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A Descriptive Study of the Effect of Payer Source on Multiple Longitudinal Outcome Measures Within the TBI Model Systems National Database Using Longitudinal HLM Analyses

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Abstract

Using longitudinal data from the TBIMS ND, this study utilized a longitudinal hierarchical linear modeling approach to describe the effect of primary payer source on individual level change in outcomes including the FIM and DRS. To facilitate the use of parametric statistics, Rasch-transformed FIM and DRS scores were utilized; thus approaching an interval level of measurement. The FIM was separated into 3 separate cognitive, mobility, and self-care subscales. In this way, rehabilitation professionals including speech, physical, and occupational therapists for this TBI sample could reference results to inform current clinical practice.

Results indicated that FIM and DRS trajectories were best modelled using a negative exponential model. Significant variability was found in each growth parameter (Asymptote, Pseudo-Intercept, and Rate) ($p <$ .05) for all unconditional models (FIM Cognitive, FIM Mobility, FIM Self-Care, and DRS). Reduced conditional models for the FIM Cognitive, FIM Mobility, FIM Self-Care, and DRS outcome variables were constructed including only covariates that related significantly to the growth parameters. Conditional model results showed that as a group, the functional status of individuals measured by the FIM and DRS outcomes in the TBIMS ND improved rapidly and then plateaued as a result of floor and ceiling effects. Characteristics such as age, education, employment, length or rehab stay, marital status, PTA, race, and sex were found to impact baseline FIM and DRS scores and the rate and extent of improvement over time. More importantly, and a primary focus of this study was the effect of payer source on FIM and DRS outcomes.

At the individual and group level, primary payer source was significantly related to the growth parameters for each FIM and DRS outcome. The strong association found between primary payer and the growth parameters suggested that initial successful rehabilitation outcomes were a function of the type of rehabilitation received and dependent on the payment source for services. These findings are especially important to rehabilitation clinicians. Clinicians can use this information to secure further funding and care resources from third party payers that will advance an individual's course in successful functional outcomes and quality of life over their lifetime.

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Chapter 1: Introduction and Review of the Literature

In the United States, acute trauma accounts for more than two million hospitalizations annually and makes up nearly 8% of all hospital admissions (MacKenzie, 2000). Acute trauma occurs when injuries are sustained suddenly. The American Psychiatric Association (2000) defines trauma as:

> A direct personal experience of an event that involves actual or threatened death or serious injury, or other threat to one's physical integrity; or witnessing an event that involves death, injury, or a threat to the physical integrity of another person; or learning about unexpected or violent death or injury experienced by a family member or other close associate (Criterion A1). The person's response to the event must involve intense fear, helplessness, or horror, or in children, the response must involve disorganized or agitated behavior (Criterion A2). (p. 463)

Acute traumatic injuries, particularly injuries consistent with traumatic brain injury (TBI), place an immense burden on the long-term health and productivity of the individuals involved and on the United States medical care systems.

A TBI is characterized by an injury that disturbs the normal function of the brain. Potential etiology arises from a "bump, blow, or jolt to the head or a penetrating head injury" (Marr & Coronado, 2002, p. 22). Common to the U.S. military are TBI due to explosive blasts. TBI severity is classified as mild, moderate, or severe. Severity is based on the clinical presentation of one's neurologic signs and symptoms (Centers for Disease Control and Prevention, 2014)

More than 1.5 million persons sustain TBIs annually resulting in 50,000 deaths and an estimated 90,000 individuals with substantial disability or physical impairment (Coronado et al., 2011; Summers, Ivins, & Schwab, 2009). In fact, of the estimated 1.5 to 2.0 million persons who suffer from TBI each year, approximately 235,000 will require hospitalization. Such numbers result in life-time economic consequences totaling 4.5 billion (Max, Mackenzie, & Rice, 1991). The Centers for Disease Control (CDC) and Prevention estimates for 2009 included 2.4 million emergency department visits, hospitalizations, and deaths marked by a TBI diagnosis and the average for 2007-2009 for outpatient clinics or physician offices was about 1.2 million visits each year (Coronado, McGuire, Faul, Sugerman, & Pearson, 2012). It has been found that nearly 90% of those hospitalized for TBI will be persons 16 years and older (CDC, 2010). Additionally, for individuals sustaining TBI that are below the age of 75, more years of life are lost in TBI-related issues than for other medical conditions including cancer, heart disease, or HIV (Human Immunodeficiency Virus) (MacKenzie, 2000). Many patients will initially survive the effects of a TBI, however a TBI introduces a chronic disease process that may ultimately lead to their deaths months to years later (Masel & Dewitt, 2010). Chronic disease contributing to mortality may encompass neurological disorders (epilepsy), neurodegenerative disorders (Alzheimer's or Parkinson's disease), neuroendocrine disorders (post-traumatic hypopituitarism), psychiatric disease, or metabolic dysfunction (Masel & Dewitt, 2010).

