion report exercising because they would feel guilty if they did not, or because it helps them relax. Among the oldest youth group, there is a slight but noticeable reversal: a sudden uptick in the proportion who "strongly agree" that ability and fitness are motivating factors. It is also notable that only a small minority of youths, regardless of age, indicate a lack of understanding about the importance of PA. See Appendix C for additional information on the mean, median, standard deviation, and percentage of missing values (NAs), which were excluded from the final dataset.

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 E 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, using the same set of motivational variables included in the SEM analysis, with the addition of two new items with slightly different wording.

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.

Residual diagnostics for conditional independence, such as standardized bivariate chi-square or bivariate residuals, were computed for the PA-related items. Some cells in the cross-tabulations of item responses were extremely sparse (proportions <1%), which mathematically inflates these statistics. As a result, the standardized bivariate chi-square values were unrealistically large and cannot serve as reliable indicators of local dependence. Given this, and that the motives (ability, importance, fitness, enjoyment, and opportunity) are substantively distinct, local dependence statistics are not reported. Instead, model evaluation relied on standard LCA fit indices (BIC, aBIC, entropy) and the interpretability and stability of the latent classes, which were robust.

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.

Table 3: Estimated slopes of each motivational factor in the SEM, with differences calculated as youth minus adult values.

var	est.youth	est.adult	diff
enjoyb	139.27	115.34	23.93
guiltb	28.74	11.88	16.86
oppb	33.19	96.44	-63.25
fitb	67.36	92.56	-25.20
socialb	32.70	56.63	-23.93
relxb	59.28	43.19	16.09

All motivational items in the model influenced physical activity in the same direction for youths and adults. Since the variables are binary (1 = strongly agree, 0 = not strongly agree), the coefficients represent the estimated difference in minutes of activity between participants who strongly endorse a motive and those who do not. While all differences between age groups were statistically significant, effect sizes were generally modest, except for opportunity, which had a greater impact in adults. Other motives, including enjoyment, guilt, fitness, and social factors, exhibited smaller differences, indicating broadly similar motivational mechanisms across age groups.

Youths were most strongly influenced by enjoyment and guilt, highlighting the role of intrinsic and internalized motivation in shaping adolescent activity. Adults, by contrast, responded more strongly to opportunity, fitness, and social motives, underscoring the importance of external facilitation, health awareness, and social engagement.

From an SDT perspective, these findings align with the framework's distinction between intrinsic, internalized, and external regulation. Youths' strong responses to enjoyment and guilt/obligation reflect intrinsic and internalized motivations, emphasizing autonomy and internalized norms as key drivers. Adults' stronger responsiveness to opportunity, fitness, and social motives reflects identified and external regulation, where structured opportunities, competence-related goals, and social reinforcement play a larger role.

Within the TPB framework, behavior is determined by intention, which is influenced by attitudes, subjective norms, and perceived behavioral control (PBC). For youths, full endorsement of enjoyment and guilt/obligation likely reflects favorable attitudes and perceived social norms supporting activity. For adults, stronger effects of opportunity, fitness, and social motives suggest that PBC, shaped by access to resources and social support, is a key driver of activity.

H1(a) is partially correct. The social aspect is more prominent in adults. * H1(a). Enjoyment, social, and guilt motives are more influential in youths than in adults.

H1(b) is correct. Will check the second part of hypothesis in lca. (add in paragraph in intro, Marcelo de Maio Nascimento, Vojko Vuckovic, Alixe H M Kilgour) * H1(b). Fitness and relaxation are more influential motives in adults than in youths, particularly in middle-aged and older groups.

Actually opportunity affects adults a lot more :O * H1(c). Environmental opportunities influence physical activity similarly across age groups.

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LCA

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

Adults
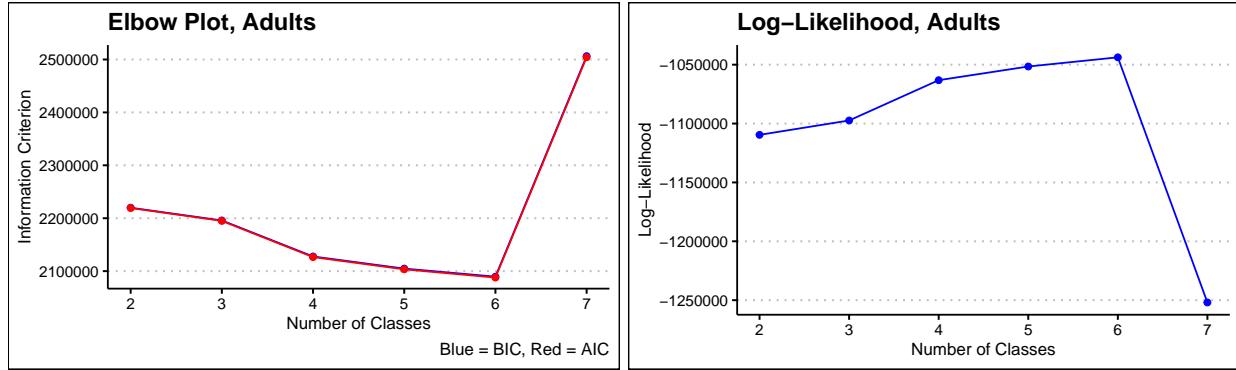
Figure 5: Elbow plot showing AIC and BIC values, and maximum likelihood plot, across different numbers of latent classes in adults.

ad.lca.output?

3 to 6 classes all have relative high likelihood and low AIC and BIC, and average posterior entropy per class. From the elbow plot, 4 classes seem to be the number of classes that start displaying diminishing return. However, the 3-class model has significantly higher relative entropy, and the four-class solution produced two classes with highly similar endorsement patterns, effectively splitting the moderate group without adding meaningful differentiation. The three-class model provides a clearer, more parsimonious representation of motivational profiles while still capturing the small but conceptually important subgroup with generally negative attitudes.
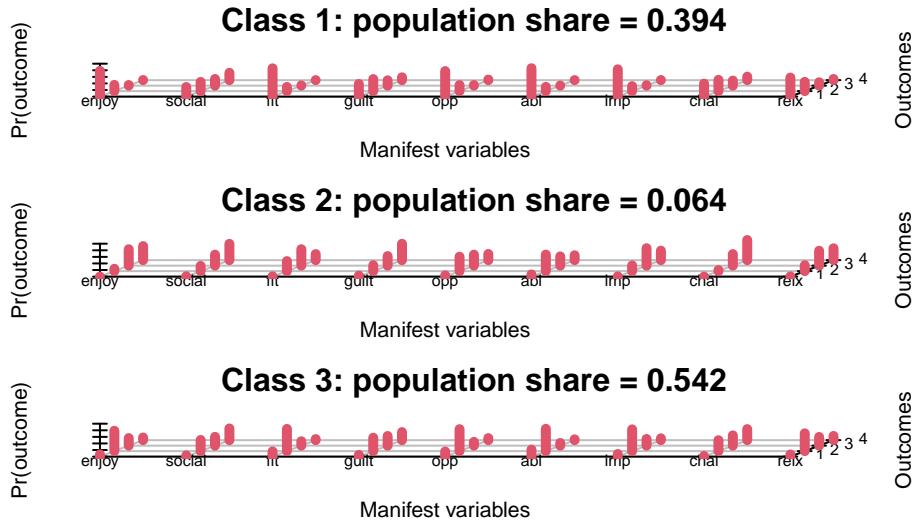
Figure 6: Frequency of adult responses for each motive by class membership.

