

Motivational Transitions in Physical Activity from Youth to Adulthood: Insights from Multigroup SEM and Latent Class Approaches

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Introduction

Physical inactivity remains a significant global public health concern, with nearly 1.8 billion individuals not meeting recommended levels of physical activity (PA) (World Health Organization, 2024), representing a 9% increase over the past two decades (Mitchell, 2019; Strain et al., 2024). Beyond its physiological consequences, insufficient PA 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 (Anderson & Shivakumar, 2013; Booth et al., 2012, White et al., 2024). Participation in PA is shaped by social, developmental, and motivational factors, with motivation consistently identified as a central determinant of behaviour (Daley & Duda, 2006; Duncan et al., 2010).

Understanding the factors that influence PA engagement is crucial for developing effective interventions. Motivation plays a central role in determining whether individuals initiate and maintain PA behaviours. Theories such as Self-Determination Theory (SDT) and the Theory of Planned Behaviour (TPB) have been instrumental in elucidating the psychological and social factors that underpin PA motivation. SDT emphasizes the importance of intrinsic motivation and the satisfaction of basic psychological needs in fostering sustained engagement in PA (Brooks et al., 2017, Deci & Ryan, 2008;). TPB, on the other hand, focuses on how attitudes, subjective norms, and PBC influence behavioural intentions and actions (Ajzen, 1991).

Despite the valuable insights provided by these frameworks, existing research often examines age-related differences in PA motivation within either youth or adult populations, without directly comparing these groups. This limits our understanding of how motivational mechanisms may differ across the transition to adulthood, and how these differences influence PA. Exploring this gap is essential for designing interventions more specific to different developmental stages. This dissertation aims to address the following research questions:

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

To answer these questions, multigroup structural equation modeling (SEM) to test whether the relationships between motives and PA differ by age, and latent class analysis (LCA) will be employed to identify unobserved 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 (2000), it emphasizes the degree to which behaviour is self-determined. Motivation is classified on the autonomy continuum as amotivation, extrinsic, and intrinsic. Within extrinsic motivation, there exist external, introjected, identified, and integrated regulation, with internalization increasing progressively from none to fully intrinsic under the minitheory Organismic Integration Theory within SDT (Standage, 2019). External regulation occurs when actions are guided by outside influences, such as rewards or punishments. Introjected regulation reflects behaviour driven by internal pressures, such as guilt. In identified regulation, individuals willingly engage in an activity because they recognize its personal value or the benefits it provides. Integrated regulation aligns behaviour completely aligned with one's identity and broader goals (Ryan & Deci, 2017). Intrinsic motivation, by contrast, arises from interest, enjoyment, or inherent satisfaction in the activity itself. While evidence on the relationship between PA and specific constructs is mixed, prior studies indicate that stronger intrinsic motives are positively associated with exercise participation, lower dropout rates, and improved physical and psychological wellbeing.(Ng et al., 2012; Teixeira et al., 2012).

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 PA adherence (Trigueros et al.). While this may be due to individual differences in baseline motivation or contextual factors, past research often overlooked the role of external constraints and structural factors, such as socioeconomic status. These external factors may interact with psychological needs in complex ways that SDT does not fully address.

Theory of Planned Behaviour

Proposed by Ajzen in 1991, TPB is a widely used framework for predicting and understanding human behaviour, emphasizing the role of intention as the proximal determinant of action. According to TPB, behavioural intentions are influenced by three key factors: attitudes toward the behaviour, subjective norms, and perceived behavioural control (PBC). Attitudes reflect an individual's positive or negative evaluation of performing the behaviour, subjective norms capture perceived social pressure, and PBC represents the perceived performance ease. These factors interact to shape intention, which in turn predicts behaviour. In the context of PA, 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 (Neipp, 2013; Wang, 2015).

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 PBC, 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. However, the theory's predictive performance varies by gender, and the role of TPB variables in predicting PA intentions is inconsistent. While perceived behavioural control (PBC) has often been found to predict both intention and behaviour (Ajzen, 1991; Godin & Kok, 1996), other studies have identified attitude as the strongest predictor, with subjective norm generally showing limited influence. However, exceptions exist, such as its positive association with behaviour among professional footballers (Moreno-Murcia et al., 2013). More recently, Kim et al. (2019) suggested that previous weak effects of subjective norms may have been a result of neglect of subjects' normative referents and inclination to comply. Nevertheless, there exists consistent evidence for the relationship between PA and TPB variables in general (Hagger et al., 2002).

Age-Related Differences

Unfortunately, intrinsic motivation tends to decline with age regardless of developmental stage (Brunet & Sabiston, 2011; Dishman et al., 2018; de Maio Nascimento, 2023), suggesting that the factors driving engagement shift across the lifespan.

Within adults, older individuals reported less intrinsic motivation and introjected regulation, with lower PA levels compared to their younger counterparts (Brunet & Sabiston, 2011). Middle-aged adults frequently report exercising for reasons aligned with personal health, fitness, and psychological well-being (Brunet & Sabiston, 2011; Nascimento et al., 2023). Relaxation and stress relief are key motivators that support adherence and psychological benefits, remaining relatively stable across age groups (de Maio Nascimento, 2023; Vuckovic, 2015; Kilgour, 2005). Contextual factors, such as access to facilities and opportunities to participate influence PA similarly across age groups (Brunet & Sabiston, 2011; Dishman et al., 2018).

For youths, intrinsic motivation, enjoyment, and social support are strong predictors of habitual PA. Longitudinal evidence indicates that adolescents who maintain higher intrinsic motivation and personally meaningful goals, particularly those emphasizing enjoyment, remain more active over time. Conversely, declines in social, competence, or appearance goals can weaken engagement (Dishman et al., 2018). However, these findings are limited to students from two school districts in South Carolina, which may reduce generalizability. Cross-sectional studies further show that higher motivation profiles in adolescents are linked to adaptive outcomes

such as responsibility, resilience, and social support (Heredia-León et al., 2023), although teacher presence during data collection may have influenced student responses.

Several methodological limitations constrain these findings. Brunet and Sabiston (2011) reported high inter-correlations between intrinsic motivation and identified regulation, suggesting potential multicollinearity that may obscure distinct motivational effects. De Maio Nascimento et al. (2021) acknowledged that recruitment from a single region, uneven group sizes, and the absence of objective fitness measures limit generalizability. Vuckovic et al. (2015) noted a relatively small subgroup of participants engaged in group or personal training, lack of recorded exercise intensity and frequency, and cultural specificity to Slovenia. Kilgour et al. (2005) highlighted that their findings were based on adults over 70, and included uneven inclusion of motivational factors.

Nevertheless, these studies 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 motives are more salient in adults. Environmental opportunities appear to exert a similar influence across age groups. Examining the differential predictive power of these motives enables a more nuanced understanding.

Hypothesis 1 (H1): The influence of exercise motives on PA 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 PA similarly across age groups.