Annually in the United States alone, more than 90,000 of the patients who have sustained a TBI become disabled (Thurman, Alverson, Dunn, Guerrero, & Sniezek, 1999) and a total of 3.5 million in the United States alone are disabled due to the sequelae of TBI (Zaloshnja, Miller, Langlois, & Selassie, 2008). According to Masel and Dewitt (2010), "Head trauma is the beginning of an ongoing, perhaps lifelong, process that impacts multiple organ systems and may be disease causative and accelerative" (p. 1529). TBI has often been referred to as a "chronic traumatic brain injury disease." The World Health Organization (WHO: 2002) further delineates a chronic disease as a process that encompasses the following characteristics; permanent, caused by non-reversible pathological alterations, requires special training of the patient for rehabilitation, and may require a long period of observation, supervision, or care. The general synopsis regarding chronic TBI is that, like other chronic medical conditions, it should be managed to optimize medical surveillance, support, and treatment (Masel & Dewitt, 2010).

TBI is a substantial rehabilitation and public health issue and can result in independence impairment among those affected (Wei, Sambamoorthi, Crystal, & Findley, 2005). What are the current recommendations to optimize treatment and outcomes? Post-hospitalization care, specifically rehabilitation therapy is widely accepted as a critical treatment intervention to improve short and long-term functional outcomes. To further strengthen trauma care and rehabilitation, Englum et al. (2011) emphasize the importance of access to evidence-based therapies that have been found to improve outcomes. Evidence-based modalities that are essential are used both in the hospital and after acute hospitalization to improve functional and additional long-term outcomes in a

rehab or skilled nursing setting. To optimize outcomes over the course of recovery for those who have sustained TBI, rehabilitation services must be matched to the specific needs of each individual (NIH Consensus Conference, 1999). Acute care professionals are active in the discharge disposition decisions for adults that have sustained moderate to severe TBI. To make such decisions, they must consider "the severity of injury, the degree of recovery, ability to function independently in daily tasks with or without family support, and ability to actively participate in rehabilitation" (Cuthbert et al., 2011, p. 722). It has been found that those individuals with TBI severe enough to warrant inpatient rehabilitation are likely to demonstrate physical, cognitive, emotional, behavioral, social, and functional problems post injury. Additional factors that contribute to decisions surrounding discharge disposition include familial and social supports, availability of funding, and post-acute discharge possibilities within the community (Cuthbert et al., 2011).

Rehabilitation specific to TBI in the post-acute period is critical to achieve improved functional outcomes and to improve quality of life (Bleakley et al., 2010; NIH Consensus Conference, 1999). Unfortunately, for those suffering from serious impairments, post-discharge care creates an enormous financial and emotional burden for their families and caregivers. Max et al. (1991) estimated the total national annual TBI-related costs to equal 37.8 billion dollars with 12% applied towards acute hospitalization, inpatient rehabilitation, and medical services. Additional short-term economic consequences of TBI during the acute and inpatient rehabilitation phases include costly medical and surgical interventions and the need for extended hospital and rehabilitation

length of stay (LOS) (Arango-Lasprilla et al., 2010). Previous TBI research exploring the factors that influence post-acute care discharge options have suggested that decisions regarding discharge destination may be based on factors other than injury severity, degree of recovery, ability to function independently and ability to actively participate in rehabilitation. Disparities in rehab placement have been observed in relation to an individual's age, race, and insurance (Chan, et al., 2001). As a physical therapist in the acute and inpatient rehabilitation setting for 15 years, I am cognizant of such disparities; particularly insurance disparities.

According to Chan et al. (2001), insurance type may significantly influence where patients receive post-acute care following TBI. There have been isolated cases where a younger individual (age 20-50) who lacks insurance benefits may be accepted to inpatient rehabilitation on charity funds. Additionally there are patients who may not qualify for inpatient rehabilitation based on their insurance benefits, but are able to privately pay for such services. Other primary payment sources (Medicare, Medicaid, Health Maintenance Organization (HMO), Preferred Provider Organization (PPO), and Workers Compensation Insurance) may only approve the patient for a set number of days to participate in an inpatient rehabilitation program, which may adversely affect their ability to optimize their rehabilitation outcomes over time. For example, Medicare, a national insurance program guaranteeing access to health insurance for Americans over 65 years of age (Medicare.gov) may reimburse facilities significantly less than their costs for the treatment of TBI. As a result, facilities may have to reduce length of stay or reduce resource use to maintain their current financial status, thus increasing the odds of an

elderly patient discharging to a lower level of care (skilled nursing versus inpatient rehabilitation) where functional outcomes cannot be optimized (Hoffman et al., 2003). Medicaid, a program funded by the U.S. government guarantees health coverage to American families and particularly individuals with low incomes and resources (Medicaid.gov). Although more comprehensive than Medicare, individuals may need to apply through secondary programs for long-term care outside of a nursing home. In this way, access to long-term care may be difficult as individuals may not be aware of the services and resources they are eligible for or how to obtain them, resulting in poorer functional outcomes over time due to delay in receiving care (Gardizi, Hanks, Millis, & Figueroa, 2014).

Similarly, managed health care (HMOs) may be limiting in that individuals are required to receive care and services from doctors and hospitals that are part of the HMO network. Any out of network services that may be required to optimize functional outcomes over time would not be covered. Using the Traumatic Brain Injury National Database (TBI NDB), this descriptive study aims to explore the patterns of rehabilitation functional outcomes over time with reference to specific payer source (Gardizi et al., 2014).