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Class 1   This class shows high probabilities of strongly agreeing with enjoyment, fitness, ability, opportunity, and importance. Members also moderately endorsed social, challenge, and guilt motives, and showed relatively high agreement with relaxation. Overall, this class represents adults who consistently report strong agreement with a broad range of motivations. This class is labelled the High Engagement class.

**Class 2**   This class is characterized by very low probabilities of strongly agreeing with enjoyment and ability, and by a higher prevalence of neutral or negative responses across most items. Members of this class express the least favorable attitudes toward PA. This class is labelled the Low Engagement class. While this class represents a relatively small proportion of the sample (~6%), it aligns with the raw data, in which very few respondents selected negative responses.

Class 3   This class has a mixed attitude toward many motives, with moderate positive endorsement toward enjoyment, fitness, opportunity, ability and importance It represents adults with more ambivalent responses. This class is labelled the Mixed Motivation class.
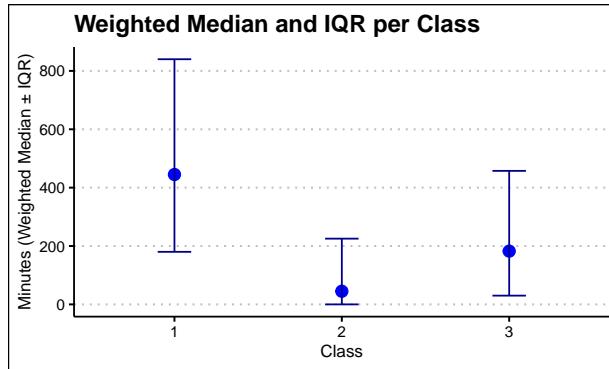

Figure 7: Weighted median and interquartile range of minutes exercised per week for adults by class.

Analysis of weekly minutes of physical activity across the adult latent classes highlights substantial differences in exercise behavior. The High Engagement class exhibits the highest levels, with a weighted median of 445 minutes per week and a wide interquartile range of 180 to 840 minutes, indicating considerable variability even among this highly active group. The Mixed Motivation class reports intermediate activity, with a median of 182.5 minutes per week and an IQR of 30 to 457.5 minutes, reflecting both moderate overall engagement and substantial individual differences. In contrast, the Low Engagement class shows markedly lower activity, with a median of only 45 minutes per week and an IQR from 0 to 225.25 minutes, highlighting that while most members are minimally active, some still achieve higher levels. Overall, the broad IQRs across all classes indicate that even within latent classes defined by motivation, actual exercise behavior varies considerably.

The distribution of age groups across the three latent classes highlights notable differences in motivational profiles. The High Engagement class is consistently the second most populous across age groups, though its representation declines gradually with increasing age. The Low Engagement class remains the smallest in all age groups, representing a relatively rare subgroup with low endorsement of motives, and its relative size is largely stable across ages. In contrast, the Mixed Motivation class contains the largest number of adults in every age group, with membership increasing steadily as age rises, suggesting that some individuals may shift from high engagement to mixed motivation over time.

Multinomial logistic regression examined the association between age and motivation profile, with the High Engagement class as reference. Examination of the odds of latent class membership across adult age groups, using the youngest group (16–34 years) as the reference, reveals clear age-related patterns. Adults in the youngest age group are over 6.6 times more likely to belong to the High Engagement class than to the Low Engagement class. Conversely, a slightly higher proportion of young adults belong to the Mixed Motivation
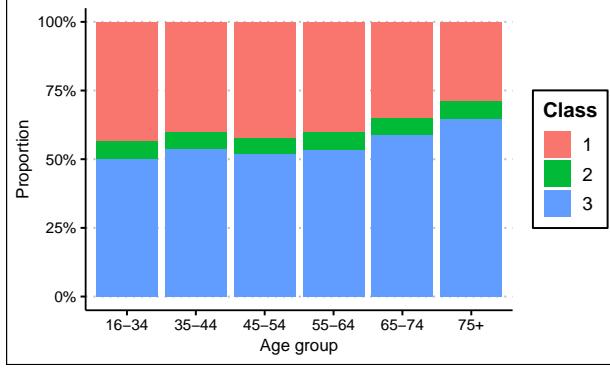
Figure 8: Proportion of adults in each class across age groups.

Table 4: Odds ratios for adult class membership across age groups, with the youngest group (16–34 years) as the reference.

	(Intercept)	age2	age3	age4	age5	age6
2	0.149	1.023	0.9118	1.046	1.143	1.515
3	1.153	1.159	1.0696	1.149	1.453	1.930

class, which may partly reflect the overall larger size of this class. For the Low Engagement class, older age groups generally show modestly higher odds of membership compared with the reference, though the differences for age groups 35–44 and 55–64 are not statistically significant. The highest odds are observed in the oldest age group (75+), suggesting that adults in this group are 1.5 times more likely to belong to the Low Engagement class than younger adults. In the Mixed Motivation class, the odds of membership increase consistently with age, with adults aged 65–74 being 1.45 times, and those 75+ being 1.93 times more likely than 16–34-year-olds to belong to this class rather than High Engagement.

These results support H2(a), which posited that the likelihood of adults belonging to classes with lower overall agreement across motivational items increases with age. The observed shift in class membership with age suggests a substantive decline in overall motivation among adults, particularly in the oldest age groups. This pattern implies that interventions targeting physical activity may need to be tailored to address the motivational needs of older adults, who are disproportionately represented in classes with lower agreement across motivational items. The steep decline among the 75+ group indicates that standard approaches effective for younger adults may be insufficient for maintaining engagement in later life. Conceptually, these findings support the idea that motivation is not static across adulthood; rather, it gradually diminishes, with older adults potentially requiring additional support, reinforcement, or environmental facilitation to sustain participation. In practical terms, understanding these shifts can inform program design, policy decisions, and public health strategies aimed at reducing age-related decreases in activity and engagement.

