TRAJECTORIES OF EMOTIONAL SYMPTOMS AMONG SURVIVORS AFTER SEVERE TRAUMATIC BRAIN INJURY

by

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The purpose of the study is to characterize emotional symptom patterns in survivors after severe Traumatic Brain Injury and also determine risk factors associated with these distinct patterns. The data used in this study were available from the University of Pittsburgh Brain Trauma Research Center (BTRC). Subjects who survived from their severe Traumatic Brain Injury were recruited and we use the subset of the collected data including the acute phase of the demographics and injury severity and the longitudinal emotional symptom data collected at 3, 6, 12 and 24 months after injury. By using a person-centered, semi-parametric group-based modeling approach, symptom phenotype data were evaluated to identify and characterize group trajectory classifications for each emotional symptom outcome as well as their co-occurrence across time. Additionally, logistic regression and/or multinomial regression models were used to evaluate the associations between trajectories of depression, anxiety and satisfaction of life and covariates such as demographics and clinical variables.

Two trajectories of depression were identified: low stable and high increasing trajectories. Three trajectories of anxiety were identified: low stable, high peak and high decreasing symptom groups. Two trajectories of satisfaction with life were identified: low decreasing and high increasing. Dual trajectory models were also conducted. The results show a strong relationship between the trajectories for depression and anxiety, anxiety and satisfaction with life, depression and satisfaction with life.

Finally multi-trajectory model were fitted. Three multi-trajectories were identified. Multi-trajectory of high depression and high anxiety and low satisfaction with life was predicted by very severe initial injury severity (OR=4.12, P=0.06) in univariate model and predicted by marital status (married, OR=0.08, P=0.06) in multivariate model. Therefore we concluded that by a person-centered, semi-parametric group-based modeling approach, we identified distinct patterns of change in depression, anxiety and satisfaction with life after severe TBI. Our results also indicated that depressive symptoms, anxiety symptoms and satisfaction with life are related. The survivors after severe TBI in high depressive trajectories were more likely also to develop high level of anxiety symptom with lower satisfaction with life. Initial injury severity and marital status have association with emotional disorder after severe traumatic brain injury. The finding of this study may help public health develop efficient preventive strategies or targeted interventions on emotional disorder for the population after severe TBI.

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1.0 INTRODUCTION/LITERATURE REVIEW

1.1 TRAUMATIC BRAIN INJURY

According to the Centers for Disease Control and Prevention (CDC), approximately 1.7 million people sustain a traumatic brain annually in the United States [1]. TBI is a contributing factor to a third (30.5%) of all injury-related deaths in the United States. Approximately 5.3 million Americans are living with a TBI-related disability, including cognitive and physical impairments. Demographic factors affect with the risk and prevalence of TBI. The age groups of children aged 0 to 4 years, older adolescents aged 15 to 19 years, and adults aged 65years and older are most likely to sustain a TBI. People who sustain a TBI over the age of 75 have the highest rates of TBI related hospitalizations and deaths. In every age group, TBI rates are higher for males than for females. Males are twice as likely as females to sustain a TBI in the civilian population [2-4].

1.1.1 Severe Traumatic Brain Injury

The Glasgow Coma Scale (GCS) is one of the most commonly used severity scoring systems. Persons with GCS scores of 3 to 8 are classified with a severe TBI, those with scores of 9 to 12 are classified with a moderate TBI, and those with scores of 13 to 15 are classified with a mild TBI. Severe TBI may lead to a wide range of short or long-term outcomes, including physical, cognitive, behavioral, and emotional alternations.

1.1.2 Emotional Alternations Post-TBI

Psychological or emotional alternations following severe traumatic brain injury are well documented. Emotional alterations post-TBI can contribute to depression, anxiety personality changes, aggression, acting out, and social inappropriateness [5].

Depression After TBI

Research has consistently confirmed that the rates of depression and anxiety are high after TBI [6]. Depression is the most common psychiatric illnesses after TBI. Depression symptoms include sadness, persistent negative thoughts, apathy, and lack of energy, cognitive distortions, nihilism, and inability to enjoy normal events in life. Depression reduces quality of life, impairs ability to function in social roles, and causes self-doubt and difficulty taking action. These symptoms will lead to delay recovery from TBI.

The prevalence of depression after TBI in TBI population, risk factors associated with depression post-TBI are inconsistent. The prevalence of depression after TBI ranged from 6 percent to 77 percent [7, 8]. This variation may be due to variety methodology used in the study including differences in depression measurement tools, the time course of depression assessment, and differences in injury severity (mild vs. severe injuries) and so on.

The Beck Depression Inventory (BDI), Hospital Anxiety and Depression Scale (HADS), Brief Symptom Inventory 18 (BSI 18) and Center for Epidemiologic Studies Depression Scale (CES-D) were most commonly used to measure depression [9].

Among previous study on depression after TBI, most have focused on identifying that potential risk factors affect depression after TBI such as demographic, injury-related, pre-injury and post-injury predictors. But age, gender has not been consistently reported as a risk factor for

depression post-TBI. The association of injury severity to depression post-TBI is also inconsistent in the literature. Some studies report depression has association primarily with more severe TBI injuries, whereas other report depression has association primarily with people who are less severely injured [10, 11] and even still some study demonstrate that injury severity is not related to depression rates [12-14].

Effective Health Care Program (2011) reviewed 112 publications from 79 distinct study populations and reported "The prevalence of traumatic brain injury is approximately 30 percent across multiple time points up to and beyond a year. Based on structured clinical Interviews, on average 27 percent met criteria for depression 3 to 6 months from injury; 32 percent at 6 to 12 months; and 33 percent beyond 12 months. Higher prevalence is reported in many study populations. No strong predictors are available to select a screening window or to advise TBI patients or their providers about risk of depression" [6].

Anxiety After TBI

According to CDC, anxiety disorders are characterized by excessive and unrealistic worry about everyday tasks or events, or may be specific to certain objects or rituals. Simple phobias involve excessive anxiety evoked by specific objects (e.g., marked fear of snakes). As its name implies, social phobias are fears of interacting with others, particularly in large groups. Although anxiety is a fairly common emotional outcome after TBI, there is limited literature available on analysis of anxiety symptom in the population of post-TBI. Anxiety was the most commonly detected co-existence with depression. The coexistence of anxiety and depression is called comorbidity in psychology. It makes the course of mental disorder more

chronic and leads to impairment functional limitation at work and in social, and substantially raises suicide risk [15].

Satisfaction With Life After TBI

Life satisfaction is a main factor in the general construct of subjective well-being. Life satisfaction can be assessed specific to a particular domain of life or globally. The SWLS (Satisfaction with Life Scale) is a global measure of life satisfaction. The SWLS consists of 5-items that are completed by the individual whose life satisfaction is being measured. Overall scores on the SWLS range from 5–35, higher scores reflect greater life. The scale has been well established for individuals with TBI and is considered a valid and reliable measure of life satisfaction [16]. Among previous literature, demographics such as age at injury, marital status, education, employment, social integration, and family satisfaction have been examine the association with satisfaction with life among a population with moderate to severe TBI [17,18]. However, the results of these researches also have been mixed. The different outcome measurement intervals may contribute to this variation.

1.2 GROUP-BASED TRAJECTORY MODELING

Group-based trajectory model (GBTM) is an application of finite mixture modeling provided in Nagin (2005) and is designed to identify clusters of individuals following similar progressions of some behavior or outcome over age or time. Group-based trajectory models are increasingly being applied in psychology research recent years. GBTMs have been applied to map the etiology and developmental course of many types of psychological symptoms or disorders

including depression, anxiety, and stress etc and also applied to analyze the various trajectories of behaviors related to psychopathology.

1.2.1 Statistical Model

Considering a population of size N and a variable of interest, let $Y_i = \{y_{i1}, yi_2, y_{it}\}$ denote the longitudinal sequence of outcome measurements on an individual *I* over T period of time. It is assumed that the group-based trajectory model is composed of a mixture of *J* underlying trajectory groups. The $P_j(Y_i)$ is denoted as the probability of Y_i given membership in group j, and π_j is denoted as the probability of membership in group *j*. $P(Y_i)$ can be written as (follows Nagin's notation and process, D.S Nagin, 2005).

$$P(Y_i) = \sum_{j}^{J} \pi_j P^j(Y_i),$$

The group membership probabilities, π_j, $j=1...J$, can be estimated by a multinomial logit function:

$$\pi_j = \frac{e^{\theta_j}}{\sum_j^J e^{\theta_j}}$$

where θ_1 is normalized to zero for identifiability purposes. We also assume that for individuals within trajectory group j, outcomes over time and individual level deviations from the group trend are uncorrelated and independent. Given this assumption, the probability of Y_i given membership in group *j* is

$$P^j(Y_i) = \prod_t^T p^j(y_{it}),$$

Therefore, the general likelihood function is presented following

$$L = \prod_i^N \sum_j^J \pi_j \prod_t^T p^j(y_{it}),$$

Three types of distributions are provides for trajectory modeling: censored normal (CNORM) for censored continuous data, zero-inflated Poisson (ZIP) to analyze count data, and Bernoulli distributions (binary logistic model) to analyze binary data. The model used in the data of this study was the CNORM. The CNORM distribution allowing for censoring is tending to cluster at the minimum of the scale and at the scale maximum. The software used in the group-base trajectory modeling is SAS PROC TRAJ that was developed by Jones et al. (2001).

Basic Proc Traj syntax for modeling the censored normal distributions

```
PROC TRAJ DATA=xxx OUT=OF OUTPLOT=OP OUTSTAT=OS OUTEST=OE ci95m itdetail;
Model cnorm; /*Censored Normal Model */
Var outcome1-outcomeK; /*name of outcome variables, all K on 1 record*/
Indep time1-timeK; /*name of time variables, all K on 1 record*/
Min 0; /*Lower Censoring Point*/
Max 100; /* Upper Censoring Point */
Id id;
ngroups ngroups;
order 2 2 2; /* to produce 3 quadratics*/
Run;
%TRAJPLOT (OP, OS, titles and axis labels) ;
%TRAJPLOTNEW (OP, OS, titles and axis labels)
```

1.2.2 Model Selection

Statistical inference criteria for trajectory model selection mainly include the Bayesian information criteria (BIC; Raftery 1995), Akaike information criterion (AIC; Akaike 1974), Lo-Mendell-Rubin likelihood ratio test (LMR-LRT; Lo et al. 2001), and entropy. The larger BIC indicates the better fit of the model. The criterion of AIC is similar with BIC. The The Lo-Mendell-Rubin test compares model fit between neighboring class models and provides a p-value to determine the ideal number of classes. Entropy indexes classification accuracy by averaging the posterior probabilities with the range 0 to 1. The value is closer to 1 indexing better precision.

On the other hand, model selection should not depend upon the statistic of model fit, and it is important to utilize the rule of parsimony to select model by combining substantive knowledge with statistical inference (Daniel S. Nagin, 2010).

Another way in the model selection is to test model adequacy. Nagin provided us the criteria for adequacy of model: the estimated probability of group membership and the proportion assigned to that group should be similar; the average of the posterior probabilities of group membership for individuals assigned to each group should be high, the minimum threshold is 0.7; the confidence interval for estimated group membership should be tight; the odds of correct classification exceed a minimum threshed of 5(Daniel S. Nagin, 2010).

1.2.3 Modeling Extensions

1.2.3.1 Dual Trajectory Modeling

The dual model was designed to analyze the developmental course of two distinct but related outcomes (Nagin and Tremblay 2001). In health and behavioral research, co-occurring disorder or heterotypic continuity behaviors were encountered frequently. These two outcomes interact with each other over time or have the longitudinal association with each other. The dual trajectory modeling provides an appealing approach for measure the linkages between these kinds of two distinct but related outcomes. There are three key points we can acquire through dual trajectory model: trajectory groups for measurement series, the probability of membership in each trajectory group, and probabilities linking membership in trajectory groups. By summarizing these linking probabilities over various trajectory groups, we can examine the multidimensional and dynamic interrelationship between two outcomes.

1.2.3.2 Multi-Trajectory Modeling

Multi-trajectory modeling is a straightforward extend to the dual model to more than two outcomes. Multi-trajectory model is designed to summarizing the within individual correspondence of multiple types of longitudinal data. The Proc Traj procedure in SAS program can model up to six outcomes for multi-trajectories. The form of the likelihood of multi-trajectory model (Jones&Nagin, 2007) is

$$P(Y1, Y2, \ldots YK) = \sum \pi j \prod fkj(YK),$$

Where *k* is the number of outcome trajectories in each trajectory group *j*.

1.2.4 Advantages And Limitation

Group-based trajectory modeling has some limitations. The method requires sufficient data and multiple time points of the outcome assessment. Small sample size and the length of follow-up may affect the number of trajectories. Individuals in the trajectory groups are only following approximately the same development course of the outcome. Group membership is not actually a state of being and individuals do not follow trajectories permanently.

However, group-based trajectory modeling has some advantages and motivation to apply in the study. It is an appealing approach for efficient data summary. Group-based trajectory models assume that the population is composed of a mixture of distinct groups defined by their developmental trajectories (Daniel S. Nagin 2010). This method can analyze inter-individual variation in a population and identify individual differences. Hierarchical modeling and latent growth curve modeling assume a monotonic and growth in the target population, whereas group-based trajectory modeling has strong assumption of distinctive developmental paths in population. Group-based trajectory modeling has wide applications through PROC TRAJ SAS software, including identifying one or more trajectories over time, examining predictors of trajectory group membership.

1.3 STATEMENT OF PURPOSE

The primary outcomes of emotional symptoms include depression, anxiety and satisfaction with life after severe TBI. The first objective of the current study was to identify the distinct trajectories of depression, anxiety and satisfaction with life among severe TBI survivors over 24 months. The second objective is to evaluate the dynamic relationship between depression trajectories, anxiety trajectories and satisfaction with life trajectories by using dual trajectory model. The last objective is to identify the trajectories of overall three outcomes using multi-trajectory modeling, and determine the association between the different trajectory membership and the potential predictors.

2.0 METHODOLOGY

2.1 PARTICIPANTS

The data used in this study were available from the University of Pittsburgh Brain Trauma Research Center (BTRC). Subjects who survived from their TBI were recruited through BTRC. Subjects in the study were all severely injured. Inclusion criteria for the study population from which these data were collected were: 1) severe head injury (hospital-admission GCS score ≤ 8 prior to the administration of paralytics or sedatives); 2) aged 16 to 75 years; and 3) CSF sampling via intraventricular pressure monitor as standard of care. Exclusion criteria are: 1) history of cardiovascular disease or conditions predisposing to cardiovascular disease (e.g., peripheral vascular disease, hypertension, cerebrovascular accident, and diabetes), 2) penetrating head injury, and 3) brain death.

We will use the subset of the collected data including the acute phase of these subjects (demographic and injury severity) and the longitudinal emotional symptom data through 2 years post-injury collected at 3,6,12,and 24 months post-injury.

2.2 MEASURES

Through the BTRC, longitudinal data related to neuropsychological measurements are assessed at 3, 6, 12 and 24 months after injury through subject or care-giver self-report (subjective symptoms), subject self-administration, and where appropriate, by a neuropsychological technician under the direction of a BTRC staff neuropsychologist (objective symptoms). Symptom measures conducted by the BTRC are based on the NIH TBI Common Data Elements module to facilitate consistent phenotyping across studies of TBI. Details about measurements follow:

2.2.1 Demographic And Descriptive Data

Demographic information on age at injury, education years, gender and marital status were available in the database.

2.2.2 Initial Severity Of Injury

Glasgow Outcome Scale (GCS) was used to rate the severity of traumatic brain injuries in the records of database. Total scores range from 3-15, with lower ratings indicating lower degree of responsiveness and greater severity of coma (Lezak, 1995). In this dataset, GCSs range from 3 to 8. The subjects in the study with scores three to eight are considered to have a severe or very severe injury.

2.2.3 Emotional Outcomes

2.2.3.1 Depression And Anxiety

The Brief System Inventory 18 is a short form of the Symptom Checklist-90-reviesd. It is a brief self-report that measures 3 dimensions (somatization, depression, anxiety) independently as well as providing a composite score with excellent reliability and validity in TBI populations [9]. Raw scores also may be converted to standardize T according to the scoring manual. Higher subscale scores indicate more symptoms with values of 63 or greater considered a positive clinical diagnosis.

2.2.3.2 Satisfaction With Life

The Diener Satisfaction with life Scale was used as a global measure of life satisfaction. It is a subject self-reported measure with 5-items to reflect overall well-being. Greater life satisfaction is indicated with a higher score on the SWLS. The mean total SWLS score for persons with TBI who had undergone rehabilitation was reported as 20.3($\pm$ 8.1) at one year post injury, which compares to a mean score of 23.5($\pm$ 6.4) [19, 20].

2.3 DATA ANALYSIS

2.3.1 Preliminary Analysis

Age at injury, education years, depression score, anxiety score and satisfaction with life score were used as continuous variables. Marital status at 3 month after TBI was coded dichotomously as (1) married or (2) not married (single/divorced/separated/other). Initial injury severity was coded dichotomously as (1) severe: GCS 5-8 (2) very severe: 3-4. Descriptive analyses of mean, standard deviation for continuous variables, and frequencies/proportions for nominal variables were performed to describe the variables. The gender difference and injury severity difference on demographics and outcomes over time were compared using $\chi 2$ and Student's t test. As an exploratory overview, bivariate inter-correlation were calculated for study variables including depression, anxiety and satisfaction with life at each time point, demographic variables such as age, years of education gender, marital status and the severity of TBI variable GCS. Time-specific mean depression, anxiety and Satisfaction with life were plotted from 3months to 24 months (four times assessment). Histograms and boxplots for depressive symptoms, anxiety, and satisfaction with life score were graphed across time points to explore its distribution. Individual profile plots, spaghetti plots were also graphed.

2.3.2 Trajectory Analysis

2.3.2.1 Data Organization

In order to apply Proc Traj, we set up the data in a wide format, where there is only one row of data for each subject and each repeated measurement is a separate variable. The variables that

describe repeated measures of the same outcome are named with consecutive numbers corresponding to the visit. If some subjects do not complete their follow up assessments, "." is denoted as missing data.

2.3.2.2 Model Selection

Depression, anxiety and satisfaction trajectory models were identified separately. We fit 2 to 6 group model with all groups set to a quadratic equation and determined the optimal number of trajectories by choosing the lowest BIC score.

After the number of groups was determined, the shape of each trajectory was examined. Parameters from linear through a quadratic order were tested for significant contribution to the model. A combination of substantive knowledge and statistical inference was used to determine the shape of each group's trajectory.

Three ways were used for measuring fit: (1) Comparative fit statistics BIC, (2) Mean posterior probabilities of 'assigned' groups should be high, (3) Theoretical proportions and 'assigned' proportions should be similar.

2.3.2.3 Associations Between Trajectory Groups

The single trajectory models were established, subjects were classified in their mostly trajectory based upon the posterior probability. Group memberships for depression, anxiety and satisfaction with life trajectories were explored using cross-tabulation, Fisher's exact, and Pearson chi-square tests. To account for trajectory group uncertainty, cross tabulation was done with unweighted way and average weights calculated from posterior probabilities. P-values less than or equal to 0.05 were considered to be statistically significant.

2.3.2.4 Dual Trajectory Modeling

The single trajectory analyses were conducted, and associations between trajectory groups were examined by cross-tabulation. We planned to apply the dual trajectory model to conduct the joint estimation of interrelationships across the trajectory groups between emotional outcomes. In dual trajectory modeling, we conduct three dual trajectory models for depression and anxiety, depression and satisfaction with life, anxiety and satisfaction with life. The number and orders of optimal trajectory groups in the dual model is consistent with the identified single trajectory models. The parameter estimates results from the single trajectory models for each outcome will be merged to create start values for the joint trajectory model.

The outputs show three key points: trajectory groups for measurement series, the probability of membership in each trajectory group, and probabilities linking membership in trajectory groups. By the dual model, we explore the interrelationship across the trajectory groups between outcomes.

2.3.2.5 Multi-Trajectory Modeling

Using multi-trajectory modeling, we identify the multi-trajectory groups of three distinct but related emotional outcomes: depression, anxiety and satisfaction with life. Here we also use a combination of substantive knowledge and statistical inference (BIC) to decide the order and the shape of each multi-trajectory group.

2.3.3 Trajectory Group Membership And Predictors

The final step in the analyses was to analyze associations between trajectory group membership and predictors. After the univariate trajectory model, dual trajectory group memberships and

multi-trajectory model were determined; the individual-level predictors (demographic variable and initial severity of injury) were examined as a function of trajectory groups. Univariate Chi-square and t-test and ANOVA tests were used to test group differences of depression groups, anxiety groups, and satisfaction with life groups and multi-trajectory groups in demographic variables (age at injury, gender, education years, marital status) and initial injury severity. The potential predictors of trajectory group membership were also tested by two approaches: adding covariates directly into the trajectory model and using logistic regression for outcomes with two trajectory groups and multinomial regression models for outcomes with more than two trajectory groups. The comparison of the results from two approaches will be conducted. The Wald statistic, odds ratios, and goodness of fit (Hosmer-Lemeshow) were used to evaluate the logistic models.