Literature Review

The level of rehabilitation an individual receives following a TBI is a key element to successful functional outcomes and reintegration into the home and community. Rehabilitation in medicine today has been found to be dictated by the payment source for services (Chan, et al., 2001). Trauma care is very costly; therefore, without insurance

coverage, many would not be able to qualify for such services. Kreutzer et al. (2001) evaluated yearly trends in charges for patients with brain injury in acute care and rehabilitation settings over a seven year period. Data were collected from 800 consecutive patients in four NIDRR (National Institute on Disability and Rehabilitation Research) TBI programs. The rate of change for acute care costs was significantly greater than for rehabilitation with annual acute care increases averaging 10% more than national medical care prices. Between the years of 1990-1996, it was found that average daily rehabilitation charges increased each year as well by approximately $83 or 7%. Weir et al. (2010) analyzed treatment cost for trauma care using a study population of 15,009 trauma patients; ages 18-64 years (12,392) and 65-84 years (2,617). For this sample, mean 1-year treatment costs were $75,210. He and his colleagues estimated treatment of adult major trauma to cost approximately $27 billion annually. Those without insurance coverage were among those with the highest total cost of care ($89,240) for the year post-injury and hospitalization costs (index and acute re-hospitalization) were the greatest contributing components. Higher percentages of total costs for those with private insurance were observed in the outpatient setting, mainly a result of physical and occupational therapy and rehab re-hospitalizations.

Determinant of Trauma Care. Payer status or insurance coverage has been found to be a determinant of trauma care in the United States (Chan, et al., 2001). Velopulos et al. (2013) further explored the national cost of care by payer status. Specifically, the authors delineated an estimate for the inpatient national trauma cost and explained the variation in cost by payer status. A total of 2,542,551 patients were included in the study.

Payer status was divided into categories including: private insurance (672,960), Medicare (1,244,817), Medicaid (262,256), self-pay (195,056), no charge (18,506), and other types of insurance (150,956). Results indicated national inpatient trauma yearly costs at approximately $37,511,328,659 with the greatest yearly trauma inpatient cost burden for patients with Medicare insurance coverage ($17,551,393,082 [46.79%]), followed by private insurance ($10,772,025,421 [28.72%]), Medicaid ($3,711,686,012 [9.89%], self-pay ($2,831,438,460 [7.55%]), and other payer types ($2,370,187,494 [6.32%]). For individuals not charged for services, the yearly trauma inpatient cost burden was $274,598,190 (0.73%). Disparities in cost of trauma care by payer status have been at the forefront of traumatic brain injury research and the overarching trauma care paradigm; specifically in areas of TBI recovery and achievement of functional outcomes.

Acute Hospitalization Care and Payer Source. For those who suffer from a traumatic brain injury, the clock of recovery is rapidly ticking from the time of onset. According to Khan, Khan, and Feyz (2002) rehabilitation after severe TBI should start in the acute phase of hospital care to optimize patients' outcomes and recovery potential. Several studies provided evidence of the benefit of early intervention. For instance, Mackay, Bernstein, Chapman, Morgan, and Milazzo (1992) found that aggressive rehabilitation during acute hospitalization decreased length of stay and produced greater functional capacity for those receiving early treatment. Sorbo et al. (2005) reported shorter hospital stays and a good outcome or living situation for patients with severe TBIs that had received an effective combination of medical and rehabilitation resources.

For the TBI population, long-term functional outcomes are dictated by acute treatment intervention and care. Information from the trauma scene and emergency department (ED) help predict functional outcomes for those patients that survive traumatic injury. Trauma registries record not only demographic data (age, gender, race, marital status, primary payer source, etc.) but also physiologic and anatomic data elements (systolic blood pressure, respiratory rate, Glasgow Coma Scale (GCS), penetrating injuries, time of injury, prehospital intubation, and positive toxicology screenings for alcohol and illegal drug use) that are used to improve trauma protocols (Nemunaitis, Roach, Claridge, & Mejia, 2015). Access to care at this stage is essential for achievement of short and long-term functional outcomes. Using the Functional Independence Measure (FIM), a tool to assess disability before and after inpatient rehabilitation, Nemunaitis et al. (2015) found that older patients with government insurance (Medicaid and Medicare) demonstrated poorer discharge scores than patients who had commercial insurance (private insurance). Such disparities in FIM score were explained by the possibility of more severe injuries for persons on Medicaid due to violence or mental illness (Wei et al., 2005) and the presence of perhaps greater comorbidities among the elderly that affect functional outcomes (Gardizi et al., 2014).

Discharge Disposition and Payer Source. In addition to access to care, previous research has shown payment source to be a predictor of discharge disposition for traumatic brain injured individuals (Cuthbert et al., 2011). Decisions by medical personnel to discharge to home or to inpatient rehabilitation are determined largely by brain and overall injury severity. However, the decision to discharge to inpatient versus

subacute care is more often driven by socio-biologic and socio-economic factors. Chan et al. (2001) found that despite insurance benefits, individuals insured with Medicaid or health maintenance organizations (HMO) were more likely (68% and 23%, respectively) to be discharged to a skilled nursing facility (SNF) than patients insured with FFS (commercial fee for service) plans. In fact, Chan et al. (2001) reported that the percentage of patients going to SNFs has consistently increased, encompassing approximately 14% of all TBI discharges in 1997.