Motivational Profiles

Motivational profiles provide a person-centred perspective on the heterogeneity of PA motives. In adults, Ostendorf et al. (2021) identified three primary motivational profiles among individuals with overweight or obesity: high autonomous, high combined, and moderate combined. They were characterized by strong intrinsic and identified motivations, elevated levels across all regulatory types, and intermediate levels on all regulations, respectively. Longitudinally, individuals in the high autonomous profile demonstrated the least decline in moderate-to-vigorous PA during transitions from supervised to unsupervised exercise, suggesting that intrinsic and identified motivations support sustained engagement, whereas moderate-to-high external regulation required additional support. However, the findings were based on a relatively small, predominantly female, non-Hispanic White sample enrolled in a structured weight-loss program, limiting generalizability. Similarly, Nuss et al. (2023) identified four motivational profiles in Canadian adults, and found that combinations of controlled and autonomous motivation may synergistically support activity, while low overall motivation corresponded to minimal engagement. Yet reliance on retrospective self-reports of PA, including pre-pandemic behaviour, introduces potential recall and overreporting bias.

In youths, 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 higher levels of PA, in addition to TPB constructs. Similarly, Heredia-León et al. (2023) identified youths in the higher motivation profiles were associated with adaptive outcomes such as responsibility, resilience, and perceived social support. These youths also demonstrated greater intention to be physically active and enjoyment in PE classes, whereas low-quality profiles corresponded to higher boredom and lower engagement. However, their inclusion of integrated regulation, typically only observed in more mature individuals (Vallerand, 1997), may have introduced construct overlap in younger participants.

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 (H2): Distinct motivational profiles exist within youths and within adults.

- H2(a). With increasing age, adults are more likely to belong to classes characterized by lower motivation.
- H2(b). With increasing age, youths are more likely to belong to classes characterized by lower motivation.

Data and Variables

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 motive items across life stages. All motive items are self-reported, single-item measures. Appendix A lists the corresponding survey questions. To maintain comparability and avoid skew from small subgroups, only cisgender adults without disabilities were retained. Ethnicity and gender were included as control variables. Due to small group sizes, ethnicity was coded as White British or Other. Observations with missing data or “I don’t know” answers on any used item were likewise excluded. Additional descriptive statistics, including percentages of missing values are provided in Appendix C.

Motive and PA Items:

- 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 PA.
- Importance – recognizing the personal value or significance of PA.
- Challenge – persistence and enjoyment in pursuing difficult tasks.
- Minutes – total weekly minutes of moderate-to-vigorous PA (see Appendix B for list of activities).

Although this study did not directly measure constructs from SDT, some of the examined motives can be conceptually mapped onto its continuum of motivational regulation. Enjoyment in exercise reflects intrinsic motivation, while exercising to stay fit, to relax, or because one understands its benefits represent forms of identified regulation. Exercising socially for fun with friends can reflect either intrinsic or identified regulation. In contrast, exercising due to guilt is a classic example of introjected regulation. These mappings should be regarded as conceptual approximations rather than definitive classifications.

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 was designed to provide a nationally representative picture of adult participation in PA 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 minimize seasonal and geographic bias. A total of 173,950 adults completed the survey. Weighting adjustments were applied to correct for differential response probabilities by Sport England. The questionnaire covered a broad range of topics, including PA frequency and duration, sports participation, volunteering, club membership, and motivational factors, along with demographic variables such as age, gender, education, and socio-economic status.

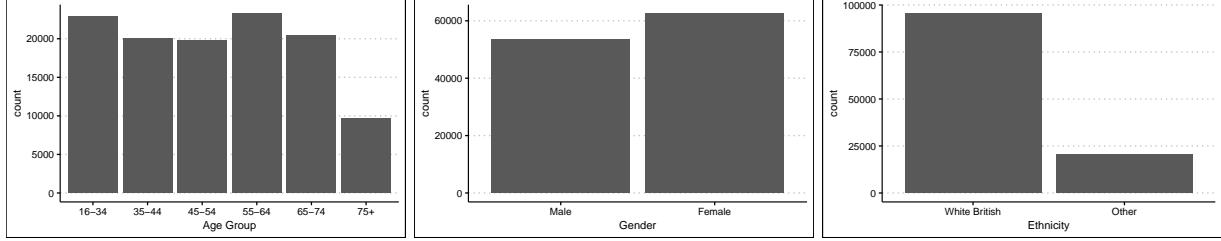


Figure 1: Distribution of age, gender, and ethnicity in adults.

Females comprised 54% of the sample, and White British participants accounted for 82%. Given no indication of meaningful differences between motivational profiles during preliminary analyses, the youngest and oldest age groups were collapsed with their neighbours due to small cell sizes at the extremes, forming six age brackets, namely 16–34, 35–44, 45–54, 55–64, 65–74, and 75+. Collapsing these categories improved model stability without obscuring theoretically relevant distinctions. After adjustment, the age distribution remained moderately skewed but acceptable for analysis.

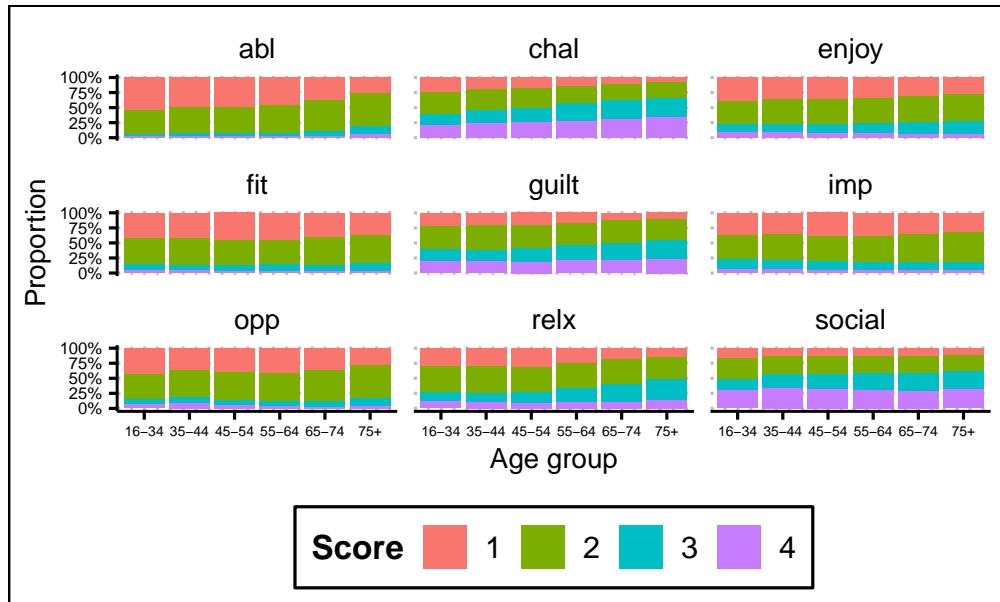


Figure 2: Distribution of adult responses for each motive on the Likert scale.

