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Application of Second-Order Growth Mixture Modeling (SO-GMM) to Longitudinal TBI Outcome Research: 15-year Trajectories of Life Satisfaction in Adolescents and Young Adults (AYA) as an Example

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Abstract

Objective.—To demonstrate the application of Second-Order Growth Mixture Modeling using life satisfaction among adolescents and young adults with TBI up to 15 years post-injury.

Design.—SO-GMM, a data-driven modeling approach that accounts for measurement errors, was adopted to uncover distinct growth trajectories of life satisfaction over 15 years post-injury. Membership in growth trajectories was then linked with baseline characteristics to understand the contributing factors to distinct growth over time.

Setting.—Traumatic Brain Injury Model System National Database

Participants.—3,756 AYAs with TBI aged 16 - 25 (M_{age}=20.49, SD_{age}=2.66; 27.24% female)

Interventions.—Not Applicable

Main Outcome Measures.—Satisfaction with Life Scale

Results.—Four quadratic growth trajectories were identified: *low-stable* (16.6%) that had low initial life satisfaction and remained low over time; *high-stable* (49.3%) that had high life satisfaction at the baseline and stayed high over time; *high-decreasing* (15.8%) that started with high life satisfaction but decreased over time; and *low-increasing* (18.2%) that started with low life satisfaction but increased over time. Sex, race, pre-injury employment status, age, and FIM cognition were associated with group assignment.

Conclusion.—This study applied SO-GMM to a national TBI database and identified four longitudinal trajectories of life satisfaction among AYAs with TBI. Findings provided data-driven evidence for development of future interventions that are tailored at both temporal and personalized levels for improved health outcomes among AYAs with TBI.

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Keywords

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Traumatic brain injury (**TBI**) poses a recognized threat to the health of U.S. populations. The Centers for Disease Control and Prevention (**CDC**) estimated that the TBI-related emergency department visits have increased dramatically in the past decade[1]. Individuals aged 16 to 25, commonly referred as adolescents and young adults (**AYAs**), have been recognized as in the "age of transformation" [2]. AYAs are particularly vulnerable to TBI, with a total of 55,616 TBI-related deaths estimated by CDC from 2008 to 2014, caused mostly by motor vehicle crashes and falls [3]. Increasing research has demonstrated both short-term and long-term impact of TBI on AYAs, including fatigue [4,5], participation [5], substance use [6], risks of attempted suicide [7], and health-related quality of life [5].

Despite the prevalence of TBI and its significant impact on AYAs, limited research has been published on how TBI impacts the long-term trajectories of post-injury outcomes among AYAs[1]. This is particularly true for *life satisfaction* – a critical rehabilitation outcome for AYAs with TBI – because individuals who experience TBI at earlier stages of life may experience continuous challenges in cognitive, emotional, and social domains, which would cloud the long-term life satisfaction throughout their life-span development [8]. Life satisfaction can be measured by several ways, including self-reported questionnaires as a single construct [9–11] or multifaceted construct that encompasses self-evaluation of physical, cognitive, and social emotional well-beings [12], interviews [13], or more recently patient-centered dairies supported by the ecological momentary assessment approach for intensive longitudinal measurement [14]. Yet few studies address the longitudinal trajectories of life satisfaction among AYAs with TBI. Most research focused on either children or adults[15] or a mixed sample with wide age ranges [16,17]. Further, most data were analyzed using techniques that often assumed individuals with TBI are a homogenous group; yet this may not be the case especially when the recovery outcomes are examined in the long term, considering the various injury mechanisms, severity, and socio-demographic factors of the patient family [18,19].

Recent advancements in statistical methodologies such as growth mixture modeling (**GMM**) have equipped us well to tackle sample heterogeneity by identifying latent classifications of recovery courses among subpopulations[20]. As a result, GMM has been used in clinical and health research on many topics including health behaviors [20,21], psychopathology disorders [20], and osteoarthritis progression [22]. Although few specifically addressed AYAs with TBI, a similar trend was found in applying GMM to TBI outcome research[18]. However, there are two important limitations in current practices. The first limitation concerns data sources. For example, one study adopted a variant of GMM named group-based trajectory modeling (**GBTM**) to analyze a population-based national survey dataset (Medical Expenditure Panel Survey) to examine perceived health status among adults with TBI [23]. However, population-based databases were not designed for the sole purpose of tracking TBI patients. The rarity of TBIs in the general population often results in relatively moderate sample sizes and shorter follow-up periods (2 years in MEPS) compared to national databases dedicated to track TBI patients [23,24] Prospectively-designed studies targeting the young adult population suffer from similar disadvantages in sample size and many focused on athletes with mild TBI [25] but not moderate to severe TBIs, which constitute a significant long-term rehabilitation burden for both the survivors and their families [26,27].

The second, and perhaps more important limitation in existing literature, is that when applying GMM to TBI outcome research, growth trajectories were usually estimated based on mean or sum composite scores across multiple items that measure a construct, such as sum of items in a life satisfaction scale [28]. At issue is the fact that when composite scores are created, it is assumed that all items contribute equally to the measurement of the underlying construct (e.g., life satisfaction) and that there is no measurement error across items of that scale, which may not often be the case. To address this, second-order GMM (**SO-GMM,** Figure 1 **right**) has been recommended[29,30]. SO-GMM incorporates a measurement model for the underlying construct and thus explicitly models the relations of items to the construct in the first order level, allowing for the presence of different weights across items (i.e., factor loadings) and measurement errors. In the second-order level, distinct growth trajectories can then be estimated based on the latent construct which more accurately reflects the longitudinal outcome of interest.