3.0 RESULTS

3.1 PRELIMINARY ANALYSIS

3.1.1 Demographic And Descriptive Analysis

For the purpose of trajectory modeling, a total of 85 subjects who provided at least two follow-up measurements of each outcome are included in the analysis.

The demographics of the sample are presented in Table 1. Of the 85 subjects, there were 68 male (79.76%) and 17 female (20.24%). The gender distribution is consistent with references of gender differences in the incidence of TBI in general population with male having a higher incidence of TBI than female [1. Faul M, 2010]. The average age at injury was 32.6 years (SD=13.77), the range from 12 to 72. At the first assessment time (3 months), 69.23 percent of subjects were single, 16.92 percent of subjects were married and 13.85% were separated or divorce. The average completed education years were 12.6 years (SD=1.93). The mean initial GCS was 6.25(SD=1.46). TBI subjects were grouped by the first available GCS score: severe (GCS=5-8) and very severe (GCS=3-4). 85.7% subjects (n=72) are severe injury TBI patients and 14.3% of subjects (n=12) are very severe injury TBI patients.

Gender differences of sample characteristics and outcomes within each time were shown in the Table 2. The mean age for male participants at injury year was 33 and the mean age for

female participants was 32; mean education years for female was 12.5 and mean education years for male was 12.6. No significant differences were found between male and female for demographic, injury severity and outcomes over time, which are displayed in Table 2. It indicated that we do not need divide the sample by gender to examine the different trajectories by gender in following trajectories analysis.

Table 1 Summary of demographics and clinical variable.

Variables		n	(%)
Gender	Male	68	(79.76)
	Female	17	(20.24)
Marital Status	Single	45	69.23)
	Married	11	(16.92)
	Separated /Divorce	9	(13.85)
Initial GCS	Severe (GCS=5-8)	72	(85.7)
	Very severe (GCS=3-4)	12	(14.3)
		N	Mean (SD)
Age at Injury		85	32.64(13.77)
Education Years		47	12.6(1.93)
Initial GCS		84	6.25(1.46)

GCS: Glasgow Coma Scale

Table 2 Demographic characteristics and outcomes at each time points by gender.

Variables			Male	Female	Gender Differences (p)
Age in Years, M (SD)			33 (13.28)	32 (16.03)	0.77
Education years, M (SD)			12.6(1.98)	12.5(1.77)	0.93
Injury Severity	Initial GCS (M, SD)		6.27(1.52)	6.18(1.24)	0.81
	Severe (%)		56(66.67%)	16(19.05%)	0.27
	Very Severe (%)		11(13.1%)	1(1.19%)	
Marital Status (n, %)	Single		35(53.85)	10(15.38)	0.70
	Married		9(13.85)	2(3.08)	
	Separated/Divorced		6(9.23)	3(4.62)	
Depression M (SD)		3 months	53.58(10.72)	52.36(15.19)	0.75
		6 months	54.90(12.77)	56.15(10.78)	0.74
		12 months	56.60(12.96)	59.53(10.47)	0.42
		24 months	56.62(13.03)	49.25(8.55)	0.13
Anxiety M (SD)		3 months	49.31(14.06)	52.27(14.54)	0.52
		6 months	52.30(13.44)	53.07(14.26)	0.85
		12 months	52.27(14.15)	53.07(13.58)	0.85
		24 months	50.38(11.46)	46.50(8.43)	0.37
Satisfaction with life M (SD)		3 months	21.96(6.50)	20.60(8.67)	0.56
		6 months	20.25(8.34)	19.36(9.89)	0.72
		12 months	18.93(8.67)	22.53(8.02)	0.15
		24 months	20.05(7.90)	23.67(10.44)	0.25

GCS: Glasgow Coma Scale

3.1.2 Outcomes Distribution And Change Over Time And Correlation

Table 3 presents means, standard deviations plus minimum and maximum values for the depressive symptoms, anxiety and satisfaction with life over time. The four repeated measures of depressive symptom show a pattern of moderate increase across first three times, peaking at the third time and then relatively sharp declining. Anxiety repeated measures showed the pattern of increase in first two times, then keeping stable-level from TIME2 to TIME3, and sharp decreasing at TIME4. The means of Satisfaction across time show a pattern of decrease across three times, and then moderate increase from TIME3 to TIME4. Average trend for depression

and anxiety scores are all below the clinical cut-off score. Majority of satisfaction with life scales less than 23.5 among healthy university students.

Individual profile plots over time for each outcome show the actual raw trajectories for each person. From spaghetti plots, some are increasing; some are decreasing; or stay the same level from first time points. They illustrate the variability of each outcome then provided support for the assumption of trajectory analysis.

The inter-correlations among outcome variables at each time point are presented in Table 4. There are strong correlations between depression and anxiety repeated measures, the correlation between them at each time points are 0.66, 0.82, 0.80, and 0.71. The SAT variables were negatively correlated with depression and anxiety, the correlation ranges from 0.33 to 0.57. However, these correlations don't reflect the longitudinal association.

Preliminary analysis plots

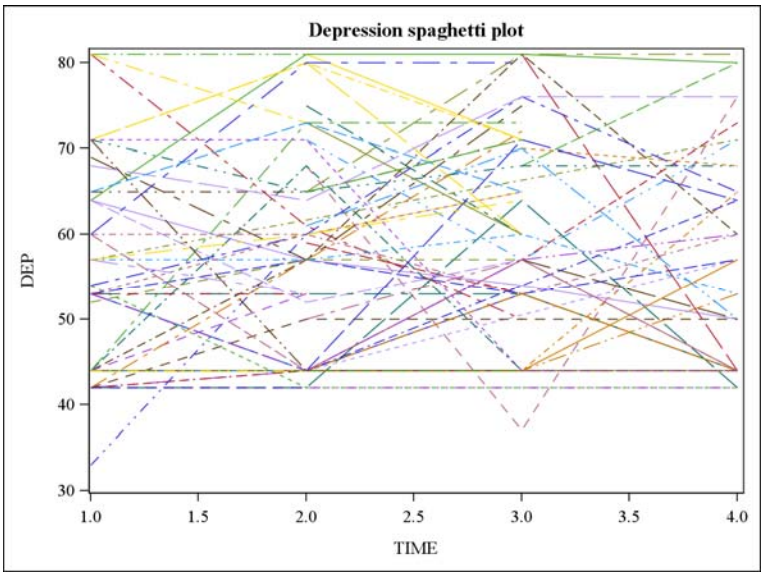

Figure 1 Spaghetti plot of depression after TBI over time.

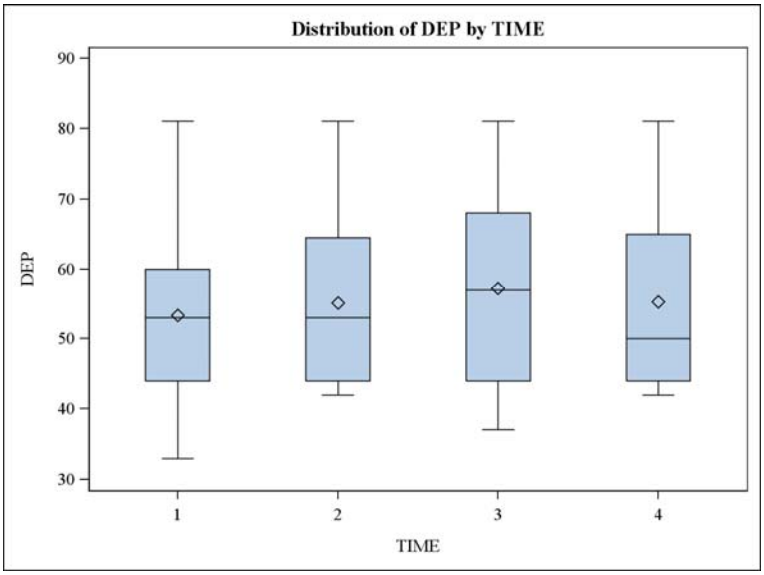

Figure 2 Boxplots of depression after TBI across time points.

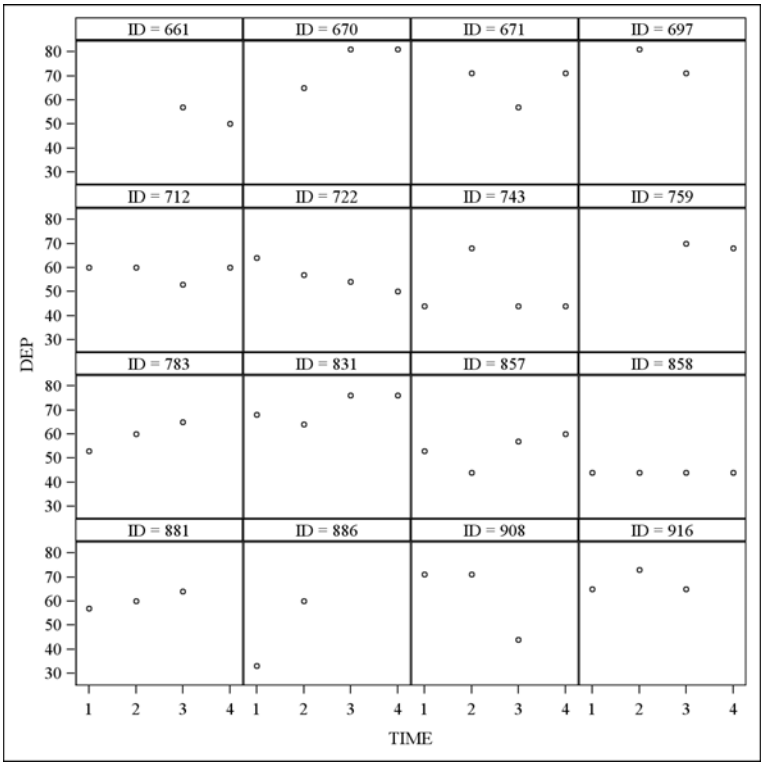

Figure 3 Individual profile plots of depression.

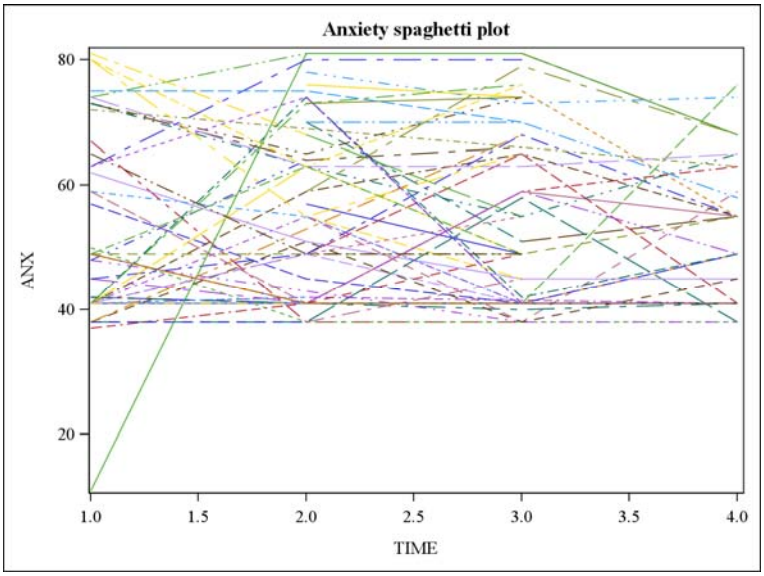

Figure 4 Spaghetti plot of anxiety after TBI over time.

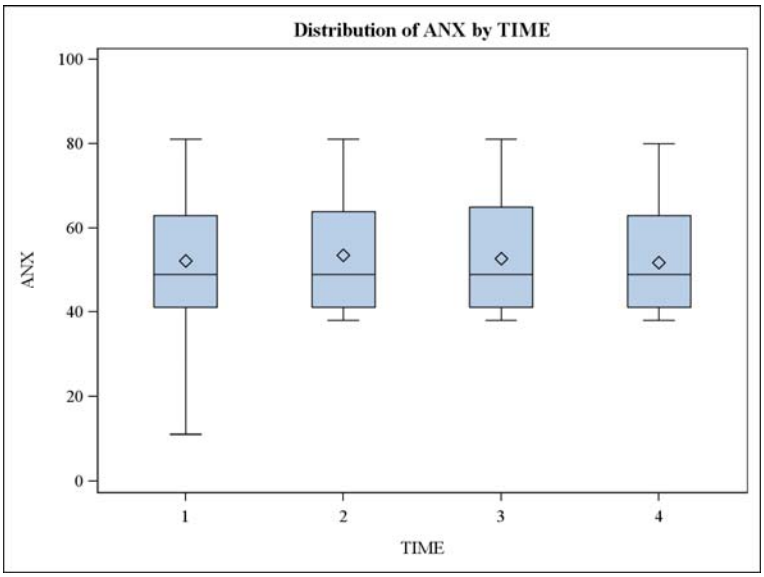

Figure 5 Boxplots of anxiety after TBI across time points.

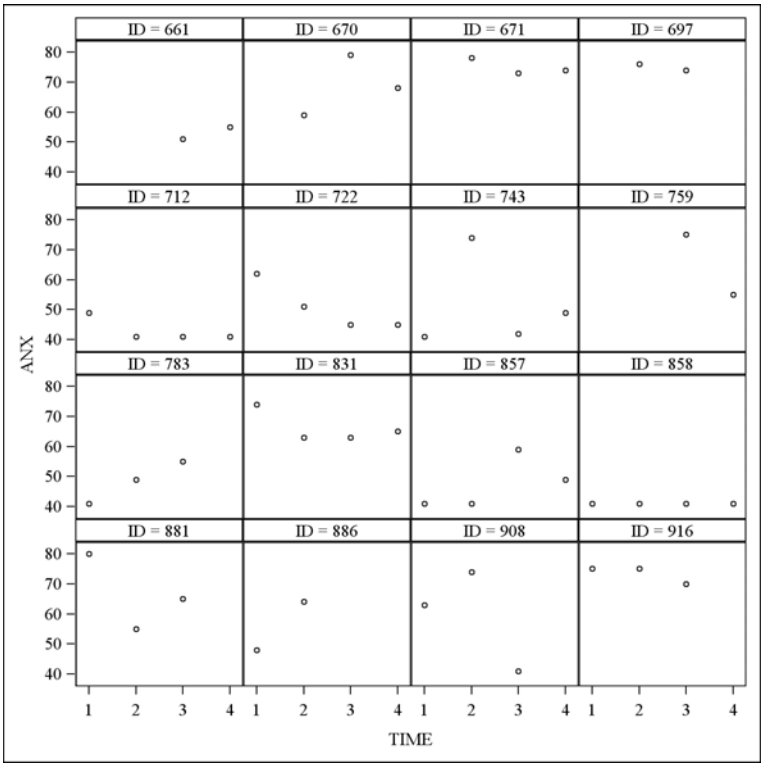

Figure 6 Individual profile plots of anxiety.

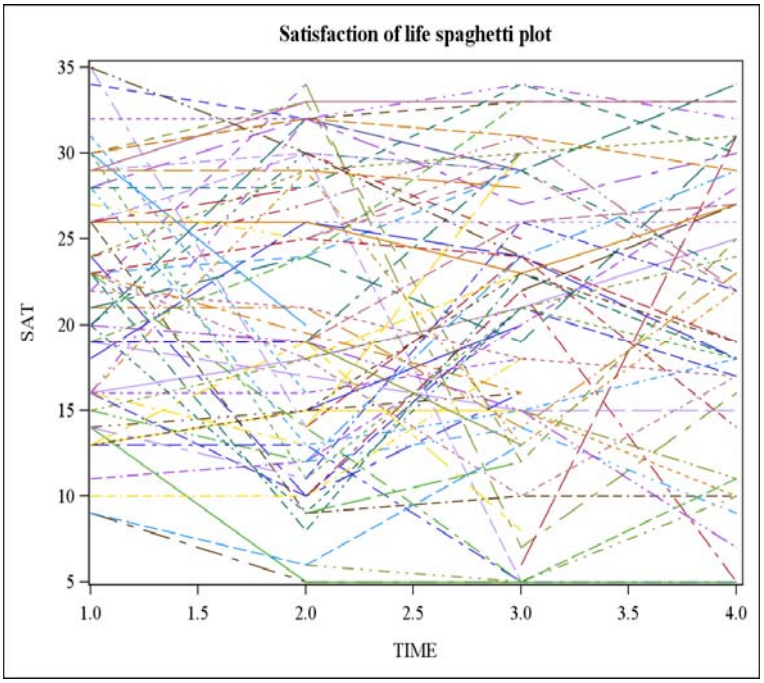

Figure 7 Spaghetti plot of satisfaction with life after TBI over time.

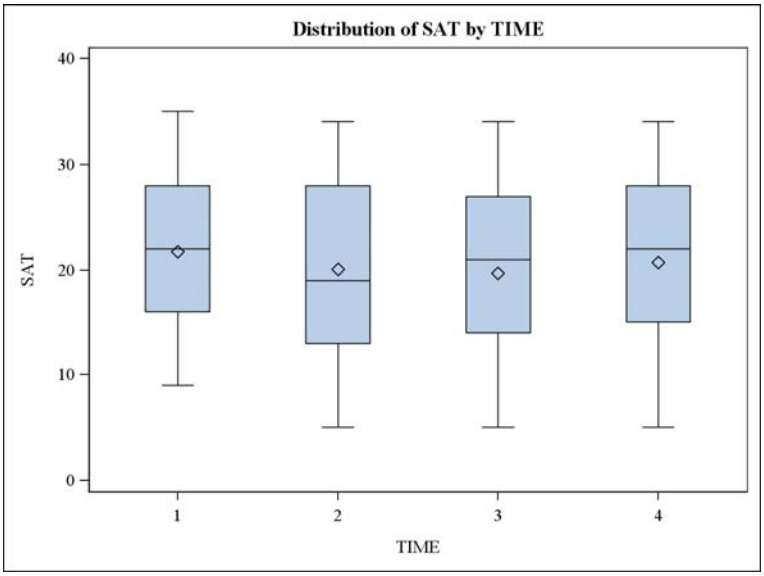

Figure 8 Boxplots of satisfaction with life after TBI across time points.

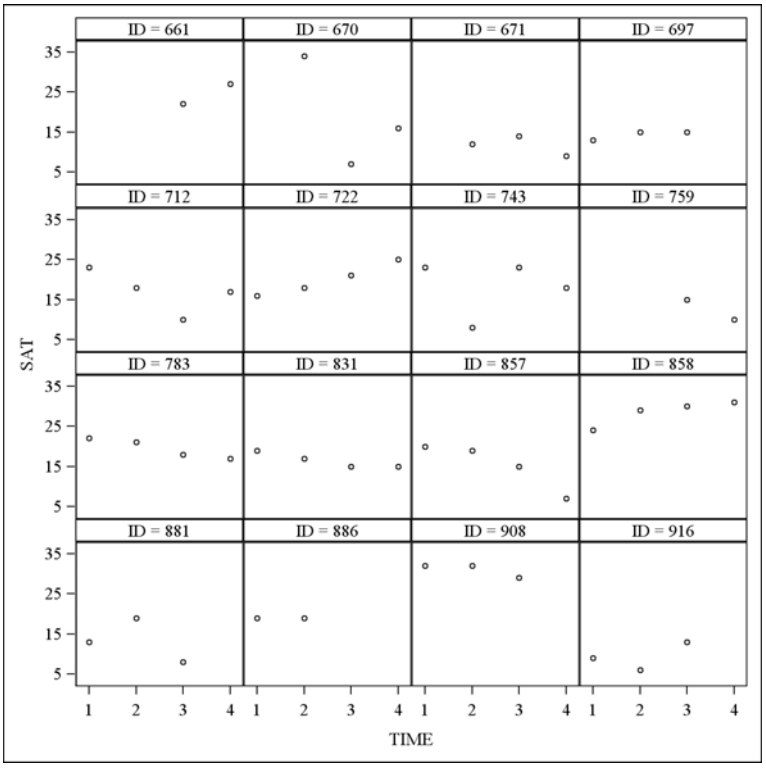

Figure 9 Individual profile plots of satisfaction with life.

Table 3 Summary statistics of outcome measures over time.