Youths

BIC plot indicates 3 or four 4 to reduce BIC the most. BLRT preferred 4 classes. Relative entropy values are 0.7998 and 0.7473 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.
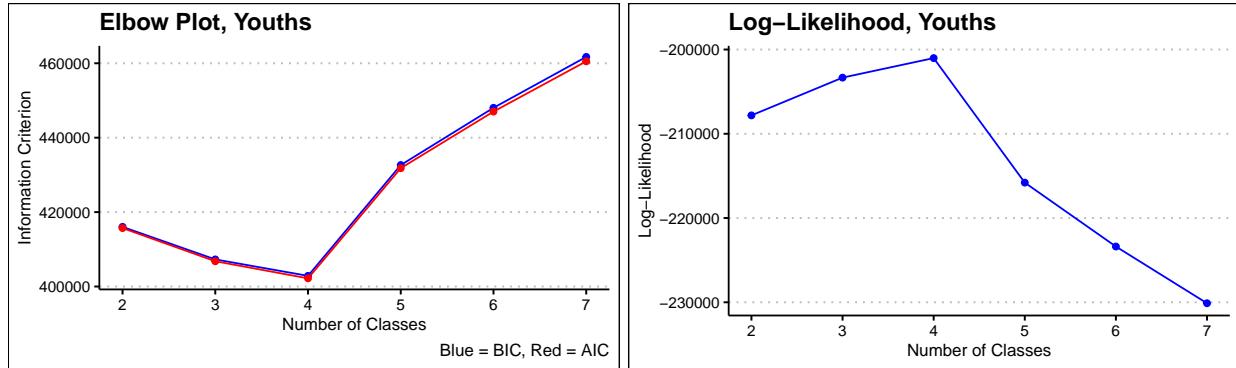
Figure 9: Elbow plot showing AIC and BIC values, and maximum likelihood plot, across different numbers of latent classes in youths.

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.
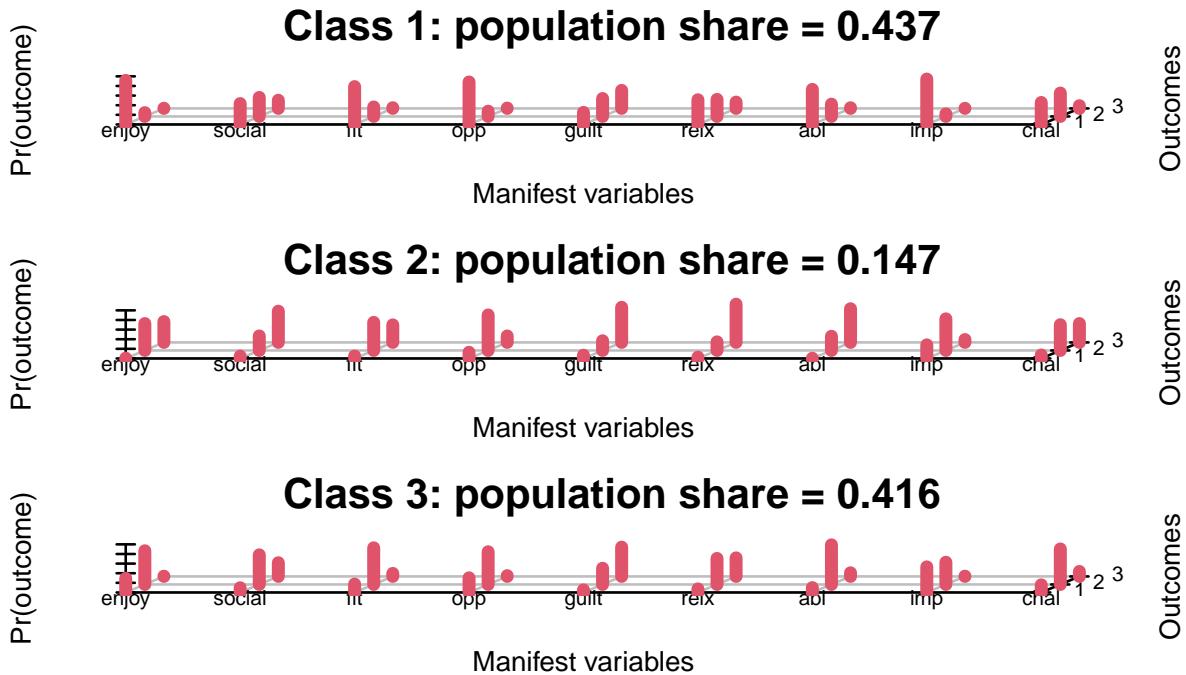
Figure 10: Frequency of adult responses for each motive by class membership.

19

Class 1   This class exhibits very high probabilities of strongly agreeing with enjoyment, fitness, opportunity, importance, and ability. Endorsement of social, challenge, and relaxation motives is somewhat more moderate, though still leaning toward agreement, and guilt shows a more even split across response options. This group is characterized by consistently positive attitudes toward a wide range of motives. This class will be labelled the High Engagement class.

Class 2   This class shows very low probabilities of strongly agreeing with all motives, and negative attitudes toward social, guilt, relaxation, and ability motives. This class will be labelled the Low Engagement class.