Despite these methodological advantages, we have yet to find any application of SO-GMM in TBI research. To address this important gap, this paper aimed to demonstrate a rigorous application of SO-GMM to TBI outcome research using life satisfaction among 3,756 AYAs with TBI from the Traumatic Brain Injury Model System National Database (**TBIMS-NDB**) up to 15 years post-admission as an example.

Method

Data Source

This study used the TBIMS-NDB (April 2020)[31]. TBIMS-NDB is the country’s first and largest prospective, longitudinal multi-center database dedicated to examining the rehabilitation trajectories and follow-up outcomes for individuals at least 16 years old treated for inpatient rehabilitation at one of the participating TBIMS centers and meet one of the following criteria: (1) Glasgow Coma Scale (**GCS**) score below 13 when assessed at the emergency department, or (2) more than 24 hours of post-traumatic amnesia, or (3) intracranial neuroimaging abnormalities, or (4) loss of consciousness for more than 30 minutes[32]. The TBIMS-NDB collected data using post-injury repeated surveys at regular intervals, with baseline information (Form I) collected in-person at inpatient rehabilitation discharge and follow-up information (Form II) collected at 1, 2, 5, and every 5 years thereafter up to 30 years post-injury, administered via telephone, in-person or mail questionnaires. Previous research has supported the representativeness of TBIMS-NDB for patients receiving hospitalization and inpatient rehabilitation for TBI in the U.S., especially for patients under 65[33]. All participants were consented at participating centers according to established standard operating procedures (SOPs) approved by local IRBs and published on TBIMS website (https://www.tbindsc.org/SOP.aspx).

Study Population

The study population was adolescents and young adults aged 16-25 in the TBIMS-NDB. The sample consisted of 3,756 individuals (Age: M = 20.49, SD = 2.66). Most of the sample (72.76%) were males, white (65.41%), employed at baseline (63%).

Outcome variable

Life satisfaction.—Life satisfaction is derived from five items of Satisfaction with Life Scale (**SWLS**) in the TBIMS-NDB: "*In most ways my life is close to my ideal*" , "*The conditions of my life are excellent*", "*I am satisfied with my life*" , "*So far I have gotten the important things I want in life*" , and "*If I could live my life over, I would change almost nothing*" in Form 2. Item scores ranged from 1 to 7[9,34]. Higher values indicated greater life satisfaction. Given that SO-GMM can directly incorporate the measurement model, all five items were used in the analysis without averaging or summing.

Covariates

*Functional Independence Measure (**FIM**) Cognitive on Admission:* sum of five FIM cognitive items with each item ranging from 1 (total assist) to 7 (complete independence) Therefore, higher values of this variable indicated greater cognitive independence[35].

Pre-injury disability: "*blindness, deafness, or a severe vision or hearing impairment*" and "*a condition that substantially limited one or more basic physical activities such as walking, climbing stairs, reaching, lifting, or carrying*" in Form 1. All pre-injury disability covariates were scored as "Yes[1]" or "No[2]"[36]

TBI severity: TBI severity was a categorical variable in Form 1 with three categories used in this study: mild[3], moderate[2], or severe[1] based on patients' total GCS scores[37].

Demographics: age at injury (AGENoPHI), sex (SEX), race (RACE), pre-injury employment status (EMPLOYMENT) in Form 1.

Statistical Analyses

First, descriptive analyses were conducted for the outcome and all covariates. Second, longitudinal measurement invariance (**MI**) was tested to ensure that changes in outcomes over time originated from changes in the construct, rather than measurement properties. Three levels of invariance were tested sequentially: configural, metric and scalar invariance that imposes constraints on equal factor structure, equal factor loadings, and equal intercepts over time, respectively. The fit of invariance models was compared: a non-significant Satorra-Bentler scaled chi-square difference test, change in comparative fit index (**CFI**) less than .01[38], and change in root mean square error of approximation (**RMSEA**) less than .015[39] indicated that imposing constraints on the measurement parameters did not deteriorate fit significantly and thus the tested level of invariance was established.

Next, the optimal growth function (linear or quadratic) was determined using second-order latent growth models (**SO-LGM**) which is identical to SO-GMM with one class. The fit of SO-LGMs with linear or quadratic growth was compared with Akaike's information criterion (**AIC**)[40], Bayesian information criterion (**BIC**)[41], and sample-size-adjusted BIC (**saBIC**)[42]. Growth function that had smaller values of these criteria was supported. We also performed visual inspection of the growth trajectories to determine growth function. Then, SO-GMM was conducted by fitting models with varying numbers of latent classes using M*plus* 8.4[43]. To decide the optimal number of latent classes, model fit was compared based on AIC, BIC, saBIC, the Lo-Mendell-Rubin (LMR) likelihood ratio test[44], adjusted LMR, and the bootstrap likelihood ratio test (BLRT)[45,46]. The latter three tests compared the fit of a k-class model versus a (k-1)-class model and p-values less than .05 indicate that the k-class model had significantly better fit to the data. Substantive interpretability was also examined in model selection to ensure that the best-fitting model provided theoretically sound solutions.

Finally, subsequent analyses were conducted using SAS software to examine the relationships between latent class membership and covariates. Specifically, chi-square tests of independence were performed for categorical covariates, i.e., pre-injury conditions, TBI severity, sex, race, and employment status. Depending on the number of latent classes, t-tests (two classes) or ANOVAs (three or more classes) were conducted for continuous covariates, including age and FIM cognition.

An in-depth version of the statistical analysis plan can be found in Supplementary Materials.

