Dissertation

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Contents

Introduction

Physical inactivity remains a significant global public health concern, with nearly 1.8 billion individuals not meeting recommended levels of physical activity (World Health Organization, 2024), representing a 9% increase over the past two decades (Mitchell, 2019; Strain et al., 2024). Beyond its physiological consequences, insufficient physical activity is a leading risk factor for numerous chronic diseases, including cardiovascular conditions, diabetes, and certain cancers, and contributes to mental health challenges such as depression and anxiety. Participation in physical activity is shaped by social, developmental, and motivational factors, with motivation consistently identified as a central determinant of behavior (Daley & Duda, 2006; Deci & Ryan, 2008; Duncan et al., 2010).

Understanding the factors that influence physical activity engagement is crucial for developing effective interventions. Motivation plays a central role in determining whether individuals initiate and maintain physical activity behaviors. Theories such as Self-Determination Theory (SDT) and the Theory of Planned Behavior (TPB) have been instrumental in elucidating the psychological and social factors that underpin physical activity motivation. SDT emphasizes the importance of intrinsic motivation and the satisfaction of basic psychological needs in fostering sustained engagement in physical activity (Brooks et al., 2017). TPB, on the other hand, focuses on how attitudes, subjective norms, and perceived behavioral control influence behavioral intentions and actions.

Despite the valuable insights provided by these frameworks, existing research often examines age-related differences in physical activity motivation within either youth or adult populations, without directly comparing these groups. This approach limits our understanding of how motivational mechanisms may differ across the lifespan and how these differences influence physical activity behaviors. Addressing this gap is essential for designing more age-specific interventions that effectively promote physical activity across various life stages.

This dissertation aims to explore this gap by comparing motivational profiles and their behavioral implications across youth and adult populations.

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 answer these questions, multigroup structural equation modeling (SEM) to test whether the relationships between motives and physical activity differ by age, and latent class analysis (LCA) will be employed to identify distinct motivational profiles within each age group.

Literature Review

Self-Determination Theory

SDT is a popular framework that has gained popularity in the past two decades. Developed by Deci & Ryan, it emphasizes the degree to which behaviour 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 distinctions have implications for physical activity, as more autonomous motives are linked to sustained engagement, positive psychological outcomes, and long-term health (CITE).

SDT has been influential in health behaviour research because it prioritizes the quality of motivation over mere quantity. Empirical evidence indicates that need-supportive interventions can enhance exercise uptake, reduce dropout, and improve both physical and psychological wellbeing (Teixeira et al., 2012; Ng et al., 2012). The framework thus functions both as a descriptive model and as a prescriptive guide for intervention design.

Nevertheless, while SDT posits that autonomy-supportive environments foster intrinsic motivation, recent studies suggest that this relationship may not be as straightforward as previously thought. For instance, interventions designed to enhance autonomy support have shown inconsistent effects on long-term physical activity adherence, possibly due to individual differences in baseline motivation or contextual factors (Trigueros et al). Additionally, the application of SDT in physical activity research often overlooks the role of external constraints and structural factors, such as socioeconomic status, that can impede motivation and behaviour change. These external factors may interact with psychological needs in complex ways that SDT does not fully address.

Theory of Planned Behaviour

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 (PBC). 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 PBC 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 PBC 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 favourable 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 behaviour, highlighting the importance of situational constraints and individual capabilities.

Like SDT, TPB has faced several critiques. Its constructs are typically measured through self-report instruments, which are vulnerable to biases such as social desirability and inaccuracies in introspection. Ajzen (2020) highlighted the complexity of assessing the beliefs underlying attitudes, subjective norms, and perceived behavioural control, noting that these measures do not always correspond perfectly with actual behaviour. In addition, TPB primarily focuses on individual-level factors and may insufficiently consider broader social, cultural, or structural influences. Its emphasis on personal perceptions of control can overlook systemic barriers or facilitators that shape behaviour.

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).

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. These motives appear to remain relatively stable across younger and older adults (de Maio Nascimento, 2021; Vuckovic, 2015; Kilgour, 2005).

While specific motives vary by age, some contextual factors influence physical activity similarly across age 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. While previous studies identify age-related patterns in motivational types, few directly quantify the differential predictive power of these motives on physical activity across youth and adult populations. Addressing this allows for a more nuanced understanding of which motives are most influential at different developmental stages.

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

Motivational profiles provide a person-centred perspective on the heterogeneity of exercise motives, capturing combinations of autonomous and controlled regulation within individuals. 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, individuals in 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 engagement, whereas moderate-to-high external regulation may require additional support for continuity.

Similarly, Nuss et al. (2023) identified four motivational profiles in Canadian adults, indicating that combinations of controlled and autonomous motivation may synergistically support activity, while low overall motivation corresponded to minimal engagement. These findings suggest that adult populations are not homogeneous in their motivational profiles, and that the prevalence of lower-engagement profiles tends to increase with age.

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 TPB constructs such as intention, subjective norm, PBC, and attitude, indicating that higher autonomous motivation supports favorable cognitions and participation behaviors. Cross-sectional studies further corroborate these trends. Similarly, 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.

While these studies collectively demonstrate heterogeneity in motivation, they vary in sample characteristics, activity settings, and statistical methods for extracting latent profiles, complicating direct comparisons across age groups. Few studies have examined whether the same latent structures are consistent between youths and adults, or whether increasing age systematically influences profile membership. Investigating these patterns using comparable data across youths and adults will provide a clearer understanding of the role of age.

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

- 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

Data

The analyses draw on large-scale survey data collected by Ipsos on behalf of Sport England (2024, 2025). These datasets were chosen because the youth and adult surveys share a parallel structure, with several items identically worded across both instruments. This allows direct comparison of motivational mechanisms across life stages. All motive items are self-reported, single-item measures. Appendix A lists the corresponding survey questions.

Descriptive statistics, bivariate correlations, and variance inflation factors (VIF) were computed for all motive variables to assess distributional properties and multicollinearity. Challenge and relaxation were excluded from the structural equation models (SEM) due to non-equivalent wording between the youth and adult questionnaires but retained for latent class analysis (LCA).

The SEM analyses included 116,873 adult and 29,798 youth respondents; the LCA included 116,018 and 28,269, respectively . To maintain comparability and avoid skew from small subgroups, only cisgender adults without disabilities were retained. Ethnicity and gender were included as control variables. Observations with missing data on relevant items were likewise deleted.

Motivational and behavioural variables:

- Enjoyment – finding exercise satisfying or pleasurable.
- Social – exercising for fun or connection with friends.
- Fitness – exercising to maintain or improve physical health.
- Guilt – exercising out of obligation or self-pressure.
- Opportunity – having access, time, or suitable conditions to exercise.
- Relaxation – exercising to relieve stress or worry.
- Ability – self-perceived competence and confidence in physical activity.
- Importance – recognising the personal value or significance of physical activity.
- Challenge – persistence and enjoyment in pursuing difficult tasks.
- Minutes – total weekly minutes of moderate-to-vigorous physical activity (see Appendix B for included activities).

Adult Dataset

The adult data derive from the Active Lives Adult Survey (Year 8: 2022–2023), conducted by Ipsos for Sport England with additional support from the Office for Health Improvement and Disparities (OHID). The survey is designed to provide a nationally representative picture of adult participation in sport and physical activity in England.

Sampling was based on the Postcode Address File (PAF), using a random probability design. Up to two adults (aged 16+) per selected household were invited to participate. A push-to-web approach was employed: two initial mailings invited online completion, followed by a third mailing with a paper questionnaire to increase response rates, and a final reminder letter. Data collection occurred from November 2022 to November 2023, with approximately 500 responses targeted per local authority to minimise seasonal and geographic bias.

A total of 173,950 adults completed the survey. Weighting adjustments were applied to correct for differential response probabilities. The questionnaire covered a broad range of topics, including physical activity frequency and duration, sports participation, volunteering, club membership, and motivational factors, along with demographic variables such as age, gender, education, and socio-economic status.