Each item is 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, negative responses of (disagree and strongly disagree) were combined to reduce sparsity and minimize distortion. For most motive items, the proportion of adults expressing strong positive agreement declines with age. Older adults were less likely than younger adults to strongly endorse beliefs such as feeling capable of engaging in PA, valuing it for the challenge, or pursuing it for enjoyment and fitness. They were also less likely to report strong guilt for not exercising, to perceive sufficient opportunities for activity, or to consider PA an important means of relaxation.

Youth Dataset

The youth data come from the Active Lives Children and Young People Survey (Year 6: 2022–2023), conducted by Ipsos on behalf of Sport England, which parallels the adult survey in design and content. 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 due to significant deviations in survey design for other years from the adult version.

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.

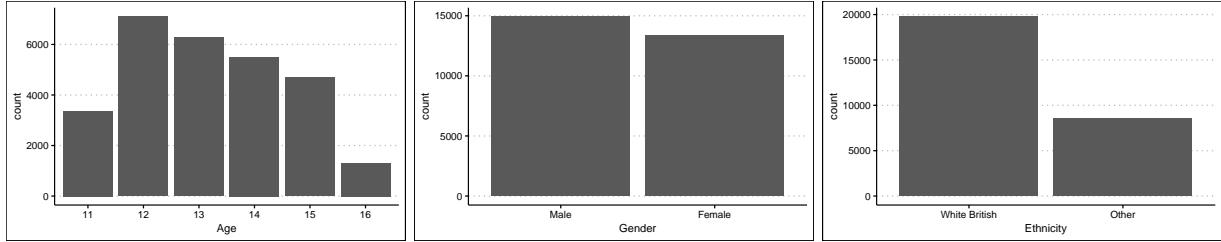


Figure 3: Distribution of age, gender, and ethnicity in youths.

47% of the sample are female, and 70% are White British. Although 16-year-olds represent a small proportion of the sample (4.63%), they were not collapsed with the 15-year-olds. The transition from age 15 to 16 marks a distinct developmental and social stage, such as reaching legal thresholds, completing compulsory schooling, and gaining increased autonomy. Retaining this distinction allows examination of possible developmental turning points.

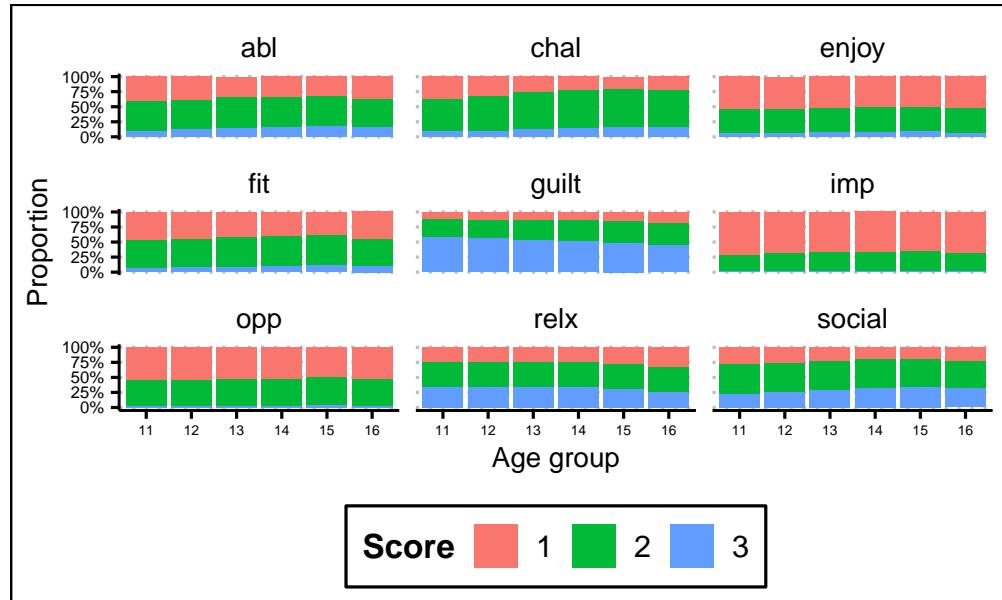


Figure 4: Distribution of youth responses for each motive on the Likert scale.

Each item was rated on a four-point Likert scale ranging from 1 (strongly agree) to 4 (strongly disagree). As with the adult data, lower-frequency disagreement categories were collapsed to reduce sparsity. 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 PA.

Statistical Analysis

Multigroup structural equation modeling (SEM) was used to examine whether the strength of associations between motive items and PA differs by age group. Latent class analysis (LCA) was conducted separately for youth and adult samples to identify distinct motivational profiles within each group, class membership was then regressed on age group using multinomial logistic regression. Two motive items (challenge and importance) were excluded from multigroup SEM due to non-equivalent wording across the surveys but were retained for LCA. Subsamples used for the two analyses were similar in terms of gender and ethnicity distributions.

Multigroup Structural Equation Modeling

Differences in the slopes of motive items were examined while controlling for demographic factors (see Appendix E for model specification). This approach directly addresses H1 by testing whether the strength of association between each motive item and weekly PA varies between youths and adults.

Table 1: Proportion of "strongly agree" responses for adults (left) and youths (right).

Proportion		Proportion	
enjoyb	0.3454	enjoyb	0.5094
socialb	0.1354	socialb	0.2328
fitb	0.4241	fitb	0.4145
guiltb	0.1813	guiltb	0.1411
oppb	0.3909	oppb	0.5205
relxb	0.2630	relxb	0.2529

To account for differences in Likert scales between adults and youths, all motive items were dichotomized into "strongly agree" and "not strongly agree". The distributions of positive responses exhibit a left skew in both adults and youths, suggesting that participants were less likely to choose the highest agreement category across items. 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. 116,873 adult and 29,798 youth respondents were included.

A freely estimated model was first fitted, followed by a series of constrained models in which individual or all motive pathways were fixed to equality across groups. This stepwise approach allowed assessment of whether the predictive strength of specific motives differed significantly between youths and adults. Ethnicity, gender, and age were controlled for in all models.

Prior to fitting the 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. Given the conceptual similarity of these motive items, a level of correlation is expected and largely unavoidable. 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 motive items (enjoyment, fitness, opportunity, and relaxation), exceeding 0.4. This misfit likely reflects conceptual overlap and the use of dichotomized indicators. Nevertheless, residuals involving demographics and PA minutes were consistently low. These localized discrepancies do not affect the primary purpose, which is to test whether the strengths of associations, rather than the predictive power of motives on PA, differ across groups.

Latent Profile Analysis

LCA was used to identify distinct motivational profiles within youths and adults, with the Likert-scale motive items serving as indicators. Ethnicity and gender were included as covariates. Ten random starts were used per class model to ensure solution stability. 116,018 adult and 28,269 youth respondents were included.

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. Multinomial logistic regression with age as a predictor was then applied, and odds ratios with 95% confidence intervals were calculated by exponentiating the estimated coefficients. This approach directly addresses Hypothesis 2 by testing whether the probability of belonging to lower-agreement profiles increases with age among adults (H2a) and youths (H2b).