Results

Descriptive Statistics

Table 1 presents descriptive statistics for all the five items of life satisfaction across the 15 years of follow-up. Among the five items, slightly higher responses were observed for "*I am satisfied with my life*" and lower response were observed for "*If I could live my life over, I would change almost nothing*". Inspection of skewness and kurtosis showed that all item responses were approximately normally distributed. Table 2 presents descriptive statistics for all the baseline covariates. Most participants (97.14% and 97.28% respectively) did not have pre-injury impairment and physical limitations. About half (49.85%) had mild TBI, followed by 30.25% severe and 19.90% moderate TBI.

Longitudinal Measurement Invariance

Table 3 presents the longitudinal measurement invariance testing results. Comparing the fit of configural and metric invariance models supported the establishment of metric invariance, ΔCFI < .01 and ΔRMSEA < .015. Similarly, scalar invariance was supported based on ΔCFI and ΔRMSEA, despite that the Satorra-Bentler chi-square difference test was significant.

SO-GMM

Prior to examining the number of optimal classes in SO-GMM, growth function was first examined by comparing the fit of a linear and quadratic SO-LGM. The quadratic growth model was chosen supported by smaller AIC, BIC, and saBIC (Table 4). Subsequently, a series of quadratic SO-GMMs with varying numbers of classes (K = 1 to 7) were fitted. We did not examine SO-GMM with 8 or more classes because one class of the seven-class SO-GMM had a small proportion of the sample (below 5%). Inconsistency among approaches to model fit comparisons was observed that the seven-class model was supported by AIC, saBIC, and BLRT whereas BIC showed the six-class had the best fit. However, the decrease in ICs was more substantial as K increased from 1 to 4 but leveled off with 5 or more classes. LMR and aLMR also favored four-class over five-class model. Therefore, we concluded that the four-class quadratic SO-GMM was the best-fitting model.

We further checked the interpretability of the four-class solution by examining the estimated growth trajectories across classes (Figure 2). Specifically, we extracted the estimated factor scores of life satisfaction at each time point and standardized the factor scores by creating Z-scores. The *high-stable* class (55%) had very high intercept and individuals' life satisfaction remained high over time. Both the linear and quadratic slopes (.78 and −.84, respectively) were statistically significant. The *low-stable* class (17%) was characterized by a low intercept at baseline and life satisfaction remained low over time. The *high-decreasing* class (11%) had high intercept, decrease in life satisfaction until the 10-year follow-up, and then increase from the 10-year to 15-year follow-up. By contrast, the *low-increasing* class (17%) had low intercept, increase until the 10-year follow-up, and then decrease afterwards. Linear and quadratic slopes were both significant, −6.77 and 5.19 for the *high-decreasing* class and 8.13 and −6.65 for the *low-increasing* class, respectively.

Latent Class Membership and Covariates

Age, sex, race, employment status, and FIM cognition showed significant relationships with latent class membership (Table 5). That is, a higher proportion of females (19.55%) were assigned to the *low-increasing* class than males (15.81%). Among racial groups, a smaller proportion of Black individuals (39.50%) belonged to the *high-stable* class as compared with White (59.59%) – Blacks were more likely to be in any of the other three classes instead. No significant relationships were found for Hispanic and other racial groups when using White as the reference group. Individuals that were unemployed at baseline were less likely to be in the *high-stable* class (41.92%) than those that were employed (56.96%). Particularly, the unemployed tended to be in the *low-stable* class. By contrast, more people who identified themselves as students (60.92%) were in the *high-stable* class than the employed. Individuals in the *high-stable* class tended to be younger and have higher FIM cognition scores than those in the *low-stable* and *low-increasing* classes.

Discussion

This study demonstrated the use of SO-GMM to analyze longitudinal health outcomes (e.g., life satisfaction) in a large sample of AYAs with TBIs. After testing the longitudinal measurement invariance for the five-item life satisfaction scale, the study found four distinct longitudinal trajectories developed over 15 years after admission: low-stable, high-stable, high-decreasing, and low-increasing. Age, sex, race, employment status, and FIM cognition were found to be significantly associated with trajectory membership. Several contributions of this study are worth noting.

First, this study is the first to apply a rigorous SO-GMM methodology to TBI outcome research. Existing research examining longitudinal TBI outcomes using sophisticated statical modeling techniques such as HLM [47] or GMM [28] have often treated a measurement scale for a latent construct as a single averaged/summed score across all items. Such an approach, despite its commonality, not only resulted in potential loss of information when creating a single composite score out of multiple scale items, but more importantly assumed (without testing) that all items in the Satisfaction with Life Scale contributed equally to the underlying latent construct - life satisfaction - without any measurement error. The SO-GMM approach addressed this critical limitation by rigorously testing the longitudinal measurement invariance and using all measured items directly in the modeling process. Therefore, all growth curve modeling and analyses of covariates were conducted under a statistical framework that satisfied its original assumptions.

Second, this study focused on the long-term life satisfaction among a unique group – AYAs with TBI. As a patient population in a critical transitional period physically and psychologically, AYAs experience rapid changes in personal life and career development hence are particularly vulnerable to the long-term detrimental effects of TBI. For example, research suggested that AYAs with TBI are more likely to report more fatigue and fewer physical activities [48], reduced reading ability [49], and more suicidal attempts[7]. Moreover, post-TBI rehabilitation may add significant economic and psychological burdens to families and society[24,50]. However, prior to the present study, long-term life satisfaction research has not sufficiently attended the AYA population with TBI, although existing research in the adult TBI population did suggest patients with various characteristics may develop differentiated trajectories over time, consistent with the current findings [28,47]