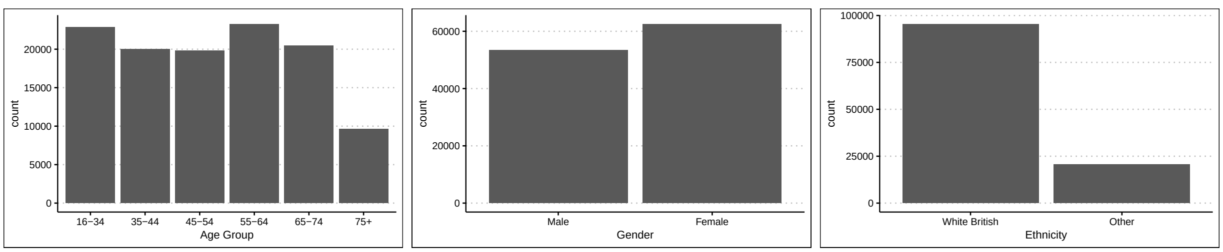


Figure 1: Distribution of age, gender, and ethnicity in adults.

Gender and ethnicity distributions were highly similar across the subsamples used for the SEM and LCA analyses. Females comprised 54% of the sample, and White British participants accounted for 82%. The youngest and oldest age groups were collapsed due to small cell sizes at the extremes. Specifically, adults aged 64–75 and 76+ were combined, as preliminary analyses indicated no meaningful differences in their motivational profiles. Collapsing these categories improved model stability without obscuring theoretically relevant distinctions, which are less pronounced in later adulthood. After adjustment, the age distribution remained moderately skewed but acceptable for analysis. Cases with missing values on any motivational variables were excluded from all models.

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

The distributions of positive responses exhibit a left skew, suggesting that participants rarely chose the highest agreement category for most items.

Each item was rated on a five-point Likert scale ranging from 1 (strongly agree) to 5 (strongly disagree). Due to low frequencies in the higher disagreement categories, responses of 4 (disagree) and 5 (strongly disagree) were combined to reduce sparsity and minimize distortion.

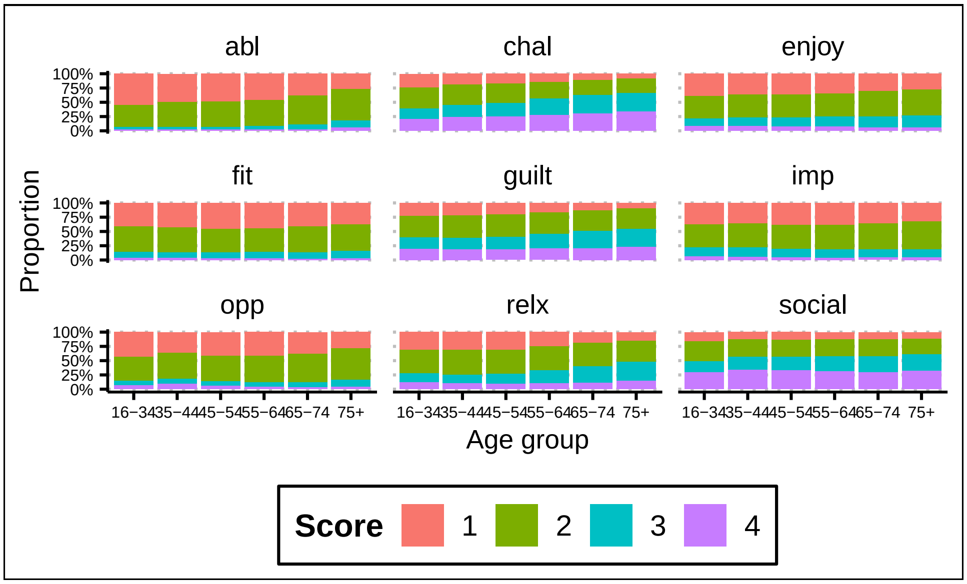


Figure 2: Distribution of adult responses for each motive on the Likert scale.

For most motive items, the proportion of adults expressing strong positive agreement declines with age. Older adults are less likely than younger adults 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 guilt for not exercising, to perceive sufficient opportunities for activity, or to consider physical activity an important means of relaxation. Additional descriptive statistics, including mean, median, standard deviation, and the percentage of missing values (excluded from the final dataset), are provided in Appendix C.

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.

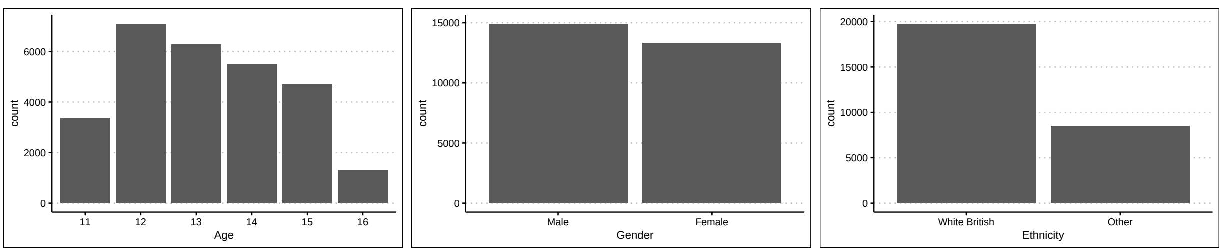


Figure 3: Distribution of age, gender, and ethnicity in youths.

47% of the youth sample are female, and 70% are White British. Most participants are aged 12–15, with only 4.63% aged 16. Although 16-year-olds represent a small proportion of the sample, they were not collapsed with the 15-year-olds. This decision was guided by substantive, rather than purely numerical, considerations: the transition from 15 to 16 marks a distinct developmental and social stage—such as reaching legal thresholds, completing compulsory schooling, and gaining increased autonomy—which may influence physical activity motives. Retaining this distinction allows examination of whether these developmental turning points are reflected in motivational patterns, even within 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

The distributions of positive responses exhibit a left skew, similar to the adults, suggesting that participants rarely chose the highest agreement category across items.

Each item was rated on a four-point Likert scale ranging from 1 (strongly agree) to 4 (strongly disagree). As with the adult dataset, responses of 3 (disagree) and 4 (strongly disagree) were combined due to low frequencies. Missing responses and “I don’t know” answers were excluded from the dataset.

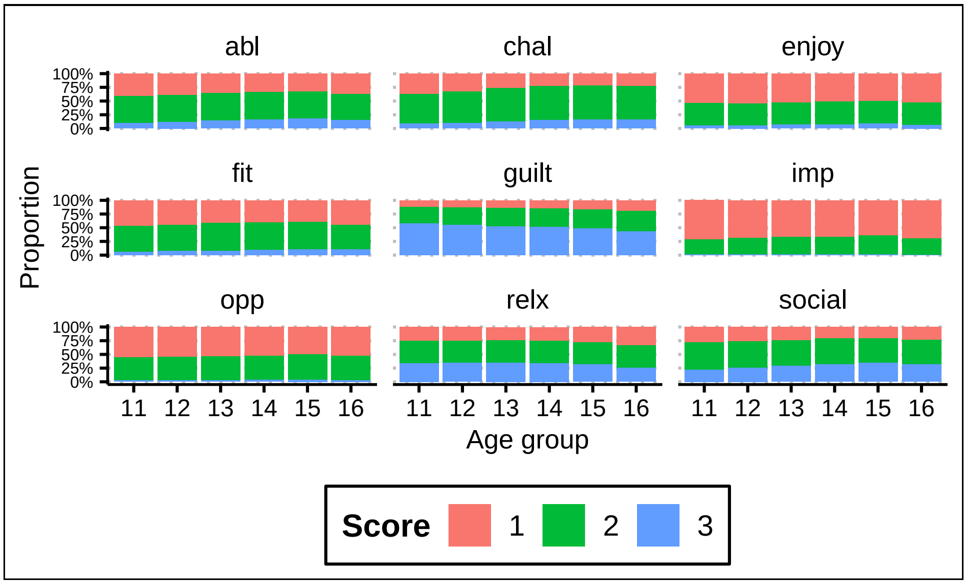


Figure 4: Distribution of youth responses for each motive on the Likert scale.