Age and Sex and Payer Source. Cuthbert et al. (2011) examined the impact of socio-biologic (age and sex) and socio-economic factors including race/ethnicity and payment source in predicting acute hospital discharge disposition following moderate to severe TBI. Age was found to be associated with discharge disposition in that older persons sustaining TBI were more likely to require additional rehabilitation and medical services than their younger counterparts. Previous research has explained this association through the relationship between age and government-funded insurance (Chan et al., 2001; Cuthbert et al., 2011; Mellick, Gerhart, & Whiteneck, 2003; Wei et al., 2005). Cuthbert et al. (2011) further elaborated this association suggesting that older persons with Medicare are more likely to be discharged to a setting in which additional medical care was available, while persons who were required to pay for additional rehab expenses out of pocket were less likely to receive inpatient post-acute care. In fact, Cuthbert and associates reported race/ethnicity and payment source were significant factors in predicting home discharge for those sustaining moderate to severe TBI, with 57% to 65% discharging directly home.

Race and Payer Source. TBI studies have emphasized the disparity of treatment by race and insurance status, particularly relating to post-hospitalization care, outcome and resource utilization, and mortality (Gary, Arango-Lasprilla, & Stevens, 2009; Meagher, Beadles, Doorey, & Charles, 2015; Sacks, Hill, & Rogers, 2011; Shafi et al., 2007). Englum et al. (2011) hypothesized that patient race, ethnicity, and insurance status were significantly associated with discharge location when controlling for other demographic variables including age, sex, mechanism of injury (MOI), and injury severity. Three insurance categories classified patients: Private Insurance (Blue Cross Blue Sheild (BCBS), private commercial insurance, workers compensation, other government, and no fault auto insurance), public insurance (Medicare and Medicaid), and uninsured (Self-Pay). Race was categorized by white, black, and Hispanic. When just looking at payer status alone, the uninsured were less likely to discharge to home health care, rehabilitation, or nursing facilities when compared to the patients holding private insurance. Those patients with public insurance were found to discharge primarily to rehabilitation or to a nursing facility. When examining the effect of race and insurance, it was found that regardless of insurance status, Hispanic patients were discharged at lower rates to all post hospitalization care facilities as compared to the non-Hispanic white patients. Racial disparities were also noted for black patients as they were less likely to be discharged to rehab facilities than privately insured white patients despite having private or public insurance. Overall, uninsured Hispanic and black patients were found to discharge to inpatient rehabilitation approximately one-fifth to one-fourth as often as privately insured white patients.

Similar to Englum et al. (2011), Asemota, George, Cumpsty-Fowler, Haider, and Schneider (2013) explored race and insurance disparities in discharge to rehab for patients who had sustained a TBI. Participants were grouped by race as white, black, Hispanic, Asian or Pacific Islander, and other. Three categories described primary insurance payer: government insured (Medicare and Medicaid), privately insured (HMO, PPO, commercial payers), and uninsured (self-pay or no charge). Asemota et al. found that overall, insured persons were more likely to be discharged to rehabilitation than uninsured persons. Subgroup analyses showed despite insurance coverage, black, Hispanic, and Asian patients had reduced odds of discharge to rehabilitation.

In reviewing adult TBI outcome and resource utilization disparities by insurance and race, Shiraldi et al. (2015) explored differences across commercially insured, Medicaid, and Medicare patients. Additionally, a second analysis encompassed a socioeconomically homogeneous group of Medicaid patients. In the first analysis of payer source, patients with Medicaid had worse outcomes, comprising inpatient mortality, complications, inpatient length of stay, and total hospital payments. Additionally, while Medicaid patients used outpatient rehabilitation services less, they were found to use emergency services with more frequency.

When analyzing the socioeconomically homogeneous group, African American and white patients demonstrated similar mortality and length of stay trends. However, higher inpatient complication rates, higher total inpatient payments, less use of outpatient rehab, and more frequent use of emergency services was found for Africa Americans in comparison to whites. Despite such findings regarding race, insurance status was shown

to have a greater impact on short and long-term outcomes than patient race (Shiraldi et al., 2015). Likewise, TBI studies investigating emergency care and the number of acute procedures performed (Missios & Bekelis, 2015) and vehicular injury (Tepas, Pracht, Orban, & Flint, 2011) disproved race as a determinant of TBI outcomes. Race was not associated with the number of procedures performed on TBI patients and although vehicular injury mechanism and race varied by insurance status, the variation did not contribute significantly to the outcomes (mortality during acute hospitalization for treatment of severe injury).