Third, findings of four distinct long-term trajectories and their associated covariates among AYAs with TBI were consistent with previous research examining life satisfaction among general population with TBI. For example, one recent study examined life satisfaction among 3012 patients with TBI over a five-year follow-up period revealed similar four-group trajectories as the best fitting model [28]. It was also consistent with existing literature that certain demographic and baseline clinical characteristics were significantly associated with trajectory membership, such as age, sex, race, and employment status. For instance, previous research has indicated that Black children were less likely to receive medical treatment than those of other racial groups, even after controlling for other socio-demographic characteristics such as age, sex, family income, parental education, and health insurance status [24]. Consistent with current findings, such lags in receiving medical care from TBI could lead to negative impact on longterm health outcomes [51]. Such findings reinforce the call for more health disparity research among disadvantaged populations. Interestingly though, the present study did not find TBI severity or pre-injury condition (impairment or limitation) as significant predictors of long-term life satisfaction trajectories. Although this finding appears in contrast with existing data from the general TBI population, [52,53] it is not surprising considering this study sample were AYAs who may have greater developmental plasticity (and generally longer time to recover after injury) than those injured at a later developmental stage [54].

Study Limitations

Several important limitations of the present study should also be noted. First, despite the benefits of SO-GMM in considering measurement errors while identifying heterogeneous trajectories, there are unresolved methodological issues in measurement invariance testing that warrant future investigations. In SO-GMM, measurement invariance across classes is needed for valid comparison of growth factors between trajectories; however, it remains unclear how to test invariance across classes when the tasks of testing longitudinal measurement invariance and identifying heterogeneous growth patterns are both present in TBI outcome research. Accordingly, measurement invariance across classes was assumed in this study but future research is needed to identify an optimal approach to testing invariance across classes in conjunction of other tasks in SO-GMM. Second, due to the nature of the TBIMS-NDB database, all patients included in this study sample must be treated at one of the sixteen participating centers, limiting the generalizability of the findings. Third, because the primary goal of this paper is to introduce SO-GMM to the TBI research community, only one outcome and a selection of covariates were analyzed. This by no means a comprehensive or even representative selection. We look forward to hearing from fellow TBI researchers to explore the utility of SO-GMM in other domains in future studies.

Conclusions

This is the first study applying SO-GMM to examine longitudinal rehabilitation outcomes among AYAs with TBI, enabling researchers to utilize all measurement information. Findings of the study could also inform evidence-based design of future rehabilitation programs based on the temporal and individualized characteristics to improve long-term outcomes for this vulnerable population.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Abbreviations:

AIC	Akaike's information criterion
AYA	adolescent and young adult
BIC	Bayesian information criterion

CDC	Centers for Disease Control and Prevention
CFI	comparative fit index
GBTM	group-based trajectory modeling
GCS	Glasgow Coma Scale
GMM	growth mixture modeling
MI	measurement invariance
saBIC	sample-size-adjusted BIC
SO-GMM	second-order growth mixture modeling
SO-LGM	second-order latent growth models
SRMR	standardized root mean square residual
RMSEA	root mean square error of approximation
TBI	traumatic brain injury
TBIMS-NDB	Traumatic Brain Injury Model System National Database

References

1. Centers for Disease Control and Prevention. Report to Congress on the Management of Traumatic Brain Injury in Children. Atlanta, GA: National Center for Injury Prevention and Control; Division of Unintentional Injury Prevention. Accessed 3–1-18. [Google Scholar];2018.
2. Sawyer SM, Azzopardi PS, Wickremarathne D, Patton GC. The age of adolescence. The Lancet Child & Adolescent Health. 2018;2(3):223–228. [PubMed: 30169257]
3. Taylor CA, Bell JM, Breiding MJ, Xu L. Traumatic brain injury–related emergency department visits, hospitalizations, and deaths—United States, 2007 and 2013. MMWR Surveillance Summaries. 2017;66(9):1.
4. Norup A, Svendsen SW, Doser K, et al. Prevalence and severity of fatigue in adolescents and young adults with acquired brain injury: a nationwide study. Neuropsychological rehabilitation. 2017.
5. van Markus-Doornbosch F, van der Holst M, de Kloet AJ, Vliet Vlieland TP, Meesters JJ. Fatigue, participation and quality of life in adolescents and young adults with acquired brain injury in an outpatient rehabilitation cohort. Developmental neurorehabilitation. 2020;23(5):328–335. [PubMed: 31746261]
6. Mackelprang JL, Harpin SB, Grubenhoff JA, Rivara FP. Adverse outcomes among homeless adolescents and young adults who report a history of traumatic brain injury. American journal of public health. 2014;104(10):1986–1992. [PubMed: 25122029]
7. Chang H-K, Hsu J-W, Wu J-C, et al. Risk of attempted suicide among adolescents and young adults with traumatic brain injury: a nationwide longitudinal study. Journal of affective disorders. 2019;250:21–25. [PubMed: 30826490]
8. Rivara FP, Koepsell TD, Wang J, et al. Disability 3, 12, and 24 months after traumatic brain injury among children and adolescents. Pediatrics. 2011;128(5):e1129–e1138. [PubMed: 22025592]
9. Diener E, Emmons RA, Larsen RJ, Griffin S. The satisfaction with life scale. Journal of personality assessment. 1985;49(1):71–75. [PubMed: 16367493]
10. Pavot W, Diener E. The satisfaction with life scale and the emerging construct of life satisfaction. The journal of positive psychology. 2008;3(2):137–152.