Time point	Depression				Anxiety				Satisfaction with life			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
1	53.37	11.48	33.00	81.00	49.83	14.07	11.00	81.00	21.74	6.82	9.00	35.00
2	55.12	12.40	42.00	81.00	52.43	13.49	38.00	81.00	20.09	8.58	5.00	34.00
3	57.23	12.45	37.00	81.00	52.44	13.94	38.00	81.00	19.7	8.60	5.00	34.00
4	55.31	12.59	42.00	81.00	49.69	11.00	38.00	76.00	20.74	8.43	5.00	34.00

Table 4 Correlations between outcomes at each time point.

PEARSON CORRELATION COEFFICIENTS PROB > |R| UNDER H0: RHO=0 NUMBER OF OBSERVATIONS							
	DEP1	ANX1	SAT1		DEP2	ANX2	SAT2
DEP1	1.00000 63	0.66092 <. 0001 63	-0.33349 0.0086 61	DEP2	1.00000 76	0.82199 <. 0001 76	-0.42095 0.0002 76
ANX1	0.66092 <. 0001 63	1.00000 63	-0.34956 0.0058 61	ANX2	0.82199 <. 0001 76	1.00000 76	-0.46594 <. 0001 76
SAT1	-0.33349 0.0086 61	-0.34956 0.0058 61	1.00000 62	SAT2	-0.42095 0.0002 76	-0.46594 <. 0001 76	1.00000 78
	DEP3	ANX3	SAT3		DEP4	ANX4	SAT4
DEP3	1.00000 70	0.80150 <. 0001 70	-0.57991 < . 0001 69	DEP4	1.00000 45	0.71466 <. 0001 45	-0.57513 <. 0001 45
ANX3	0.80150 <. 0001 70	1.00000 70	-0.51338 <. 0001 69	ANX4	0.71466 <. 0001 45	1.00000 45	-0.38142 0.0097 45
SAT3	-0.57991 <. 0001 69	-0.51338 <. 0001 69	1.00000 69	SAT4	-0.57513 <. 0001 45	-0.38142 0.0097 45	1.00000 47

Table 5 Wide-form datasets set up for analysis with Proc Traj.

	T1	T2	T3	T4	DEP1	DEP2	DEP3	DEP4	ANX1	ANX2	ANX3	ANX4	SAT1	SAT2	SAT3	SAT4	EDU	Marital	Age	Gender	GSC
703	1	2	3	4	42	42	64	42	38	38	58	38	20	32	29	34	11	1	17	0	7
719	1	2	3	4	54	42	42	42	50	38	38	38	30	11	21	18	.	2	28	0	5
722	1	2	3	4	64	57	54	50	62	51	45	45	16	18	21	25	12	1	21	0	6
723	1	2	3	4	.	60	65	.	.	55	45	.	.	18	23	.	.	.	63	0	6
746	1	2	3	4	69	57	75	.	73	64	66	.	9	5	5	.	14	2	24	0	6
750	1	2	3	4	42	.	42	42	48	.	38	38	16	32	34	32	11	1	16	0	6

3.2 TRAJECTORY ANALYSIS

3.2.1 Data Organization

The wide-form data ready for use with Proc Traj is shown in Table 5. The outcome variable Depression was denoted by the variables DEP1, DEP2, DEP3, DEP4; Anxiety was denoted by ANX1, ANX2, ANX3, and ANX4; Denial satisfaction with life was denoted by SAT1, SAT2, SAT3, and SAT4. These four variables correspond to four repeated measurements taken at four different times. The four time points of assessments were denoted by T1, T2, T3, and T4.

3.2.2 Univariate Trajectories Modeling On Emotional Outcome

3.2.2.1 Model Selection And Model Adequacy

Using a combination of the Bayesian Information Criterion and substantive knowledge for model selection, a two-group trajectory model was identified for both depressive symptoms and satisfaction with life, and a three-group trajectory model was estimated for anxiety symptoms. Table 8, Table 10 and Table 12 displays the SAS Proc Traj output parameters and the results of model adequacy assessment for three single outcome trajectory models.

3.2.2.2 Depression Trajectories

Models for two through six classes were fit to identify depression trajectories across four time points. The BIC scores for the quadratic 2-, 3-, 4-, 5- and 6- class models were listed in Table 6.

The lowest BIC score was found for the 2-class model. A two-group linear model of depression developmental trajectories was identified. The posterior probabilities of group memberships were 96.4% for the low symptom group, 92.6% for high symptom group, suggesting reasonably low classification errors.

Figure 10 displays the trajectories of the final 2-group model. 63.9% of the subjects (n=54) are classified as exhibiting low depression score and relatively stable levels of depression score. 36.1% of the subjects (n=31) start out with high levels of depression scores and somewhat increasing levels of depression score.

Table 6 Depression trajectory model fit indices.

Classes	2	3	4	5	6
BIC Scores	**-971.09**	-972.91	-977.28	-977.05	-981.56
AIC	**-961.32**	-958.25	-957.74	-952.62	-952.25
L	**-953.32**	-946.25	-941.74	-932.62	-928.25

Table 7 Estimated trajectory parameters, percentages, and posterior assignment probabilities for depression trajectory groups.

Depression Groups	**Average posterior probability**	**%Estimated population**	**%Assigned proportions**	**β_0 (Constant)**	**P value**	**β_1 (Linear)**	**P value**
Low-stable	0.964	63.95	63.53	47.233 (1.745)	0.0000	0.800 (0.667)	0.2313
High-stable	0.926	36.06	36.47	75.730 (3.151)	0.0000	1.273 (1.071)	0.2358

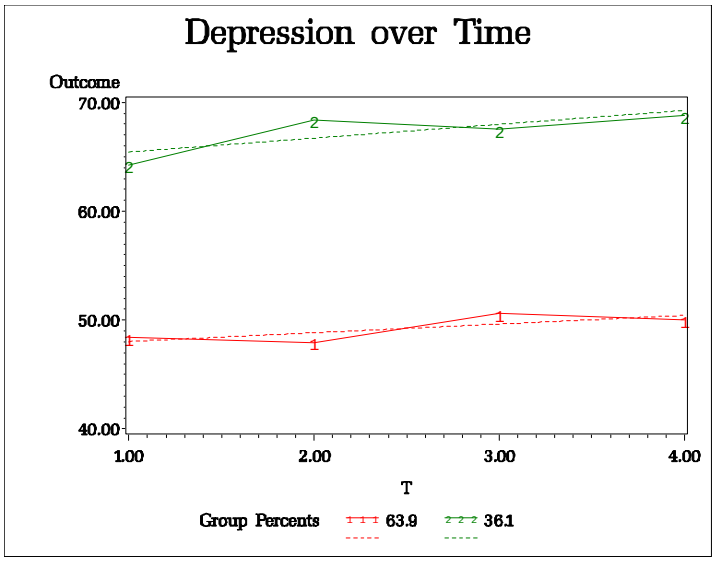

Figure 10 Two classes of depression trajectories among TBI survivors**.**

3.2.2.3 Anxiety Trajectories

The best fitting model of Anxiety trajectories contained 3 groups according to the BIC score (Table8). Table 9 displays the SAS Proc Traj output parameters and the results of model adequacy assessment. A three-group model of Anxiety developmental trajectories was identified: high-peak, low-stable, high decreasing. The polynomial term was quadratic for the high peak and linear for the other two groups (low-stable and high decreasing). 7.6% subjects are classified as the high peak group, start out with low level of anxiety then increase to the high peak over the first three time assessments and then decrease after the third assessment. The low-stable group included the largest percentage, 70.4 %of subjects with low and stable level of anxiety score. 22% subjects start out with high score of anxiety and then decrease over times (Figure 11). The posterior probabilities of group memberships were 77.4% for high-peak group, 98.2% for low-stable group and 90.4% for high-decreasing group.

Table 8 Anxiety trajectory model fit indices.

Classes	2	3	4	5	6
BIC Scores	-986.44	**-973.66**	-982.55	-991.43	-997.18
AIC	-976.67	**-959.01**	-963.01	-967.01	-967.87
L	-968.67	**-947.01**	-947.01	-947.01	-943.87

Table 9 Estimated trajectory parameters, percentages, and posterior assignment probabilities for anxiety trajectory groups.

Anxiety Trajectory Groups	Average Posterior Probability	%Estimated Population	%Assigned Proportions	β_0 (Constant)	P	β_1 (Linear)	P	β_2 (Quadratic)	P
High peak	0.774	7.63	7.06	-21.671 (15.314)	0.16	67.76 (13.354)	0.00	-11.686 (2.510)	0.00
Low-stable	0.982	70.37	70.59	45.705 (1.543)	0.00	-0.097 (0.613)	0.87		
High-decreasing	0.904	22.0	22.35	75.730 (3.151)	0.00	-3.026 (1.310)	0.02		

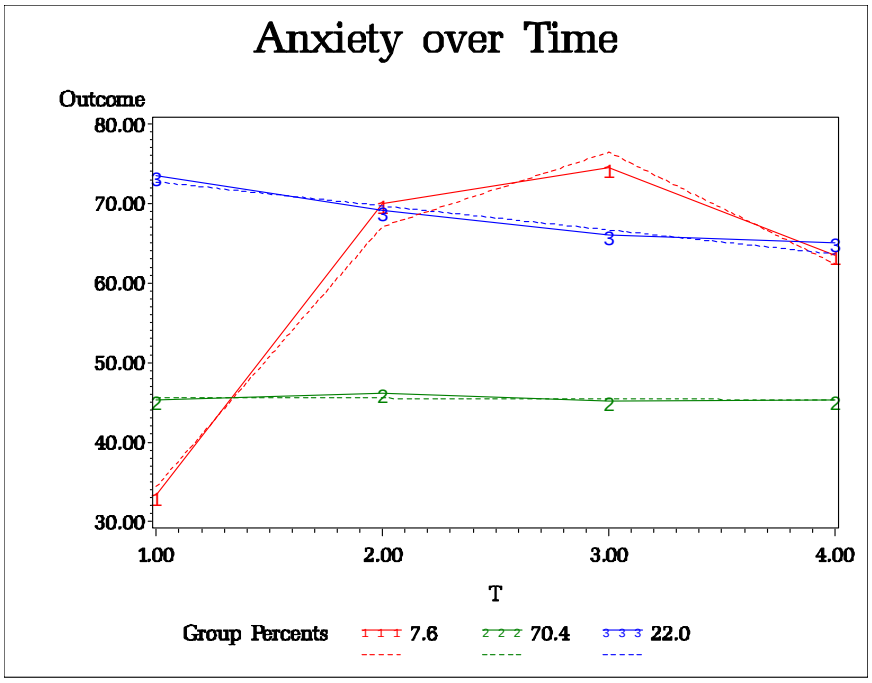

Figure 11 Three classes of anxiety trajectories among TBI survivors.

3.2.2.4 Denial Satisfaction With Life Trajectories

The lowest BIC score was found for the 2-class model. The single final model for Satisfaction with life trajectories results were shown in following Figure 12 and Table 10, Table 11.

Two distinct satisfaction trajectories were identified. 56.7 percent of subjects are classified as exhibiting low satisfaction with life with parabolic change over time. 43.3 percent of subjects represent high satisfaction with life with somewhat levels of increasing. The polynomial term was quadratic for the low satisfaction with life group and linear for the high satisfaction with life group.

Table 10 Satisfaction with life trajectory model fit indices.

Classes	2	3	4	5	6
BIC Scores	**-884.81**	-885.97	-890.00	-898.03	-906.58
AIC	**-875.03**	-871.31	-870.46	-873.60	-877.26
L	**-867.03**	-859.31	-854.46	-853.60	-853.26

Table 11 Estimated trajectory parameters, percentages, and posterior assignment probabilities for satisfaction with life trajectory groups.

Satisfaction Trajectory Groups	Average posterior probability	%Estimated population	%Assigned proportions	β_0 (constant)	p	β_1 (linear)	p	β_2 (Quadratic)	p
Low decreasing	0.938	56.68	56.47	24.147 (3.060)	0.00	-7.117 (2.734)	0.009	1.287 (0.542)	0.02
High increasing	0.914	43.32	43.53	25.389 (1.544)	0.00	0.514 (0.597)	0.389		

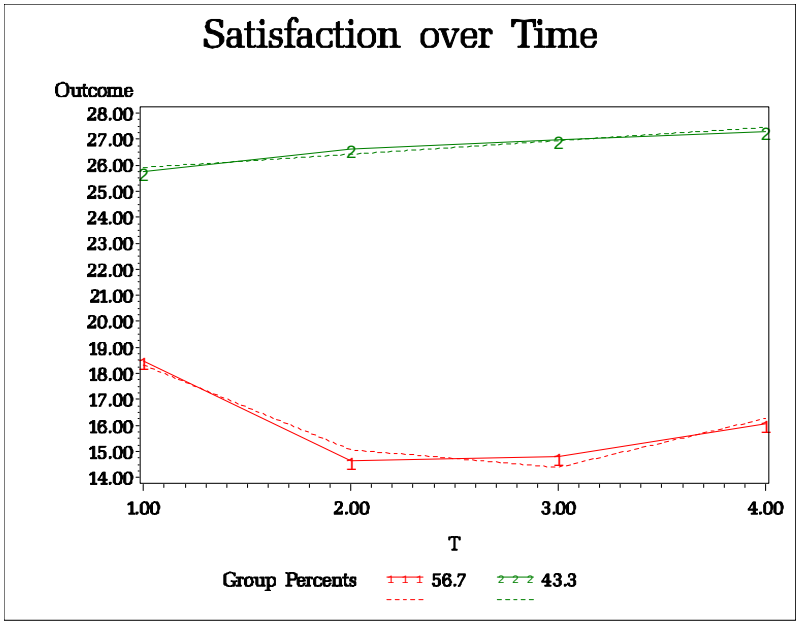

Figure 12 Two classes of satisfaction with life trajectories among TBI survivors.

3.2.2.5 Associations Between Single Trajectory Groups

Table 12 shows descriptive statistics of each outcome for the sample and by trajectory membership for univariate trajectory modeling. The subject in low depression score group exhibited lower level depression, and lower anxiety score and high satisfaction with life over each time respectively. The low anxiety group was with lowest mean of depression over each time and highest mean of satisfaction with life score over each time among three anxiety trajectory groups. The subject in low satisfaction with life score group exhibited high leveler mean of depression over each time, and also higher anxiety score over each time respectively compared these with the high satisfaction of life group.

The results presented below (Table13) only reflect the unweighted cross-tabluations. The analysis with weights was not significantly different from those run with unweighted. The strong pair-wise association was observed between trajectory group membership for depression and anxiety ($\chi2$ (2, N=85) = 54.72, $p<0.001$), depression and satisfaction with life ($\chi2$ (1, N=85) = 11.60, $p=0.0007$), anxiety and satisfaction with life ($\chi2$ (2, N=85) = 11.74, $p=0.0028$). For pair-wise associations between depression and anxiety, 62.35% of subjects were in the low depressive symptoms trajectory group and the low-stable anxiety group; and an estimated 22.35% were in the high-decreasing anxiety group and high-stable depression group (see Table 13). For pair-wise associations between depression and satisfaction with life, 27.06% of subject were in the low depressive symptoms trajectory group and the low declining group; an estimated 36.47% were in low depressive symptoms group and the high-increasing satisfaction with life group (see table 13).

For pair-wise associations between anxiety and satisfaction with life, 31.76% of subjects were in the low satisfaction with life and low-stable anxiety group, 17.65 of subjects were in the low satisfaction with life and the high-decreasing anxiety trajectory group. 38.82% subjects were in the high-increasing satisfaction with life and the low-stable anxiety group (see table 13).

Table 14 shows the cross-tabulation between anxiety group and satisfaction with life group stratified by depression trajectory groups. The results indicated that in the majority of the subgroup of the low depression (n=54) tended to be 40.74% of subjects in the low satisfaction trajectory group and low-stable anxiety group, and 57.41% of subjects in the high satisfaction trajectory group and low-stable anxiety group. In the majority of the subjects in the high depression group (n=31), fifteen subjects (48.39%) were in the high-decreasing anxiety trajectory with low satisfaction with life. No subjects were classified in both the low depression group and the high-decreasing anxiety.

Table 12 Means and standard deviations of outcomes according to trajectory group membership for single trajectory modeling and time of assessment.

Outcomes		Sample	Depression Trajectory		Anxiety Trajectory			Satisfaction with life Trajectory	
			Low (n=54)	High (n=31)	High-peak (n=6)	Low (n= 60)	High-decreasing (n=19)	Low (n=48)	High (n=37)
Depression (MEAN,SD)	3 months	53.36(11.48)	48.52(7.66)	64.58(11.14)	48.50(10.38)	50.04(9.30)	68.00(7.92)	56.44(12.03)	49.76(9.81)
	6 months	55.12(12.40)	47.53(6.21)	68.89(8.16)	69.00(10.32)	49.42(8.37)	70.29(7.73)	59.26(12.44)	50.00(10.39)
	12 months	57.23(12.45)	50.36(7.75)	67.54(11.02)	78.17(4.40)	51.33(8.78)	67.06(8.71)	61.38(12.53)	51.00(9.52)
	24 months	55.31(12.59)	49.97(8.50)	68.46(11.45)	66.25(17.71)	52.00(10.70)	67.33(8.98)	59.11(13.18)	50.11(9.85)
Anxiety (MEAN,SD)	3 months	49.83(14.07)	44.80(6.79)	61.47(19.16)	32.75(14.57)	45.26(7.30)	73.42(5.78)	53.23(16.77)	45.83(8.75)
	6 months	52.43(13.49)	45.26(8.56)	65.44(10.79)	68.00(10.89)	45.95(8.69)	69.76(7.12)	57.19(13.87)	46.56(10.48)
	12 months	52.44(13.94)	45.07(7.57)	63.50(14.06)	75.00(6.90)	44.98(7.41)	66.38(10.80)	56.93(15.38)	45.71(7.68)
	24 months	49.69(11.00)	43.97(5.97)	63.77(7.06)	64.75(6.50)	45.63(8.37)	63.33(6.59)	52.23(12.06)	46.21(8.48)
Satisfaction with life (MEAN,SD)	3 months	21.74(6.83)	23.66(6.11)	17.06(6.33)	21.50(5.20)	23.40(6.25)	16.08(6.47)	18.03(5.58)	26.25(5.37)
	6 months	20.09(8.58)	22.53(8.06)	15.48(7.67)	15.50(12.87)	21.93(8.00)	15.00(7.35)	14.67(6.54)	26.42(5.93)
	12 months	19.71(8.60)	22.51(7.52)	15.61(8.56)	8.17(4.26)	22.11(8.00)	17.00(7.36)	14.67(6.41)	27.56(4.87)
	24 months	20.74(8.44)	23.22(7.21)	15.47(8.66)	15.50(11.27)	21.70(8.13)	18.33(8.19)	15.93(7.00)	27.84(4.36)

Table 13 Pair-wise associations between trajectory group memberships for depressive symptoms, anxiety and satisfaction with life.

Trajectory group		Anxiety						Satisfaction with life			
		High-peak (7.63%)		Low-stable (70.37%)		High-decreasing (22%)		Low declining (56.68%)		High increasing (43.32)	
		n	%	n	%	n	%	n	%	n	%
Depressive symptoms	Low stable (63.95%)	1	1.18	53	62.35	0	0.00	23	27.06	31	36.47
	High stable (36.06%)	5	5.88	7	8.24	19	22.35	25	29.41	6	7.06
		χ^2 (2, N=85)= 54.72, p<0.001						χ^2 (1, N=85)= 11.60, p=0.0007			
Satisfaction with life	Low declining (56.68%)	6	7.06	27	31.76	15	17.65				
	High increasing (43.32%)	0	0	33	38.82	4	4.71				
		χ^2 (2, N=85)= 11.74, p=0.0028									

Table 14 Cross-tabulation between anxiety and satisfaction with life by depression (n, %).

Depression Trajectory group	Anxiety Trajectory group	Satisfaction with life	
		Low	High
Low stable	High-peak	1(1.85)	0
	Low-stable	22(40.74)	31(57.41)
	High-decreasing	0	0
High stable	High-peak	5(16.3)	0
	Low-stable	5(16.3)	2(6.45)
	High-decreasing	15(48.39)	4(12.90)

3.2.3 Dual Trajectory Model

As stated above, the dual trajectory model analysis uses the parameter estimates from the previously single trajectory model of each outcome. We conducted the following three dual trajectory models to identify the interrelationship across the trajectory groups among those outcomes.

3.2.3.1 Anxiety And Depression

Table 15 reports three alternative representations of the linkage between anxiety and depression.

Table 15 panel A shows the probability of membership in each of depression trajectories, conditional on membership in each of the anxiety trajectory groups. Each column of the probabilities sums to 1.0. As shown in the table if a subject is assigned to low anxiety trajectory groups, the subject is most likely to also be classified in low stable depression trajectory group. If a subject is assigned to the 'high-peak' or 'high decreasing' anxiety trajectory group, the subject is most likely to be assigned to the high depression trajectory group.