Shafi et al. (2007) specifically examined the relationship between ethnicity and functional outcome. As other authors found, results indicated that this relationship became non-significant when insurance was taken into account. Like Schiraldi et al. (2015), Jimenez et al. (2015) shed light on disparities by insurance and race. The difference was Jimenez and colleagues were interested in the effect of such disparities on a pediatric population including minority children and adolescents (6 months to 18 years, 2002-2012). Results determined that functional independence at discharge was significantly associated with functional independence at admission, patient age, and insurance status. Although results indicated that Hispanic and NHB (non-Hispanic black) children were less likely to have private insurance and less likely to be accepted to rehabilitation facilities within pediatric hospitals, insurance status more heavily influenced functional independence at discharge. Those who had Medicaid or other governmental insurance were found to have lower discharge scores compared to patients with private insurance (Jimenez et al., 2015).

Finally, researchers have suggested that race and insurance status are risk factors for trauma mortality in populations including adults and children. Haider et al. (2008) reviewed a total of 429,751 adult patients from the National Trauma Data Bank (NTDB) within the years 2001 to 2005. Haider et al. were interested in examining if race and insurance contributed to trauma mortality. Results indicated that African American and Hispanic patient were indeed less likely to be insured, were more likely to sustain penetrating trauma, and had higher mortality rates than white patients. Although it was found that African American and Hispanic patients had worse outcomes, insurance status continued to demonstrate the stronger association with mortality after trauma. Haider et al. (2008) suggest that insurance status may be "a surrogate for other factors that affect mortality in a critically injured patient (e.g., health education, awareness and management of comorbidities, substance abuse, and risk-taking behaviors)" (p. 948).

Hekmeh, Barker, Szpunar, Fox, and Irvin (2010) also explored if insurance or race affected trauma outcomes in pediatric trauma populations. Similar to Haider et al. (2008), data were retrieved from the NTDB. Using a sample of 70,781, Hekmeh et al. found insurance status and race to be independent predictors of mortality. Results from Haider et al.'s adult population were found to be consistent with results of Hekmeh et al.'s child population in that lack of insurance was the stronger marker of increased mortality. Similar to previous research regarding disparities surrounding race, Hekmeh et al. found that African American and Hispanic pediatric patients fared worse than white patients.

Mortality and Payer Source. In a report by the Institute of Medicine (IOM), it was found that uninsured patients are less likely to be admitted to the hospital, receive less services, and are more likely to die than insured patients. White, French, Zwerner, and Fairbanks (2007) studied visits to one ED over 6 months for adult patients with potentially life threatening conditions and found a lower hospital admission rate for uninsured patients as compared to insured patients with similar diagnoses. Similarly, insurance status was found to be a significant predictor of admission and the number of radiology tests; as insured patients received 68% more tests than the uninsured. White et al. (2007) postulated these differences to be the result of an uninsured patient being perhaps more cognizant of the costs associated with more extensive lab or radiology tests and thus refusing such services.

Despite the Emergency Medical Treatment and Active Labor Act (EMTALA), ensuring access to care, uninsured patients demonstrate higher rates of mortality in comparison to insured patients. Alban et al. (2010) found lack of insurance to be a growing risk factor for mortality in individuals that have sustained TBI. When evaluating the most severe head injured patients, mortality was shown to be higher for the uninsured (none or self-pay) TBI patients versus their insured (Medicaid, Medicare, commercial insurance, workers compensation, etc.) counterparts (30.2% vs. 27.2%). Further analysis revealed that uninsured head injured patients were at an increased risk for mortality as compared to patients with commercial insurance (AOR (Adjusted Odds Ratio) 1.65; 95% CI: 1.42-1.90, $p < 0.001$).

Previous research has elucidated disparities in care that have detrimental effects on long-term functional outcome achievement. Haas and Goldman (1994) evaluated 15,008 trauma patients at a single Massachusetts site and reported that uninsured trauma patients were found to be less likely to undergo an operative procedure or physical therapy than patients with private insurance. Similarly, Missios and Bekelis (2015) found that in comparison to insured patients presenting with similar characteristics, uninsured TBI patients were less likely to undergo multiple procedures. Rosen, Saleh, Lipsitz, Meara, and Rogers Jr. (2009) used the NTDB to evaluate the role of insurance status on outcomes for 2.7 million trauma patients. He too found that overall, uninsured patients had a higher adjusted mortality rate (AOR 1.39; 95% CI: 1.36-1.42, $p < 0.001$). Rosen et al. (2009) suggested possible mechanisms to include treatment delay, different care (fewer diagnostic tests), and decreased health literacy. In a study of pediatric orthopedic injuries, Sabharwal, Shao, McClemens, and Kaufmann (2007) found that children who were insured through Medicaid, were receiving charity care, or were uninsured were subjected to a delay in care for injuries when compared to privately insured children. Additionally, a higher percentage of these children had visited multiple emergency departments and hospitals before receiving effective treatment. White et al. (2007) reported that despite similar treatment in terms of the number of lab tests ordered, consultations received, and length of stay in ED, uninsured patients received fewer radiographic studies and were less likely to be admitted to the hospital. Nirula, Nirula, and Gentilello (2009) also found that uninsured trauma patients were less likely to be transferred to a rehabilitation center after adjusting for comorbidities such as age, injury

severity, physiology, and ethnicity; thus suggesting that uninsured patients are receiving different aftercare than those with insurance. Finally, research has indicated that uninsured patients may present with a lower rate of health literacy. As a result, clinical outcomes may be negatively impacted due to patient's inability to communicate symptoms, poor family involvement in care, and the inability to dialogue with their health care providers (Baker et al., 1996; Wallace et al., 2007).