11. Emerson SD, Guhn M, Gadermann AM. Measurement invariance of the Satisfaction with Life Scale: reviewing three decades of research. Quality of Life Research. 2017;26(9):2251–2264. [PubMed: 28324322]
12. Harner CJ, Heal LW. The Multifaceted Lifestyle Satisfaction Scale (MLSS): Psychometric properties of an interview schedule for assessing personal satisfaction of adults with limited intelligence. Research in Developmental Disabilities. 1993;14(3):221–236. [PubMed: 8316684]
13. Mellor D, Cummins RA, Loquet C. The gold standard for life satisfaction: Confirmation and elaboration using an imaginary scale and qualitative interview. International Journal of Social Research Methodology. 1999;2(4):263–278.
14. Lenaert B, Colombi M, van Heugten C, Rasquin S, Kasanova Z, Ponds R. Exploring the feasibility and usability of the experience sampling method to examine the daily lives of patients with acquired brain injury. Neuropsychological rehabilitation. 2019;29(5):754–766. [PubMed: 28562164]
15. Ketchum JM, Almaz Getachew M, Krch D, et al. Characteristics associated with satisfaction with life 1 year post traumatic brain injury in a population of Hispanic individuals. NeuroRehabilitation. 2012;30(1):23–33. [PubMed: 22349839]
16. Meule A, Voderholzer U. Life satisfaction in persons with mental disorders. Quality of Life Research. 2020;29(11):3043–3052. [PubMed: 32556822]
17. Johnston MV, Goverover Y, Dijkers M. Community activities and individuals’ satisfaction with them: quality of life in the first year after traumatic brain injury. Archives of physical medicine and rehabilitation. 2005;86(4):735–745. [PubMed: 15827926]
18. Yeates KO, Taylor HG, Rusin J, et al. Longitudinal trajectories of postconcussive symptoms in children with mild traumatic brain injuries and their relationship to acute clinical status. Pediatrics. 2009;123(3):735–743. [PubMed: 19254996]
19. Covington NV, Duff MC. Heterogeneity is a hallmark of traumatic brain injury, not a limitation: A new perspective on study design in rehabilitation research. American journal of speech-language pathology. 2021;30(2S): 974–985. [PubMed: 33556261]
20. Nagin DS, Odgers CL. Group-based trajectory modeling in clinical research. Annual review of clinical psychology. 2010;6:109–138.
21. Caldeira KM, O’Grady KE, Garnier-Dykstra LM, Vincent KB, Pickworth WB, Arria AM. Cigarette smoking among college students: longitudinal trajectories and health outcomes. Nicotine & Tobacco Research. 2012;14(7):777–785. [PubMed: 22589418]
22. Verkleij SP, Hoekstra T, Rozendaal RM, et al. Defining discriminative pain trajectories in hip osteoarthritis over a 2-year time period. Annals of the rheumatic diseases. 2012;71(9):1517–1523. [PubMed: 22492782]
23. Feldman B, Shen J, Chen C, Shi J, Xiang H. Perceived health after adult traumatic brain injury: a Group-Based Trajectory Modeling (GBTM) analysis. Brain injury. 2020;34(6):741–750. [PubMed: 32320317]
24. Shen J, Shi J, Cooper J, Chen C, Taylor HG, Xiang H. A Population-Based Study of the Incidence, Medical Care, and Medical Expenditures for Pediatric Traumatic Brain Injury. Journal of Surgical Research. 2021;268:87–96. [PubMed: 34298211]
25. Henry LC, Elbin R, Collins MW, Marchetti G, Kontos AP. Examining recovery trajectories after sport-related concussion with a multimodal clinical assessment approach. Neurosurgery. 2016;78(2):232–241. [PubMed: 26445375]
26. Kumar RG, Ketchum JM, Corrigan JD, Hammond FM, Sevigny M, Dams-O’Connor K. The longitudinal effects of comorbid health burden on functional outcomes for adults with moderate to severe traumatic brain injury. The Journal of head trauma rehabilitation. 2020;35(4):E372–E381. [PubMed: 32108718]
27. Devi Y, Khan S, Rana P, et al. Cognitive, behavioral, and functional impairments among traumatic brain injury survivors: impact on caregiver burden. Journal of Neurosciences in Rural Practice. 2020;11(04):629–635. [PubMed: 33144802]
28. Juengst SB, Adams LM, Bogner JA, et al. Trajectories of life satisfaction after traumatic brain injury: Influence of life roles, age, cognitive disability, and depressive symptoms. Rehabilitation psychology. 2015;60(4):353. [PubMed: 26618215]