After collapsing, the items are generally balanced, except for social, guilt, and relaxation. Response patterns among youths are less consistent than those observed in adults. With increasing age, youths are less likely to report exercising for challenge or social reasons, while a larger proportion indicate exercising due to guilt or for relaxation. Among the oldest youth group, there is a slight but noticeable increase in the proportion who "strongly agree" that ability and fitness are motivating factors. Across all ages, only a small minority report lacking understanding of the importance of physical activity. Additional descriptive statistics, including means, medians, standard deviations, and percentages of missing values (excluded from analysis), are provided in Appendix C.

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 specifications).

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” versus “not strongly agree.” Demographic covariates included gender, age, and ethnicity. Gender was limited to female and male due to small sample sizes in other categories, and ethnicity was collapsed into White British and Non-White British. Youth participants included only those aged 11 and older who responded to the relevant items. Adults were grouped into age ranges (16–34, 35–44, 45–54, 55–64, 65–74, 75+) because exact ages were unavailable. The youngest and oldest two adult groups were further collapsed to reduce skew and ensure more balanced distributions. A cap of 1,680 minutes per week was applied to reported PA to minimize the influence of extreme values or potential data entry errors.

Multigroup SEM was used to assess how each motive predicts weekly minutes of PA, allowing direct comparison of pathway strengths between youths and adults. A freely estimated model was first fitted and then compared to constrained models, in which individual or all motive pathways were fixed to equality across groups. This approach enabled evaluation of whether the effects of specific motives differed by age group. Differences in the predictive strength of each motive on PA minutes were also calculated.

Prior to fitting SEM models, assumptions were assessed. Moderate correlations were observed among the motivational predictors in both youth and adult samples, with most values ranging between 0.2 and 0.5. The highest correlations were between enjoyment and ability in youths ($r = 0.656$) and between enjoyment and perceived importance in adults ($r = 0.674$), slightly exceeding the conventional threshold of $r = 0.6$ for concern about multicollinearity. Standardized residual correlations were also examined to evaluate local fit for both youth and adult SEMs. Most residuals were below 0.35, indicating generally acceptable correspondence between observed and model-implied correlations. The largest residuals occurred among closely related motivational items (enjoyment, fitness, opportunity, and relaxation), with several exceeding 0.4, reflecting misfit due to conceptual overlap and the use of dichotomized indicators. Residuals involving demographics and physical activity minutes were consistently low. These localized discrepancies do not affect the primary purpose of testing whether the strengths of associations between motives and physical activity differ across groups.

Latent Profile Analysis (LCA)

Latent class analysis (LCA) was conducted separately for youths and adults to explore age-related differences in motivational profiles, using the same set of motivation variables included in the SEM, with the addition of two items with slightly different wording.

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

The optimal number of classes was determined based on 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 used to assess the effect of age on class membership. Odds ratios and 95% confidence intervals were derived by exponentiating the estimated coefficients and their standard errors:

(

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

)

Conditional independence among PA-related items was assessed using standardized bivariate chi-square statistics. However, extremely sparse cells (<1% of observations) inflated these values, making them unreliable indicators of local dependence. Additionally, the key motivational items represent conceptually distinct constructs, so minor violations of conditional independence are less concerning than they would be for highly overlapping indicators. Instead, model evaluation relied on conventional LCA fit indices, including BIC and entropy, alongside substantive interpretability. These criteria indicated that the identified profiles were robust and meaningful despite the limitations of the conditional independence tests.

Software and Packages (CHECK

All analyses were conducted in R (version 4.4.3). Multigroup structural equation modeling was performed using the lavaan package (Rosseel, 2012), which allows for flexible specification of path models, multigroup comparisons, and model fit evaluation. Latent class analysis (LCA) was conducted separately for youths and adults using poLCA (Linzer & Lewis, 2011) and poLCAExtra (Choi, 2023), providing tools for estimation of class probabilities, fit statistics, and post-hoc regression of class membership on covariates.

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 were significant differences in the impact of each motivational factor between youths and adults. As the variables were binary, the coefficients represent how strongly agreeing to the specific variable changes weekly minutes of PA.

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

For H1(a), the difference in the effect of enjoyment between youths and adults was 24 minutes, with youths showing a stronger effect (139 minutes) compared to adults (115 minutes). Similarly, guilt had a greater influence on youths, with a difference of 17 minutes (29 minutes for youths vs. 12 minutes for adults). In contrast, social motives had a larger effect in adults, with a difference of 24 minutes (57 minutes for adults vs. 33 minutes for youths). This hypothesis is partially supported, as enjoyment and guilt were more influential in youths, but social influence was stronger in adults. Fitness had a difference of -25 minutes, with adults showing a stronger effect (93 minutes) compared to youths (67 minutes). On the other hand, relaxation was more impactful in youths, with a difference of 16 minutes (59 minutes for youths vs. 43 minutes for adults). This aligns with H1(b), which is largely supported—fitness was a stronger motivator in adults, while relaxation had a greater impact on youths. Opportunity showed a difference of -63 minutes, with adults showing a significantly stronger effect (96 minutes) compared to youths (33 minutes). This finding does not support H1(c), as environmental opportunities had a stronger effect on adults than on youths.

The results suggest a shift in motivational drivers as individuals age. For youths, internal factors such as enjoyment and guilt play a central role in driving physical activity. This aligns with the framework of SDT, which posits that intrinsic motivation and internalized social norms are key drivers of behavior, particularly in younger individuals. The stronger influence of enjoyment and guilt in youths reflects their higher engagement in physical activity when these factors are internally rewarding. This suggests that youths are more likely to engage in physical activity when it is personally enjoyable or when they feel a sense of obligation, aligning with the intrinsic and internalized forms of motivation emphasized in SDT.

In contrast, adults are more influenced by external factors such as opportunity, fitness, and social motives. This finding is consistent with SDT's concept of external regulation, where structured opportunities and social reinforcement become more important as individuals age. The stronger influence of opportunity in adults—marked by a difference of 63 minutes—highlights how external environmental factors, such as access to fitness programs or support systems, play a more significant role in motivating adults. In SDT terms, this reflects a shift from intrinsic to more extrinsic motivations as individuals age, with external factors like access to resources and social validation becoming increasingly central to sustaining activity.

From a TPB perspective, the results suggest that intention, which is influenced by attitudes, subjective norms, and PBC, varies across age groups. For youths, the stronger response to enjoyment and guilt aligns with the idea that personal attitudes and subjective norms are more influential for this group. These internal motives likely reflect youths' favorable attitudes toward physical activity and their internalized perceptions of social norms around exercise. In contrast, adults' greater responsiveness to opportunity and social motives indicates that PBC, or perceived control over the ability to engage in activity, plays a more significant role in their behavior. The greater impact of opportunity in adults, in particular, suggests that their physical activity is more contingent on external factors such as availability of resources, structured opportunities, and social support systems.

These results highlight a shift in the motivational landscape from intrinsic to extrinsic motivations as individuals transition from youth to adulthood. For youths, intrinsic factors such as enjoyment and internalized norms are key drivers of behavior, consistent with SDT's focus on autonomy and intrinsic motivation. In adulthood, external factors, such as social support and structured opportunities, become more influential, reflecting the external regulation emphasized in SDT and the PBC component of TPB. This shift in motivational influences suggests that interventions targeting physical activity in youths may benefit from focusing on enhancing intrinsic enjoyment and leveraging internalized norms, while interventions for adults may be more effective if they focus on providing external opportunities and fostering social support. The stronger influence of opportunity in adults aligns with SDT's notion that as individuals age, external factors such as access to resources, competence-building opportunities, and social reinforcement become increasingly important. For youths, however, the higher influence of enjoyment and guilt reinforces SDT's emphasis on intrinsic motivation, where fostering a sense of enjoyment and aligning physical activity with personal values are more effective strategies.

LCA

Due to the skewed distribution of minutes exercised (right-skewed), median minutes per class were calculated rather than the mean.