Class 3   This class primarily endorsed "agree" across most motives, with the exception of guilt. Disagreement is relatively uncommon, but strong agreement is also less prevalent than in the High Engagement class. This class falls between the other two, representing generally positive but not strongly emphatic motivation toward PA. This class will be labelled the Moderate Engagement class.
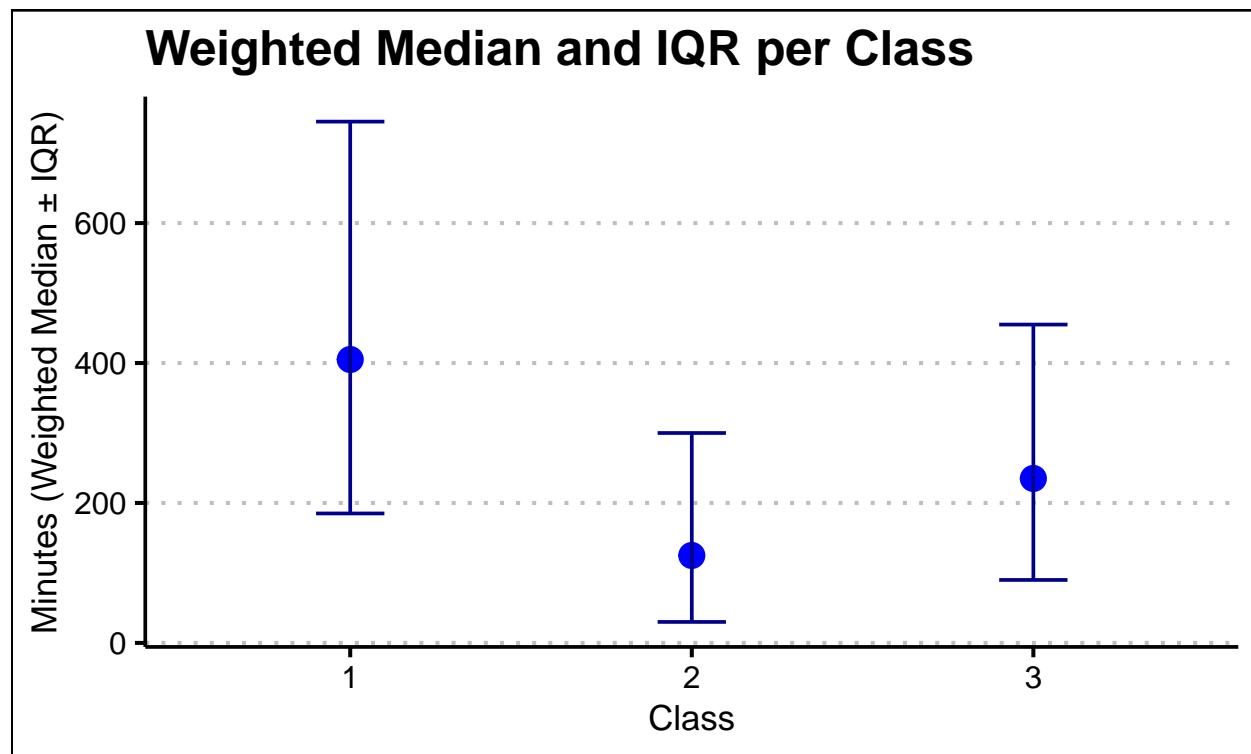
Figure 11: Weighted median and interquartile range of minutes exercised per week for youths by class.

Analysis of weekly minutes of physical activity across the youth latent classes reveals meaningful differences in exercise behavior. The High Engagement class reports the highest levels, with a weighted median of 405 minutes per week and an interquartile range of 185 to 745 minutes, indicating substantial variability even among the most motivated youths. The Mixed Motivation class shows intermediate activity, with a median of 235 minutes per week and an IQR from 90 to 455 minutes, reflecting moderate engagement with considerable individual differences. The Low Engagement class exhibits the lowest activity, with a median of 125 minutes per week and an interquartile range of 30 to 300 minutes, suggesting that while most members are less active, some still achieve moderate levels. These patterns imply that, similar to adults, class membership captures meaningful distinctions in motivation that are associated with actual physical activity.

The distribution of age groups across the three latent classes highlights notable differences in motivational profiles among youths. The High Engagement and Mixed Motivation classes are roughly similar in size, with the High Engagement class generally decreasing across age groups but showing a sudden increase at age 16.
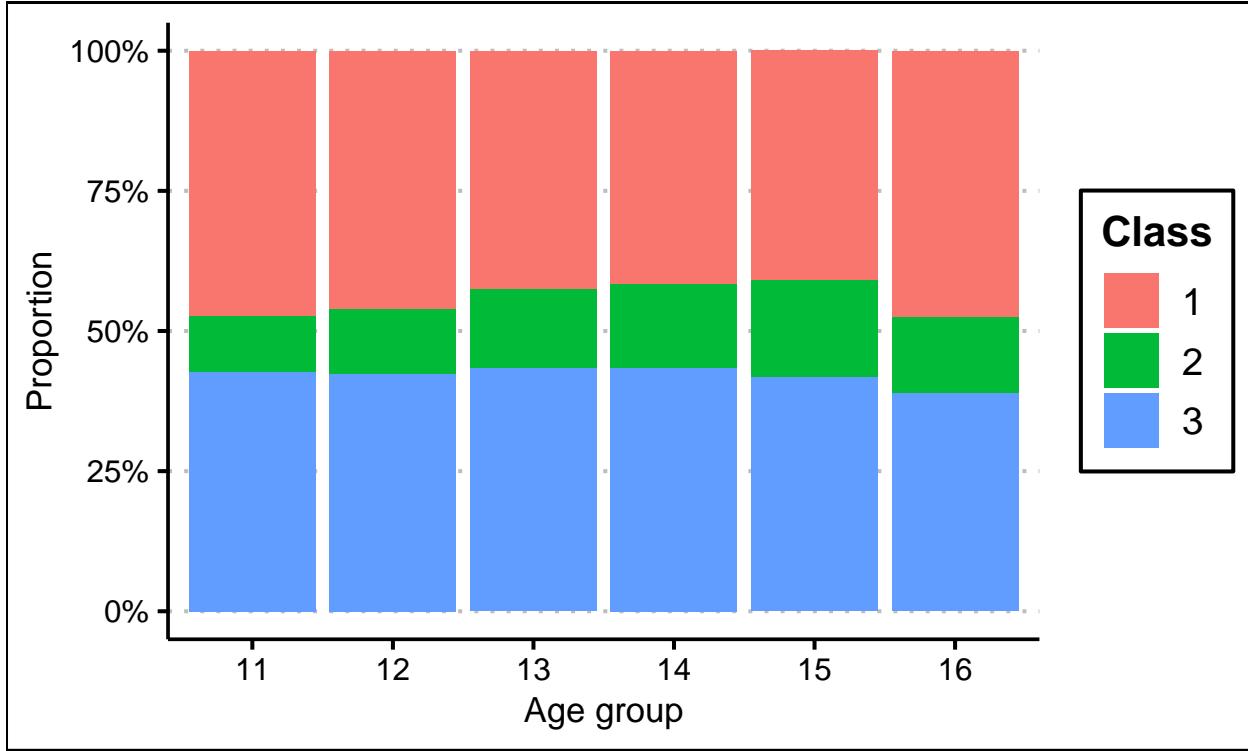
Figure 12: Proportion of youths in each class by age.

The Low Engagement class is smaller than the other two but not as rare as in the adult sample; it increases steadily with age, with a slight dip at age 16. These patterns suggest that while high engagement may decline during adolescence, a substantial portion of youths maintain strong or mixed motivation, and low engagement gradually becomes more common over time. The sudden increase in High Engagement at age 16 indicates that some youths may experience a late boost in motivation during this stage of adolescence.

Table 5: Odds ratios for youth class membership across ages, with 11-year-olds as the reference.