29. Ram N, Grimm KJ. Methods and measures: Growth mixture modeling: A method for identifying differences in longitudinal change among unobserved groups. International journal of behavioral development. 2009;33(6):565–576. [PubMed: 23885133]
30. Kim ES, Wang Y. Class enumeration and parameter recovery of growth mixture modeling and second-order growth mixture modeling in the presence of measurement noninvariance between latent classes. Frontiers in psychology. 2017;8:1499. [PubMed: 28928691]
31. Traumatic Brain Injury Model Systems Program. Traumatic Brain Injury Model Systems National Database. In. https://osf.io/a4xzb/ ed: Traumatic Brain Injury Model Systems National Data and Statistical Center; 2020.
32. Tso S, Saha A, Cusimano MD. The Traumatic Brain Injury Model Systems National Database: A Review of Published Research. Neurotrauma Reports. 2021;2(1):149–164. [PubMed: 34223550]
33. Corrigan JD, Cuthbert JP, Whiteneck GG, et al. Representativeness of the traumatic brain injury model systems national database. The Journal of head trauma rehabilitation. 2012;27(6):391. [PubMed: 21897288]
34. Pavot W, Diener E. Review of the satisfaction with life scale. Psychological Assesment, 5 (2), 164–172.Diunduh pada tanggal. 1993;16.
35. Linacre JM, Heinemann AW, Wright BD, Granger CV, Hamilton BB. The structure and stability of the Functional Independence Measure. Archives of physical medicine and rehabilitation. 1994;75(2):127–132. [PubMed: 8311667]
36. Council NR. The 2000 census: Counting under adversity. National Academies Press; 2004.
37. Teasdale G, Jennett B. Assessment and prognosis of coma after head injury. Acta neurochirurgica. 1976;34(1):45–55. [PubMed: 961490]
38. Cheung GW, Rensvold RB. Evaluating goodness-of-fit indexes for testing measurement invariance. Structural equation modeling. 2002;9(2):233–255.
39. Chen FF. Sensitivity of goodness of fit indexes to lack of measurement invariance. Structural equation modeling: a multidisciplinary journal. 2007;14(3):464–504.
40. Akaike H A new look at the statistical model identification. IEEE transactions on automatic control. 1974;19(6):716–723.
41. Schwarz G Estimating the dimension of a model. The annals of statistics. 1978:461–464.
42. Sclove SL. Application of model-selection criteria to some problems in multivariate analysis. Psychometrika. 1987;52(3):333–343.
43. Muthén LK, Muthén B. Mplus user's guide: Statistical analysis with latent variables, user's guide. Muthén & Muthén; 2017.
44. Lo Y, Mendell NR, Rubin DB. Testing the number of components in a normal mixture. Biometrika. 2001;88(3):767–778.
45. McCutcheon AL. Latent class analysis. Sage; 1987.
46. Peel D, McLachlan GJ. Robust mixture modelling using the t distribution. Statistics and computing. 2000;10(4):339–348.
47. Caplan B, Bogner J, Brenner L, et al. Trajectories of life satisfaction over the first 10 years after traumatic brain injury: race, gender, and functional ability. Journal of Head Trauma Rehabilitation. 2016;31(3):167–179. [PubMed: 25699619]
48. van Markus-Doornbosch F, Peeters E, van der Pas S, Vlieland TV, Meesters J. Physical activity after mild traumatic brain injury: What are the relationships with fatigue and sleep quality? European Journal of Paediatric Neurology. 2019;23(1):53–60. [PubMed: 30522904]
49. Pei Y, O'Brien KH. Reading abilities post traumatic brain injury in adolescents and adults: a systematic review and meta-analysis. American journal of speech-language pathology. 2021;30(2):789–816. [PubMed: 33755512]
50. Lalonde G, Bernier A, Beaudoin C, Gravel J, Beauchamp MH. Investigating social functioning after early mild TBI: The quality of parent–child interactions. Journal of Neuropsychology. 2018; 12(1):1–22. [PubMed: 27012315]
51. Rivara FP, Ennis SK, Mangione-Smith R, MacKenzie EJ, Jaffe KM, Indicators NEPftDoPRQC. Quality of care indicators for the rehabilitation of children with traumatic brain injury. Archives of physical medicine and rehabilitation. 2012;93(3):381–385. e389. [PubMed: 22280892]

52. Resch JA, Villarreal V, Johnson CL, et al. Trajectories of life satisfaction in the first 5 years following traumatic brain injury. Rehabilitation Psychology. 2009;54(1):51. [PubMed: 19618703]

53. Davis LC, Sherer M, Sander AM, et al. Preinjury predictors of life satisfaction at 1 year after traumatic brain injury. Archives of physical medicine and rehabilitation. 2012;93(8):1324–1330. [PubMed: 22840830]

54. Laubach ZM, Perng W, Dolinoy DC, Faulk CD, Holekamp KE, Getty T. Epigenetics and the maintenance of developmental plasticity: extending the signalling theory framework. Biological Reviews. 2018;93(3):1323–1338. [PubMed: 29356358]