Many studies researching TBI mortality by payer status are completing research that groups the array of insurance options by "insured" or "uninsured" (Green et al., 2010; Taghavi et al., 2012). Weygandt et al. (2012) furthered their examination by categorizing TBI patients (age 18 to 64) sustaining blunt injury by insurance type: Private/Commercial (PRIV), Blue Cross Blue Shield (BCBS), Medicaid (MCAD), Medicare (MCAR), Workers' Compensation (WCMP) No Fault Auto (NFLT), Other (OTHE), Other Government (OTHG), Not Billed (NOBI), and Self-Pay (SLFP). Mortality ranged from 3.2 to 6% by insurance type. PRIV, BCBS, WCMP, and MCAD showed the lowest relative odds of death while Not Billed and Self-Pay yielded the highest. When compared with Private Insurance, odds of mortality were higher for NFLT, NOBI and SLFP. Like Weyhangdt et al. (2012), Rosen (2009) investigated mortality across children (age 17 years or younger) that sustained a blunt or penetrating trauma injury. Insurance type was classified into three categories: uninsured (self-pay and uninsured), publicly insured (Medicaid), and commercially insured (auto, BCBS, no fault, workers compensation, other commercial indemnity plan, or managed care organization). Analyses found that uninsured children and adolescents had the highest

odds of mortality compared with commercially insured children as did publicly insured children. Chikani et al. (2015) studied the association of insurance status with health outcomes following traumatic injury. Insurance statuses were broken down into four categories including private insurance, Medicare, Medicaid, and self-pay. Results were comparable to the previous studies mentioned in that mortality was higher for self-pay and Medicare patients as compared to patients with private insurance. These studies allowed for isolated examination of the contribution of each payer source; thus providing evidence to support advocacy for greater reimbursement and care. As the United States implements the Patient Protection and Affordable Care Act (PPACA) of 2010, in which insurance coverage will be expanded to approximately 32 million currently uninsured Americans, research by insurance type is essential to determine which specific insurance types are associated with better or poorer outcomes over time.

Previous TBI research has addressed disparities between insurance status and factors including access to emergency and hospitalization services, discharge disposition, race, and mortality. Were individuals more successful in achieving functional goals based on the type of insurance they possessed? Did some have more access to services to allow them to progress more globally in functional outcomes over time? Studies varied in timeframe and results. Conditions and variables were not consistent across time periods for each study performed. To lessen the effect of disparities in TBI care, research must provide sound evidence and establish criteria to inform future treatment efforts and healthcare legislation. As researchers and practitioners we must be vested in development of a sound method to measure outcome achievement over time.

Assessment of longitudinal change. Assessing longitudinal change in patient functioning is paramount in the field of rehabilitation clinical practice and research. Individuals who have sustained a TBI, their families, and even political stakeholders are interested in the time and to what extent they will recover. Through funding by the National Institute on Disability and Rehabilitation Research (NIDRR) and the U.S. Department of Education, the Traumatic Brain Injury Model Systems (TBIMS) and the Traumatic Brain Injury Model Systems National Database (TBIMS ND) was established in 1987. The central purpose of the TBINDSC (The Traumatic Brain Injury Model Systems National Data and Statistical Center) was to improve medical rehabilitation by enhancing the rigor and proficiency of scientific efforts to longitudinally assess an individual's experience with traumatic brain injury (TBI).

The Traumatic Brain Injury Model Systems National Database (TBIMS ND) is a longitudinal long-term follow-up data set that documents pre-injury characteristics, acute care and rehabilitation services, and long-term rehabilitation outcomes for individuals that have sustained a TBI in the United States (TBINDSC, 2009). It has acquired data over time for over 11,000 persons with TBI. Included are outcomes that have been assessed at rehabilitation admission and discharge, and 1, 2, 5, and every subsequent 5 years post-injury. Using data from the TBIMS ND, researchers can track the growth or change in individuals that have sustained a TBI, measure patient progress, and determine the most effective treatment interventions to foster successful rehabilitation outcomes and reintegration into the home and community.

There have been numerous studies within the TBIMS ND implementing longitudinal analysis strategies to explain changes in outcome over time. A majority of TBI outcome research comprises cross-sectional or pre-post treatment models that explore the associations between injury characteristics and outcome at a specific time point versus assessing change over time. Examples of the statistical methods used include multivariate linear or logistic regression (Corrigan et al., 2015; deGuise et al., 2008; Hammond, Hart, Bushnik, Corrigan, & Sasser, 2004; Hammond et al., 2004; Horn et al., 2015; Scholten et al., 2015; Tasaki et al., 2009) repeated measures ANOVA (Nakase-Richardson et al., 2012; Sandhaug, Andelic, Langhammer, & Mygland, 2015), paired t-tests (Scholten et al., 2015), and non-parametric paired rank tests or Wilcoxin signed rank tests (Lippert-Gruner, Lefering, & Svestkova, 2007). Using these methods, only the baseline and a single endpoint are considered.