	(Intercept)	age2	age3	age4	age5	age6
2	0.2086	1.197	1.586	1.701	2.036	1.3617
3	0.8991	1.021	1.129	1.158	1.134	0.9087

Examination of the odds of latent class membership across youth age groups, using 11-year-olds as the reference, reveals distinct developmental patterns. At age 11, youths are approximately 5 times less likely to belong to the Low Engagement class compared with High Engagement, whereas they are about equal in odds to belong to the Mixed Motivation class. For the Low Engagement class, the odds of membership increase steadily with age, with 12-year-olds about 1.2 times more likely, 13-year-olds 1.6 times more likely, 14-year-olds 1.7 times more likely, and 15-year-olds 2 times more likely than 11-year-olds to belong to this class, before slightly declining at age 16 (1.4 times more likely). In the Mixed Motivation class, the odds of membership increase modestly from ages 12–15, ranging from 1.0 to 1.2 times more likely than 11-year-olds, before declining slightly at age 16 (0.9 times as likely). These patterns indicate that as youths age, they increasingly shift from High Engagement toward Low Engagement or Mixed Motivation, with a subtle rise in motivation at age 16 suggesting that some youths regain or consolidate engagement in physical activity.

The trends indicate a gradual decline in motivation throughout adolescence, with older youths more frequently represented in classes showing moderate or lower endorsement of motivational items, aligning with

H2(b). This pattern suggests that interventions aimed at promoting physical activity in younger populations may need to account for declining motivation with age, emphasizing strategies that sustain engagement through the middle to late teen years. The relative stability in the youngest ages followed by a shift around 15–16 years highlights a critical period for reinforcing positive attitudes toward physical activity. Conceptually, these results indicate that motivation in youths is dynamic and susceptible to age-related changes, reinforcing the importance of early and sustained intervention to maintain high levels of agreement across motivational factors.

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.

Limitations

adult data Push-to-web design: Reliance on online completion may underrepresent groups with lower digital literacy or internet access (e.g., older adults, lower-income households), even though a paper option was provided at the third mailing. Response bias: Out of over 560,000 households invited, only ~173,000 valid responses were obtained. This implies a relatively low response rate, raising the possibility that respondents are more health-conscious or sport-engaged than non-respondents. Household-level sampling: Allowing up to two respondents per household could introduce intra-household clustering, potentially inflating similarities between responses. Mode effects: Differences between online and paper responses could influence reported activity levels or willingness to disclose sensitive demographic details. Split questionnaire design: Some questions were only asked to subsets of participants, which led to the exclusion of data from participants who did not answer key questions required for this analysis.

youths data Self-report data: Pupils' answers, especially younger ones, may be influenced by recall issues, comprehension, or social desirability (e.g., overreporting activity). Mode of administration: Conducted in schools, often under teacher supervision, which may affect how candid pupils are in reporting behaviours or wellbeing.

No factor analysis Wording slightly different between datasets for 2 vars Correlation moderate in sem inter-preattion may be diff despite same skewed data (like most self-reports did not log transform minutes, rather just took the median, results are extremely similar and does not detract from comparison removed "does not know" from youths rather than using it as neutral answer only counted moderate to heavy exercises, but for older adults they may only be able to perform and benefit equally from light exercises

demogrpahics like gender, ethnicity, disability, relationship, not considered

motive items limited to only the ones that are worded the same or extremely similar data is cross sectinoal

- Discuss implications for theory and/or policy based on what you found.

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Appendix A - Survey Questions

Adults

Table 6: Adult survey questions.

Variable	Origianl Variable Name	Survey Question
enjoy	Motiva_POP	Motivation for sport/exercise: I find sport/exercise enjoyable and satisfying.
social	motivex2c	I exercise socially for fun with friends.
fit	motivex2a	I exercise to stay fit and healthy.
opp	READYOP1_POP	Readiness for activity: Opportunity,
guilt	motivc_POP	Motivation for sport/exercise: I feel guilty when I don't do sport/exercise.
imp	motivb_POP	Motivation for sport/exercise: It's important to me to do sport/exercise regularly.
chal	motivex2d	I exercise to challenge myself (either against myself or others).
abil	READYAB1_POP	Readiness for activity: Ability.
relx	motivex2b	I exercise to help me relax and worry less about things.

Youths

Table 7: Youth survey questions.

Variable	Origianl Variable Name	Survey Question
enjoy	PL_Enjoy_bc_ans	I enjoy taking part in exercise and sports.
social	MO_Fun_c	I exercise socially for fun with friends.
fit	MO_Fit_c	I exercise to stay fit and healthy.
opp	MO_Opp_c	I feel that I have the opportunity to be physically active.
guilt	MO_Guilt_c	I feel guilty when I don't exercise.
imp	PL_GdMe_bc_ans	I understand why exercise and sports are good for me.
chal	Try_bc	If I find something difficult, I keep trying until I can do it.
abil	PL_Conf_bc_ans	I feel confident when I exercise and play sports.
relx	MO_Relax_c	I exercise to help me relax and worry less about things .

Appendix B - Exercise Types

Adults

The total minutes of exercise in this dissertation are calculated as the sum of vigorous (original variable: DUR_HVY_CAPPED_SPORTCOUNT_A01) and moderate plus (original variable: DUR_MOD_CAPPED_SPORTCOUNT_A01) activities.

Vigorous Exercises

Definition Activity capped: Moderate intensity minutes per week: Sport (count definition), capped at 1680 mins/wk.

- 11 a-side football
- 13 a-side rugby league
- 15 a-side rugby union
- Bootcamp (e.g. drill sergeant military fitness)
- Boxing
- Boxing class (e.g. Boxercise body combat)
- Cardio class (e.g. aerobics step aerobics body attack)
- Circuit or cross training, cross fit, HIT or boot camp
- Circuit training
- Cross fit
- Cross training
- Cycle class (e.g. spinning RPM)
- Cyclo-cross
- Fell or trail running
- Field hockey
- Futsal
- High intensity (e.g. HIT insanity)
- Hockey
- Indoor cycling - in a class
- Ju-Jitsu
- Karate
- Mountain biking
- Obstacle course (e.g. Tough Mudder Spartan Rat Race)
- Parkour or free running
- Road cycling or racing
- Rugby union
- Running or jogging
- Small sided football
- Squash or racketball
- Taekwondo
- Track and field athletics
- Triathlon (includes aquathlon and duathlon)
- Weightlifting or powerlifting (using a barbell)

Moderate Exercises

Definition: Activity capped: Moderate intensity minutes per week: Sport (count definition), capped at 1680 mins/wk.