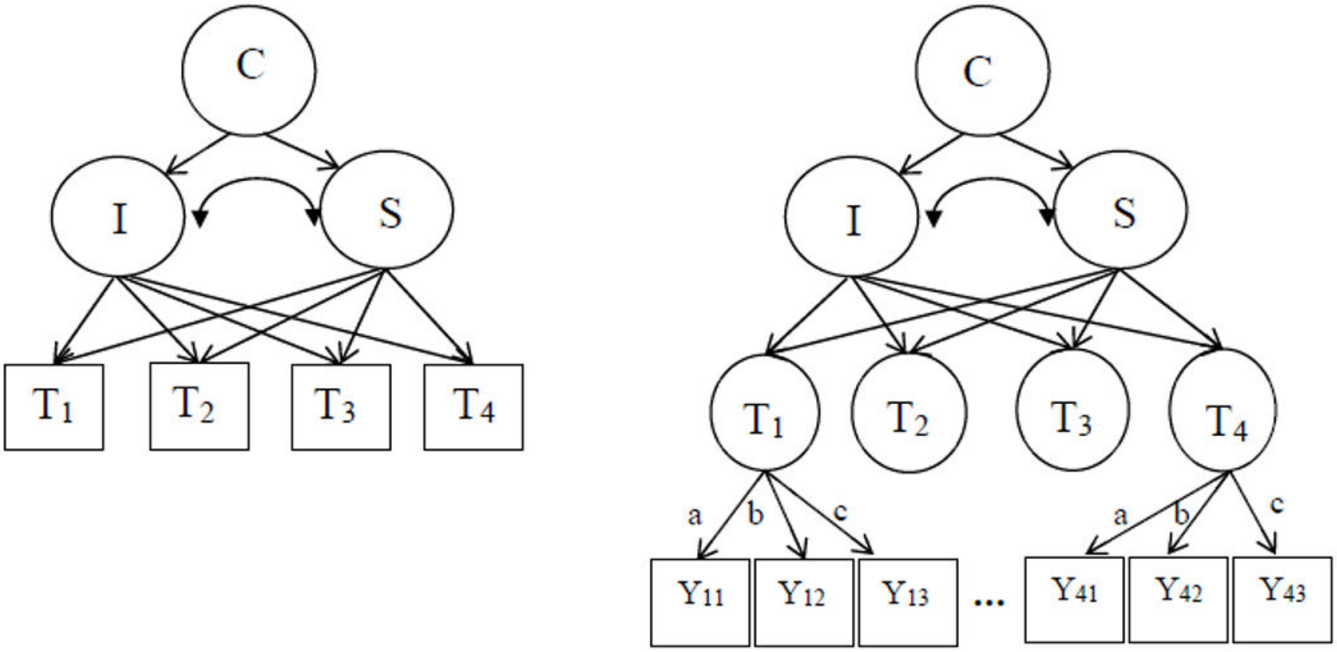

Figure 1.
Growth Mixture Modeling (GMM; left) and Second-Order Growth Mixture Modeling (SO-GMM; right). C = latent class variable; I = intercept; S = slope (assuming linear growth); T1 – T4 are observed longitudinal outcome variables (squares) in GMM, but latent factors (circles) in SO-GMM. Y11 – Y43 are observed items of latent factors, T1 – T4. Note that Y21 – Y33 are not shown due to space limit. Paths a-c represent measurement invariance over time.

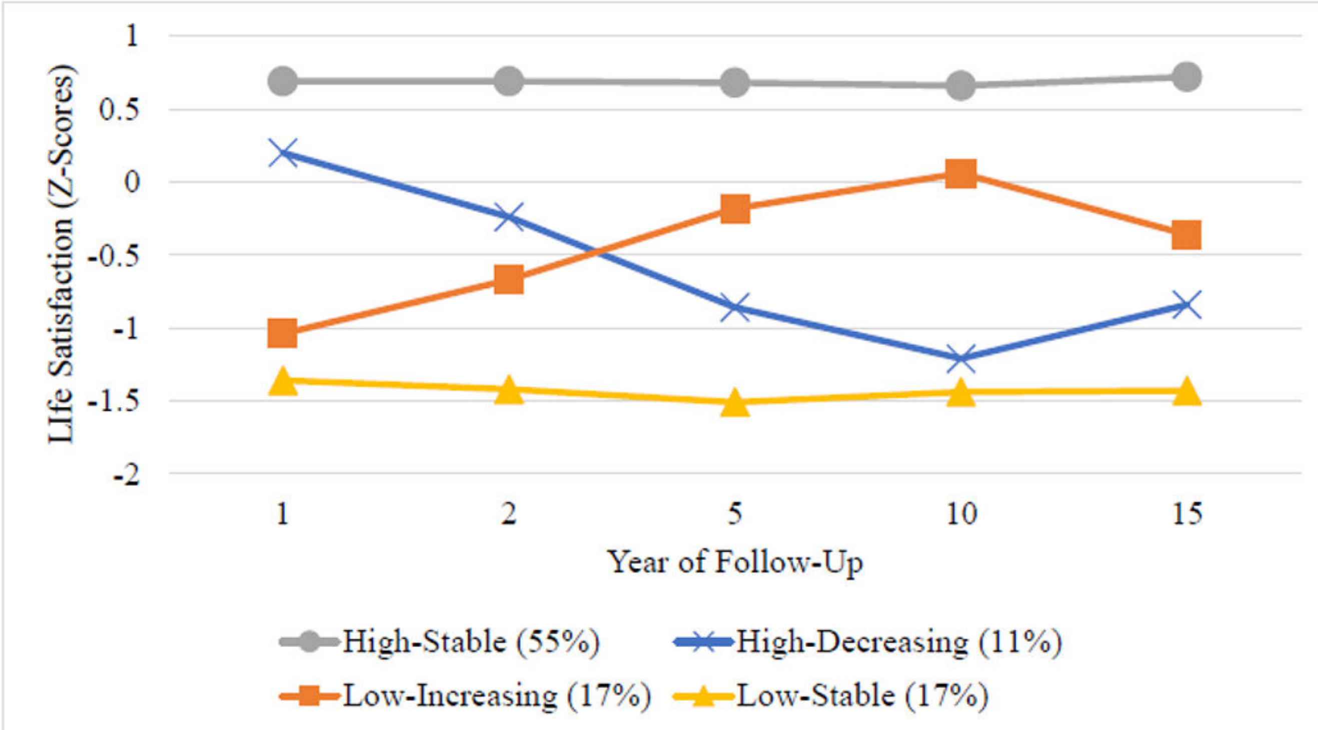

Figure 2.
Growth Trajectories of Satisfaction with Life

Table 1.

Descriptive Statistics for Life Satisfaction Across the 15-Year Follow-up Period

Variable	Year	N	Mean	SD	Skewness	Kurtosis
In most ways my life is close to my ideal	1	2988	4.29	1.99	−.32	−1.27
	2	2686	4.41	2.00	−.40	−1.23
	5	2121	4.52	2.00	−.47	−1.17
	10	1338	4.47	2.06	−.41	−1.25
	15	625	4.35	2.09	−.30	−1.30
The conditions of my life are excellent	1	2992	4.37	2.03	−.30	−1.30
	2	2688	4.56	1.98	−.46	−1.15
	5	2122	4.59	1.97	−.48	−1.15
	10	1339	4.56	1.99	−.44	−1.15
	15	626	4.46	2.04	−.40	−1.25
I am satisfied with my life	1	2992	4.90	1.96	−.75	−.79
	2	2687	5.03	1.87	−.86	−.53
	5	2122	5.02	1.90	−.83	−.62
	10	1339	5.00	1.92	−.83	−.60
	15	625	4.88	1.99	−.70	−.89
So far I have gotten the important things I want in life	1	2990	4.64	1.98	−.52	−1.10
	2	2685	4.64	1.97	−.54	−1.08
	5	2120	4.77	1.97	−.65	−.96
	10	1339	4.81	1.91	−.68	−.84
	15	626	4.75	2.04	−.58	−1.08
If I could live my life over, I would change almost nothing	1	2986	3.82	2.26	.10	−1.59
	2	2683	3.92	2.25	.03	−1.60
	5	2118	4.03	2.26	−.05	−1.61
	10	1338	4.06	2.27	−.06	−1.60
	15	626	3.87	2.23	.11	−1.57

Table 2.