Cross Sectional Research. In cross sectional research predictors and outcomes are observed or measured simultaneously in a population. Associations between the predictor and outcome can be observed; however, in such designs cause and effect cannot be inferred. Cross sectional techniques claim to model change over time, however time in such analyses is not directly related to the outcome of interest. In these instances, "time" is simply glimpses of group means at meaningful time points such as admission, discharge, or 1 year follow-up. In cross sectional studies where individuals are assessed at several time points (admission, discharge, 1 year follow-up); correlations of the individual's repeated measures are ignored. Treating correlated observations as independent results in inaccurate representation of the parameter estimates variance as

well as the inferences derived from such estimates (Dunlop, 1994; Kozlowski, Pretz, Dams-O'Connor, Kreider, & Whiteneck, 2013). Similarly, in pre-post designs, important information explaining the nature of change is lost when interval measures are removed from analyses and change found at initial status or baseline to endpoint is combined into, for instance, a "difference score" (Kozlowski et al, 2013; Rogosa, Brandt, & Zimowski, 1982; Rogosa & Willett, 1985).

The Difference Score. In the statistical and psychometric literature, there has been much controversy over the use of the difference score in the study of change (Bereiter, 1963; Cronbach & Furby, 1970; Linn & Slinde, 1977; Lord, 1956, 1963; McNemar, 1958; Rogosa et al., 1982; Rogosa & Willett, 1985; Zimmerman & Williams, 1982a, 1982b). Two major issues discussed revolve around "the reliability of the difference score and its inverse relationship to the correlation χ_2 andχ_1" and "the correlation between the difference score and initial status (χ_1) and its implications for using the difference score to study correlates of change" (Francis, Fletcher, Stuebing, Davidson, & Thompson, 1991, p. 28). The inverse relationship is of concern for researchers primarily because the correlation is observed as denoting the degree to which the instrument measures the same construct at both times (pre and post-test). The problem therein is that the individuals may be changing at different rates between the two time periods. The reliability of the difference score between two time points encompasses three major components: precision in the individual measures, the length of time between the two measurements, and the variability in true change (Rogosa et al., 1982). If the rate of change is constant, then as each component mentioned above increases, the reliability of

the difference score will increase. In the case where individuals are changing at different rates, it would be inaccurate to interpret a low correlation between the pre and post-test as an indication that the tests are measuring different constructs.

Willett (1988) does not agree that there is necessarily a flaw in the difference score, but rather a problem with the conceptualization of change that is associated with its use. To emphasize this notion, Willett (1988) states:

> Between the *idea* of measuring change and the *reality* of its empirical measurement has fallen the shadow of an unnatural, or at least unhelpful, conceptualization…. It is a conceptualization that views individual learning, not as a process of continuous development over time, but as the quantized acquisition of skills, attitudes, and beliefs. It is as though the individual is delivered of a quantum of learnings in the time period that intervenes between the premeasure and the post measure, and that our only concern should be with the *size* of the "chunk." (p.347)

The correlation between the difference score and initial status is a major problem for many researchers in that if subjects are indeed changing at different rates, then the time chosen to represent initial status will impact the size and/or sign of the correlation (Rogosa & Willett, 1983). The correlation between initial status and change is largely affected by the presence of measurement error in the pre and post-test (Rogosa & Willett, 1985); thus creating a negative bias in the observed correlation between status and change. For instance, if the parameter of interest is small but positive, or zero, the correlation between observed status and change is expected to be negative. When correlations between the true initial status and true change is small or zero, the resulting interpretations of the observed correlation between the difference score and initial status will likely be invalid.

Repeated Measures ANOVA. Unlike the difference score, repeated measures analysis of variance (ANOVA) accounts for correlations between measures taken on the same individual. The limitation found in this method and others including paired t-tests and non-parametric paired rank tests is that they are limited to comparing only group means; thus analysis at the individual level is not possible (Fitzmaurice, Laird, & Ware, 2011; Hedeker & Gibbons, 2006; Raudenbush & Bryk, 2002).

This type of analysis is utilized when one is concerned with evaluating the mean change. What is misleading about this idea of mean change is that two waves of data are sufficient to study change and that all individuals must be studied at the same fixed time points. When using only two waves of data, the ANOVA and MANOVA approaches to repeated measures analysis of variance will yield identical results, however when using greater than two waves of data results are different as are the assumptions of each method. In studying change, particularly longitudinal change, data for all individuals may be dispersed across time points dependent on their compliance to complete follow-up assessments. Missing data is problematic when using repeated measures analysis of variance techniques. A large amount of data may require imputation and often times it is not known for sure if the type of imputation chosen is legitimate. Finally, repeated measures analysis of variance does not allow for the incorporation of continuous predictors of growth.

Within-group individual differences in intra-individual change are treated as error; therefore researchers are unable to examine significant relations. This method is well suited for short repeated measures studies (less than 4 observation points), with no missing data, and where the primary interest is not assessment of individual or subgroup trajectories of change.