Table 15 panel B reports the probability of membership in each of the anxiety trajectories conditional upon membership in each of the depression trajectory groups. The probabilities in

each row sum to 1.0. If the subjects classified as the low depression trajectory group are most likely to be classified in low anxiety trajectory groups. If a subject is assigned to the high depression trajectory group, the subject is classified as high-peak anxiety group (28%) or high-decreasing anxiety trajectory group (67.7%).

The Table 15 panel C is the joint probability in a specific depression trajectory group and a specific anxiety trajectory group. This part shows all the possible combinations of depression groups and anxiety groups. The 12 joint probabilities sum to 1.

Three alternative representations of the linkage indicated a strong relationship between depression and anxiety. The results show that subjects in the high-peak anxiety trajectory group and high-decreasing anxiety trajectory group are most likely to be members of the high depression trajectory group. By contract, the subjects in low anxiety trajectory group are most likely to be members of the low depression trajectory group.

3.2.3.2 Anxiety And Satisfaction With Life

Table 16 reports three alternative representations of the linkage between anxiety and satisfaction with life.

Table 16 panel A shows the probability of membership in each of anxiety group trajectories, conditional on membership in each of the satisfaction with life trajectory groups. If a subject is assigned to low anxiety trajectory groups, the subject is most likely to be classified in high satisfaction with life trajectory group (65.49%) and other 34.51% subjects is classified as the low satisfaction with life trajectory group. If a subject is assigned to the high-decreasing anxiety group, the subject is most likely to being assigned to the low satisfaction with life trajectory group (88.17%). If a subject is assigned to high-peak anxiety trajectory group, there is

no chance to being assigned to the low satisfaction with life group and 100% chance to being assigned to the high satisfaction with life group.

Table 16 panel B reports the probability of membership in each of the anxiety trajectories conditional upon membership in each of the Satisfaction trajectory groups. If the subjects classified as the low satisfaction with life trajectory group are most likely to be classified in low anxiety trajectory groups (46%) or high-decreasing anxiety trajectory group (35.6%). If a subject is assigned to the high satisfaction with life trajectory group, the subject is most likely to be classified as the low anxiety trajectory group (94.8%).

Table 16 panel C is the joint probability in a specific depression trajectory group and a specific anxiety trajectory group. This part shows all the possible combinations of depression groups and anxiety groups.

Three alternative representations of the linkage indicated a strong relationship between anxiety and satisfaction. The results show that subjects in the high-decreasing anxiety trajectory group and high-peak anxiety trajectory group are most likely to be members of the low satisfaction trajectory group. By contract, the subjects in low anxiety trajectory group are likely to be members of the high satisfaction trajectory group.

3.2.3.3 Depressions And Satisfaction With Life

Table 17 reports three alternative representations of the linkage between depression and satisfaction with life.

Table 17 panel A shows the probability of membership in each of depression trajectories, conditional on membership in each of the satisfaction trajectory groups. If a subject is assigned to low depression trajectory groups, the subject is most likely to be classified in high satisfaction with life trajectory group (68.99%) and other 31.0% subjects is classified as the low satisfaction

with life trajectory group. If a subject is assigned to the high depression group, the subject is most likely to being assigned to the low satisfaction with life trajectory group (92.1%). Table 17 panel B reports the probability of membership in each of the depression trajectories conditional upon membership in each of the Satisfaction trajectory groups. If the subjects classified as the low satisfaction with life trajectory group are most likely to be classified in high depression trajectory groups (62.9%). If a subject is assigned to the high satisfaction with life trajectory group, the subject is most likely to be classified as the low depression trajectory group (92.1%). The Table 17 panel C is the joint probability in a specific depression trajectory group and a specific satisfaction trajectory group. This part shows all the possible combinations of depression groups and satisfaction groups.

Three alternative representations of the linkage indicated a strong relationship between depression and satisfaction. The results show that subjects in the high depression trajectory group are most likely to be members of the low satisfaction trajectory group. By contract, the subjects in low depression trajectory group are likely to be members of the high satisfaction trajectory group.

3.2.3.4 Comparison Of Estimates From The Dual Model And Cross Classification Analysis

Table 18 compares estimates of probabilities from the dual model and from cross-tabulation based on the single trajectory models. The correspondence between the estimates for memberships from these two approaches is very close on most, but not equal to exact.

Table 15 Interrelationship of anxiety and depression in the dual trajectory model.

A. Probability of depression group conditional on anxiety group			
Depression Trajectory group	Anxiety trajectory group		
	1-High-peak (9.5%)	2-Low (67.7%)	3-High (22.8%)
1-low (66.3%)	0	97.87067	0
2-high (33.7%)	100	2.12933	100
B. Probability of anxiety group conditional on depression group			
Depression Trajectory group	Anxiety trajectory group		
	1-High-peak (9.5%)	2-Low (67.7%)	3-High (22.8%)
1-low (66.3%)	0	100	0
2-high (33.7%)	28.0	4.3	67.7
C. Joint probability of anxiety group and depression group			
Depression Trajectory group	Anxiety trajectory group		
	1-High-peak (9.5%)	2-Low (67.7%)	3-High (22.8%)
1-low (66.3%)	0	66.3	0
2-high (33.7%)	9.5	1.4	22.8

Table 16 Interrelationship of anxiety and satisfaction with life in the dual trajectory model.

A. Probability of anxiety group conditional on satisfaction group			
Satisfaction with life Trajectory group	Anxiety trajectory group		
	1-High-peak (9.54%)	2-Low (69.43%)	3-High (21.03%)
1-low (52%)	100	34.51	88.17
2-high (48%)	0	65.49	11.83
B. Probability of satisfaction group conditional on anxiety group			
Satisfaction with life Trajectory group	Anxiety trajectory group		
	1-High-peak (9.54%)	2-Low (69.43%)	3-High (21.03%)
1-low (52%)	18.3	46	35.6
2-high (48%)	0	94.8	5.2
C. Joint probability of anxiety group and satisfaction group			
Satisfaction with life Trajectory group	Anxiety trajectory group		
	1-High-peak (9.54%)	2-Low (69.43%)	3-High (21.03%)
1-low (52%)	9.5	24	18.5
2-high (48%)	0	45.5	2.5

Table 17 Interrelationship of depression and satisfaction with life in the dual trajectory model.

A. Probability of depression group conditional on satisfaction group		
Satisfaction with life Trajectory group	Depression trajectory group	
	1-Low (63.06%)	2-High (36.94%)
1-low (52.8%)	31.0	92.1
2-high (47.2%)	68.99	7.9
B. Probability of Satisfaction group conditional on depression group		
Satisfaction with life Trajectory group	Depression trajectory group	
	1-Low (63.06%)	2-High (36.94%)
1-low (52.8%)	37.1	62.9
2-high (47.2%)	92.1	7.9
C. Joint probability of depression group and satisfaction group		
Satisfaction with life Trajectory group	Depression trajectory group	
	1-Low (63.06%)	2-High (36.94%)
1-low (52.8%)	19.6	33.2
2-high (47.2%)	43.5	3.7

Table 18 A comparison of joint probability from the dual model and from cross-tabulations of single trajectory model.

Panel A				
Depression Trajectory	Estimator	Anxiety Trajectory		
		1-High-peak	2-Low	3-High
1-Low	Dual Model	0	66.3%	0
	Cross-tabulation	1.18%	62.35%	0
2-High	Dual Model	9.5%	1.4%	22.8%
	Cross-tabulation	5.88%	8.24%	22.35%
Panel B				
Satisfaction with life Trajectory	Estimator	Anxiety trajectory		
		1-High-peak	2-Low	3-High
1-Low	Dual Model	9.5%	24%	18.5%
	Cross-tabulation	7.06%	31.76%	17.65%
2-High	Dual Model	0	45.5%	2.5%
	Cross-tabulation	0	38.82%	4.71%
Panel C				
Satisfaction with life Trajectory	Estimator	Depression Trajectory		
		1-Low	2-High	
1-Low	Dual Model	19.6%	33.2%	
	Cross-tabulation	27.06%	29.41%	
2-High	Dual Model	43.5%	3.7%	
	Cross-tabulation	36.47%	7.06%	

3.2.4 Multi-Trajectory Modeling

When the multi-trajectory modeling was conducted, the joint trajectory group number that we chose was three based on a combination of BIC score and stability of the model. The multi-trajectory plots for three outcomes (Anxiety, depression and satisfaction with life) are shown in Figure 13-Figure 15. Three trajectory groups were identified: 38.4% of the subjects (n=33) are classified as trajectory group1, which represent low scores of depression and anxiety, and high satisfaction with life; 33.1% of subjects (n=28) are classified as group 2 and exhibit moderate level of three outcomes; 28.5 percent of subjects (n=24) are classified as group3 and show high score of depression and anxiety compared with high score of satisfaction with life.

MULTI-TRAJECTORY ANALYSIS PLOTS

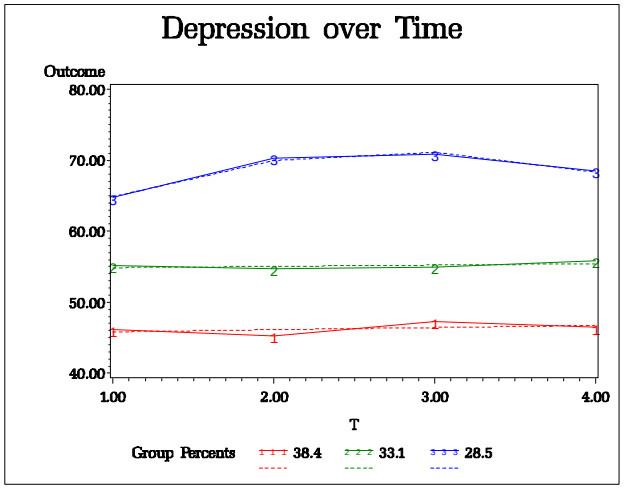

Figure 13 Three classes of depression in multi-trajectory group model.

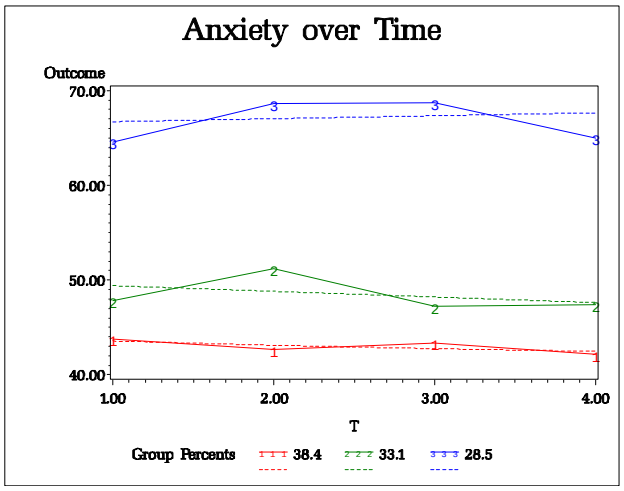

Figure 14 Three classes of anxiety in multi-trajectory group model.

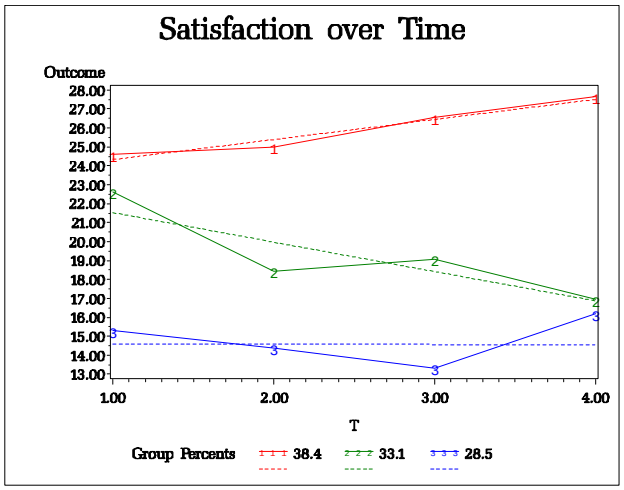

Figure 15 Three classes of satisfaction with life in multi-trajectory group model.

3.2.5 Predictors Of Trajectory Group Membership

After the exploratory trajectory analysis, the single trajectory group memberships, the multi-trajectory group memberships were conducted. Predictors of these trajectory group memberships were identified in this part. The variables considered were age gender, education years, marital status, and initial injury severity.

3.2.5.1 Descriptive Statistic Of Predictors By The Trajectory Group Membership

3.2.5.1.1 Demographic Characteristics And Initial Injury Severity By The Single Trajectory Group Membership

Table 19 shows the demographic characteristics of the trajectory classes for the single trajectory modeling. T-test and Chi-square analyses were used to test the relationship between trajectory group memberships.

For depression trajectory group membership, the low depression group is made up of 81.48% of males, as compared to 77.42 % in high depression group. The subjects in the low depression group have the mean age of 31.1 at injury, compared to mean age of 35 for high depression group. 88.6% subjects in the low depression group are not married, compared to 71.4% in the high depression group. The mean of initial GCS of the low depression group (mean=6.41) was higher than the mean initial GCS of the high depression group (mean=5.97). However, among demographics and initial injury severity, only GCS variable is significantly different between two trajectories, the proportion of injury severity is significantly different between two trajectories.

For anxiety trajectory group membership, there is no significantly difference for demographic characteristics and initial injury severity between three anxiety trajectory groups. The mean of initial GCS for low anxiety trajectory group was 6.41, compared to mean initial GCS of 5.33 in high-peak anxiety group and 6.05 in high-decreasing group.

For the satisfaction with life trajectory groups, the low satisfaction with life group is made up of 81.25% of males, as compared to 78.37 % in high satisfaction with life group. The subjects in the low satisfaction with life group have the mean age of 35 at injury, compared to mean age of 30 for high satisfaction with life group. 76.47 % subjects in the low satisfaction with life group are not married, compared to 90.32% in the high satisfaction group. The mean of initial GCS of the low satisfaction with life group (mean=6.06) was lower than the mean initial GCS of the high satisfaction group (mean=6.49). However, there is no significantly difference between two trajectories among demographics and initial injury severity.

3.2.5.1.2 Demographic Characteristics And Initial Injury Severity By The Multi-Trajectory Group Membership

Table 20 displays the demographic characteristics, initial injury severity of subjects reported by each of the three multi-trajectory groups. T-test and Chi-square analyses were used to test the relationship between trajectory group memberships. The multi-trajectory groups are not statistically different in their demographic characteristics. The multi-trajectory groups are statistically different in their initial injury severity (p=0.046). The group1 is made up of 81.82% of males, as compared to only 78.57% in group2, 79.17% in group3. The subjects in the group 1 have the mean age of 31.3 at injury, compared to mean age of 33.7 for group2, 33.2 for group 3. The mean of initial GCS for group1 was 6.33, compared to mean initial GCS of 6.59 in group2

and 5.75 in group3. 86.23 % subjects in group1 are not married, compared to 90 % in group2 and 68.75% in group3.

Table 19 Demographic characteristics, Initial injury severity by the trajectory group membership for single trajectory modeling.

Variables		Sample	Depression Trajectory		Anxiety Trajectory			Satisfaction with life Trajectory	
			Low (n=54)	High (n=31)	High-peak (n=6)	Low decreasing (n=60)	High (n=19)	Low (n=48)	High (n=37)
Gender (Male n, %)		68(79.76)	44(81.48)	24(77.42)	5(5.88)	49(57.65)	14(16.47)	39(45.88)	29(34.12)
Marital Status (n,%)	Single	45(69.23)	33(50.77)	12(18.46)	2(3.08)	35(53.85)	8(12.31)	21(32.31)	24(36.92)
	Married	11(16.92)	5(7.69)	6(9.23)	1(1.54)	5(7.69)	5(7.69)	8(12.31)	3(4.62)
	Separated /Divorce	9(13.85)	6(9.23)	3(4.62)	1(1.54)	7(10.77)	1(1.54)	5(7.69)	4(6.15)
Age at Injury		33(13.77)	31.1(13.9)	35(13.38)	35(11.15)	32(14.52)	35(12.10)	35(13.53)	30(13.81)
Education Years		12.6(1.93)	12.7(2.2)	12.1(1.10)	13	12.7(2.17)	12.2(1.11)	12.56(1.68)	12.54(2.21)
Injury Severity	Initial GCS	6.25(1.46)	6.41(1.24)	5.97(1.76)	5.33(1.86)	6.41(1.35)	6.05(1.61)	6.06(1.52)	6.49(1.37)
	Severe (%)	72(85.71)	49(58.33)	23(27.38)**	4(4.76)	53(63.1)	15(17.86)	38(45.24)	34(40.48)
	Very Severe (%)	12(14.29)	4(4.76)	8(9.52) **	2(2.38)	6(7.14)	4(4.76)	9(10.71)	3(3.57)

**** $p < 0.05$**

Table 20 Demographic characteristics, Initial injury severity by the multi-trajectory group membership.

Variables		Multi- Trajectory Groups		
		Group1 Low depression Low anxiety High satisfaction (n=33)	Group2 Medium depression Medium anxiety Medium satisfaction (n=28)	Group3 High depression High anxiety Low satisfaction (n=24)
Gender (Male n, %)		27(81.82%)	22(78.57%)	19(79.17%)
Marital Status (Not married, n,%)		25(86.23%)	18(90%)	11(68.75%)
Age at Injury (mean, sd)		31.4(14.57)	33.7(14.55)	33.2(12.05)
Education Years (mean, sd)		12.6 (2.32)	12.9 (1.99)	12.2(1.09)
Injury Severity**	Initial GCS (mean, sd)	6.33(1.33)	6.59(1.27)	5.75(1.72)
	Severe (%)	30(90.91%)	25(92.59%)	17(70.83%)
	Very Severe (%)	3(9.09%)	2(7.41%)	7(29.17%)

**** $p < 0.05$**

3.2.5.2 Adding Covariate Into The Trajectory Model

The associations of the predictor variables to trajectory group membership were examined by adding covariate directly into the trajectory model. The results for the single trajectory group memberships are shown in Table 21. The results report that marital status and initial GCS are two important predictors.

In the depression trajectory model, initial GCS is a significant predictor for the high depression group membership with the presence of a single predictor (OR=4.48, p=0.038) or with all other covariates (OR^a=13.58, p=0.056). Marital status is a predictor for the high depression group membership probabilities with all covariates (OR=0.07, p=0.056), the subjects who were married and who had very severe initial injury were likely to be the membership in high depression group.

In the anxiety trajectory model, marital status is a significant predictor for the high anxiety group membership probabilities with the presence of a single predictor (OR=0.21, p=0.05) or with all other covariates (OR^a=0.01, p=0.045). The subjects who were married were likely to be the membership in high anxiety group. Initial GCS is a significant predictor for the high anxiety group membership probabilities with the presence of a single predictor (OR=4.25, p=0.069) and only with marital status (OR=8, P=0.031). The subjects who were married and who had very severe initial injury were significantly likely to be the membership in high anxiety group.

There are no significant covariates to predict the probability of trajectory group membership in satisfaction with life trajectory model.

When adding covariate marital status and initial GCS directly into three dual trajectory modeling (using Proc traj syntax in SAS) to examine the association of these two individual-level variables to the conditional probabilities linking trajectories across dual outcomes, we found that both marital status and initial GCS have no effects on trajectory transition probabilities for anxiety and depression dual trajectory model, anxiety and satisfaction with life dual trajectory model, and depression and satisfaction with life dual trajectory model.

Pro traj syntax in SAS do not expand capabilities for adding covariate directly into multi-trajectory modeling, thus we do not conduct this examination for multi-trajectory group memberships.

Table 21 Adding covariates into single trajectory group model.