- A session combining several gym or fitness machines or activities
- Aikido
- Badminton
- Baseball or softball
- Basketball
- BMX
- Body weight exercises (e.g. pull ups press ups sit ups)
- Cheerleading
- Chinese martial arts
- Climbing or bouldering wall
- Climbing or mountaineering
- Cross training machine (e.g. Cross trainer SkiErg)
- Cycling for leisure
- Cycling for leisure
- Cycling for Leisure and all other cycling
- Cycling for travel (including commuting)
- Cycling for travel incl commuting
- Dance-based class (e.g. Zumba fitsteps ravercise or body jam)
- Dance-based class (e.g. Zumba, fitsteps, ravercise or body jam)
- Dressage
- Eventing
- Exercise bike
- Exercise machine
- Football
- Free weights (includes kettlebells and dumb-bells)
- Gymnastics
- Gymnastics or trampolining
- Handball
- Hill and mountain walking, hiking, mountaineering
- Hill or mountain walking or hiking
- Hill or mountain walking or hiking
- Indoor cycling - not in a class
- Judo
- Lacrosse
- Martial arts
- Mountaineering and scrambling
- Netball
- Other exercise machine
- Other football
- Other horse riding
- Resistance weights machines
- Rock climbing or bouldering
- Rounders
- Rounders
- Rowing
- Rowing machine
- Rowing machine
- Rugby league
- Rugby sevens
- Running machine or treadmill
- Schooling
- Show jumping
- Skiing
- Skiing or snowboarding

- Skipping
- Snowboarding
- Step machine
- Surfing, body surfing or body boarding
- Tag or other rugby league
- Tag or other rugby union
- Tennis
- Touch rugby
- Touch rugby league
- Touch rugby league
- Touch rugby union
- Touch rugby union
- Track cycling
- Trampolining
- Treadmill
- Volleyball
- Walking football
- Water based rowing
- Water polo
- Water polo
- Water-based class (e.g. aquaerobics aquafit)
- Weights (did not specify whether free weights or resistance weights)
- Weights-based class (e.g. body pump kettlebell)
- Wrestling

Youths

Moderate and vigorous activities are encompassed under the same variable (original variable name: mins_modplus_outschool_Week_ALL). Deinition: Mins spent in week (moderate plus mins) outside school: All activities

According to Sports England (2024), activities were categorized based on the following definition:

> Moderate activity: This is defined as activity where you raise your heart rate and feel a little out of breath (In academic year 2017-18 (Year 1) pupils were asked whether it made them breathe faster, but since academic year 2019-20 (Year 3) have been asked whether it made them breathe faster than sitting down reading. In Year 2 (18-19), half the children were asked the year 3 version and half were asked the year 1 version across the whole year).

> Vigorous activity: This is defined as when you are out of breath or are sweating - you may not be able to say more than a few words without pausing for breath (pupils were asked whether it made them hot or tired).

More specifically, these acvities were included

- Cycling for fun
- Dancing (include online or TV led e.g. TikTok dances)
- Trampolining (including in a garden, at a trampoline centre, or as part of a club)
- Playing it, tag, chase, sardines or other running game
- Football
- Netball
- Hockey
- Rugby (including tag rugby)

- Touch or tag Rugby
- Contact rugby (rugby union)
- Rugby league (contact)
- Basketball
- Cheerleading
- Running, jogging, cross-country
- Field athletics
- Gym or fitness (fitness/online class e.g., push-ups, sit-ups, yoga, etc or using exercise machines e.g. rowing machine, exercise bike, running machine)
- Judo, karate, taekwondo and other martial arts
- Sports day events
- Boxing

Appendix C - Other tables

Table 8: Statistics on Likert-scale responses in adults.

Variable	Mean	Median	SD	PercentNA
Enjoyment	2.126	2.0	1.0249	4.344
Social	2.887	3.0	1.1603	6.383
Fitness	1.863	2.0	0.8631	3.942
Guilt	2.553	2.0	1.1045	5.036
Opportunity	2.010	2.0	0.9913	4.018
Importance	1.980	2.0	0.9118	4.214
Challenge	2.757	3.0	1.1512	6.143
Relaxation	2.263	2.0	1.0125	5.332
Minutes.Exercised	493.496	337.5	475.1089	0.000

Table 9: Statistics on Likert-scale responses in youths.

Variable	Mean	Median	SD	PercentNA
Enjoyment	1.653	2	0.7189	9.818
Social	2.185	2	0.8673	42.212
Fitness	1.780	2	0.7032	40.950
Opportunity	1.613	2	0.6290	39.725
Guilt	2.521	3	0.9115	42.623
Importance	1.414	1	0.5802	6.787
Challenge	1.871	2	0.7528	16.348
Relaxation	2.224	2	0.9051	42.035
Minutes.Exercised	426.587	290	427.9877	1.044

Appendix D - R Code (Data Cleaning)

```
> # 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',
>                                   # 'MO_Relax_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','motivex2b_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: 32
$ 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~
$ MO_Relax_c_SA                     <int> 2, 1, 2, 2, 2, 2, 1, -98, -98, -98, -9~


> glimpse(adult.var)
Rows: 172,968
Columns: 37
$ 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,~
$ motivex2b_GR2                     <int> 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0~


> # 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, MO_Relax_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,
+                 relxb=MO_Relax_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,relxb), ~ 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),
```

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```
+                                  if_all(c(Motiva_POP_GR2, motivex2c_GR2,
+                                           motivex2a_GR2, motivc_POP_GR2,
+                                           READYOP1_POP_GR2, motivex2b_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,
+                 relxb=motivex2b_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 LCA -------------------------------------------------------
>
> # # 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)
>
> # Check which motive responses need to be collapsed
> prop.table(table(child.var$PL_Enjoy_bc_ans))

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

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

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

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

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

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

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

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

> prop.table(table(adult.var$Motiva_POP))

> prop.table(table(adult.var$motivex2c))

> prop.table(table(adult.var$motivex2a))

> prop.table(table(adult.var$motivc_POP))

> prop.table(table(adult.var$READYOP1_POP))

> prop.table(table(adult.var$READYAB1_POP))

> prop.table(table(adult.var$motivb_POP))

> prop.table(table(adult.var$motivex2d))

> prop.table(table(adult.var$motivex2b))