Adults

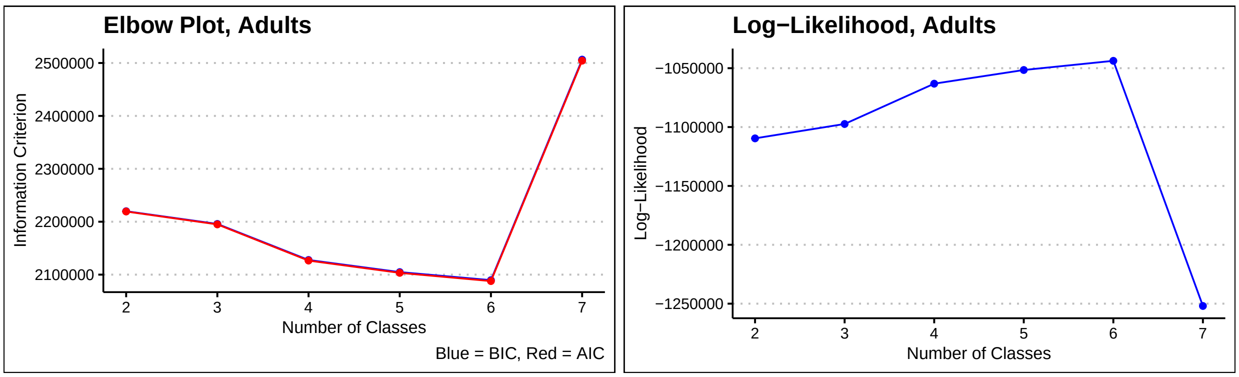


Figure 5: Elbow plot showing AIC and BIC values, and maximum likelihood plot, across different numbers of latent classes in adults.

Latent class models ranging from 3 to 6 classes all demonstrated relatively high likelihoods, low AIC and BIC values, and reasonable average posterior entropy per class. From the elbow plot, the 4-class model appeared to show diminishing returns, suggesting that adding more than three classes did not provide a substantial improvement in model fit. However, the 3-class model displayed significantly higher relative entropy, indicating a more nuanced classification of individuals. While they both have good entropy values at 0.7998 and 0.7473, the 4-class solution resulted in two groups with nearly identical endorsement patterns, effectively splitting the moderate group without introducing meaningful differentiation. Hence, the three-class model is favored for its balance between simplicity and the ability to distinguish meaningful motivational profiles.

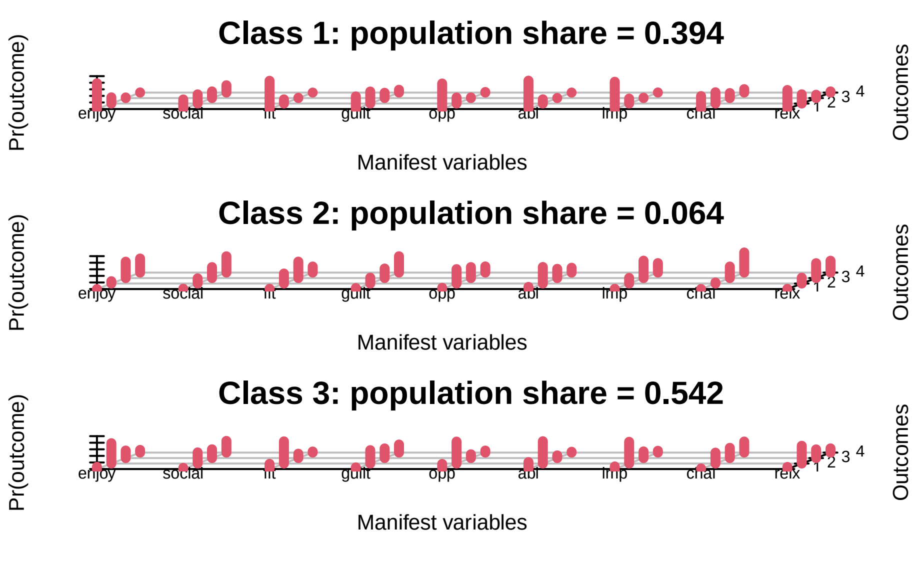


Figure 6: Frequency of adult responses for each motive by class membership.

Class 1 Class 1 represents adults who consistently report strong agreement across a broad range of motivations. Members show high probabilities of strongly agreeing with motives related to enjoyment, fitness, ability, opportunity, and importance. They also moderately endorse social, challenge, and guilt motives, and express relatively high agreement with relaxation. This group is labeled the High Engagement class.

Class 2 Class 2 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 other items. Members tend to express the least favorable attitudes toward physical activity. Labelled the Low Engagement class, it represents a relatively small proportion of the sample (~6%). Despite its size, this class aligns with the raw data, where very few respondents selected negative responses.

Class 3 Class 3 exhibits a mixed attitude toward various motives, with moderate positive endorsements of enjoyment, fitness, opportunity, ability, and importance. It represents adults who show more ambivalent responses overall. This group is labeled the Mixed Motivation class.

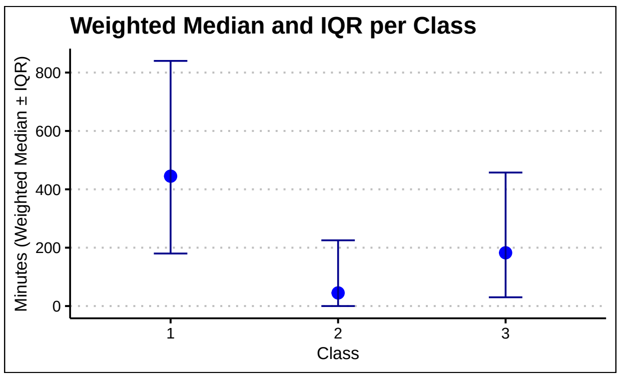


Figure 7: Weighted median and interquartile range of minutes exercised per week for adults by class.

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

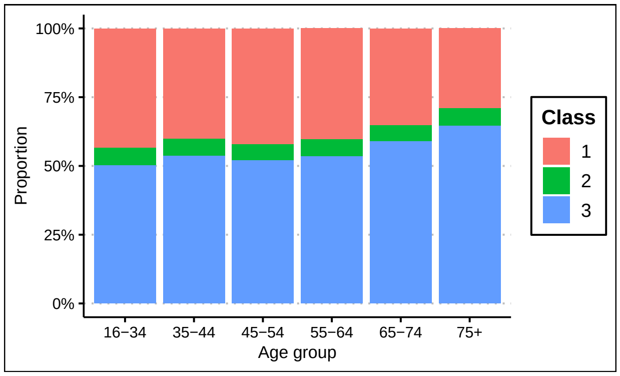


Figure 8: Proportion of adults in each class across age groups.

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 gradually diminishes with older adults potentially requiring additional support, reinforcement, or environmental facilitation to sustain participation.

Youths

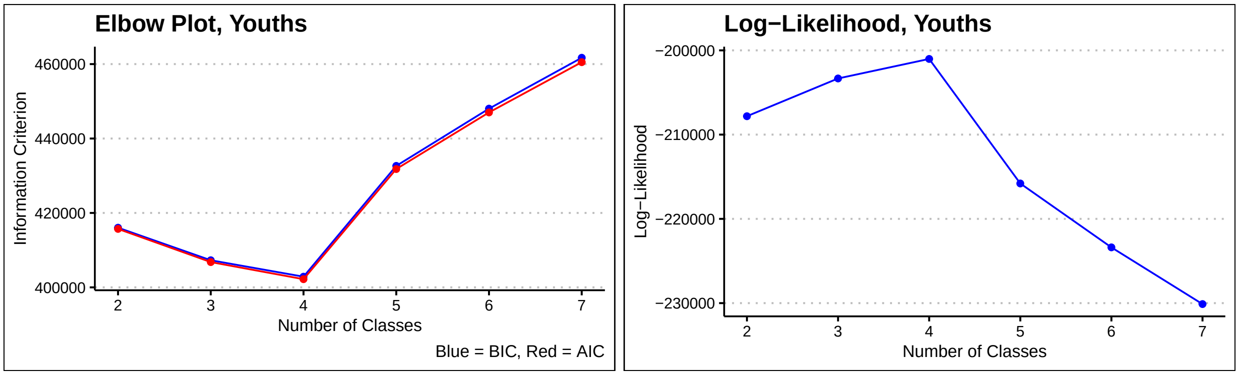


Figure 9: Elbow plot showing AIC and BIC values, and maximum likelihood plot, across different numbers of latent classes in youths.