Variables	Adding covariates into the Depression trajectory model			
	Low Depression trajectory group is set as reference group			
	Univariate model		Multivariate model	
	Odds Ratio	P value	Odds Ratio	P value
Age In injury year	1.02	0.28	0.97	0.46
Gender (female)	0.76	0.66	0.66	0.74
Education (years)	0.84	0.36	0.79	0.39
Marital Status (married)	0.37	0.16	0.07	**0.06**
Initial GCS (severe)	4.48	**0.038**	13.85	**0.056**
Variables	Adding covariates into the Satisfaction with life trajectory model.			
	High Satisfaction with life trajectory group is set as reference group			
	Univariate model		Multivariate model	
	Odds Ratio	P value	Odds Ratio[a]	P value
Age In injury year	1.02	0.27	0.96	0.43
Gender (female)	1.54	0.51	1.46	0.73
Education (years)	1.03	0.86	0.89	0.72
Marital Status (married)	0.91	0.25	0.11	0.18
Initial GCS (severe)	2.90	0.19	2.66	0.45

Variables	Adding covariates into the Anxiety trajectory models									
	High peak vs. Low stable Low stable is set as reference group				High decreasing vs. Low stable Low stable is set as reference group					
	Univariate model		Multivariate model		Univariate model		Multivariate model			
	Odds Ratio	P value	Odds Ratio	P value	Odds Ratio	P value	Odds Ratio[a]	P value	Odds Ratio[a]	P value
Age In injury year	1.02	0.51			1.01	0.58			0.93	0.29
Gender (female)	0.45	0.52	0.29	0.20	0.77	0.74			2.48	0.63
Education (years)	1.07	0.89			0.86	0.46			0.69	0.34
Marital Status (married)	0.53	0.61	0.53	0.63	0.21	**0.05**	0.17	**0.037**	0.01	**0.045**
Initial GCS (severe)	5.37	0.14	2.44	0.55	4.25	**0.069**	8.00	**0.031**	8.20	0.15

Note: Odds Ratio[a], adjusted odds ratio

3.2.5.3 Logistic And Multinomial Regression Analysis

3.2.5.3.1 Single Trajectory Group Membership And Predictors

Depression Trajectory Group And Predictors

On the basis of the two depression trajectory groups, we conducted the univariate logistic regression and the multivariate regression to examine the predictors of the depression trajectory group. The low depression group was set as the reference group. The results are shown in Table23, Initial injury severity was significantly associated with high depression group; the crude odds ratio is 4.26 (P=0.03). There were no significant associations between high depression group and other demographic characteristics in univariate analysis. The multivariable analysis containing the variables Age in injury year, Gender, Education, Marital Status and Initial Injury Severity listed in Table22, initial GCS and Marital status was significantly associated with high depression group. The TBI survivors with very severe injury were more likely to be in the high depression trajectory group than with severe injury compared with low depression trajectory group, the adjusted OR is 14.4 (P=0.04). The subjects who were married were more likely to belong to the high depression trajectory group; the adjusted OR is 0.08 (P=0.04).

Anxiety Trajectory Group And Predictors

The results for the multinomial logistic model of the anxiety trajectory groups were shown in Table22. The low anxiety group was set as the reference group. There is significant association between marital status and high anxiety trajectories group in univariate analysis or after adjusted with other demographics and initial injury severity. The subjects who are married were more

likely to be in the high anxiety trajectories groups (the crude odds ratio is 0.21, p=0.04; the adjusted odds ratio is 0.07, P=0.04). There were no significant associations between other demographics and initial injury severity and belonging to the high anxiety group. The subjects who are married and had very severe initial were likely to be in the high anxiety trajectories within the model only including these two variables, the adjusted odds ratio for marital status is 0.18 (p=0.026), the adjusted odds ratio for initial GCS is 5.31(p=0.046).

Satisfaction With Life Trajectory Group And Predictors

On the basis of the satisfaction with life trajectory groups, we also conducted the univariate logistic regression and the multivariate regression to examine the predictors of the satisfaction with life trajectory group. The low satisfaction with life group was set as the reference group. The results are shown in Table 22. There were no significant associations between low satisfaction group and demographic characteristics and initial injury severity in univariate analysis and multivariable analysis.

3.2.5.3.2 Multi-Trajectory Group And Predictors

On the basis of the three multi-trajectory groups, we conducted the univariate logistic regression and the multivariate regression to examine the predictors of the multi-trajectory groups. The group 1 classified as low depression, low anxiety and high satisfaction with life was set as the reference group. The results of univariate analysis are shown in Table 23. Initial injury severity was significantly associated with multi-trajectory group3, which is classified as high depression, high anxiety and low satisfaction with life; the crude odds ratios are 4.12 (P=0.06). The subjects in multi-trajectory group3 were more likely to have very severe GCS. The multivariable analysis containing the variables Age in injury year, Gender, Education, Marital Status and Initial Injury

Severity listed in Table 23, marital status has significant trend to be associated with multi-trajectory group 3, the adjusted odds ratio of Marital status was 0.08 (p=0.06). The subjects who were married were more likely to belong to multi-trajectory group 3, whereas initial GCS became non-significant for the multi-trajectory group 3 after adjusting by other demographic variables. None of other variable was significantly associated with trajectory membership.

Table 22 Logistic regression model for the single trajectory groups.

Variables	Logistic regression model for the Depression trajectory groups			
	Low Depression trajectory group is set as reference group			
	Odds Ratio	P value	Odds Ratio[a]	P value
Age In injury year	1.02	0.17	0.98	0.53
Gender (female)	1.28	0.65	0.42	0.37
Education (years)	0.84	0.34	0.82	0.40
Marital Status (married)	0.32	0.09	0.08	**0.04**
Initial GCS (severe)	4.26	**0.03**	14.46	**0.04**
Variables	Logistic regression model for the Satisfaction trajectory groups			
	High satisfaction trajectory group is set as reference group			
	Odds Ratio	P value	Odds Ratio[a]	P value
Age In injury year	1.03	0.12	0.99	0.74
Gender (female)	1.12	0.74	0.90	0.90
Education (years)	1.004	0.98	0.99	0.93
Marital Status (married)	0.35	0.15	0.16	0.14
Initial GCS (severe)	2.68	0.16	1.38	0.77

Variables	Logistic regression model for the Anxiety trajectory groups									
	High peak vs. Low stable Low stable is set as reference group				High decreasing vs. Low stable Low stable is set as reference group					
	Odds Ratio	P value	Odds Ratio[a]	P value	Odds Ratio	P value	Odds Ratio[a]	P value	Odds Ratio[a]	P value
Age In injury year	1.02	0.57	1.02	0.56	1.02	0.31	1	0.32		
Gender (female)	1.12	0.92			0.63	0.45	0.29	0.19		
Education (years)	1.07	0.88			0.87	0.44	0.80	0.38		
Marital Status (married)	0.36	0.4			0.21	**0.04**	0.07	**0.04**	0.18	**0.026**
Initial GCS (severe)	4.42	0.12	4.5	0.12	2.36	0.22	6.23	0.13	5.31	**0.046**

Note: Odds Ratio[a] , adjusted odds ratio

Table 23 Logistic regression model for multi-trajectory group.

	Multi-trajectory Group							
	Multi-trajectoryGroup2 vs. Multi-trajectory Group1 Group1: Low depression, Low anxiety, High Satisfaction Group2: Medium depression, medium anxiety, Medium satisfaction Group1 is set as reference group				Multi-trajectory Group3 vs. Multi-trajectory Group1 Group1: Low depression, Low anxiety, High Satisfaction Group3: High depression, High anxiety ,Low satisfaction Group1 is set as reference group			
	Odds Ratio	P value	Odds Ratio[a]	P value	Odds Ratio	P value	Odds Ratio[a]	P value
Age In injury year	1.01	0.53	0.99	0.83	1.01	0.62	0.98	0.49
Gender (female)	0.82	0.75	0.77	0.81	0.84	0.80	0.35	0.32
Education (years)	1.07	0.68	1.10	0.60	0.91	0.63	0.88	0.61
Marital Status (married)	1.44	0.69	0.38	0.58	0.35	0.17	0.08	**0.06**
Initial GCS (severe)	0.8	0.81	2.34	0.57	4.12	**0.06**	6.82	0.16

Note: Odds Ratio[a] , adjusted odds ratio (adjusted for age in injury year gender education years, marital status and initial injury severity.

4.0 DISCUSSION

Two trajectories were identified in depression after severe TBI in the study. Both of the depression trajectories demonstrated stable levels of depressive scores over 2 years. One trajectory that started with low level depression scores (near the population norm mean score) at 3 month respectively showed no significant change over time. The other one that characterized by a high level of depression scores (above cutoff point for clinically depression case) showed a slight increasing across time.

Three trajectories were identified in anxiety after severe TBI. Most of TBI survivors showed no sign of anxiety symptoms and kept a stable level over 24 months. Some survivors after severe TBI reported scores above cutoff point for clinically anxiety symptoms and with a slightly improvement over time. A small proportion of TBI survivors in our sample most often differed from other two trajectories. It showed that they had no anxiety symptom at the time point of 3 month but had symptoms in following 21 months.

For satisfaction with life after severe life, it is identified to two trajectories group. One half of severe TBI survivors with a high Satisfaction with Life Scale show a slight and steady increasing over time. The remaining survivors maintained a low SWLS over 24 months and significantly decreased at first year and slightly increased in second year.

In this study depression and anxiety were assessed by the Brief Symptom Inventory-18. The depression subscale was used and the clinical cut-off score for this measure is 63. Higher scores on the BSI 18 indicate more depressive symptoms or more. A T score of ≥ 63 on any scale corresponds to the 90th percentile in the norm population. Depression score at or above the recommended T-score≥63 was considered to have clinically significant depression symptoms. Anxiety subscale also used this clinical cut-off score [12, 27, 28].

Based on this clinical cut-off score, Most TBI survivors in the high depression trajectory group are considered as the clinically significant depression symptoms, Most of TBI survivors in the high-decreasing anxiety trajectory group are also considered as the clinically significant depression symptoms.

By using single trajectory analysis, we demonstrated that the heterogeneity of changes in depression, anxiety and satisfaction with life after severe TBI and help us map the distinctive patterns of our outcomes of interest.

This study also examined links between emotional symptoms after severe TBI over 24 months by applying the dual trajectories procedure to examine the joint trajectories of anxiety and depression, anxiety and satisfaction with life, depression and satisfaction with life. By three dual trajectory models, the results show a strong relationship between the trajectories for depression and anxiety, anxiety and satisfaction with life, depression and satisfaction with life. Widely and increasingly recognized as a common feature of psychological outcomes, the term ”comorbidity” or ”co-occurrence” were introduced to characterize overlapping symptomatology, or multidimensional of psychological disorder. Co-occurrence of depression and anxiety is highly prevalent and it is well documented that both disorders are related to reduce functional status and quality of life [7].

We applied multi-trajectory model to combine all outcomes of our interest. We found three multi-trajectory groups: low scores of depression and anxiety, and high satisfaction with life (group1), moderate level of three outcomes (group2) and high score of depression and anxiety compared with high score of satisfaction with life (group3). The results led us to an insight into the link of depression-anxiety-satisfaction with life. It indicated that depressive symptoms and anxiety symptoms and satisfaction with life are related. The survivors after severe TBI in high depressive trajectories were more likely also to develop high level of anxiety symptom with lower satisfaction with life.

We found marital status and initial injury severity are the different among trajectories and are the significant predictors of the trajectory memberships. Multi-trajectory of high depression and high anxiety and low satisfaction with life was predicted by very severe initial injury severity (OR=4.12, 0.06) in univariate model and predicted by marital status (married, OR=0.08, P=0.06) in multivariate model.

Many applications of group-based modeling are applied in the study including single or dual or multi- trajectory modeling, identifying predictors of trajectory group membership. Firstly, identifying the optimal number of groups and the order of the trajectories starts with the single trajectory modeling. Then the dual trajectory models were conducted. Compared with the single summary statistic to measure the association of two outcomes (correlation coefficient or multiple regression coefficient), the dual model provides more informative and detailed summary of multiple and dynamic associations between the two outcomes. The linking probabilities are the key advantage of the dual model. The cross-tabulation of group memberships from single trajectory models is an alternative approach to estimate the linking probabilities of group memberships between two outcomes. The comparison of estimates from two approaches was conducted in our study. The cross-tabulation strategy does not provide a valid basis for computing the standard errors of the estimates

of conditional probabilities and joint probabilities, and the classify-analyze leads to classification error. In contract, the dual model can provide consistent estimates [25]. Thus, we conduct three dual trajectory models to examine the association between depression and anxiety, depression and satisfaction with life, and anxiety and satisfaction with life. Finally the multiple trajectory models were also used to analyze the data. The trajectories of a single dimension of emotional outcomes after severe TBI have been well studied. There are no literatures to study three emotional outcomes after TBI by group-based modeling. Multi-trajectory modeling provides an approach to identify the multidimensional emotion trajectories after severe TBI.

After the single trajectory groups, dual trajectory groups and multi-trajectory groups were assigned, predictors of these trajectory group memberships were identified. There are two approaches to identify risk and protective factors associated with group membership. The first approach is to go one step to link group memberships to individual level covariates. A functional relationship between probabilities of group membership and covariates is specified and the association of each of these covariates with probabilities of group membership can be estimated simultaneously with the estimation of the trajectories themselves. The specified functional linkage makes it possible to test whether and by how much the covariate affect the probabilities of group membership, because the relationship of these individual-level covariates to trajectory group membership is estimated jointly with the trajectories themselves [25]. This approach can avoid the problem of classification error. The inclusion of risk factors directly into the model can accounts for assignment uncertainty automatically [Clogg 1995;Roeder ed al. 1999]. However, the joint search for the number and order of groups along with predictors of group membership probability is usually unnecessary due to practical matter. This method typically has insensitivity of trajectory estimates to the introduction of predictors of trajectory group probabilities. The reason for this is that the trajectories are time-varying, whereas the risk

and protective factors are time-stable, thus these covariates may not predict or define the actual form of trajectory over time. The second approach is widely applied in research. It is two-steps procedures. First step is to identify a trajectory model without predictors. The second step is the identification of significant predictors of group membership probability by multinomial logistic models. This classify-analyze procedure does not account for the uncertainty in group assignment and can lead to assignment error or bias [25]. Despite of this limitation, this approach is widely recommended. It is easy to perform and it ensures that the standard errors can be properly computed and generates confidence intervals, correct estimates of parameter variance and covariance through the analysis.

In this study, we applied both approaches: using logistic regression model and adding covariates directly in the model, and we got the similar results when examining the associations of predictors with the group membership probability of single trajectory models, Compared with one-step approach, using logistic regression model in second procedures is more practical in our circumstances.

It is important to consider the limitations of the current study when interpreting the results. Firstly, the high-peak anxiety trajectory group in single trajectory modeling consisted of only 6 subjects, whereas the posterior probabilities of group membership was 77.4%. It indicated that the high-peak anxiety trajectory group has a solid establishment. Small sample size in the study may lead to this. Future studies with large sample size would contribute to add information for trajectories identified. Secondly; small number of measurement time points and the short length of time interval may affects trajectory group classes, group shapes, and group memberships. We identified only two trajectories for depression after severe TBI, two trajectories for satisfaction with life, and three trajectories for anxiety after severe TBI in

standard trajectory analysis. Longer time period for future study would help to identify more informative trajectories. Thirdly; the data used in the study is a cohort study with multiple assessments. There may be information bias during data collection. Potential selection bias also may have occurred in the study. The study purpose is to characterize emotional disorder patterns after severe TBI. The participants were recruited in the study and completed the measurements over several follow-ups. It indicated average of their emotional status may be better in this population. It might weaken the link between emotional outcomes. And also therefore low stable depression trajectory group and low stable anxiety trajectory account for more than one half of samples. The last limitation is that the follow-up rate was a little bit lower. It might affect the results of trajectories analysis and lead to weaken the validation of analysis. Although this study has some limitations, it is the first study to seek to characterize emotional symptom development trajectories after severe TBI.

5.0 CONCLUSION

By a person-centered, semi-parametric group-based modeling approach, we identified distinct patterns of change in depression, anxiety and satisfaction with life after severe TBI: two trajectories of depression after severe TBI, two trajectories for satisfaction with life, three trajectories for anxiety after severe TBI in single trajectory model; and three distinct multi-trajectories for emotional disorder in multi-trajectory model. Our results also indicated that depressive symptoms and anxiety symptoms and satisfaction with life are related. The survivors after severe TBI in high depressive trajectories were more likely also to develop high level of anxiety symptom with lower satisfaction with life. The predictive models further indicate that initial injury severity and marital status has association with emotional disorder after severe Traumatic brain injury. These findings may help public health develop preventive strategies or targeted interventions on emotional disorder for the population after severe TBI.