Conditional independence among PA-related items was assessed using standardized bivariate chi-square statistics. Extremely sparse cells (<1% of observations) inflated these values, making them unreliable indicators of local dependence. Given that the key motive items represent conceptually distinct constructs, minor violations are less concerning than for highly overlapping indicators. 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

All analyses were conducted in R (version 4.4.3). Multigroup SEM was performed using the lavaan package (Rosseel, 2012). LCA and related statistics were conducted using packages poLCA (Linzer & Lewis, 2011) and poLCExtra (Choi, 2023).

Results & Discussion

Multigroup SEM

Significant differences between adults and youths were observed in the strength of associations between motive items and weekly PA. Coefficients (Table 2) represent the estimated change in weekly PA minutes associated with strong agreement for each binary motive.

Table 2: Estimated slopes of each motivational factor in the SEM, with differences calculated as youth minus adult values. All differences were statistically significant ($p < 0.05$).

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

Enjoyment and guilt both have a stronger effect in youths than in adults, although the magnitude of these effects remains modest at 24 and 17 minutes, respectively. While this supports H1(a), social motive has a larger effect in adults instead at a difference of 24 minutes. The observed discrepancy may be attributed to several methodological and conceptual factors. Variations in survey question wording could influence how respondents interpret and respond to items assessing social motives. For instance, Geller (2018) defines social motives as the extrinsic drive to socially interact and meet new people during physical activities, emphasizing the external nature of this motivation. In contrast, Bragg (2018) categorizes social motive as “social influence”, encompassing the impact of friends, parents, family members, coaches, and health professionals on an individual’s PA choices. These differing definitions may lead to variations in how social motives are perceived and reported across studies. In addition, the conflation of various forms of PA in survey instruments can obscure the specific motives associated with different activities. For example, Vuckovic (2024) found that social motives were less influential in fitness activities but more significant in sport participation. However, in surveys that combines all types of PA without distinguishing between them, such as the one used for this dissertation, the unique impact of social motives on each activity type may be masked.

Fitness was a stronger predictor among adult, with a difference of 25 minutes. Though it was assumed that adults would place greater value on stress-relief methods, relaxation was more influential in youths. Similar to H1(a), not all elements of H1(b) are supported. Nevertheless, several developmental and contextual factors may provide insight. Not only was achieving relaxation was one of the most commonly reported motives for participation of PA in adolescents aged 16 and older (Ashfold, 1993), it’s also a key determinant of fun in youth sports that promotes sustained engagement (Visek, 2015). In addition, Teuber (2024) reported that engagement in PA not only reduced stress but also enhanced perceived academic performance in university students. While this sample is older than the youths in the present study, the academic pressure context is analogous. On the other hand, elevated momentary stress was found to predicts lower subsequent PA (Do et al.,). Since the present study does not assess causality, there is the possibility that relaxation drive higher PA rather than the reverse. More broadly, personal experiences appear to foster understanding of the benefits of PA, which may in turn drive PA engagement (Kostamo, 2019). Although relaxation serves as a more prominent motive for females (Kondric, 2013), the fairly balanced gender distribution in our youth sample suggests this factor does not meaningfully influence the overall pattern observed.

Contrary to H1(c), environmental opportunity had a stronger effect among adults, with the biggest difference among all motives at 63 minutes. This discrepancy may be due to youths having more consistent access to facilities such as school gyms and playgrounds, while adults are limited by the rising opportunity costs associated with PA participation. This is particularly true among highly educated adults who are aware of

the health benefits, but often hold sedentary (Brown & Roberts, 2011). Furthermore, women often face fewer chances to engage in PA than men, particularly in cultural contexts where they are primarily responsible for household caretaking, which restricts access to outdoor or leisure-based activity (Jalaluddin, 2024). These findings demonstrate clear shifts in motivational drivers. Youths appear more responsive to internalized motives, whereas external factors play a larger role in adults. Notably, the effect of opportunity is far larger than that of any other motive, suggesting that adult engagement in PA is strongly contingent on factors such as access, time, and environmental support. Within the SDT framework, this would suggest that as youths transition to adulthood, intrinsic, identified, and introjected regulation tend to weaken. The social motive may be an exception because it helps fulfill needs that are less satisfied by intrinsic enjoyment in adulthood. Alternatively, it may be interpreted that the determinants of intention appear to shift with age. In the context of the TPB, the results imply personal valuation and perceived social expectations have a stronger influence on youths and decreases with age. However, despite these patterns, the differences for most motives are weak to moderate in magnitude, suggesting that the overall motivational structure may be largely similar.

LCA

Adults

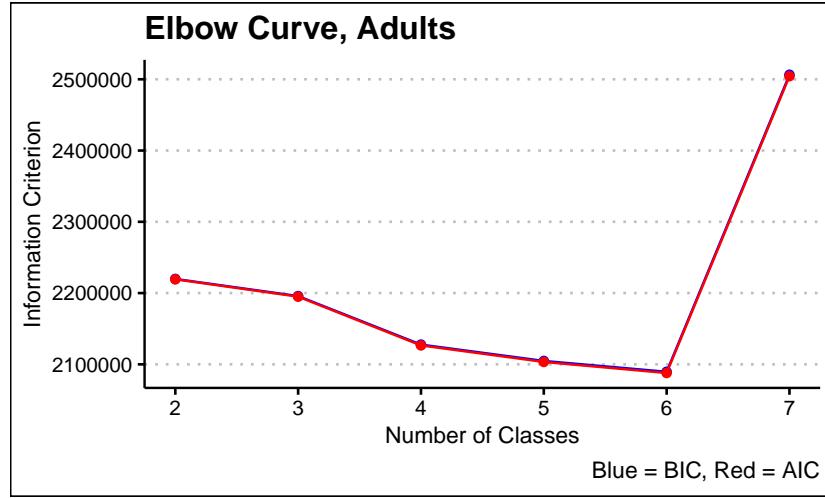


Figure 5: Elbow curve of AIC and BIC values across different numbers of latent classes in adults.

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. Starting from the 4-class model, there appears to be diminishing returns in lowering AIC and BIC values (Figure 5), suggesting that adding more than 4 classes did not provide a substantial improvement in model fit. While both the 3-class and 4-class models have adequate relative entropy values at 0.8916 and 0.7945, respectively, the 4-class solution contains two groups with nearly identical response patterns, which undermines substantive interpretation. The bootstrap likelihood ratio test was used to assess the significance of performance differences. All models except the 7-class were found to be significant, with a preference for the 6-class solution. Nevertheless, the 3-class model is selected for its balance between simplicity and the ability to distinguish meaningful motivational profiles. Fit indices for all models can be found in Appendix D.