The AIC/BIC plot did not show the typical elbow shape, as adding more classes beyond four actually resulted in a decrease in model fit. This could be due to the log-likelihood not increasing significantly with the addition of more classes, causing BIC's penalty for model complexity to outweigh any improvement in fit. Nevertheless, both the 3-class and 4-class solutions resulted in the most substantial reductions in BIC. The Bootstrap Likelihood Ratio Test (BLRT) preferred the 4-class model. However, when considering relative entropy values, which were 0.7998 for the 3-class model and 0.7473 for the 4-class model, the 3-class solution provided better separation between classes. The likelihood values for the 3-class and 4-class models were similar, but the average posterior probabilities were higher in the 3-class model, with all classes exhibiting a posterior probability greater than 0.80. Additionally, the 4-class model resulted in two very similar classes, suggesting that the additional class did not add meaningful differentiation. Given these considerations, the 3-class model was selected for its better separation and more parsimonious structure.

Class 1 Class 1 represents youths who consistently report strong agreement across a broad range of motivations. Members show high probabilities of strongly agreeing with motives related to enjoyment, fitness, opportunity, importance, and ability. They also moderately endorse social, challenge, and relaxation motives, and express relatively high agreement with guilt. This group is characterized by consistently positive attitudes toward a wide range of motives. This class is labeled the High Engagement class.

Class 2 Class 2 is characterized by very low probabilities of strongly agreeing with any motives, and by a higher prevalence of neutral or negative responses across most other items. Members tend to express the least favorable attitudes toward physical activity. Labeled the Low Engagement class, this group represents a relatively small proportion of the sample, aligning with the raw data in which very few respondents selected negative responses.

Class 3 Class 3 exhibits a mixed attitude toward various motives, with moderate positive endorsements of enjoyment, fitness, opportunity, ability, and importance. Disagreement is relatively uncommon, but strong agreement is also less prevalent than in the High Engagement class. This group falls between the other two, representing generally positive but not strongly emphatic motivation toward physical activity. This class is labeled the Moderate Engagement 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

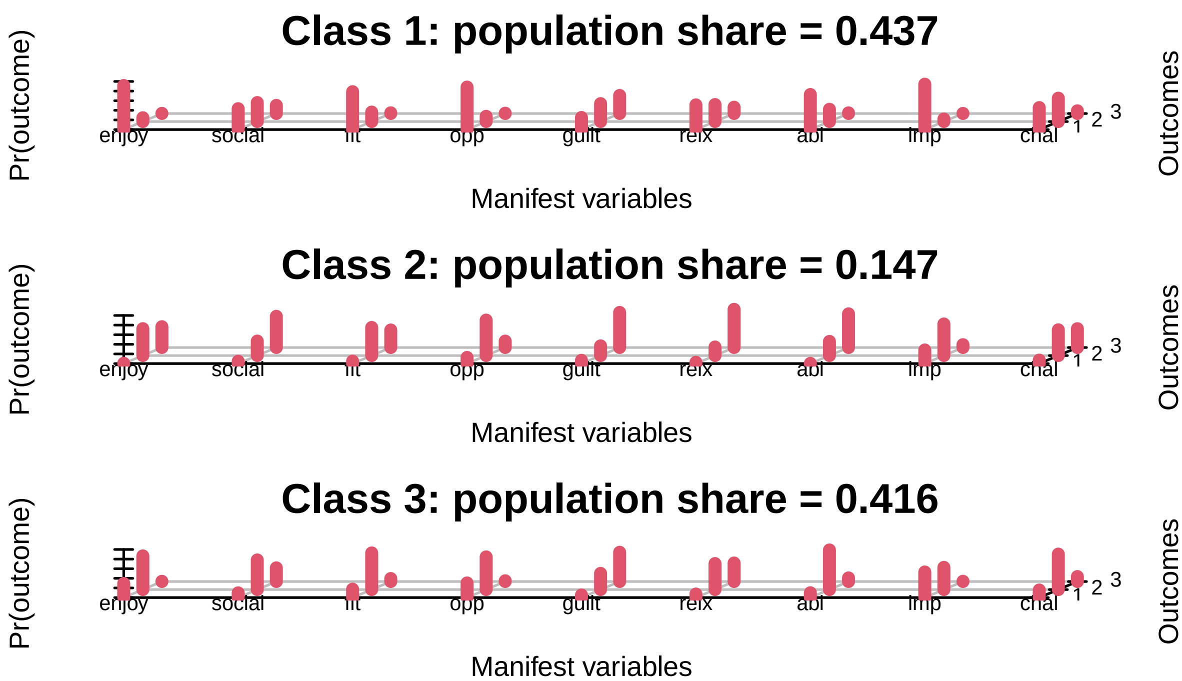


Figure 10: Frequency of adult responses for each motive by class membership.

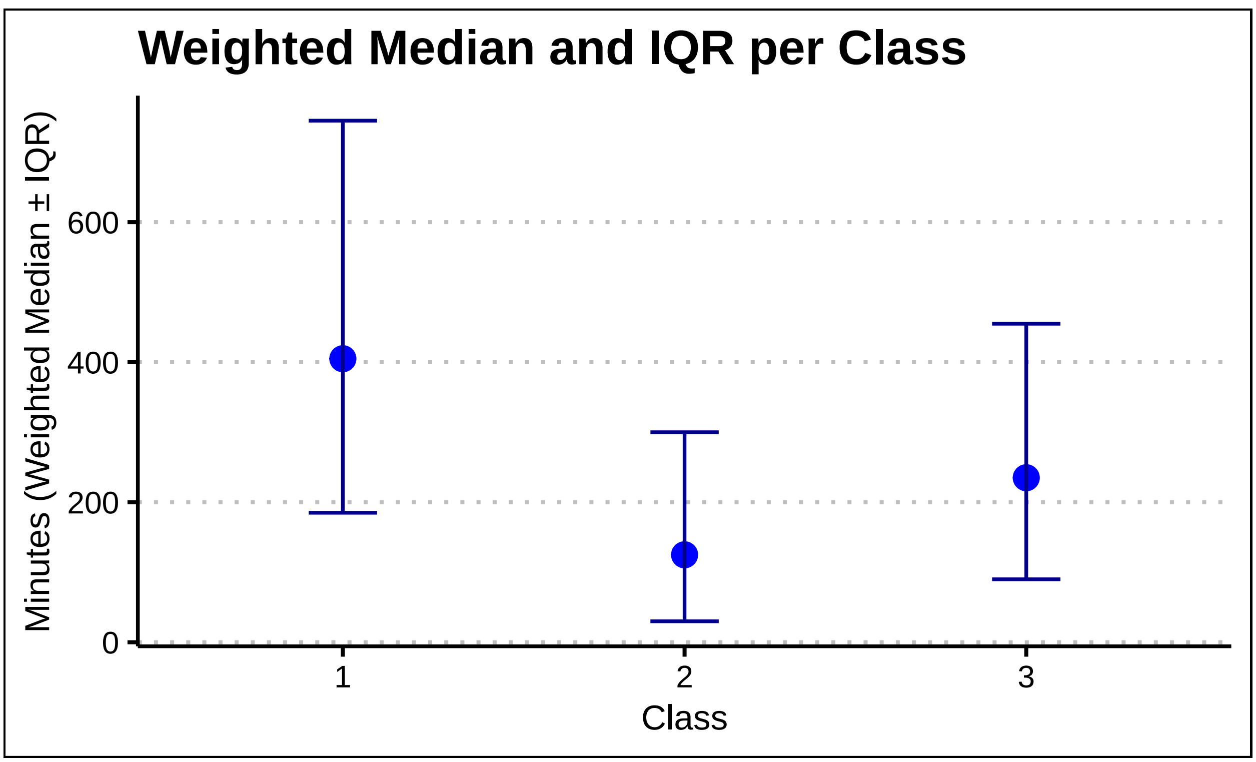


Figure 11: Weighted median and interquartile range of minutes exercised per week for youths by class.