Descriptive Statistics for Baseline Covariates

Continuous Covariates		**N**	**Mean**	**SD**
	Age	3701	20.49	2.66
	FIM Cognition	3731	15.53	7.77
Categorical Covariates		**Level**	**N**	**%**
	Gender			
		Females	1023	27.24
		Males	2733	72.67
	Race			
		White	2455	65.41
		Black	676	18.01
		Hispanic	418	11.13
		Others	204	5.44
	TBI Severity			
		Mild	824	49.85
		Moderate	329	19.90
		Severe	500	30.25
	Pre-Injury Employment Status			
		Employed	2358	63.34
		Student	783	21.03
		Unemployed	582	15.63
	Pre-Injury Impairment			
		No	2141	97.14
		Yes	63	2.86
	Pre-Injury Physical Limitation			
		No	2144	97.28
		Yes	60	2.72

Table 3.

Testing Results for Longitudinal Measurement Invariance

Model	# of Free Parameters	χ^2(df)	Scaling Correction Factor	RMSEA†	CFI‡	SRMR§	$\Delta\chi^2$(Δdf)	ΔCFI	ΔRMSEA
Configural invariance	88	1029(262) *	1.193	.028	.962	.046			
Metric invariance	72	1074(278) *	1.174	.028	.961	.047	39(16) *	−.001	.001
Scalar invariance	56	1118(294) *	1.162	.027	.960	.047	40(16) *	−.001	.000

Note.

* $p<0.05$;

† RMSEA = root mean square error of approximation;

‡ CFI = comparative fit index;

§ SRMR = standardized root mean square residual.

Table 4.

Second-Order Latent Growth Modeling (SO-LGM) and Second-Order Growth Mixture Modeling (SO-GMM) for Life Satisfaction

Model[a]	AIC	BIC	saBIC	LMR	aLMR	BLRT
Linear SO-LGM	183333	183620	183474	—	—	—
Quadratic SO-LGM (K = 1)	183301	183613	183454	—	—	—
Quadratic SO-GMM (K = 2)	183029	183334	183178	.0004	.0005	< .0001
Quadratic SO-GMM (K = 3)	182800	183129	182961	.0002	.0003	< .0001
Quadratic SO-GMM (K = 4)	182571	182927	182746	.0121	.0134	< .0001
Quadratic SO-GMM (K = 5)	182503	182883	182689	.0888	.0936	< .0001
Quadratic SO-GMM (K = 6)	182427	182832	182625	.0083	.0092	< .0001
Quadratic SO-GMM (K = 7)	182406	182836	182617	.2596	.2684	< .0001

Note. K = the number of classes; AIC = Akaike's information criterion; BIC = Bayesian information criterion; saBIC = sample-size-adjusted BIC; LMR = the Lo-Mendell-Rubin test; aLMR = adjusted LMR test; BLRT = the bootstrap likelihood ratio test. Values for the LMR, aLMR, and BLRT columns are the *p*-values of the test. "—" indicates that the test was not applicable for LGM because technically there was one class or one homogeneous sample with LGM and we could not compare the fit of 1-class and 0-class model. Variances of linear and quadratic slopes were constrained to be zero in SO-GMMs with K=2 or more.

Table 5.

Characterization of Latent Classes with Covariates

Covariates	Low-Stable	High-Stable	High-Decreasing	Low-Increasing	Test Statistic
Age	20.75[a]	20.34[b]	20.39[ab]	20.80[a]	7.14(3,3697) **
Sex					
Male	17.34%	55.54%	11.31%	15.81%	
Female	16.13%	54.64%	9.68%	19.55%	8.77(3) *
Race					
White	14.75%	59.59%	9.98%	15.68%	
Black	25.44%	39.50%	14.94%	20.12%	89.60(3) **
Hispanic	17.70%	55.26%	9.33%	17.70%	1.37(3)
Other	14.71%	55.88%	11.27%	18.14%	.93(3)
Employment Status					
Employed	15.90%	56.96%	10.05%	17.09%	
Unemployed	25.60%	41.92%	12.71%	19.76%	59.79(3) **
Student	13.15%	60.92%	12.01%	13.92%	19.55(3) **
Pre-Injury Impairment					
No	15.23%	58.24%	9.39%	17.14%	
Yes	6.35%	71.43%	6.35%	15.87%	.0002[c]
Pre-Injury Physical Limitation					
No	15.07%	58.54%	9.38%	17.02%	
Yes	11.67%	61.67%	6.67%	20.00%	.0022[c]
TBI Severity					
Mild	19.90%	49.88%	11.53%	18.69%	
Moderate	19.45%	53.80%	10.64%	16.11%	.94(3)
Severe	16.80%	55.40%	10.40%	17.40%	3.23(3)
FIM Cognition	14.95[a]	16.04[b]	15.05[ab]	14.76[a]	6.78(3,3727) **

Note. Parentheses are the degrees of freedom associated with the test. For age and FIM cognition, numbers with different subscripts are statistically significant at alpha = .05. For all categorical variables, the first category served as the reference group.

[c] Fisher's Exact test was conducted as an alternative to chi-square test of independence, due to less than five counts in one cell.

* $p < .05$;

** $p < .0001$.