> 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"
+                  relx=MO_Relax_c,
+
+                  abl=PL_Conf_bc_ans,
+                  imp=PL_GdMe_bc_ans,
+                  chal=Try_bc,
+
+                  dsbl=Disab_All_POP,
```

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```
+                 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,abl),
+                  ~ .x > -1 & .x < 5)) %>%
+    mutate(
+      mins = ifelse(mins > 1680, 1680, mins),
+      across(c(enjoy,social,fit,guilt,imp,chal,opp,relx,abl),
+             ~ 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,
+
+                  abl=READYAB1_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,abl),
```

```
+                    ~ 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
>
> # Check adult lik corr
> cor(child.lik.back0 %>% dplyr::select(-gender,-eth, -age), method = "pearson")

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

> # Check sparsity of highly correlated (>.05) items
> prop.table(table(child.lik$abl, child.lik$enjoy))

> prop.table(table(adult.lik$fit, adult.lik$enjoy))

> prop.table(table(adult.lik$imp, adult.lik$enjoy))

> prop.table(table(adult.lik$fit, adult.lik$imp))

> prop.table(table(adult.lik$abl, adult.lik$opp))

> child.lik.back <- child.lik

> adult.lik.back <- adult.lik

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

> vif(vif_model)
```

Appendix E - R Code (SEM)

```
> # 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
+   relxb~ c(a6_adult, a6_youth)*age + c(g6_adult, g6_youth)*gender + c(e6_adult, e6_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(b6_adult, b6_youth)*relxb
+          + c(c_adult, c_youth)*age +
+          c(g7_adult, g7_youth)*gender + c(e7_adult, e7_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
+ indirect_age_relxb_adult := a6_adult * b6_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 + indirect_age_relxb_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
+ indirect_age_relxb_youth := a6_youth * b6_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 + indirect_age_relxb_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
+   relxb ~ age + gender + eth
+
+   # Main outcome
+   mins ~ c("a1","a1")*enjoyb + guiltb + oppb + fitb + socialb + age + gender + eth + relxb
+ '

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

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

> m4 <- '
+   # Mediators
```

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

> m5 <- '
+     # Mediators
+     enjoyb ~ age + gender + eth
+     guiltb ~ age + gender + eth
+     oppb ~ age + gender + eth
+     fitb ~ age + gender + eth
+     socialb ~ age + gender + eth
+     relxb ~ age + gender + eth
+
+     # Main outcome
+     mins ~ enjoyb + guiltb + oppb + fitb + c(a,a)*socialb + age + gender + eth + relxb
+ '

> m6 <- '
+     # Mediators
+     enjoyb ~ age + gender + eth
+     guiltb ~ age + gender + eth
+     oppb ~ age + gender + eth
+     fitb ~ age + gender + eth
+     socialb ~ age + gender + eth
+     relxb ~ age + gender + eth
+
+     # Main outcome
+     mins ~ enjoyb + guiltb + oppb + fitb + c(a,a)*relxb + age + gender + eth + socialb
+ '

> # 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)


> f6 <- sem(m6, 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)

> anova(f0, f6)

> # 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
+   ) %>%
+   filter(!var %in% c("gender","eth","age")) %>%
+   dplyr::select(-se.youth, -se.adult)

> slopes.diff
```

Appendix F - R Code (LCA)

```
> # 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 31056.670788
iter  10 value 28676.812139
final  value 28091.735008
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 -------------------------------------------------------------
>
> adult.lik <- adult.lik.back

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

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

> # 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
>
> post6.ad <- LCAE.ad$LCA[[5]]$posterior

> class6.ad <- apply(post6.ad, 1, which.max)

> class.size6.ad <- prop.table(table(class6.ad))

> ave.pp6.ad <- sapply(1:ncol(post6.ad), function(k) {
+   inds <- which(class6.ad == k)
+   mean(post6.ad[inds, k])
+ })

> ave.pp6.ad

> 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 127458.800507
iter  10 value 108640.273108
iter  20 value 100457.045377
iter  20 value 100457.044488
iter  20 value 100457.044435
final  value 100457.044435
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)
```

Appendix G - R Code (Visualization)

```
> set.seed(2025)

> library(tidyverse)

> library(ggplot2)

> library(poLCA)

> library(poLCAExtra)

> library(scales)

> library(ggthemes)

> options(digits = 4)

> # Descriptive -------------------------------------------------------
> child.summary.bi <- data.frame(colMeans(
+   child.bi[, setdiff(names(child.bi),
+                      c("gender", "eth", "age", "mins"))], na.rm = TRUE))

> colnames(child.summary.bi) <- ("Proportion")

> adult.summary.bi <- data.frame(colMeans(
+   adult.bi[, setdiff(names(adult.bi),
+                      c("gender", "eth", "age","mins"))], na.rm = TRUE))

> colnames(adult.summary.bi) <- ("Proportion")

> 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.:
+             SD = sd(mins_modplus_outschool_Week_ALL[mins_modplus_outschool_Week_ALL > 0], na.rm = TRUI
+             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
> adult.lik$gender <- factor(adult.lik$gender, levels = c(1, 2),
+                            labels = c("Male", "Female"))

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

> # Age
> adult.lik$age <- factor(adult.lik$age, levels = c(1,2,3,4,5,6),
+                         labels = c("16-34", "35-44", "45-54",
+                                    "55-64", "65-74", "75+"))

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

> # Ethnicity
> adult.lik$eth <- factor(adult.lik$eth, levels = c(1, 2),
+                         labels = c("White British", "Other"))

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

> # Education
> # gg.ad.edu <- ggplot(adult.lik, aes(x = as.factor(edu))) +
> #   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
> child.lik$gender <- factor(child.lik$gender, levels = c(1, 2),
+                            labels = c("Male", "Female"))

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

> # Age
```

```
> child.lik$age <- factor(child.lik$age, levels = c(1,2,3,4,5,6),
+                          labels = c(11,12,13,14,15,16))

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

> # Ethnicity
> child.lik$eth <- factor(child.lik$eth, levels = c(1, 2),
+                          labels = c("White British", "Other"))