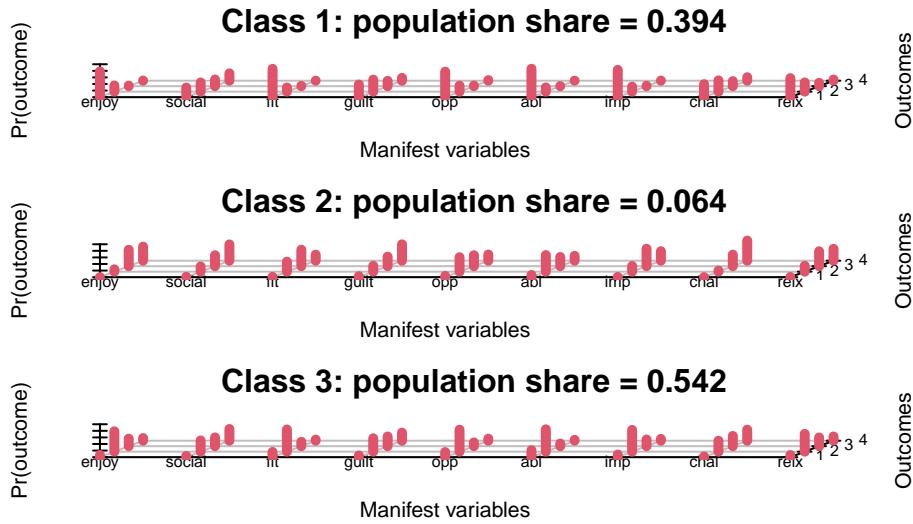


Figure 6: Frequency of adult responses for each motive by class membership.

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

Class 2 is characterized by very low probabilities of strongly agreeing with opportunity 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 PA. This group is labelled the Low Motivation class. It represents a relatively small proportion of the sample (~6%), which corresponds to the patterns observed in the raw data, where very few respondents selected negative responses in general.

Class 3 exhibits a mixed attitude toward various motives, with an almost even mix of positive and negative endorsement across the board. It represents adults who show more ambivalent responses overall. This group is labeled the Mixed Motivation class.

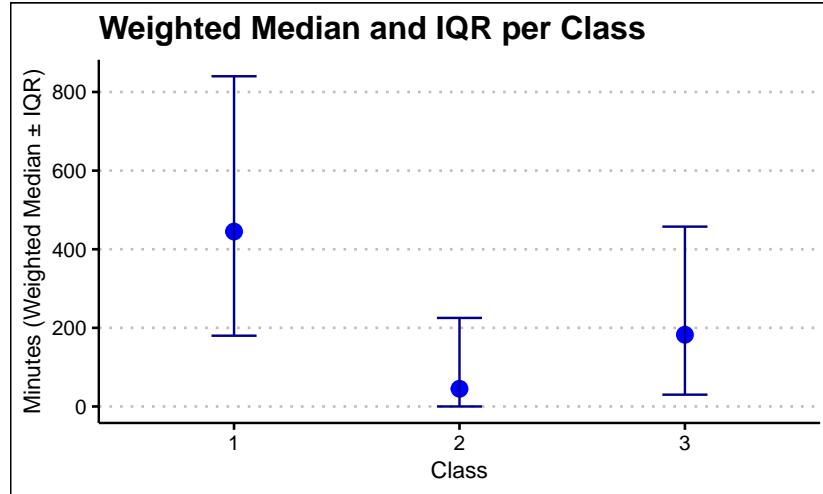


Figure 7: Weighted median and interquartile range of minutes exercised per week for adults by class.

There exists substantial differences in the median of weekly PA minutes. The High Motivation class exhibits the highest levels (445), followed by the Mixed Motivation class (182.5), and finally the Low Motivation class (45). Notably, the interquartile range is positively associated with activity level, highlighting considerable variability, particularly among the most highly active class.

The distribution of age groups highlights notable patterns in motivational profiles. The High Motivation class is consistently the second most populous across age groups, gradually declining with increasing age. The Low Motivation class remains the smallest in all age groups, with its relative size 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 to mixed motivation over time.

Table 3: Odds ratios for adult class membership across age groups, with the youngest group (16–34 years) as the reference.

	16–34 (ref)	35–44	45–54	55–64	65–74	75+
Low Motivation	0.149	1.023	0.9118	1.046	1.143	1.515
Mixed Motivation	1.153	1.159	1.0696	1.149	1.453	1.930

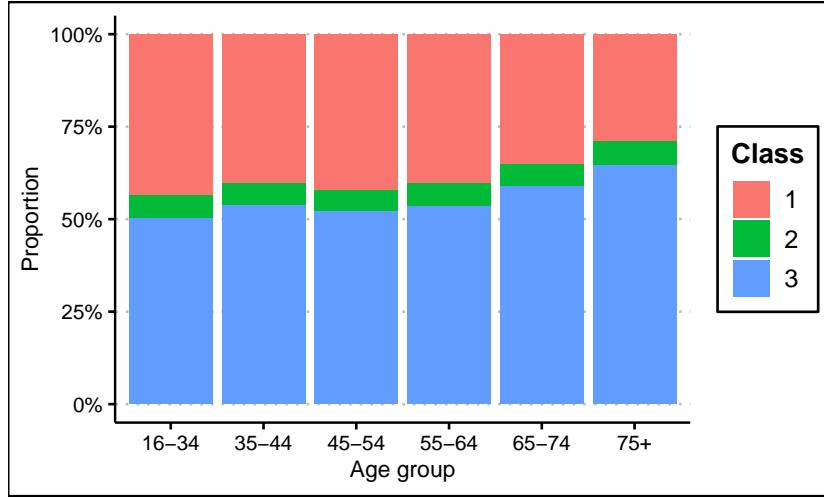


Figure 8: Proportion of adults in each class across age groups.

Multinomial logistic regression was applied to directly examine the relationship between age groups and class membership, with the High Motivation class and youngest group (16–34) as reference (Table 3). The youngest adults are more than 6.6 times as likely to belong to the High Motivation class compared to the Low Motivation class. Although their odds of falling into the Mixed Motivation group are 15% higher, this may be due to the larger size of that group. For the Low Motivation category, no statistically significant differences are found between the 35–44 and 55–64 age groups and the reference category. Other age groups show similar odds, except for those aged 75 and above, who are 1.5 times more likely to be in the Low Motivation class. Meanwhile, the likelihood of being in the Mixed Motivation group rises with age, with adults aged 65–74 being 1.45 times and those aged 75+ being 1.93 times more likely than the youngest adults. These patterns suggest that older adults are more likely to belong to lower motivation classes, which is consistent with H2(a).

As adults age, external motivations, such as maintaining health, improving fitness, or fulfilling social obligations, may take precedence over purely intrinsic factors. This gradual shift from intrinsic to extrinsic regulation is partially reflected in the Mixed Motivation class, which shows a combination of both internally driven motives (e.g., enjoyment, personal challenge) and less autonomous motives (e.g., opportunity, social engagement). In contrast, the Low Motivation class, characterized by low motivation across both intrinsic and extrinsic domains and correspondingly low PA, becomes increasingly prominent among older adults, suggesting that some individuals may experience an overall decline in motivational drivers with age. The characteristics of this class, along with its lowest weekly PA minutes, may indicate amotivation, where individuals have neither intrinsic nor extrinsic reasons to engage in PA. This trend may also be explained by changes in the determinants of intention. Older adults may experience lower PBC due to physical limitations or decreased social support. Existing health conditions, physical fitness, “feeling too old”, and safety were major barriers, especially for the oldest adults (Kilgour, 2024). Normative beliefs and subjective norms may weaken as individuals move beyond life stages where social expectations strongly influence behaviour.