APPENDIX SAS CODE

```
OPTIONS NODATE NOCENTER LINESIZE=81 PAGESIZE=66 ;
libname mylib 'D:\My thesis\thesis\origin Ren files';
libname TBI 'D:\My thesis\thesis\origin Ren files';
/***part of format***/
proc format library=TBI.formats;
value Gender 0='female'
             1='male';
value Marital_status 1='single'
                     2='married'
                     3='divorced'
                     4='separated'
                     5='unknown';

/*set up wideform dataset*/
data temp;
set mylib.Subdataset_fanjun_06_07_2012;
run;
data temp;
set temp;
drop Age;
run;
data templong;
set temp;
rename Post_Injury_Test_Period=TIME Deiner_Satisfaction_of_Life=SAT
ID_Number=ID;
run;
proc sort data= templong;
by ID;
run;
proc contents data= templong;
run;
proc print data=templong noobs;
run;
proc freq data=templong noprint;
tables ID/out=counts(KEEP=ID COUNT RENAME=(COUNT=N_VISITS));
run;
proc print data=counts;
run;
proc freq data=counts;
table N_VISITS;
run;
data VISITNUM;
set counts;
run;
```

```
proc print data=VISITNUM;
run;
data VISITNUM;
set VISITNUM;
if  N_VISITS=1 then delete;
run;
proc print data=VISITNUM;
run;
proc sql;
create table long as
select templong.*
from templong ,VISITNUM
where templong.ID=VISITNUM.ID;
quit;
proc print data=long;
run;
proc freq data=long noprint;
tables ID/out=counts2(KEEP=ID COUNT RENAME=(COUNT=N_VISITS));
run;
proc print data=counts2;
run;
proc freq data=counts2;
table N_VISITS;
run;
data templong;
set long;
run;
data tempwide;
set templong;
by ID;
keep ID DEP1-DEP4 ANX1-ANX4  SAT1-SAT4 E1-E4 M1-M4 ;
retain  DEP1-DEP4 ANX1-ANX4  SAT1-SAT4 E1-E4 M1-M4;
ARRAY aDEP{4} DEP1-DEP4;
ARRAY aANX{4} ANX1-ANX4;
ARRAY aSAT{4} SAT1-SAT4;
ARRAY aEducation{4} E1-E4;
ARRAY aMarital_Status{4} M1-M4;
 IF first.ID THEN
 DO;
 DO i=1 to 4;

  aDEP( i ) = .;
  aANX( i ) = .  ;
  aSAT( i ) = . ;
  aEducation( i ) = . ;
  aMarital_Status( i )=.;
    END;
END;

aDEP( TIME) = DEP ;
 aANX( TIME ) = ANX;
 aSAT( TIME ) = SAT;
 aEducation( TIME ) = Education;
 aMarital_Status(TIME)=Marital_Status;
 IF last.ID THEN OUTPUT ;
 run;
 proc print data=tempwide;
```

```
 run;
proc transpose data=templong out=timeflat
prefix=TIME;
by ID;
id TIME;
var TIME;
run;
data wideform(drop=_name_ );
merge timeflat
      tempwide;
by ID;
run;
proc print data=wideform;
run;
data wide;
set wideform;
if DEP1=. and DEP2=. and DEP3=. and DEP4=. and ANX1=. and ANX2=. and
ANX3=. and ANX4=. and SAT1=. and SAT2=. and SAT3=. and SAT4=. then
delete;
run;
proc print data=wide;
run;
data widetraj;
set wide;
if TIME1=. then TIME1=1;
if TIME2=. then TIME2=2;
if TIME3=. then TIME3=3;
if TIME4=. then TIME4=4;
run;
proc contents data=widetraj;
run;
proc print data=widetraj;
run;
data missing;
set widetraj;
array vars(4) DEP1--DEP4;
numMissing=cmiss(of vars[*]);
run;
proc print data=missing;
run;
data missing;
set missing;
if numMissing ge 3 then delete;
run;
proc print data=missing;
run;
data missing;
 set missing;
 array vars(4) ANX1--ANX4;
 numMissing2=cmiss(of vars[*]);
 run;
 proc print data=missing;
run;
data missing;
set missing;
if numMissing2 ge 3 then delete;
run;
```

```
proc print data=missing;
run;
data missing;
 set missing;
 array vars(4) SAT1--SAT4;
 numMissing3=cmiss(of vars[*]);
 run;
 proc print data=missing;
run;
data missing;
set missing;
if numMissing3 ge 3 then delete;
run;
proc print data=missing;
run;
data widetraj;
set missing;
drop numMissing numMissing2 numMissing3;
run;
proc print data=widetraj;
run;
proc import out=WORK.all datafile="D:\all" DBMS=xlsx REPLACE;
GETNAMES=YES;
run;
data all;
set WORK.all;
run;
proc contents data= all order=VARNUM;
run;
data temp;
set all;
keep Post_Injury_Test_Period ID_Number
DOI
BD
;
run;
data temp;
set temp;
rename ID_Number=ID;
run;
proc sort data=temp;
by ID;
run;
data temp;
set temp;
where Post_Injury_Test_Period=1;
days=DOI-BD;
Age=floor(days/365);
drop DOI BD days Post_Injury_Test_Period;
run;
proc sort data=temp out=age nodups;
by ID;
run;
proc print data=age noobs;
run;
proc sql;
create table widetraj as
```

```
select widetraj.*,age.*
from widetraj,age
where age.ID=widetraj.ID;
quit;
proc print data=widetraj;
run;
proc  import  out=WORK.gendergcs  datafile="C:\Documents  and  Settings\Jun
Fan\Desktop\BTRC_Gender_GCS" DBMS=xlsx REPLACE;
RANGE="Sheet1$A1:C1000";
GETNAMES=yes;
run;
data gendergcs;
set WORK.gendergcs;
run;
data gendergcs;
set gendergcs;
rename UID=ID;
run;
proc sort data=gendergcs;
by ID;
run;
proc print data=gendergcs;
run;
proc sql;
create table widetraj as
select widetraj.*, gendergcs. Gender, gendergcs. Initial_GCS
from widetraj, gendergcs
where widetraj.ID=gendergcs.ID;
quit;
data widetraj;
set widetraj;
rename E1=Education
M1=Marital;
run;
data widetraj;
set widetraj;
if Initial_GCS=0 then Initial_GCS=.;
run;
proc means data=widetraj;
var Initial_GCS;
run;
proc sort data=widetraj;
by gender;
run;
proc means data=widetraj;
class gender;
var Initial_GCS;
run;
data widetraj;
set widetraj;
if Initial_GCS=0 then GCS=.;
if (Initial_GCS=3) or (Initial_GCS=4) then GCS=1;
if (5<=Initial_GCS<=8) then GCS=0;
run;
proc sort data=widetraj;
by GCS;
run;
```

```
proc means data=widetraj;
class GCS;
var Initial_GCS;
run;
proc print data=widetraj;
run;
data widetraj;
set widetraj;
if Marital=1 then Maritalgroup=1;
if Marital=2 then Maritalgroup=2;
else if Marital=3 or Marital=4 then Maritalgroup=3;
run;
data widetraj;
set widetraj;
if Marital=2 then Maritalgrp=1;
else if Marital=1 or Marital=3 or Marital=4 then Maritalgrp=2;
run;
data widetraj;
set widetraj;
drop E2-E4  M2-M4;
run;
proc print data=widetraj;
run;
/*set up longform dataset*/
data longtraj;
set widetraj;
TIME=1;
DEP=DEP1;
ANX=ANX1;
SAT=SAT1;
M=M1;
E=E1;
output;

TIME=2;
DEP=DEP2;
ANX=ANX2;
SAT=SAT2;
M=M2;
E=E2;
output;

TIME=3;
DEP=DEP3;
ANX=ANX3;
SAT=SAT3;
M=M3;
E=E3;
output;

TIME=4;
DEP=DEP4;
ANX=ANX4;
SAT=SAT4;
M=M4;
E=E4;
output;
```

```
drop DEP1-DEP4  ANX1-ANX4  SAT1-SAT4  M1-M4 E1-E4 TIME1-TIME4;
run;
proc print data=longtraj;
run;
/*Descriptive statistics Analysis and Plot*/
proc univariate data=widetraj;
run;
ods rtf FILE="D:\My thesis\descriptive.rtf";
title 'Descriptive Statistics for DEP, ANX, SAT over time';
proc sort data=longtraj;
by TIME;
run;
proc means data=longtraj;
class TIME;
var DEP ANX SAT;
run;
quit;
ods rtf close;
title;
ods rtf FILE="D:\My thesis\individualplot.rtf";
title 'Individual depression score over time';
proc gplot data=longtraj;
plot DEP*TIME=ID/nolegend;
symbol v=none repeat=126 i=sm50s color=grey width=1;
run;
title;
title 'Individual Anxiety score over time';
proc gplot data=longtraj;
plot ANX*TIME=ID/nolegend ;
symbol v=none repeat=126 i=sm50s color=grey width=1;
run;
title;
title 'Individual Satisfaction of life over time';
proc gplot data=longtraj;
plot SAT*TIME=ID/nolegend;
symbol v=none repeat=126 i=sm50s color=grey width=1;
run;
quit;
ODS RTF CLOSE;
title;
/* spaghetti plot and boxplot*/
symbol1 value = circle color = black interpol = join;
ODS rtf FILE="D:\My thesis\Spaplotandboxplot.rtf";
TITLE 'Depression spaghetti plot';
PROC SGPLOT NOAUTOLEGEND DATA=longtraj;
SERIES X=TIME Y=DEP / GROUP = ID LINEATTRS = (THICKNESS=1);
RUN;
title;
title 'Box Plot for Depressive over time';
proc sort data= longtraj;
by TIME;
run;
proc boxplot DATA=longtraj;
        plot DEP*TIME / boxstyle = schematic;
run;
quit;
title;
```

```
TITLE 'Anxiety spaghetti plot';
PROC SGPLOT NOAUTOLEGEND DATA=longtraj;
SERIES X=TIME Y=ANX / GROUP = ID LINEATTRS =
(THICKNESS=1);
RUN;
title;
title 'Box Plot for ANX over time';
proc sort data= longtraj;
by TIME;
run;
proc boxplot DATA=longtraj;
        plot ANX*TIME / boxstyle = schematic;
run;
quit;
title;
TITLE 'Satisfaction of life spaghetti plot';
PROC SGPLOT NOAUTOLEGEND DATA=longtraj;
SERIES X=TIME Y=SAT / GROUP = ID LINEATTRS =
(THICKNESS=1);
RUN;
title;
title 'Box Plot for SAT over time';
proc sort data= longtraj;
by TIME;
run;
proc boxplot DATA=longtraj;
        plot SAT*TIME / boxstyle = schematic;
run;
quit;
title;
ods rtf close;

/*Individual profile plot*/

ods rtf FILE="D:\My thesis\individualpanelplot.rtf";
/*DEP*/
proc sgpanel data = longtraj;
  panelby ID /columns=4 rows= 4;
  scatter y = DEP x = TIME;
  where ID in
(661,670,671,697,712,722,743,759,783,831,857,858,881,886,908,916);
run;
proc sgpanel data = longtraj;
  panelby ID /columns=4 rows= 4;
 pbspline y = DEP x = TIME;
  where ID in
(661,670,671,697,712,722,743,759,783,831,857,858,881,886,908,916);
run;
proc sgplot data = longtraj;
 scatter y = DEP x = TIME/group=TIME;
run;
proc sgpanel data = longtraj;
title "Histogram for DEP by TIME";
panelby TIME /columns=4;
histogram DEP;
density DEP;
run;
```

```
title;
/*ANX*/
proc sgpanel data = longtraj;
  panelby ID /columns=4 rows= 4;
  scatter y = ANX x = TIME;
  where ID in
(661,670,671,697,712,722,743,759,783,831,857,858,881,886,908,916);
run;
proc sgpanel data = longtraj;
  panelby ID /columns=4 rows= 4;
 pbspline y = ANX x = TIME;
  where ID in
(661,670,671,697,712,722,743,759,783,831,857,858,881,886,908,916);
run;
proc sgplot data = longtraj;
 scatter y = ANX x = TIME/group=TIME;
run;
proc sgpanel data = longtraj;
title "Histogram for ANX by TIME";
panelby TIME /columns=4;
histogram ANX;
density ANX;
run;
title;
/*SAT*/
proc sgpanel data = longtraj;
  panelby ID /columns=4 rows= 4;
  scatter y = SAT x = TIME;
  where ID in
(661,670,671,697,712,722,743,759,783,831,857,858,881,886,908,916);
run;
proc sgpanel data = longtraj;
  panelby ID /columns=4 rows= 4;
 pbspline y = SAT x = TIME;
  where ID in
(661,670,671,697,712,722,743,759,783,831,857,858,881,886,908,916);
run;
proc sgplot data = longtraj;
 scatter y = SAT x = TIME/group=TIME;
run;
proc sgpanel data = longtraj;
title "Histogram for SAT by TIME";
panelby TIME /columns=4;
histogram SAT;
density SAT;
run;
title;
ODS RTF CLOSE;
proc freq data=widetraj;
table Marital Gender GCS;
run;
proc freq data=widetraj;
table Gender*GCS/chisq fisher nocol norow;
run;
proc freq data=widetraj;
table Gender*Marital/chisq fisher nocol norow;
run;
```

```
proc freq data=widetraj;
table GCS*Marital/chisq fisher nocol norow;
run;
proc freq data=widetraj;
table GCS*Gender/chisq fisher nocol norow;
run;
proc means data=widetraj;
run;
proc sort data=widetraj;
by Gender;
run;
proc means data=widetraj;
class gender;
run;
proc ttest;
class Gender;
var DEP1 DEP2 DEP3 DEP4;
run;
proc ttest;
class Gender;
var ANX1-ANX4;
run;
proc ttest;
class Gender;
var SAT1-SAT4;
run;
proc ttest data=widetraj;
class Gender;
var Initial_GCS;
run;
proc ttest data=widetraj;
class Gender;
var Education;
run;
proc ttest data=widetraj;
class Gender;
var Age;
run;
proc sort data=widetraj;
by GCS;
run;
proc means data=widetraj;
class GCS;
run;
proc ttest;
class GCS;
var DEP1 DEP2 DEP3 DEP4;
run;
proc ttest;
class GCS;
var ANX1-ANX4;
run;
proc ttest;
class GCS;
var SAT1-SAT4;
run;
proc ttest;
```

```
class GCS;
var Age;
run;
proc ttest data=widetraj;
class GCS;
var Initial_GCS;
run;
proc ttest data=widetraj;
class GCS;
var Education;
run;
proc sort data=widetraj;
by Id;
run;

/* Trajectory Analysis*/
/* Univariate Trajectory Analysis*/
PROC TRAJ  DATA=widetraj  OUT=depoput  OUTPLOT=depplot  OUTSTAT=depstat ci95m;
id id;
var DEP1-DEP4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 1 1;
run;
%trajplot(depplot,depstat,'Depression over Time');
title;
PROC TRAJ  DATA=widetraj  OUT=anxoput  OUTPLOT=anxplot  OUTSTAT=anxstat ci95m;
id id;
var ANX1-ANX4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1 1;
run;
%trajplot(anxplot,anxstat,'Anxiety over Time');
title;
PROC TRAJ  DATA=widetraj  OUT=satoput  OUTPLOT=satplot  OUTSTAT=satstat ci95m;
id id;
var SAT1-SAT4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1;
run;
%trajplot(satplot,satstat,'Satisfaction over Time');
title;
proc print data=depoput;
run;
proc print data=anxoput;
run;
proc print data=satoput;
run;
proc sql;
```

```
create table trajgroup as
select depoput.ID,depoput.GROUP as DEPGROUP,
       anxoput.GROUP as ANXGROUP,
       satoput.GROUP as SATGROUP
from depoput, anxoput, satoput
where depoput.ID=anxoput.ID=satoput.ID;
quit;
proc print data=trajgroup;
run;
proc freq data=trajgroup;
table DEPGROUP*ANXGROUP/fisher chisq norow nocol ;
run;
proc freq data=trajgroup;
table DEPGROUP*SATGROUP/fisher chisq norow nocol;
run;
proc freq data=trajgroup;
table ANXGROUP*SATGROUP/fisher chisq norow nocol;
run;
proc freq data=depoput;
table GROUP;
run;
proc means data=depoput(where=(GROUP=1));
var GRP1PRB;
run;
proc means data=depoput(where=(GROUP=2));
var GRP2PRB;
run;
proc freq data=anxoput;
table GROUP;
run;
proc means data=anxoput(where=(GROUP=1));
var GRP1PRB;
run;
proc means data=anxoput(where=(GROUP=2));
var GRP2PRB;
run;
proc means data=anxoput(where=(GROUP=3));
var GRP3PRB;
run;
proc freq data=satoput;
table GROUP;
run;
proc means data=satoput(where=(GROUP=1));
var GRP1PRB;
run;
proc means data=satoput(where=(GROUP=2));
var GRP2PRB;
run;
/*Dual model*/
/*ANX&DEP*/
ODS RTF FILE="D:\My thesis\dualmodel.rtf";
PROC  TRAJ    DATA=widetraj    OUT=Oput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=depplot  OUTSTAT2=depstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
```

```
var2 DEP1-DEP4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 1 1;
start
-21.671181    67.759502   -11.685920 /*model ANX trajectory parameters*/
45.705227    -0.097312
75.730199    -3.025663
8.068714                                                /*model ANX sigma*/
7.630931    70.372254    21.996815    /*model ANX group percentages*/

47.233980     0.799818    /*model DEP trajectory parameters*/
   64.165871     1.272935
   8.650229                        /*model DEP sigma*/

50 50  50 50  50 50; /*Model 2 given model 1 conditional group percentages*/
run;
%trajplot(depplot,depstat,'Depression over Time');
title;
%trajplot(anxplot,anxstat,'Anxiet over Time');
title;
/*ANX&SAT*/
PROC  TRAJ     DATA=widetraj     OUT=Oput     OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
start
-21.671181  67.759502   -11.685920   /*model ANX trajectory parameters*/
45.705227    -0.097312
75.730199    -3.025663
8.068714                                                /*model ANX sigma*/
7.630931    70.372254    21.996815    /*model ANX group percentages*/

24.146541    -7.117120     1.286956     /*model SAT trajectory parameters*/
25.388292     0.514618
6.045919                                                  /*model SAT sigma*/

50  50    50  50    50  50;  /*Model  SAT  given  model  ANX  conditional  group
percentages*/
run;

%trajplot(anxplot,anxstat,'Anxiet over Time');
title;
%trajplot(satplot,satstat,'Satisfaction over Time');
title;
/*DEP&SAT*/
PROC  TRAJ     DATA=widetraj     OUT=Oput     OUTPLOT=depplot  OUTSTAT=depstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var  DEP1-DEP4;  indep  TIME1-TIME4;  model  cnorm;  min  0;  max  100;  ngroups  2;
order 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
start
   47.233980     0.799818    /*model DEP trajectory parameters*/
   64.165871     1.272935
```

```
   8.650229                          /*model DEP sigma*/
   63.945157     36.054843     /*model DEP group percentages*/

24.146541    -7.117120     1.286956     /*model SAT trajectory parameters*/
25.388292     0.514618
6.045919                                                /*model SAT sigma*/

50 50  50 50 ; /*Model SAT given model DEP conditional group percentages*/
run;
%trajplot(depplot,depstat,'Depression over Time');
title;
%trajplot(satplot,satstat,'Satisfaction over Time');
title;
ods rtf close;


/*multi-trajectory*/
PROC  TRAJ     DATA=widetraj     OUT=Oput     OUTPLOT=depplot  OUTSTAT=depstat
OUTPLOT2=anxplot  OUTSTAT2=anxstat OUTPLOT3=satplot
OUTSTAT3=satstat;
id id;
var DEP1-DEP4; indep TIME1-TIME4; model cnorm; min 0; max 100; ngroups 3;
order 2 2 2;
var2 ANX1-ANX4;indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2 3;
order2 2 2 2;
var3 SAT1-SAT4; indep3 TIME1-TIME4; model3 cnorm; min 0; max3 100; ngroups3
3;order3 2 2 2;
multgroups 3;
run;
%trajplot(depplot,depstat,'Depression over Time');
title;
%trajplot(anxplot,anxstat,'Anxiety over Time');
title;
%trajplot(satplot,satstat,'Satisfaction over Time');
title;
/*multi-trajectory*/
ods rtf FILE="D:\multimodel.rtf";
PROC  TRAJ     DATA=widetraj     OUT=Oput     OUTPLOT=depplot  OUTSTAT=depstat
OUTPLOT2=anxplot  OUTSTAT2=anxstat OUTPLOT3=satplot
OUTSTAT3=satstat;
id id;
var DEP1-DEP4; indep TIME1-TIME4; model cnorm; min 0; max 100; ngroups 3;
order 1 1 2;
var2 ANX1-ANX4;indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2 3;
order2 2 1 1;
var3 SAT1-SAT4; indep3 TIME1-TIME4; model3 cnorm; min 0; max3 100; ngroups3
3;order3 1 1 1;
multgroups 3;
run;
%trajplot(depplot,depstat,'Depression over Time');
title;
%trajplot(anxplot,anxstat,'Anxiety over Time');
title;
%trajplot(satplot,satstat,'Satisfaction over Time');
title;
proc print data=Oput;
run;
```

```
ods rtf close;
proc sql;
create table REG as
select Oput.GROUP, widetraj.*
from Oput, widetraj
where Oput.ID=widetraj.ID;
quit;
proc sort data=trajgroup;
by ID;
run;
proc sql;
create table logreg as
select trajgroup.*, REG.*
from trajgroup, REG
where trajgroup.ID=REG.ID;
quit;
proc sort data=logreg;
by ID;
run;
proc print data=logreg;
run;
data logreg;
set logreg;
Age_c=Age-26;
Education_c=Education-12;
run;
data logreg;
set logreg;
if Age<=21 then Agegroup=1;
if 21<Age<=41 then Agegroup=2;
else if Age>=42 then Agegroup=3;
run;
proc print data=logreg;
run;
proc freq data=logreg;
table Agegroup;
run;
/***part of format***/
proc format;
value DEPGROUP 1='Low'
                          2='High';
value ANXGROUP 1='High-peak'
                           2='Low'
                           3='High-decreasing';

value SATGROUP 1='Low'
                           2='High';
value GROUP
1="multigroup1"
2="multigroup2"
3="multigroup3";
value Gender 0="female"
             1="male";
value Maritalgrp 1="married"
                         2="not married";
value GCS 0="severe"
          1="very severe";
```

```
run;
/*correlation*/
ods rtf FILE="D:\correlation1.rtf";
proc     corr     data=logreg     pearson     spearman     kendall     hoeffding
plots=matrix(histogram);
var DEP1 ANX1 SAT1;
run;
proc print data=corr;
title " Correlations of outcomes at 3 months"
run;
title;
ods rtf close;
ods rtf FILE="D:\correlation2.rtf";
proc     corr     data=logreg     pearson     spearman     kendall     hoeffding
plots=matrix(histogram);
var DEP2 ANX2 SAT2;
run;
proc print data=corr;
title " Correlations of outcomes at 6 months"
run;
title;
ods rtf close;
ods rtf FILE="D:\correlation3.rtf";
proc     corr     data=logreg     pearson     spearman     kendall     hoeffding
plots=matrix(histogram);
var DEP3 ANX3 SAT3;
run;
proc print data=corr;
title " Correlations of outcomes at 12 months"
run;
title;
ods rtf close;
ods rtf FILE="D:\correlation4.rtf";
proc     corr     data=logreg     pearson     spearman     kendall     hoeffding
plots=matrix(histogram);