> gg.ch.eth <- ggplot(child.lik, aes(x = as.factor(eth))) +
+   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)
```
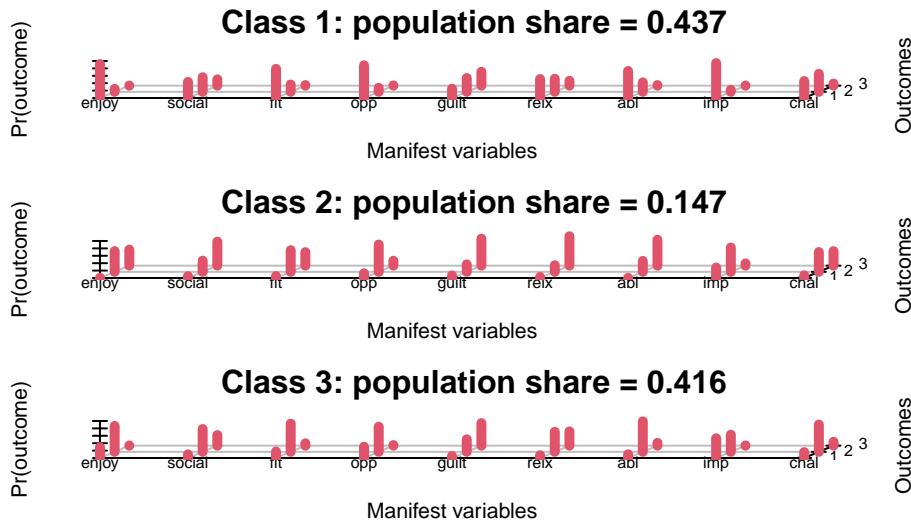
Class 1: population share = 0.437

Pr(outcome)

enjoy social fit opp guilt relx abl imp chal 1 2 3

Outcomes

Manifest variables

Class 2: population share = 0.147

Pr(outcome)

enjoy social fit opp guilt relx abl imp chal 1 2 3

Outcomes

Manifest variables

Class 3: population share = 0.416

Pr(outcome)

enjoy social fit opp guilt relx abl imp chal 1 2 3

Outcomes

Manifest variables

```
> # 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", axis.text.y = element_text(size = 6))


> # 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

> tb.class4.ad <- data.frame(
+   Class = 1:ncol(post4.ad),
+   Proportion = as.numeric(class.size4.ad),
+   Avg_Posterior = round(ave.pp4.ad, 4)
+ )

> tb.class4.ad

> tb.class5.ad <- data.frame(
+   Class = 1:ncol(post5.ad),
+   Proportion = as.numeric(class.size5.ad),
+   Avg_Posterior = round(ave.pp5.ad, 5)
+ )

> tb.class5.ad

> tb.class6.ad <- data.frame(
+   Class = 1:ncol(post6.ad),
+   Proportion = as.numeric(class.size6.ad),
+   Avg_Posterior = round(ave.pp6.ad, 6)
+ )

> tb.class6.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
```
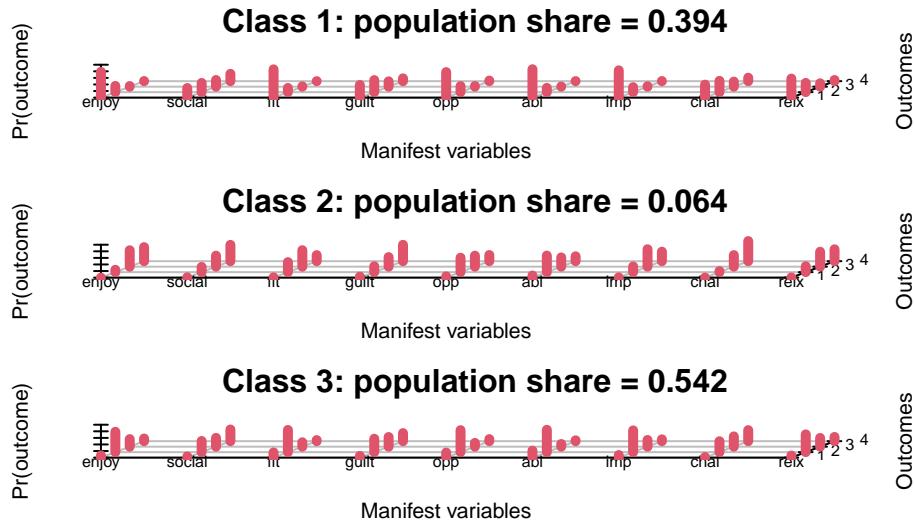
```
> plot(LCAE.ad, nclass = 2)
```

Class 1: population share = 0.394

Pr(outcome) | Outcomes

enjoy   social   fit   guilt   opp   abl   imp   chal   relx   1 2 3 4

Manifest variables

Class 2: population share = 0.064

Pr(outcome) | Outcomes

enjoy   social   fit   guilt   opp   abl   imp   chal   relx   1 2 3 4

Manifest variables

Class 3: population share = 0.542

Pr(outcome) | Outcomes

enjoy   social   fit   guilt   opp   abl   imp   chal   relx   1 2 3 4

Manifest variables

```
> # 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", axis.text.y = element_text(size = 6),
+         axis.text.x = element_text(size = 6))

> gg.vars.ad

> # Survey questions
> # youths
> vc1 <- c('enjoy','social','fit','opp','guilt','imp','chal','abil','relx')

> vc2 <- c('PL_Enjoy_bc_ans','MO_Fun_c','MO_Fit_c','MO_Opp_c','MO_Guilt_c',
+          'PL_GdMe_bc_ans','Try_bc','PL_Conf_bc_ans','MO_Relax_c')

> vc3 <- c("I enjoy taking part in exercise and sports.",
+          "I exercise socially for fun with friends.",
+          "I exercise to stay fit and healthy.",
+          "I feel that I have the opportunity to be physically active.",
+          "I feel guilty when I don't exercise.",
+          "I understand why exercise and sports are good for me.",
+          "If I find something difficult, I keep trying until I can do it.",
+          "I feel confident when I exercise and play sports.",
+          "I exercise to help me relax and worry less about things ."
+          )

> vc <- data.frame(vc1,vc2,vc3)

> colnames(vc) <- c("Variable", "Origianl Variable Name", "Survey Question")

> va1 <- c('enjoy','social','fit','opp','guilt','imp','chal','abil','relx')

> va2 <- c('Motiva_POP','motivex2c','motivex2a','READYOP1_POP','motivc_POP',
+          'motivb_POP','motivex2d','READYAB1_POP','motivex2b')

> va3 <- c("Motivation for sport/exercise: I find sport/exercise enjoyable and satisfying.",
+          "I exercise socially for fun with friends.",
+          "I exercise to stay fit and healthy.",
+          "Readiness for activity: Opportunity,",
+          "Motivation for sport/exercise: I feel guilty when I don't do sport/exercise.",
+          "Motivation for sport/exercise: It's important to me to do sport/exercise regularly.",
+          "I exercise to challenge myself (either against myself or others).",
+          "Readiness for activity: Ability.",
+          "I exercise to help me relax and worry less about things."
+          )

> va <- data.frame(va1,va2,va3)
```

```
> colnames(va) <- c("Variable", "Origianl Variable Name", "Survey Question")
```

Appendix H - R code (R Markdown)

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

gg.vars.ad


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

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

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.ad


gg.byage.ad

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

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


plot(LCAE.ch, nclass = 2)


gg.mins.ch


gg.byage.ch

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