Youths

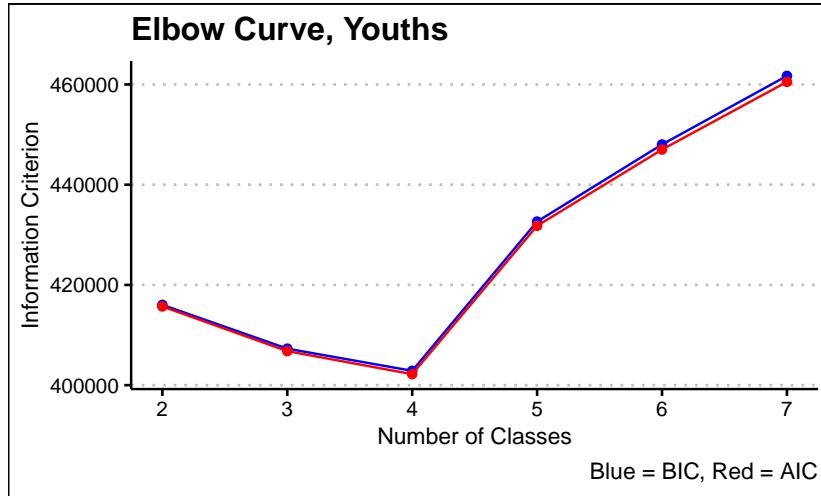


Figure 9: Elbow curve of AIC and BIC values across different numbers of latent classes in youths.

Increasing the number of classes beyond 4 led to a decrease, as evidenced by a sharp increase in AIC and BIC. The penalty for model complexity likely outweighed any improvements in fit. Consequently, the 3-class and 4-class solutions were the only viable candidates. The BLRT further supports this, indicating significance only for these two models, with a preference for the 4-class solution. Both models show acceptable relative entropy values at 0.7998 and 0.7473, but the higher relative entropy for the 3-class model suggests it offers a more nuanced classification of individuals. Similar to the adults, the 4-class model also 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.

Class 1 represents youths who consistently report positive attitudes toward a wide range of motives. 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 class is labeled the High Motivation class.

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 PA. This class is labeled the Low Motivation class, and represents a relatively small proportion of the sample. This is consistent with the raw data, where few respondents selected negative responses.

Class 3 exhibits a moderate attitude toward most motives, with moderate positive endorsements of enjoyment, fitness, opportunity, ability, and importance. Disagreement and strong agreement are both uncommon. This group falls in the middle, representing generally positive but not strongly emphatic motivation toward PA. This class is labeled the Moderate Engagement class.

Similar to adults, significant differences in the median weekly PA minutes are observed across the classes, along with substantial variability within each class. The High Motivation class boasts the highest number (405) and highest interquartile range, followed by the Mixed Motivation class (235), and then the Low Motivation class(125).

The distribution of age groups highlights notable differences in motivational profiles. The High and Mixed Motivation classes are roughly similar in size, with the latter decreasing with age, except for the sudden

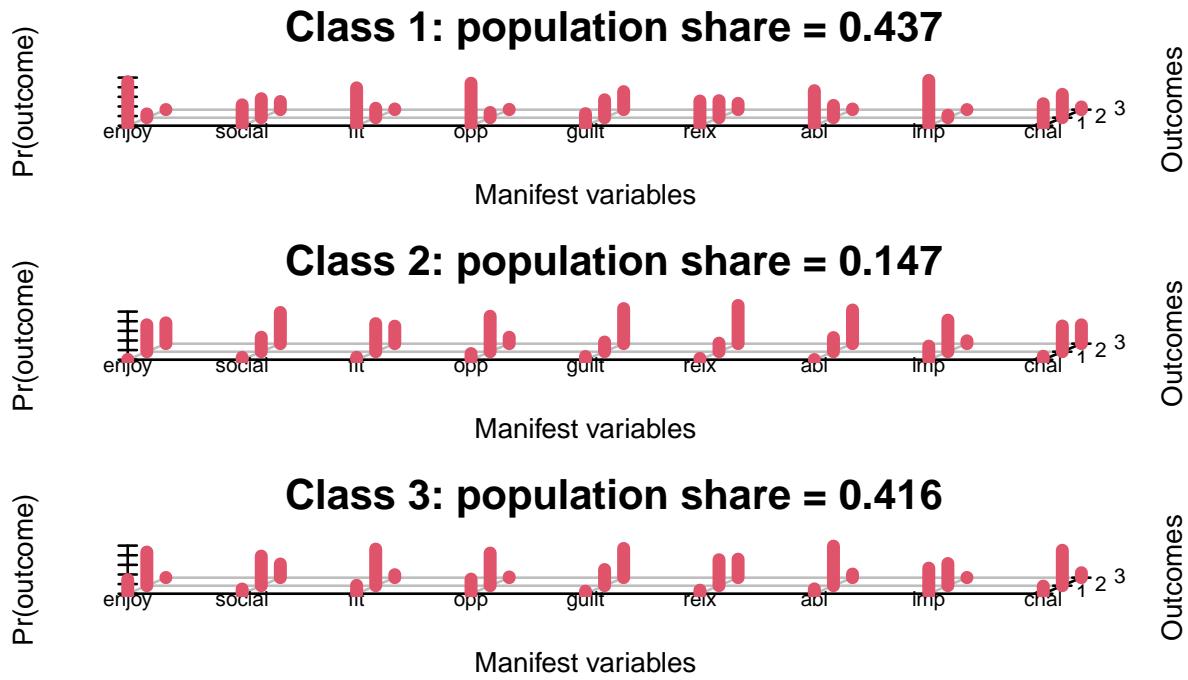


Figure 10: Frequency of adult responses for each motive by class membership.

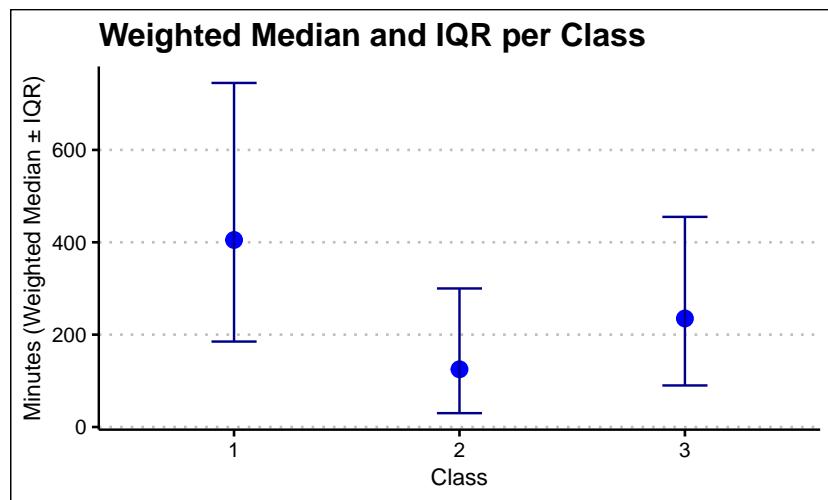


Figure 11: Weighted median and interquartile range of minutes exercised per week for youths by class.