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.

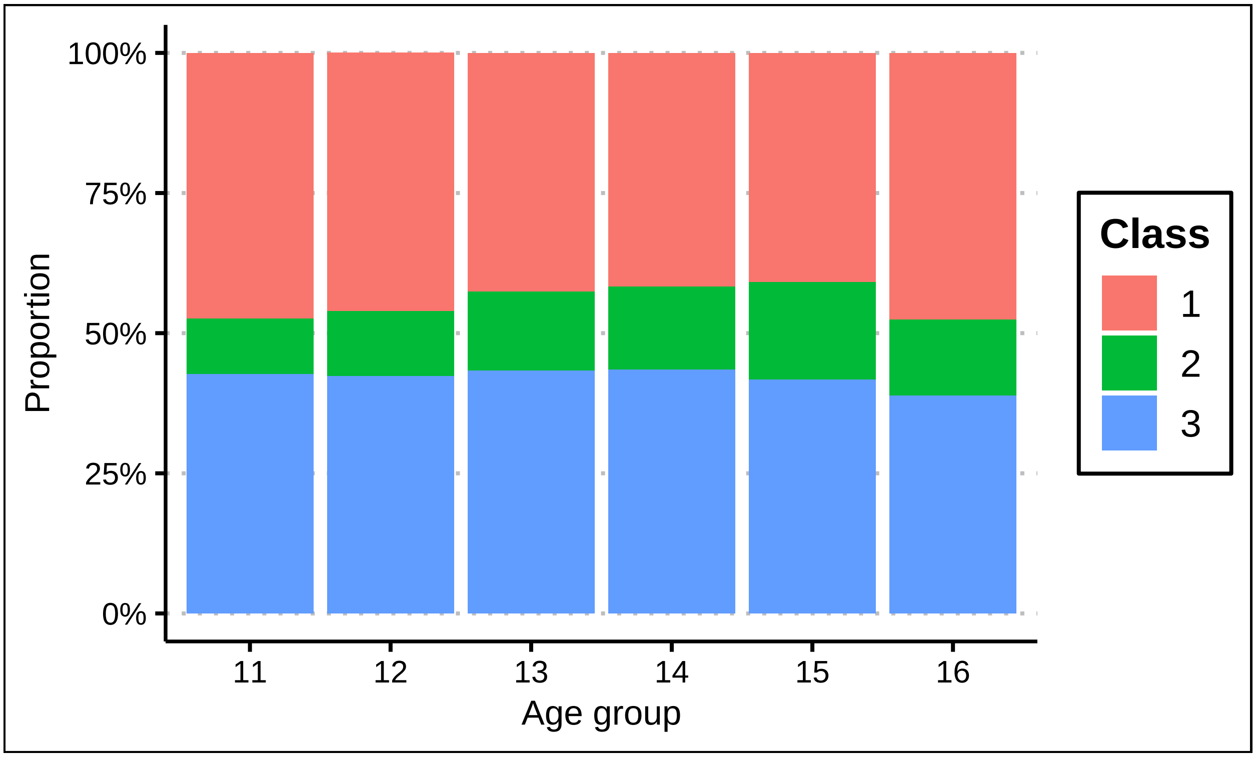


Figure 12: Proportion of youths in each class by age.

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. 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.

Conceptual Interpretation

The results from both youth and adult latent class analyses highlight significant age-related changes in motivation and physical activity patterns.

Adults

The High Engagement class in adults is most prevalent among younger adults. This finding is consistent with SDT, which posits that younger individuals are more likely to engage in physical activity for intrinsic reasons, driven by autonomy and competence. As adults age, however, there is a noticeable shift toward external regulation, as seen in the Mixed Motivation and Low Engagement classes. As people grow older, they begin to internalize external motivations, such as health, fitness, or social norms, which gradually shift toward extrinsic forms of motivation. This transition from intrinsic to extrinsic regulation is also observable in the Mixed Motivation class, which blends both intrinsic and extrinsic motivations. The Low Engagement class, characterized by low motivation and disengagement, is particularly prominent in older adults. This class potentially reflects amotivation, where individuals lack both intrinsic and extrinsic reasons to engage in physical activity. SDT would argue that this decline in motivation can be attributed to a lack of autonomy (e.g., reduced opportunities) and competence (e.g. physical decline), leading to lower participation in physical activity.

As people age, their PBC likely diminishes. This could be due to physical limitations, reduced access to exercise opportunities, or less social support. TPB suggests that if an individual perceives a lack of control over their behavior, they are less likely to engage in that behavior. This is consistent with the higher likelihood of older adults falling into the Low Engagement class, which likely reflects lower perceived behavioral control and a decline in intrinsic motivation.

Youths

For youths, the latent class results show a pattern of strong intrinsic motivation at younger ages, followed by a gradual decline as they age, consistent with the SDT framework. The High Engagement class in youths, which is characterized by high intrinsic motivation (e.g., enjoyment, fitness, ability), is most prominent among younger adolescents and declines with age. SDT suggests that early adolescence is a time when youths are still driven by intrinsic motivation—they engage in physical activity because it is inherently enjoyable and satisfying, and their autonomy is high.

As youths age, particularly around the ages of 12–15, there is a shift toward more mixed motivation and increasing external regulation. This shift is reflected in the growing prominence of the Mixed Motivation and Low Engagement classes. According to SDT, this transition could be due to an erosion of autonomy as adolescents encounter increasing external pressures (e.g., academic demands, peer influences). As autonomy decreases, youths may internalize external regulations (e.g., health or social approval) to maintain their participation, but this internalization may not be fully integrated, leading to the Mixed Motivation class. These adolescents may engage in physical activity because of social pressures, such as fitting in with peers or conforming to societal expectations, rather than for enjoyment or personal satisfaction.

The Low Engagement class in youths is particularly notable because it reflects a group that, unlike the Mixed Motivation class, shows low endorsement of all motivational factors. As youths age, the likelihood of falling into the Low Engagement class increases, particularly at ages 15–16. This pattern is consistent with the SDT framework, which would attribute this decline to a perceived lack of competence and autonomy in physical activity. In adolescence, when individuals are still in the process of developing a sense of self and competence, a lack of self-determined activity and failure to internalize positive values about physical activity may result in amotivation—the lack of motivation to engage in physical activity.

Age-Related Trends

In both youth and adult groups, the shift from High Engagement to Mixed Motivation and Low Engagement suggests a general trend toward external regulation and disengagement as individuals age. This trend aligns with the SDT understanding that motivation evolves from intrinsic to extrinsic regulation, and as autonomy and competence decrease, amotivation becomes more common. The role of PBC may also explain this trend, particularly in adults and older youths, as reduced PBC leads to decreased participation in physical activity.

The fact that both youth and adult samples show this shift emphasizes the importance of addressing autonomy, competence, and PBC at each developmental stage. For youths, interventions should focus on maintaining intrinsic motivation and autonomy in early adolescence, helping them develop internalized, self-determined reasons for engaging in physical activity. For adults, particularly older adults, interventions should focus on enhancing PBC, addressing barriers such as physical limitations, and fostering environments where external support and motivation can maintain engagement in physical activity.

Conclusions

The analyses identified clear motivational profiles in both youths and adults, revealing meaningful differences in physical activity (PA) engagement across age groups. Among youths, three latent classes emerged—high engagement, moderate engagement, and low engagement—reflecting varying degrees of positive endorsement across enjoyment, fitness, ability, and opportunity motives. For adults, three corresponding classes—high engagement, mixed motivation, and low engagement—were observed, with older individuals more likely to belong to classes characterized by weaker intrinsic motivation and more ambivalent attitudes. Across both age groups, class membership was strongly associated with PA levels, with high engagement groups reporting the greatest weekly activity, low engagement groups the least, and intermediate classes in between.