var DEP4 ANX4 SAT4;
run;
proc print data=corr;
title " Correlations of outcomes at 24 months"
run;
title;
ods rtf close;

/* Trajectory Analysis+predictors*/
ODS RTF FILE="D:\My thesis\single trajectory model with predictors.rtf";
/*DEP*/
PROC TRAJ  DATA=logreg  OUT=depoput  OUTPLOT=depplot  OUTSTAT=depstat ci95m;
id id;
var DEP1-DEP4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 1 1;
run;
PROC TRAJ  DATA=logreg  OUT=depoput  OUTPLOT=depplot  OUTSTAT=depstat ci95m;
id id;
```

```
var DEP1-DEP4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 1 1;
risk Age_c Gender Education_C Maritalgrp GCS;
start  47.233980      0.799818     64.165871      1.272935      8.650229     -
0.572985 0 0 0 0 0;
run;
PROC TRAJ  DATA=logreg  OUT=depoput  OUTPLOT=depplot  OUTSTAT=depstat ci95m;
id id;
var DEP1-DEP4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 1 1;
risk Age_c;
start  47.233980      0.799818     64.165871      1.272935      8.650229     -
0.572985 0;
run;
PROC TRAJ  DATA=logreg  OUT=depoput  OUTPLOT=depplot  OUTSTAT=depstat ci95m;
id id;
var DEP1-DEP4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 1 1;
risk Gender;
start  47.233980      0.799818     64.165871      1.272935      8.650229     -
0.572985 0;
run;
PROC TRAJ  DATA=logreg  OUT=depoput  OUTPLOT=depplot  OUTSTAT=depstat ci95m;
id id;
var DEP1-DEP4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 1 1;
risk Education_C ;
start  47.233980      0.799818     64.165871      1.272935      8.650229     -
0.572985 0;
run;
PROC TRAJ  DATA=logreg  OUT=depoput  OUTPLOT=depplot  OUTSTAT=depstat ci95m;
id id;
var DEP1-DEP4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 1 1;
risk Maritalgrp;
start  47.233980      0.799818     64.165871      1.272935      8.650229     -
0.572985 0 ;
```

```
run;
PROC TRAJ  DATA=logreg  OUT=depoput  OUTPLOT=depplot  OUTSTAT=depstat ci95m;
id id;
var DEP1-DEP4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 1 1;
risk GCS;
start  47.233980      0.799818     64.165871      1.272935      8.650229     -
0.572985 0;
run;

/*ANX*/
PROC TRAJ  DATA=logreg  OUT=anxoput  OUTPLOT=anxplot  OUTSTAT=anxstat ci95m;
id id;
var ANX1-ANX4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1 1;
run;
PROC TRAJ  DATA=logreg  OUT=anxoput  OUTPLOT=anxplot  OUTSTAT=anxstat ci95m;
id id;
var ANX1-ANX4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1 1;
risk Age_c Gender Education_C Maritalgrp GCS;
start   -21.671181      67.759502     -11.685920      45.705227      -0.097312
75.730199
   -3.025663     8.068714     2.221589  0 0 0 0 0   1.058688   0 0 0 0 0   ;
run;
PROC TRAJ  DATA=logreg  OUT=anxoput  OUTPLOT=anxplot  OUTSTAT=anxstat ci95m;
id id;
var ANX1-ANX4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1 1;
risk Age_c;
refgroup 2;
start   -21.671181      67.759502     -11.685920      45.705227      -0.097312
75.730199
   -3.025663     8.068714     2.221589  0    1.058688   0  ;
run;
PROC TRAJ  DATA=logreg  OUT=anxoput  OUTPLOT=anxplot  OUTSTAT=anxstat ci95m;
id id;
var ANX1-ANX4;
indep TIME1-TIME4;
model cnorm;
min 0;
```

```
max 100;
order 2 1 1;
risk Gender;
refgroup 2;
start   -21.671181      67.759502     -11.685920      45.705227      -0.097312
75.730199
   -3.025663     8.068714     2.221589  0  1.058688   0   ;
run;
PROC TRAJ  DATA=logreg  OUT=anxoput  OUTPLOT=anxplot  OUTSTAT=anxstat ci95m;
id id;
var ANX1-ANX4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1 1;
risk Education_C ;
refgroup 2;
start   -21.671181      67.759502     -11.685920      45.705227      -0.097312
75.730199
   -3.025663     8.068714     2.221589  0   1.058688   0    ;
run;
PROC TRAJ  DATA=logreg  OUT=anxoput  OUTPLOT=anxplot  OUTSTAT=anxstat ci95m;
id id;
var ANX1-ANX4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1 1;
risk Maritalgrp ;
refgroup 2;
start   -21.671181      67.759502     -11.685920      45.705227      -0.097312
75.730199
   -3.025663     8.068714     2.221589  0   1.058688   0   ;
run;
PROC TRAJ  DATA=logreg  OUT=anxoput  OUTPLOT=anxplot  OUTSTAT=anxstat ci95m;
id id;
var ANX1-ANX4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1 1;
risk GCS;
refgroup 2;
start   -21.671181      67.759502     -11.685920      45.705227      -0.097312
75.730199
   -3.025663     8.068714     2.221589  0   1.058688   0   ;
run;
PROC TRAJ  DATA=logreg  OUT=anxoput  OUTPLOT=anxplot  OUTSTAT=anxstat ci95m;
id id;
var ANX1-ANX4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
```

```
order 2 1 1;
run;
PROC TRAJ  DATA=logreg  OUT=anxoput  OUTPLOT=anxplot  OUTSTAT=anxstat ci95m;
id id;
var ANX1-ANX4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1 1;
risk Age_c Gender Education_c  Maritalgrp GCS;
refgroup 2;
start   -21.671181      67.759502     -11.685920      45.705227      -0.097312
75.730199
   -3.025663     8.068714     2.221589  0 0 0 0 0   1.058688   0 0 0 0 0   ;
run;
PROC TRAJ  DATA=logreg  OUT=anxoput  OUTPLOT=anxplot  OUTSTAT=anxstat ci95m;
id id;
var ANX1-ANX4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1 1;
run;
PROC TRAJ  DATA=logreg  OUT=anxoput  OUTPLOT=anxplot  OUTSTAT=anxstat ci95m;
id id;
var ANX1-ANX4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1 1;
risk Gender  Maritalgrp GCS;
refgroup 2;
start   -21.671181      67.759502     -11.685920      45.705227      -0.097312
75.730199
   -3.025663     8.068714     2.221589  0 0 0    1.058688   0 0 0  ;
run;

/*SAT*/

PROC TRAJ  DATA=logreg  OUT=satoput  OUTPLOT=satplot  OUTSTAT=satstat ci95m;
id id;
var SAT1-SAT4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1;
run;
PROC TRAJ  DATA=logreg  OUT=satoput  OUTPLOT=satplot  OUTSTAT=satstat ci95m;
id id;
var SAT1-SAT4;
indep TIME1-TIME4;
model cnorm;
min 0;
```

```
max 100;
order 2 1;
risk Age_c Gender Education_C Maritalgrp GCS;
refgroup 2;
start   24.146541      -7.117120       1.286956      25.388292       0.514618
6.045919
   -0.268874 0 0 0 0 0;
run;
PROC TRAJ  DATA=logreg  OUT=satoput  OUTPLOT=satplot  OUTSTAT=satstat ci95m;
id id;
var SAT1-SAT4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1;
risk Age_c ;
refgroup 2;
start   24.146541      -7.117120       1.286956      25.388292       0.514618
6.045919
   -0.268874 0 ;
run;
PROC TRAJ  DATA=logreg  OUT=satoput  OUTPLOT=satplot  OUTSTAT=satstat ci95m;
id id;
var SAT1-SAT4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1;
risk Gender ;
refgroup 2;
start   24.146541      -7.117120       1.286956      25.388292       0.514618
6.045919
   -0.268874 0 ;
run;
PROC TRAJ  DATA=logreg  OUT=satoput  OUTPLOT=satplot  OUTSTAT=satstat ci95m;
id id;
var SAT1-SAT4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1;
risk Education_c;
refgroup 2;
start   24.146541      -7.117120       1.286956      25.388292       0.514618
6.045919
   -0.268874 0;
run;
PROC TRAJ  DATA=logreg  OUT=satoput  OUTPLOT=satplot  OUTSTAT=satstat ci95m;
id id;
var SAT1-SAT4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
```

```
order 2 1;
risk  Maritalgrp ;
refgroup 2;
start   24.146541      -7.117120       1.286956      25.388292       0.514618
6.045919
   -0.268874 0 ;
run;
PROC TRAJ  DATA=logreg  OUT=satoput  OUTPLOT=satplot  OUTSTAT=satstat ci95m;
id id;
var SAT1-SAT4;
indep TIME1-TIME4;
model cnorm;
min 0;
max 100;
order 2 1;
risk GCS;
refgroup 2;
start   24.146541      -7.117120       1.286956      25.388292       0.514618
6.045919
   -0.268874 0;
run;

/*Dual trajectory model with predictors*/
ODS RTF FILE="D:\My thesis\dualmodelpredictor.rtf";
/*ANX&DEP*/
PROC   TRAJ     DATA=logreg     OUT=adput     OUTPLOT=anxplot   OUTSTAT=anxstat
OUTPLOT2=depplot  OUTSTAT2=depstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 DEP1-DEP4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 1 1;
start
-21.671181    67.759502   -11.685920 /*model ANX trajectory parameters*/
45.705227    -0.097312
75.730199    -3.025663
8.068714                                                /*model ANX sigma*/
7.630931    70.372254    21.996815    /*model ANX group percentages*/

47.233980     0.799818    /*model DEP trajectory parameters*/
   64.165871     1.272935
   8.650229                        /*model DEP sigma*/

50 50  50 50  50 50; /*Model 2 given model 1 conditional group percentages*/
run;
PROC   TRAJ     DATA=logreg     OUT=adpput     OUTPLOT=anxplot   OUTSTAT=anxstat
OUTPLOT2=depplot  OUTSTAT2=depstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 DEP1-DEP4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 1 1;

risk2 Age_c;
refgroup2 1;
run;
```

```
PROC  TRAJ    DATA=logreg    OUT=adpput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=depplot  OUTSTAT2=depstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 DEP1-DEP4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 1 1;
risk2 Gender;
refgroup2 1;
run;
PROC  TRAJ    DATA=logreg    OUT=adpput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=depplot  OUTSTAT2=depstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 DEP1-DEP4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 1 1;
risk2 Education_c;
refgroup2 1;
run;
PROC  TRAJ    DATA=logreg    OUT=adpput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=depplot  OUTSTAT2=depstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 DEP1-DEP4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 1 1;
risk2 Maritalgrp;
refgroup2 1;
run;
PROC  TRAJ    DATA=logreg    OUT=adpput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=depplot  OUTSTAT2=depstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 DEP1-DEP4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 1 1;
risk2 GCS;
refgroup2 1;
run;
PROC  TRAJ    DATA=logreg    OUT=adpput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=depplot  OUTSTAT2=depstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 DEP1-DEP4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 1 1;
risk2 Maritalgrp GCS;
refgroup2 1;
run;
PROC  TRAJ    DATA=logreg    OUT=adpput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=depplot  OUTSTAT2=depstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 DEP1-DEP4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 1 1;
```

```
risk2 Age_c Gender Education_C Maritalgrp GCS;
refgroup2 1;
run;

/*ANX&SAT*/
PROC  TRAJ    DATA=logreg    OUT=asput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
start
-21.671181  67.759502   -11.685920   /*model ANX trajectory parameters*/
45.705227    -0.097312
75.730199    -3.025663
8.068714                                                /*model ANX sigma*/
7.630931    70.372254    21.996815    /*model ANX group percentages*/

24.146541    -7.117120     1.286956     /*model SAT trajectory parameters*/
25.388292     0.514618
6.045919                                                  /*model SAT sigma*/

50  50    50  50    50  50;  /*Model  SAT  given  model  ANX  conditional  group
percentages*/
run;
PROC  TRAJ    DATA=logreg    OUT=aspput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 Age_c Gender Education_C Maritalgrp GCS;
refgroup2 2;
run;
PROC  TRAJ    DATA=logreg    OUT=aspput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 Age_c;
refgroup2 2;
run;
PROC  TRAJ    DATA=logreg    OUT=aspput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 Gender ;
refgroup2 2;
run;
```

```
PROC  TRAJ    DATA=logreg    OUT=aspput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 Education_C ;
refgroup2 2;
run;
PROC  TRAJ    DATA=logreg    OUT=aspput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 Maritalgrp;
refgroup2 2;
run;
PROC  TRAJ    DATA=logreg    OUT=aspput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 GCS;
refgroup2 2;
run;
PROC  TRAJ    DATA=logreg    OUT=aspput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 Education_C Maritalgrp GCS;
refgroup2 2;
run;
/*DEP&SAT*/
PROC  TRAJ    DATA=logreg    OUT=dsput    OUTPLOT=depplot  OUTSTAT=depstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var DEP1-DEP4; indep TIME1-TIME4; model cnorm; min 0; max 100; ngroups 2;
order 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
start
   47.233980     0.799818    /*model DEP trajectory parameters*/
   64.165871     1.272935
   8.650229                        /*model DEP sigma*/
   63.945157     36.054843     /*model DEP group percentages*/

24.146541    -7.117120     1.286956     /*model SAT trajectory parameters*/
25.388292     0.514618
6.045919                                              /*model SAT sigma*/
```

```
50 50  50 50 ; /*Model SAT given model DEP conditional group percentages*/
run;
PROC  TRAJ    DATA=logreg    OUT=dspput    OUTPLOT=depplot  OUTSTAT=depstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var DEP1-DEP4; indep TIME1-TIME4; model cnorm; min 0; max 100; ngroups 2;
order 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 Age_c Gender Education_C Maritalgrp GCS;
refgroup2 2;
run;
PROC  TRAJ    DATA=logreg    OUT=dspput    OUTPLOT=depplot  OUTSTAT=depstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var DEP1-DEP4; indep TIME1-TIME4; model cnorm; min 0; max 100; ngroups 2;
order 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 Age_c;
refgroup2 2;
run;
PROC  TRAJ    DATA=logreg    OUT=dspput    OUTPLOT=depplot  OUTSTAT=depstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var DEP1-DEP4; indep TIME1-TIME4; model cnorm; min 0; max 100; ngroups 2;
order 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 Gender;
refgroup2 2;
run;
PROC  TRAJ    DATA=logreg    OUT=dspput    OUTPLOT=depplot  OUTSTAT=depstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var DEP1-DEP4; indep TIME1-TIME4; model cnorm; min 0; max 100; ngroups 2;
order 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 Education_C;
refgroup2 2;
run;
PROC  TRAJ    DATA=logreg    OUT=dspput    OUTPLOT=depplot  OUTSTAT=depstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var DEP1-DEP4; indep TIME1-TIME4; model cnorm; min 0; max 100; ngroups 2;
order 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 Maritalgrp;
refgroup2 2;
run;
PROC  TRAJ    DATA=logreg    OUT=dspput    OUTPLOT=depplot  OUTSTAT=depstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
```

```
var DEP1-DEP4; indep TIME1-TIME4; model cnorm; min 0; max 100; ngroups 2;
order 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
risk2 GCS;
refgroup2 2;
run;
ods rtf close;


ods rtf FILE="D:\REG2.rtf";
/*logistic regression*/
/*logistic regression for DEP trajectory group*/
proc logistic data=logreg order=data;
class GCS(param=ref ref="severe");
model DEPGROUP(event="High")=GCS/rsq lackfit stb;
format DEPGROUP DEPGROUP. GCS GCS.;
run;
proc logistic data=logreg order=data;
model DEPGROUP(event="High")=Age_c/rsq lackfit stb;
format DEPGROUP DEPGROUP.;
run;
proc logistic data=logreg order=data;
model DEPGROUP(event="High")=Education_c/rsq lackfit stb;
format DEPGROUP DEPGROUP.;
run;
proc logistic data=logreg order=data;
class maritalgrp(param=ref ref="married");
model DEPGROUP(event="High")=maritalgrp/rsq lackfit stb;
format DEPGROUP DEPGROUP. Maritalgrp maritalgrp.;
run;
proc logistic data=logreg order=data;
class Gender(param=ref ref="female");
model DEPGROUP(event="High")=Gender/rsq lackfit stb;
format DEPGROUP DEPGROUP. Gender Gender.;
run;
proc logistic data=logreg order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model  depgroup(event="High")=Age_c  Education_c   Gender  GCS  maritalgrp/rsq
lackfit stb;
format DEPGROUP DEPGROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
run;
proc logistic data=logreg order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model  depgroup(event="High")=Education_c   Gender  GCS  maritalgrp/rsq  lackfit
stb;
format DEPGROUP DEPGROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
proc logistic data=logreg order=data;
class  GCS(ref="severe") maritalgrp(ref="married");
model DEPGROUP(event="High")=Age_c  GCS maritalgrp/rsq lackfit stb;
format DEPGROUP DEPGROUP. GCS GCS. Maritalgrp maritalgrp.;
run;

/*logistic regression for SAT trajectory group*/
proc logistic data=logreg order=data;
class GCS(param=ref ref="severe");
model SATGROUP(event="Low")=GCS/rsq lackfit stb;
```

```
format SATGROUP SATGROUP. GCS GCS.;
run;
proc logistic data=logreg order=data;
model SATGROUP(event="Low")=Age_c/rsq lackfit stb;
format SATGROUP SATGROUP.;
run;
proc logistic data=logreg order=data;
model SATGROUP(event="Low")=Education_c/rsq lackfit stb;
format SATGROUP SATGROUP.;
run;
proc logistic data=logreg order=data;
class maritalgrp(param=ref ref="married");
model SATGROUP(event="Low")=maritalgrp/rsq lackfit stb;
format SATGROUP SATGROUP. Maritalgrp maritalgrp.;
run;
proc logistic data=logreg order=data;
class Gender(param=ref ref="female");
model SATGROUP(event="Low")=Gender/rsq lackfit stb;
format SATGROUP SATGROUP. Gender Gender.;
run;
proc logistic data=logreg order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model  satgroup(event="Low")=Age_c  Education_c    Gender  GCS  maritalgrp/rsq
lackfit stb;
format SATGROUP SATGROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
run;
proc logistic data=logreg order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model satgroup(event="Low")=Education_c  Gender GCS maritalgrp;
format satGROUP satGROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
run;
proc logistic data=logreg order=data;
class  GCS(ref="severe") maritalgrp(ref="married");
model SATGROUP(event="Low")=Age_c  GCS maritalgrp/rsq lackfit stb;
format SATGROUP SATGROUP. GCS GCS. Maritalgrp maritalgrp.;
run;
/* logistic regression for ANX trajectory group*/
data anxreg1;
set logreg;
where anxgroup=1 or anxgroup=2;
run;
proc logistic data=anxreg1 order=data;
class GCS(param=ref ref="severe");
model ANXGROUP(event="High-peak")=GCS/rsq lackfit stb;
format ANXGROUP ANXGROUP. GCS GCS.;
run;
proc logistic data=anxreg1 order=data;
model ANXGROUP(event="High-peak")=Age_c/rsq lackfit stb;
format ANXGROUP ANXGROUP.;
run;
proc logistic data=anxreg1 order=data;
model ANXGROUP(event="High-peak")=Education_c/rsq lackfit stb;
format ANXGROUP ANXGROUP.;
run;
proc logistic data=anxreg1 order=data;
class maritalgrp(param=ref ref="married");
model ANXGROUP(event="High-peak")=maritalgrp/rsq lackfit stb;
```

```
format ANXGROUP ANXGROUP. Maritalgrp maritalgrp.;
run;
proc logistic data=anxreg1 order=data;
class Gender(param=ref ref="female");
model ANXGROUP(event="High-peak")=Gender/rsq lackfit stb;
format ANXGROUP ANXGROUP. Gender Gender.;
run;
proc logistic data=anxreg1 order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model    ANXGROUP(event="High-peak")=Age_c    Education_c        Gender    GCS
maritalgrp/rsq lackfit stb;
format ANXGROUP ANXGROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
run;
proc logistic data=anxreg1 order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model ANXGROUP(event="High-peak")=Education_c  Gender GCS maritalgrp;
format ANXGROUP ANXGROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
run;
data anxreg3;