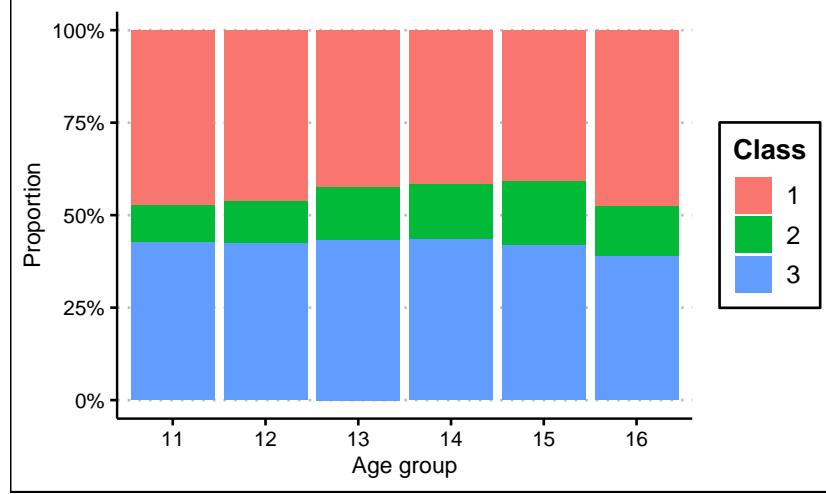


Figure 12: Proportion of youths in each class by age.

increase at age 16. The Low Motivation class is smaller than the other two but still larger than in the adult sample. It steadily gains size with age, with a slight dip at age 16. These patterns suggest that while motivation generally declines during adolescence, a significant portion of youths maintain strong or mixed motivation throughout. Additionally, some youths may experience a boost in motivation during late adolescence.

Table 4: Odds ratios for youth class membership across ages, with 11-year-olds as the reference.

	11 (ref)	12	13	14	15	16
Low Motivation	0.2086	1.197	1.586	1.701	2.036	1.3617
Moderate Motivation	0.8991	1.021	1.129	1.158	1.134	0.9087

The multinomial logistic regression revealed statistically significant differences across all age groups and classes, with the reference group being 11-year-olds in the High Motivation class. At age 11, youths are approximately 5 times less likely to belong to the Low Motivation class compared to the reference group, while their odds of belonging to the Mixed Motivation class are about the same. For the Low Motivation class, the odds of membership increase steadily with age, peaking at age 15, before slightly decreasing at age 16, from twice as likely to 1.36 times as likely. This supports the pattern observed in Figure 12, suggesting that these individuals may have shifted to the High Motivation class. In contrast, the odds for the Moderate Motivation class remain relatively stable across ages, with a slight decrease at age 11 and 16. These findings highlight a shift toward lower motivation as youths age, with the slight exception of 16-year-olds, generally supporting H2(b).

Between ages 12 and 15, there is a notable shift toward mixed motivation and greater reliance on external

The sudden increase in motivation for PA around age 16 may reflect several developmental and social fac-

Conclusion

This study examined how perceived exercise motives influence PA across developmental stages and how age shapes dominant motives within youth and adult groups. Specifically, it addressed the research questions: (1) Do perceived exercise motives influence PA differently in youths and adults? and (2) How do age differences shape dominant exercise motives within youth and adult groups? The findings provide some support for the proposed hypotheses. Results indicated that exercise motives do differ in their influence on PA across age groups, generally supporting Hypothesis 1. However, the patterns for social and relaxation motives did not align with predictions: social motives were stronger in adults rather than youths, and relaxation motives were stronger in youths rather than adults, meaning H1(a) and H1(b) are only partially supported. Hypothesis 2 was largely supported. Distinct motivational profiles were identified within both youths and adults. Consistent with H2(a), motivation among adults gradually declined with age, with the oldest adults exhibiting the steepest drop to low motivation. H2(b) was only partially supported, as a similar gradual decline in high motivation class membership was observed among youths, but a sharp increase occurred in the oldest youth group.

Policy Implications

For adolescents, policies should prioritize autonomy and intrinsic motivation. Choice in activity type, intensity, and scheduling can sustain engagement. Fun, low-pressure activities are recommended since relaxation and stress relief are key motives. Social interaction remains important but should focus on cooperative play without performance pressure. Around age 16, adolescents gain more control over their schedules. Policies should support this by providing access and guidance for self-directed activity to help translate newfound autonomy into sustained participation.

For adults, structural and social opportunities strongly influence PA. Workplace initiatives, flexible scheduling, and accessible community facilities can reduce the opportunity cost of PA for those balancing work, family, and other responsibilities. As intrinsic motives like enjoyment may decline with age, social motives can sustain engagement through extrinsic reinforcement. Policies should also address differential access, particularly for women with domestic responsibilities, by providing inclusive, low-barrier options.

In older adulthood, declines in intrinsic motivation and physical capacity necessitate targeted environmental and social support. Policies should prioritize safe, accessible spaces for light-to-moderate activity and structured programs that provide social interaction, alongside more facilities or green spaces (Kilgour, 2024).

The developmental patterns observed suggest that motivation toward PA is dynamic across the lifespan. Future research should examine longitudinal trajectories of motivation and investigate how interventions can effectively support intrinsic and extrinsic regulation across different age groups.

Limitations

Several limitations may affect the interpretation of these results. All data were self-reported and therefore susceptible to recall errors, comprehension difficulties, and social desirability bias, especially among students responding under teacher supervision. The adult sample, collected primarily online, may underrepresent individuals with limited digital literacy or internet access, such as older adults or lower-income households. Allowing up to two respondents per household could have increased intra-household similarity, and minor differences between online and paper formats may have affected reported PA or demographic details. To ensure comparability, only motive items with identical or near-identical wording were retained, possibly omitting relevant constructs. PA measures were highly skewed, though the use of medians and response collapsing mitigated non-normality. Analyses focused on moderate-to-vigorous PA, which may underestimate meaningful engagement among older adults who benefit from light activity. Finally, demographic factors such as socioeconomic status, weight, education, relationship status were not considered, and the cross-sectional design prevents causal inference about developmental changes in motivation or behaviour. Due to computational limitations, BLRT only had 5 reps.

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Appendix A - Survey Questions

Adults

Table 5: Adult survey questions.

Variable	Original 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 6: Youth survey questions.