These patterns align with SDT's continuum of motivational regulation. Youths demonstrated a predominantly intrinsic orientation, particularly toward enjoyment and mastery motives, indicating that autonomy and competence are primary drivers of adolescent PA. Adults showed greater variability, with mixed motivation suggesting coexistence of intrinsic and extrinsic regulation, and low engagement reflecting predominantly external constraints or reduced internalized motivation. The shift toward external regulation with age suggests that structured opportunities, social reinforcement, and health-oriented goals increasingly influence adult PA participation.

Within the framework of TPB, these findings indicate age-related differences in behavioral determinants. Younger individuals appear to hold more positive attitudes toward PA and perceive higher control, facilitating engagement. Older adults, however, display reduced perceived control and are more influenced by social norms and environmental factors, suggesting that behavior is increasingly contingent on external facilitation. The combined interpretation using SDT and TPB implies that while sustaining intrinsic motivation is critical in youths, supporting perceived control and accessibility is key for adults.

The results provide empirical support for the hypotheses that motivational profiles differ systematically between youths and adults, that intrinsic motives are stronger in younger cohorts, and that declining perceived control and increasing reliance on external regulation are associated with lower engagement in older adults. For intervention design, these findings suggest that programs for youths should emphasize autonomy-supportive environments, enjoyment, and skill mastery, while adult interventions should focus on removing barriers, providing structured opportunities, and leveraging social support to enhance participation. Policy implications include tailoring resources by age group, investing in environments that facilitate PA for older adults, and prioritizing early intervention to maintain high motivation during adolescence.

Limitations

Several limitations may affect the interpretation of these results. Adult data relied primarily on an online survey design, which may underrepresent individuals with limited digital literacy or internet access, such as older adults or lower-income households. Although paper questionnaires were provided in a third mailing, the overall response rate was low, raising the possibility that respondents were more health-conscious or active than non-respondents. Allowing up to two respondents per household may have inflated intra-household similarity, and differences between online and paper responses could have influenced reported PA or demographic details. The use of a split questionnaire design meant that some participants did not answer all key items, reducing the usable sample for certain analyses.

Youth data were self-reported, which may be affected by recall errors, comprehension difficulties, and social desirability, particularly under teacher supervision in school settings. Across both datasets, only motive items with identical or near-identical wording were included, possibly omitting other relevant constructs. No factor analysis was conducted to verify the dimensionality of motive items. PA measures were highly skewed, though using medians mitigated the influence of non-normality. Coding differences across datasets (e.g., handling of "does not know" responses in youths) could slightly affect estimates. Only moderate-to-vigorous PA was analyzed, which may underestimate meaningful engagement in older adults who benefit from light activity. Demographic factors such as gender, ethnicity, disability, and relationship status were not modeled, and the cross-sectional design limits causal inference regarding changes in motivation or behavior over time.

Despite these limitations, the findings have clear theoretical and practical implications. They suggest that motivation toward PA is dynamic across the lifespan, shifting from predominantly intrinsic and competence-driven in youths to a mix of intrinsic and extrinsic influences in adults, with declining perceived control contributing to reduced engagement. Interventions and policies should be age-specific: promoting enjoyment, mastery, and autonomy in youths, and enhancing accessibility, structured opportunities, and social support in adults. Early intervention and sustained support may help maintain high motivation and prevent declines in PA, particularly during critical developmental windows in adolescence and later adulthood.

References

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. Human Behavior and Emerging Technologies, 2(4), 314–324. https://doi.org/10.1002/hbe2.195

Trigueros R, Aguilar-Parra JM, López-Liria R, Rocamora P. The Dark Side of the Self-Determination Theory and Its Influence on the Emotional and Cognitive Processes of Students in Physical Education. Int J Environ Res Public Health. 2019 Nov 12;16(22):4444. doi: 10.3390/ijerph16224444. PMID: 31726790; PMCID: PMC6888335.

Brooks JM, Iwanaga K, Chiu CY, Cotton BP, Deiches J, Morrison B, Moser E, Chan F. Relationships between self-determination theory and theory of planned behavior applied to physical activity and exercise behavior in chronic pain. Psychol Health Med. 2017 Aug;22(7):814-822. doi: 10.1080/13548506.2017.1282161. Epub 2017 Jan 22. PMID: 28111983; PMCID: PMC6013835.

World Health Organization. (2024, June 26). Nearly 1.8 billion adults at risk of disease from not doing enough physical activity. https://www.who.int/news/item/26-06-2024-nearly-1.8-billion-adults-at-risk-of-disease-from-not-doing-enough-physical-activity

Sport England. (2024). Active Lives Children and Young People Survey, 2022-2023. [data collection]. UK Data Service. SN: 9286, DOI: http://doi.org/10.5255/UKDA-SN-9286-1

Sport England, Ipsos. (2025). Active Lives Adults Survey, 2022-2023. [data collection]. 2nd Edition. UK Data Service. SN: 9288, DOI: http://doi.org/10.5255/UKDA-SN-9288-2

Vuckovic, V., & Duric, S. (2024). Motivational variations in fitness: a population study of exercise modalities, gender and relationship status. Frontiers in psychology, 15, 1377947. https://doi.org/10.3389/fpsyg.2024.1377947

Ostendorf, D.M., Schmiege, S.J., Conroy, D.E. et al. Motivational profiles and change in physical activity during a weight loss intervention: a secondary data analysis. Int J Behav Nutr Phys Act 18, 158 (2021). https://doi.org/10.1186/s12966-021-01225-5

Moreno-Murcia, J. A., Cervelló Gimeno, E., Hernández, E. H., Pedreño, N. B., & Rodríguez Marín, J. J. (2013). Motivational profiles in physical education and their relation to the theory of planned behavior. Journal of sports science & medicine, 12(3), 551–558.

Nuss, K., Sui, W., Rhodes, R., & Liu, S. (2023). Motivational Profiles and Associations With Physical Activity Before, During, and After the COVID-19 Pandemic: Retrospective Study. JMIR formative research, 7, e43411. https://doi.org/10.2196/43411

Ajzen, Icek (1991). "The theory of planned behavior". Organizational Behavior and Human Decision Processes. 50 (2): 179–211. doi:10.1016/0749-5978(91)90020-T. hdl:11323/1038. S2CID 260959149.

Dishman, R. K., McIver, K. L., Dowda, M., & Pate, R. R. (2018). Declining Physical Activity and Motivation from Middle School to High School. Medicine and science in sports and exercise, 50(6), 1206–1215. https://doi.org/10.1249/MSS.0000000000001542

Varma, V. R., Dey, D., Leroux, A., Di, J., Urbanek, J., Xiao, L., & Zipunnikov, V. (2017). Re-evaluating the effect of age on physical activity over the lifespan. Preventive medicine, 101, 102–108. https://doi.org/10.1016/j.ypmed.2017.05.030

Salvy, S. J., Roemmich, J. N., Bowker, J. C., Romero, N. D., Stadler, P. J., & Epstein, L. H. (2009). Effect of peers and friends on youth physical activity and motivation to be physically active. Journal of pediatric psychology, 34(2), 217–225. https://doi.org/10.1093/jpepsy/jsn071

Biddle, Stuart J. H. , Atkin, Andrew J. , Cavill, Nick and Foster, Charlie(2011) 'Correlates of physical activity in youth: a review of quantitative systematic reviews', International Review of Sport and Exercise Psychology, 4:1, 25 — 49. URL:http://dx.doi.org/10.1080/1750984X.2010.548528

Shao, T., & Zhou, X. (2023). Correlates of physical activity habits in adolescents: A systematic review. Frontiers in physiology, 14, 1131195. https://doi.org/10.3389/fphys.2023.1131195

Choi, J., Lee, M., Lee, Jk. et al. Correlates associated with participation in physical activity among adults: a systematic review of reviews and update. BMC Public Health 17, 356 (2017). https://doi.org/10.1186/s12889-017-4255-2

Alixe H M Kilgour, Matthew Rutherford, Joanna Higson, Samantha J Meredith, Jessica McNiff, Stephanie Mitchell, Anusan Wijayendran, Stephen E R Lim, Susan D Shenkin, Barriers and motivators to undertaking physical activity in adults over 70—a systematic review of the quantitative literature, Age and Ageing, Volume 53, Issue 4, April 2024, afae080, https://doi.org/10.1093/ageing/afae080

Lee IM, Shiroma EJ, Lobelo F, Puska P, Blair SN, Katzmarzyk PT. Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy. Lancet (London, England). 2012, 380(9838):219–229.