set logreg;
where anxgroup=2 or anxgroup=3;
run;
proc logistic data=anxreg3 order=data;
class GCS(param=ref ref="severe");
model ANXGROUP(event="High-decreasing")=GCS/rsq lackfit stb;
format ANXGROUP ANXGROUP. GCS GCS.;
run;
proc logistic data=anxreg3 order=data;
model ANXGROUP(event="High-decreasing")=Age_c/rsq lackfit stb;
format ANXGROUP ANXGROUP.;
run;
proc logistic data=anxreg3 order=data;
model ANXGROUP(event="High-decreasing")=Education_c/rsq lackfit stb;
format ANXGROUP ANXGROUP.;
run;
proc logistic data=anxreg3 order=data;
class maritalgrp(param=ref ref="married");
model ANXGROUP(event="High-decreasing")=maritalgrp/rsq lackfit stb;
format ANXGROUP ANXGROUP. Maritalgrp maritalgrp.;
run;
proc logistic data=anxreg3 order=data;
class Gender(param=ref ref="female");
model ANXGROUP(event="High-decreasing")=Gender/rsq lackfit stb;
format ANXGROUP ANXGROUP. Gender Gender.;
run;
proc logistic data=anxreg3 order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model   ANXGROUP(event="High-decreasing")=Age_c   Education_c     Gender   GCS
maritalgrp/rsq lackfit stb;
format ANXGROUP ANXGROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
run;
proc logistic data=anxreg3 order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model ANXGROUP(event="High-decreasing")=Education_c  Gender GCS maritalgrp;
format ANXGROUP ANXGROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
run;
/*logistic regression for multitrajectory*/
```

```
data GROUP2;
set logreg;
where GROUP=1 or GROUP=2;
run;
proc logistic data=GROUP2 order=data;
class GCS(param=ref ref="severe");
model GROUP(event="multigroup2")=GCS/rsq lackfit stb;
format GROUP GROUP. GCS GCS.;
run;
proc logistic data=GROUP2 order=data;
class GCS(param=ref ref="severe");
model GROUP(event="multigroup2")=GCS/rsq lackfit stb;
format GROUP GROUP. GCS GCS.;
run;
proc logistic data=GROUP2 order=data;
model GROUP(event="multigroup2")=Age_c/rsq lackfit stb;
format GROUP GROUP.;
run;
proc logistic data=GROUP2 order=data;
model GROUP(event="multigroup2")=Education_c/rsq lackfit stb;
format GROUP GROUP.;
run;
proc logistic data=GROUP2 order=data;
class maritalgrp(param=ref ref="married");
model GROUP(event="multigroup2")=maritalgrp/rsq lackfit stb;
format GROUP GROUP. Maritalgrp maritalgrp.;
run;
proc logistic data=GROUP2 order=data;
class Gender(param=ref ref="female");
model GROUP(event="multigroup2")=Gender/rsq lackfit stb;
format GROUP GROUP. Gender Gender.;
run;
proc logistic data=GROUP2 order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model GROUP(event="multigroup2")=Age_c Education_c  Gender GCS maritalgrp/rsq
lackfit stb;
format GROUP GROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
run;
proc logistic data=GROUP2 order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model GROUP(event="multigroup2")=Education_c  Gender GCS maritalgrp;
format GROUP GROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
run;
data GROUP3;
set logreg;
where GROUP=1 or GROUP=3;
run;
proc logistic data=GROUP3 order=data;
class GCS(param=ref ref="severe");
model GROUP(event="multiGROUP3")=GCS/rsq lackfit stb;
format GROUP GROUP. GCS GCS.;
run;
proc logistic data=GROUP3 order=data;
model GROUP(event="multiGROUP3")=Age_c/rsq lackfit stb;
format GROUP GROUP.;
run;
proc logistic data=GROUP3 order=data;
```

```
model GROUP(event="multiGROUP3")=Education_c/rsq lackfit stb;
format GROUP GROUP.;
run;
proc logistic data=GROUP3 order=data;
class maritalgrp(param=ref ref="married");
model GROUP(event="multiGROUP3")=maritalgrp/rsq lackfit stb;
format GROUP GROUP. Maritalgrp maritalgrp.;
run;
proc logistic data=GROUP3 order=data;
class Gender(param=ref ref="female");
model GROUP(event="multiGROUP3")=Gender/rsq lackfit stb;
format GROUP GROUP. Gender Gender.;
run;
proc logistic data=GROUP3 order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model GROUP(event="multiGROUP3")=Age_c Education_c  Gender GCS maritalgrp/rsq
lackfit stb;
format GROUP GROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
run;
proc logistic data=GROUP3 order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model GROUP(event="multiGROUP3")=Education_c  Gender GCS maritalgrp;
format GROUP GROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
run;
/*catmod multitrajectory*/
proc catmod data=logreg;
direct Age_c;
model GROUP=Age_c;
format GROUP GROUP.;
run;
proc catmod data=logreg;
direct Gender;
model GROUP=Gender;
format GROUP GROUP. Gender Gender.;
run;
proc catmod data=logreg;
direct Maritalgrp;
model GROUP=Maritalgrp;
format GROUP GROUP. Maritalgrp Maritalgrp.;
run;
proc catmod data=logreg;
direct GCS;
model GROUP=GCS;
format GROUP GROUP. GCS GCS.;
run;
proc catmod data=logreg;
direct Education_c;
model GROUP=Education_c;
format GROUP GROUP.;
run;
proc catmod data=logreg;
direct  GCS maritalgrp Gender Age_c Education_c  ;
model GROUP=Age_c Education_c  Gender GCS maritalgrp;
format GROUP GROUP. GCS GCS. Maritalgrp maritalgrp. Gender Gender.;
run;
/* catmod for ANX trajectory group*/
proc catmod data=logreg;
```

```
direct Age_c;
response logits;
model ANXGROUP=Age_c;
format ANXGROUP ANXGROUP.;
run;
proc catmod data=logreg;
direct Gender;
response logits;
model ANXGROUP=Gender;
format ANXGROUP ANXGROUP. Gender Gender.;
run;
proc catmod data=logreg;
direct Maritalgrp;
response logits;
model ANXGROUP=Maritalgrp;
format ANXGROUP ANXGROUP. Maritalgrp Maritalgrp.;
run;
proc catmod data=logreg;
direct GCS;
response logits;
model ANXGROUP=GCS;
format ANXGROUP ANXGROUP. GCS GCS.;
run;
proc catmod data=logreg;
direct Education_c;
response logits;
model GROUP=Education_c;
format ANXGROUP ANXGROUP.;
run;
proc catmod data=logreg;
direct  GCS maritalgrp Gender Age_c Education_c  ;
response logits;
model ANXGROUP=Age_c Education_c  Gender GCS maritalgrp;
format ANXGROUP ANXGROUP. GCS GCS. Maritalgrp Maritalgrp. Gender Gender. ;
run;
proc catmod data=logreg;
direct  GCS  Gender Age_c  ;
response logits;
model ANXGROUP=Gender GCS Age_c  ;
format ANXGROUP ANXGROUP. GCS GCS. Gender Gender. ;
run;
quit;
ods rtf close;
ods rtf FILE="D:\MULTIDIS.rtf";
proc sort data=logreg;
by GROUP;
run;
proc freq data=logreg;
table GCS*GROUP/NOROW  CHISQ FISHER;
format GCS GCS. GROUP GROUP.;
run;
proc freq data=logreg;
table GENDER*GROUP/NOROW  CHISQ FISHER;
format GENDER GENDER. GROUP GROUP.;
run;
proc freq data=logreg;
table Maritalgrp*GROUP/NOROW  CHISQ FISHER;
```

```
format Maritalgrp Maritalgrp. GROUP GROUP.;
run;
proc means data=logreg;
by GROUP;
var Age Education;
format GROUP GROUP.;
run;
proc ttest data=GROUP2;
class GROUP;
var Age Education;
format GROUP GROUP.;
run;
proc ttest data=GROUP3;
class GROUP;
var Age Education;
format GROUP GROUP.;
run;
proc anova data=logreg;
class GROUP;
model GCS=GROUP;
run;
proc anova data=logreg;
class GROUP;
Model Age=GROUP;
MEANS GROUP;
run;
proc anova data=logreg;
class GROUP;
Model Education=GROUP;
MEANS GROUP;
run;
quit;
proc means data=logreg;
class GROUP;
var DEP1-DEP4 ANX1-ANX4  SAT1-SAT4 initial_GCS;
run;
ods rtf close;
ods rtf FILE="D:\TRAJDES.rtf";
/* Descriptive statistics for symptom trajectory membership*/
proc sort data=logreg;
by DEPGROUP;
run;
proc means data=logreg;
class DEPGROUP;
var Age Education;
format DEPGROUP DEPGROUP.;
run;
proc freq data=logreg;
table Gender*DEPGROUP/chisq fisher norow;
format DEPGROUP DEPGROUP. GENDER GENDER.;
run;
proc freq data=logreg;
table Maritalgrp*DEPGROUP/chisq fisher  norow;
format DEPGROUP DEPGROUP. Maritalgrp Maritalgrp.;
run;
proc freq data=logreg;
table GCS*DEPGROUP/chisq fisher norow;
```

```
format DEPGROUP DEPGROUP. GCS GCS.;
run;
proc ttest data=logreg;
class DEPGROUP;
var DEP1 DEP2 DEP3 DEP4;
format DEPGROUP DEPGROUP.;
run;
proc ttest data=logreg;
class DEPGROUP;
var ANX1-ANX4;
format DEPGROUP DEPGROUP.;
run;
proc ttest data=logreg;
class DEPGROUP;
var SAT1-SAT4;
format DEPGROUP DEPGROUP.;
run;
proc ttest data=logreg;
class DEPGROUP;
var Initial_GCS;
format DEPGROUP DEPGROUP.;
run;
proc ttest data=logreg;
class DEPGROUP;
var Education;
format DEPGROUP DEPGROUP.;
run;
proc ttest data=logreg;
class DEPGROUP;
var Age;
format DEPGROUP DEPGROUP.;
run;
proc sort data=logreg;
by ANXGROUP;
run;
proc means data=logreg;
class ANXGROUP;
var Age Education;
format ANXGROUP ANXGROUP.;
run;
proc freq data=logreg;
table Gender*ANXGROUP/chisq fisher  norow;
format ANXGROUP ANXGROUP. Gender Gender.;
run;
proc freq data=logreg;
table Maritalgrp*ANXGROUP/chisq fisher norow;
format ANXGROUP ANXGROUP. Maritalgrp Maritalgrp.;
run;
proc freq data=logreg;
table GCS*ANXGROUP/chisq fisher norow;
format ANXGROUP ANXGROUP. GCS GCS.;
run;
proc anova data=logreg;
class ANXGROUP;
Model Age=ANXGROUP;
MEANS ANXGROUP;
format ANXGROUP ANXGROUP.;
```

```
run;
proc anova data=logreg;
class ANXGROUP;
Model Education=ANXGROUP;
MEANS ANXGROUP;
format ANXGROUP ANXGROUP.;
run;
proc sort data=logreg;
by SATGROUP;
run;
proc means data=logreg;
class SATGROUP;
run;
proc freq data=logreg;
table Gender*SATGROUP/chisq fisher  norow;
run;
proc freq data=logreg;
table Maritalgrp*SATGROUP/chisq fisher  norow;
run;
proc freq data=logreg;
table GCS*SATGROUP/chisq fisher norow;
run;
proc ttest data=logreg;
class SATGROUP;
var Initial_GCS;
run;
proc ttest data=logreg;
class SATGROUP;
var Education;
run;
proc ttest data=logreg;
class SATGROUP;
var Age;
run;
quit;
ods rtf close;
/*DUAL MODELING ANALYSIS*/
ods rtf FILE="D:\Dual.rtf";
PROC  TRAJ    DATA=widetraj    OUT=DADOput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=depplot  OUTSTAT2=depstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 DEP1-DEP4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 1 1;
start
-21.671181    67.759502   -11.685920 /*model ANX trajectory parameters*/
45.705227    -0.097312
75.730199    -3.025663
8.068714                                                /*model ANX sigma*/
7.630931    70.372254    21.996815    /*model ANX group percentages*/

47.233980     0.799818    /*model DEP trajectory parameters*/
   64.165871     1.272935
   8.650229                        /*model DEP sigma*/

50 50  50 50  50 50; /*Model 2 given model 1 conditional group percentages*/
```

```
run;
%trajplot(depplot,depstat,'Depression over Time');
title;
%trajplot(anxplot,anxstat,'Anxiet over Time');
title;
/*ANX&SAT*/
PROC  TRAJ    DATA=widetraj    OUT=DASOput    OUTPLOT=anxplot  OUTSTAT=anxstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var ANX1-ANX4;indep TIME1-TIME4; model cnorm;min 0; max 100;ngroups 3; order
2 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
start
-21.671181  67.759502   -11.685920   /*model ANX trajectory parameters*/
45.705227    -0.097312
75.730199    -3.025663
8.068714                                                /*model ANX sigma*/
7.630931    70.372254    21.996815    /*model ANX group percentages*/

24.146541    -7.117120     1.286956     /*model SAT trajectory parameters*/
25.388292     0.514618
6.045919                                                  /*model SAT sigma*/

50  50    50  50    50  50;  /*Model  SAT  given  model  ANX  conditional  group
percentages*/
run;

%trajplot(anxplot,anxstat,'Anxiet over Time');
title;
%trajplot(satplot,satstat,'Satisfaction over Time');
title;
/*DEP&SAT*/
PROC  TRAJ    DATA=widetraj    OUT=DDSOput    OUTPLOT=depplot  OUTSTAT=depstat
OUTPLOT2=satplot  OUTSTAT2=satstat  itdetail;
id id;
var DEP1-DEP4; indep TIME1-TIME4; model cnorm; min 0; max 100; ngroups 2;
order 1 1;
var2 SAT1-SAT4; indep2 TIME1-TIME4; model2 cnorm; min 0; max2 100; ngroups2
2;order2 2 1;
start
   47.233980     0.799818    /*model DEP trajectory parameters*/
   64.165871     1.272935
   8.650229                        /*model DEP sigma*/
   63.945157     36.054843     /*model DEP group percentages*/

24.146541    -7.117120     1.286956     /*model SAT trajectory parameters*/
25.388292     0.514618
6.045919                                                  /*model SAT sigma*/

50 50  50 50 ; /*Model SAT given model DEP conditional group percentages*/
run;
%trajplot(depplot,depstat,'Depression over Time');
title;
%trajplot(satplot,satstat,'Satisfaction over Time');
title;
proc print data=DADOput;
```

```
run;
proc print data=DASOput;
run;
proc print data=DDSOput;
run;
proc sql;
create table dadgroup as
select DADOput.GROUP as DADAGROUP, DADOput.GROUP2 as DADDGROUP,  logreg.*
from DADOput, logreg
where DADOput.ID=logreg.ID;
quit;
proc sort data=dadgroup;
by ID;
run;
proc print data=dadgroup;
run;
proc sql;
create table dasgroup as
select DASOput.GROUP as DASAGROUP, DASOput.GROUP2 as DASSGROUP,  logreg.*
from DASOput, logreg
where DASOput.ID=logreg.ID;
quit;
proc sort data=dasgroup;
by ID;
run;
proc print data=dasgroup;
run;
proc sql;
create table ddsgroup as
select DDSOput.GROUP as DDSDGROUP, DDSOput.GROUP2 as DDSSGROUP,  logreg.*
from DDSOput, logreg
where DDSOput.ID=logreg.ID;
quit;
proc sort data=ddsgroup;
by ID;
run;
proc print data=ddsgroup;
run;
data dadgroup;
set dadgroup;
if DADAGROUP=2 and DADDGROUP=1 then DADGROUP=1;
if DADAGROUP=3 and DADDGROUP=2 then DADGROUP=2;
run;
data dadgroup;
set dadgroup;
where DADGROUP=1 or DADGROUP=2;
run;
proc print data=dadgroup;
run;
data dasgroup;
set dasgroup;
if DASAGROUP=2 and DASSGROUP=2 then DASGROUP=1;
if DASAGROUP=3 and DASSGROUP=1 then DASGROUP=2;
run;
data dasgroup;
set dasgroup;
where DASGROUP=1 or DASGROUP=2;
```

```
run;
proc print data=dasgroup;
run;
data ddsgroup;
set ddsgroup;
if DDSDGROUP=1 and DDSSGROUP=2 then DDSGROUP=1;
if DDSDGROUP=2 and DDSSGROUP=1 then DDSGROUP=2;
run;
data ddsgroup;
set ddsgroup;
where DDSGROUP=1 or DDSGROUP=2;
run;
proc print data=ddsgroup;
run;
/*DUAL descritive*/
/*DAD*/
proc sort data=dadgroup;
by DADGROUP;
run;
proc means data=dadgroup;
class DADGROUP;
var Age Education;
run;
proc freq data=dadgroup;
table Gender*DADGROUP/chisq fisher norow;
format GENDER GENDER.;
run;
proc freq data=dadgroup;
table Maritalgrp*DADGROUP/chisq fisher  norow;
format  Maritalgrp Maritalgrp.;
run;
proc freq data=dadgroup;
table GCS*DADGROUP/chisq fisher norow;
format GCS GCS.;
run;
proc ttest data=dadgroup;
class DADGROUP;
var DEP1 DEP2 DEP3 DEP4;
run;
proc ttest data=dadgroup;
class DADGROUP;
var ANX1-ANX4;
run;
proc ttest data=dadgroup;
class DADGROUP;
var SAT1-SAT4;
run;
proc ttest data=dadgroup;
class DADGROUP;
var Initial_GCS;
run;
proc ttest data=dadgroup;
class DADGROUP;
var Education;
run;
proc ttest data=dadgroup;
class DADGROUP;
```

```
var Age;
run;
/*DAS*/
proc sort data=dasgroup;
by DASGROUP;
run;
proc means data=dasgroup;
class DASGROUP;
var Age Education;
run;
proc freq data=dasgroup;
table Gender*DASGROUP/chisq fisher norow;
format GENDER GENDER.;
run;
proc freq data=dasgroup;
table Maritalgrp*DASGROUP/chisq fisher  norow;
format  Maritalgrp Maritalgrp.;
run;
proc freq data=dasgroup;
table GCS*DASGROUP/chisq fisher norow;
format GCS GCS.;
run;
proc ttest data=dasgroup;
class DASGROUP;
var DEP1 DEP2 DEP3 DEP4;
run;
proc ttest data=dasgroup;
class DASGROUP;
var ANX1-ANX4;
run;
proc ttest data=dasgroup;
class DASGROUP;
var SAT1-SAT4;
run;
proc ttest data=dasgroup;
class DASGROUP;
var Initial_GCS;
run;
proc ttest data=dasgroup;
class DASGROUP;
var Education;
run;
proc ttest data=dasgroup;
class DASGROUP;
var Age;
run;
/*DDS*/
proc sort data=ddsgroup;
by DDSGROUP;
run;
proc means data=ddsgroup;
class DDSGROUP;
var Age Education;
run;
proc freq data=ddsgroup;
table Gender*DDSGROUP/chisq fisher norow;
format GENDER GENDER.;
```

```
run;
proc freq data=ddsgroup;
table Maritalgrp*DDSGROUP/chisq fisher  norow;
format  Maritalgrp Maritalgrp.;
run;
proc freq data=ddsgroup;
table GCS*DDSGROUP/chisq fisher norow;
format GCS GCS.;
run;
proc ttest data=ddsgroup;
class DDSGROUP;
var DEP1 DEP2 DEP3 DEP4;
run;
proc ttest data=ddsgroup;
class DDSGROUP;
var ANX1-ANX4;
run;
proc ttest data=ddsgroup;
class DDSGROUP;
var SAT1-SAT4;
run;
proc ttest data=ddsgroup;
class DDSGROUP;
var Initial_GCS;
run;
proc ttest data=ddsgroup;
class DDSGROUP;
var Education;
run;
proc ttest data=ddsgroup;
class DDSGROUP;
var Age;
run;
/*logistic regression for dual trajectory group*/
/*DAD*/
proc logistic data=dadgroup order=data;
model DADGROUP(event="2")=Age_c/rsq lackfit stb;
run;
proc logistic data=dadgroup order=data;
class Gender(param=ref ref="female");
model DADGROUP(event="2")=Gender/rsq lackfit stb;
format Gender Gender.;
run;
proc logistic data=dadgroup order=data;
model DADGROUP(event="2")=Education_c/rsq lackfit stb;
run;
proc logistic data=dadgroup order=data;
class Maritalgrp(param=ref ref="married");
model DADGROUP(event="2")=Maritalgrp/rsq lackfit stb;
format Maritalgrp maritalgrp.;
run;
proc logistic data=dadgroup order=data;
class GCS(param=ref ref="severe");
model  DADGROUP(event="2")=GCS/rsq lackfit stb;
format GCS GCS.;
run;
proc logistic data=dadgroup order=data;
```

```
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model  DADGROUP(event="2")=Age_c  Gender  Education_c    Maritalgrp  GCS/rsq
lackfit stb;
format GCS GCS. Maritalgrp Maritalgrp. Gender Gender.;
run;
/*DAS*/
proc logistic data=dasgroup order=data;
model DASGROUP(event="2")=Age_c/rsq lackfit stb;
run;
proc logistic data=dasgroup order=data;
class Gender(param=ref ref="female");
model DASGROUP(event="2")=Gender/rsq lackfit stb;
format Gender Gender.;
run;
proc logistic data=dasgroup order=data;
model DASGROUP(event="2")=Education_c/rsq lackfit stb;
run;
proc logistic data=dasgroup order=data;
class Maritalgrp(param=ref ref="married");
model DASGROUP(event="2")=Maritalgrp/rsq lackfit stb;
format Maritalgrp maritalgrp.;
run;
proc logistic data=dasgroup order=data;
class GCS(param=ref ref="severe");
model  DASGROUP(event="2")=GCS/rsq lackfit stb;
format GCS GCS.;
run;
proc logistic data=dasgroup order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
model  DASGROUP(event="2")=Age_c  Gender  Education_c    Maritalgrp  GCS/rsq
lackfit stb;
format GCS GCS. Maritalgrp Maritalgrp. Gender Gender.;
run;
/*DDS*/
proc logistic data=ddsgroup order=data;
model DDSGROUP(event="2")=Age_c/rsq lackfit stb;
run;
proc logistic data=ddsgroup order=data;
class Gender(param=ref ref="female");
model DDSGROUP(event="2")=Gender/rsq lackfit stb;
format Gender Gender.;
run;
proc logistic data=ddsgroup order=data;
model DDSGROUP(event="2")=Education_c/rsq lackfit stb;
run;
proc logistic data=ddsgroup order=data;
class Maritalgrp(param=ref ref="married");
model DDSGROUP(event="2")=Maritalgrp/rsq lackfit stb;
format Maritalgrp maritalgrp.;
run;
proc logistic data=ddsgroup order=data;
class GCS(param=ref ref="severe");
model  DDSGROUP(event="2")=GCS/rsq lackfit stb;
format GCS GCS.;
run;
proc logistic data=ddsgroup order=data;
class  GCS(ref="severe") maritalgrp(ref="married") Gender(ref="female");
```

```
model  DDSGROUP(event="2")=Age_c  Gender  Education_c    Maritalgrp  GCS/rsq
lackfit stb;
format GCS GCS. Maritalgrp Maritalgrp. Gender Gender.;
run;
ods rtf close;
```

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