Variable	Original 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

Adult

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 raverercise or body jam)
- Dance-based class (e.g. Zumba, fitsteps, raverercise 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

Youth

Moderate and vigorous activities are encompassed under the same variable (original variable name: mins_modplus_outschool_Week_ALL). Definition: 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 activities 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 - Likert-Scale Response Summary Statistics

Table 7: 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 8: 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 - LCA Models and Fit Indices

Adult

Table 9: LCA fit indices, adults.

nclass	llike	AIC	BIC	Rel.Entropy	LMR	p
2	-1109600	2219314	2219864	0.8908	295306	0
3	-1097393	2194960	2195800	0.8916	23736	0
4	-1063172	2126578	2127708	0.7945	66540	0
5	-1051546	2103386	2104807	0.7968	22605	0
6	-1043751	2087857	2089567	0.7980	15156	0
7	-1251957	2504327	2506327	0.9931	-404839	1

Table 10: BLRT results, adults.

test	H0_llik	X2loglik_diff	npar	mean	s.e.	p
2 vs 1	-1261474	303747	28	37.83	10.158	0
3 vs 2	-1109600	24414	28	43.09	8.093	0
4 vs 3	-1097393	68442	28	3860.44	8531.979	0
5 vs 4	-1063172	23251	28	46.22	5.767	0
6 vs 5	-1051546	15590	28	51.65	5.543	0
7 vs 6	-1043751	-416411	28	37.03	16.117	1

Youth

Table 11: LCA fit indices, youths.

nclass	llike	AIC	BIC	Rel.Entropy	LMR	p
2	-207816	415711	416032	0.8436	53567	0
3	-203336	406791	407286	0.7998	8679	0
4	-201018	402198	402866	0.7473	4489	0
5	-215798	431800	432642	0.8382	-28629	1
6	-223382	447010	448025	0.9577	-14690	1
7	-230114	460516	461704	0.9897	-13040	1

Table 12: BLRT results, youths.

test	H0_llik	X2loglik_diff	npar	mean	s.e.	p
2 vs 1	-235471	55309	19	25.40	11.693	0
3 vs 2	-207816	8961	19	26.85	7.667	0
4 vs 3	-203336	4635	19	26.49	4.933	0
5 vs 4	-201018	-29560	19	26.57	11.658	1

Appendix E - R Code (Data Cleaning)

NOTE: The initial section of the code, which handles basic reading and processing of the raw data files, has been commented out since the data were saved as RDS objects to reduce computation time during report knitting.

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

> library(tidyverse)

> # 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
$ PLEnjoy_bc_ans <int> 4, 1, 2, 2, 1, 5, 1, 4, 2, 1, 2, 1, 1, ~
$ PLConf_bc_ans <int> 4, 1, 2, 3, 1, 2, 1, 2, 1, 1, 2, 2, 2, ~
$ PLEasy_bc_ans <int> 4, 2, 2, 3, 2, 3, 2, 2, 2, 1, 5, 3, 3, ~
$ PLGdMe_bc_ans <int> 1, 1, 2, 2, 1, 1, 1, 2, 5, 1, 2, 1, 2, ~
$ PLKnow_c_ans <int> 2, 2, 2, 2, 1, 2, 1, -98, -98, -98, -9~
$ MOOpp_c <int> 1, 2, 2, 2, 1, 2, 1, -98, -98, -98, -9~
$ MOFit_c <int> 99, 1, 2, 3, 2, 2, 1, -98, -98, -98, -~
$ MORelax_c <int> 3, 1, 3, 3, 2, 3, 1, -98, -98, -98, -9~
$ MOFun_c <int> 4, 2, 3, 2, 3, 3, -98, -98, -98, -9~
$ MOGuilt_c <int> 4, 1, 2, 3, 1, 4, 2, -98, -98, -98, -9~
$ MOHaveto_b_36 <int> -98, -98, -98, -98, -98, -98, 1, ~
$ MOHaveto_c_711 <int> 2, 4, 3, 3, 3, 2, 4, -98, -98, -98, -9~
$ PRFam_c <int> 4, 3, 2, 3, 3, 2, 3, -91, -91, -91, -9~
$ PROth_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, 1, 2, ~
$ outdoor_bcd_Overall <int> 3, 3, 3, 2, 3, 3, -98, -98, -98, -9~
$ Exeramt_bc <int> 1, 2, 1, 1, 1, 1, 3, 1, 1, 3, 1, 1, ~
$ ExeramtMore_bc1_2 <int> 1, -98, 0, 1, 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, 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, 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, -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, 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, ~
$ motivvb_POP <int> 1, 2, 2, 2, 3, 2, 2, 3, 2, 3, 1, 1~
$ motivvc_POP <int> 2, -95, -98, 2, 3, 2, 2, -99, 3, 4, 3, 3~
$ motivvd_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, 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, 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, -98, 2~
$ DUR_HVY_CAPPED_SPORTCOUNT_A01 <dbl> 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~
$ 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, 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, ~
$ 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, 1, 0, 0, ~
$ motivex2a_GR2 <int> 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1~
$ motivvc_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, 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 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 F - R Code (SEM)

```
> ##### SEM Process #####
>
> # 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
+   ,

> 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 G - 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=5)
> # 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)

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

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

> # 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))

> colnames(or.ch) <- c("11 (ref)", "12", "13", "14", "15", "16")

> rownames(or.ch) <- c("Low Motivation", "Moderate Motivation")

> 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 = 5)
> # 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)

> # 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))

> colnames(or.ad) <- c("16-34 (ref)", "35-44", "45-54", "55-64", "65-74", "75+")

> rownames(or.ad) <- c("Low Motivation", "Mixed Motivation")

> 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")

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

```

Appendix H - R Code (Visualization)

```
> ##### All visualizations used in final report #####
> 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 = TRUE),
+   Median = median(mins_modplus_outschool_Week_ALL[mins_modplus_outschool_Week_ALL > 0 ], na.rm = TRUE),
+   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)

> # 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()

> # 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()

> # 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 Curve, Youths",
+       caption = "Blue = BIC, Red = AIC") +
+   theme_clean()

> 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()

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

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

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

> 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()

> 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),
+         , axis.text.x = element_text(size = 5))

> # 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 Curve, Adults",
+        caption = "Blue = BIC, Red = AIC") +
+   theme_clean()

> 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()

> # 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.class4.ad <- data.frame(
+   Class = 1:ncol(post4.ad),
+   Proportion = as.numeric(class.size4.ad),

```

```

+   Avg_Posterior = round(ave.pp4.ad, 4)
+ )

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

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

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

> 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.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()

> 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 = 5))

> # 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 I - 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

gg.vars.ad

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

gg.vars.ch

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

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'))

gg.elbow.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'))  
opts <- options(knitr.kable.NA = '')  
kable(list(ad.lca.output),align='c',booktabs = T) %>%  
  kable_styling(position = 'center', font_size = 10,  
                latex_options = c('striped',  
                                   'hold_position'))  
opts <- options(knitr.kable.NA = '')  
kable(list(blrt.ad$output),align='c',booktabs = T) %>%  
  kable_styling(position = 'center', font_size = 10,  
                latex_options = c('striped',  
                                   'hold_position'))  
opts <- options(knitr.kable.NA = '')  
kable(list(ch.lca.output),align='c',booktabs = T) %>%  
  kable_styling(position = 'center', font_size = 10,  
                latex_options = c('striped',  
                                   'hold_position'))  
opts <- options(knitr.kable.NA = '')  
kable(list(blrt.ch$output),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)
```