Hallal PC, Andersen LB, Bull FC, Guthold R, Haskell W, Ekelund U. Global physical activity levels: surveillance progress, pitfalls, and prospects. Lancet (London, England). 2012, 380(9838):247–257.

Tapia-Serrano, M. Á., López-Gajardo, M. Á., Sánchez-Miguel, P. A., Llanos-Muñoz, R., & Burgueño, R. (2024). Analysis of motivational profiles of physical activity behavior in primary school students: A self-determination theory-based perspective. Personality and Individual Differences, 231, 112837. https://doi.org/10.1016/j.paid.2024.112837

Sebire, S.J., Jago, R., Fox, K.R. et al. Testing a self-determination theory model of children's physical activity motivation: a cross-sectional study. Int J Behav Nutr Phys Act 10, 111 (2013). https://doi.org/10.1186/1479-5868-10-111

Heredia-León, D. A., Valero-Valenzuela, A., Gómez-Mármol, A., & Manzano-Sánchez, D. (2023). Motivational Profiles in Physical Education: Differences at the Psychosocial, Gender, Age and Extracurricular Sports Practice Levels. Children (Basel, Switzerland), 10(1), 112. https://doi.org/10.3390/children10010112

Geller, K., Renneke, K., Custer, S., & Tigue, G. (2018). Intrinsic and Extrinsic Motives Support Adults' Regular Physical Activity Maintenance. Sports medicine international open, 2(3), E62–E66. https://doi.org/10.1055/a-0620-9137

Brunet, J., & Sabiston, C. M. (2011). Exploring motivation for physical activity across the adult lifespan. Psychology of Sport and Exercise, 12(2), 99–105. https://doi.org/10.1016/j.psychsport.2010.09.006

Oyibo, K., Adaji, I., & Vassileva, J. (2018). Social cognitive determinants of exercise behavior in the context of behavior modeling: a mixed method approach. Digital health, 4, 2055207618811555. https://doi.org/10.1177/2055207618811555

Netz, Yael & Raviv, Shulamith. (2004). Age Differences in Motivational Orientation Toward Physical Activity: An Application of Social—Cognitive Theory. The Journal of psychology. 138. 35-48. 10.3200/JRLP.138.1.35-48.

Beauchamp, M. R., Crawford, K. L., & Jackson, B. (2019). Social cognitive theory and physical activity: Mechanisms of behavior change, critique, and legacy. Psychology of Sport and Exercise, 42, 110–117. https://doi.org/10.1016/j.psychsport.2018.11.009

de Maio Nascimento, M., Gouveia, É. R., Gouveia, B. R., Marques, A., França, C., Campos, P., Martins, F., García-Mayor, J., & Ihle, A. (2023). Differential Patterns in Motivations for Practicing Sport and Their Effects on Physical Activity Engagement across the Lifespan. Healthcare (Basel, Switzerland), 11(2), 274. https://doi.org/10.3390/healthcare11020274

National, regional, and global trends in insufficient physical activity among adults from 2000 to 2022: a pooled analysis of 507 population-based surveys with 5 · 7 million participants. Strain, TessaAbdul Raheem, Raheema et al. The Lancet Global Health, Volume 12, Issue 8, e1232 - e1243

Neipp, Mª & Quiles, María & Leon, Eva & Rodríguez-Marín, Jesús. (2013). Theory of Planned Behavior and physical exercise: Differences between people who do regular physical exercise and those who do not. Wulfenia. 20. 324-335.

Wang, L., & Wang, L. (2015). Using Theory of Planned Behavior to Predict the Physical Activity of Children: Probing Gender Differences. BioMed research international, 2015, 536904. https://doi.org/10.1155/2015/536904

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),
```

```
+                                   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,
```

```
+                  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)

> # check residual
> resid(f0, type = "cor")
```

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)

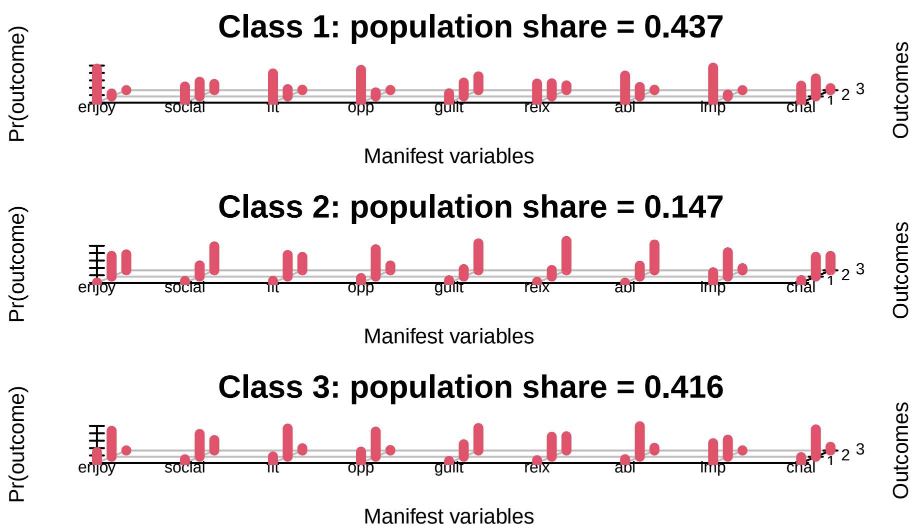
```
> set.seed(2025)

> 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.r
+             SD = sd(mins_modplus_outschool_Week_ALL[mins_modplus_outschool_Week_ALL > 0], na.rm = TRUE
+             PercentNA = mean(mins_modplus_outschool_Week_ALL < 0, na.rm = TRUE) * 100)

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

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

```
> #   theme_clean()
>
> # Gender
> 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)
```

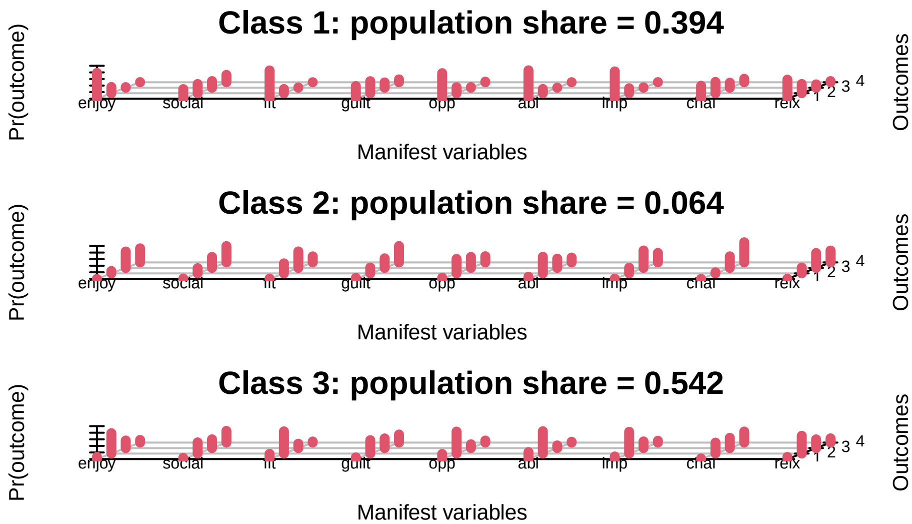



```
> # Bootstrap Vuong-Lo-Mendell-Rubin Likelihood Ratio Test
> or.ch

> # 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)
```




```
> # 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)

```
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)
```