Longitudinal HLM and Individual Growth. It is imperative to have access to longitudinal analytic methodology that encompasses time, accounts for correlations between data points that result from repeated measures taken from the same individual, includes information about individual and group change, and allows for missing data without excluding individuals. Individual growth curve (IGC) modeling also referred to as latent growth curve analysis, hierarchical linear modeling (HLM), mixed-effect modeling, random effects modeling, and multi-level modeling, is able to assess change over time, explicate change at the individual, subgroup, and group level, and is able to explain change through the use of covariates. This methodology has been available for over 30 years, but has not been applied to rehabilitation research until just recently. Necessary to its use are appropriate longitudinal data, powerful statistical software, and the skillset to implement the analyses, components that have been limited in the rehabilitation field until recently. In combination with training for longitudinal data analyses and access to datasets such as the TBIMS ND, and advanced software packages such as SAS, SPSS, Stata, HLM-7, RStudio, and MPlus, researchers are now more equipped to manage such methodology (Koslowski et al., 2013; Pretz, Malec, & Hammond, 2013).

Use of HLM to model individual growth unlike traditional regression modeling, allows for simultaneous modeling of outcomes at the individual and group level. It is flexible, and in addition to emphasizing individual change, it accounts for the correlates of change as well. According to Francis et al. (1991), "subject characteristics that correlate with change will relate systematically to parameters of the individual growth curves" (p. 31). HLM is capable of handling more than two waves of data, and with this ability it is possible to directly estimate the reliability of growth parameters. Such reliabilities then can be used to disattenuate estimated correlations between subject characteristics and true change (Francis et al., 1991). A main advantage allows for all of the available data for a given subject to be used, even if there are not measurements for all of the occasions on which that subject was measured; provided there is enough data to estimate the parameters. Finally, HLM allows for the use of discrete or continuous predictors, permits the number and spacing of time points to vary across subjects, and accepts the use of time-varying covariates whose effects are fixed or random (Bryk & Raudenbush, 1987; Goldstein, 1987; Francis et al., 1991).

When modeling at the individual level, measurements of an outcome of interest can be directly related to time through an array of mathematical functions ranging from simple to complex. This is a critical step in the modeling of individual change as outcome measures may not always change consistently over time (linear change); rather they may demonstrate curvature (quadratic change), present with rising and falling patterns (cubic change), or exhibit floor or ceiling effects (nonlinear change) (Kozlowski et al., 2013; Pretz et al., 2013; Raudenbush & Bryk, 2002).

Linear Change. A linear change or trend is characterized by a pattern of data that represents a straight line. In this fashion, linear change relates time to outcome by two parameters. In IGC analyses, these parameters are called growth parameters and encompass an intercept (persons initial status) and a slope (his/her rate of change). The equation representing linear change or relating time to outcome in its most basic form is shown as:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 (Time)$$

The interceptβ_0, in this case denotes the average baseline (initial status) score and β_1 represents the slope, or the average constant rate of change. The slope is referred to as "constant" because the change in outcome does not change over equal intervals of time. When the rate of change is positive, as time increases, outcome increases. Likewise, a negative rate of change suggests that as time increases, outcomes decrease. The $\hat{y}$ represents the estimate of the average outcome at a particular time point. Finally, *Time* is the researcher's time point of interest (Pretz et al., 2013; Raudenbush & Bryk, 2002).

Quadratic Change. Unlike linear change which is characterized by two parameters, quadratic change is described by three parameters. The third parameter accounts for a rate of change that varies at each time point. A rate of change that is time dependent is an instantaneous rate of change (IRC); thus the rate of change is different for each time point. An IRC plot is often utilized to illustrate IRC versus time. These plots are useful in showing when the outcome changes rapidly, gradually, or not at all. Also important in these plots is the local minimum or maximum that is illustrated as a peak or trough, found at the intersection of the IRC function and time axis. The closer

the IRC moves towards zero, the more gradual the change while at zero no change is occurring. A positive IRC signifies the change is increasing whereas a negative IRC implies change is decreasing. At any given time point the following equation is used to calculate the estimated value of the outcome ($\hat{y}$) with $\hat{\beta}_0$ representing the estimate of the average outcome at initial status (baseline), $\hat{\beta}_1$ representing an estimate of linear change, $\hat{\beta}_2$ representing an estimate of quadratic change and $\beta_1 + 2\beta_2$ (*Time*) representing the average IRC (Pretz et al., 2013; Raudenbush & Bryk, 2002).

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1(Time) + \hat{\beta}_2(Time)^2$$

Cubic Change. In the instance of cubic change, the outcome increases, decreases, and then increases again. This can occur also occur in the opposite direction. The intercept and the rate of change (time dependent) are similar to that found in quadratic change. The difference between quadratic change and the cubic change is that the IRC requires an additional parameter β_3 to account for the further complexity. Like quadratic change, there are peaks (local maximum) and troughs (local minimum). Using an IRC plot one can locate the specific points in which the local maximum and minimum occur at the intersection of the IRC function and time axis. Like the quadratic, the IRC assists to determine times when changes in outcome are rapid or gradual and the direction of the change.

In addition, in cubic change there is an inflection point which signifies when the outcome transitions from decreasing to increasing or vice versa and the time associated with such an inflection is found at the maximum or minimum location of the IRC plot. As seen below, the equation used to calculate the estimate of the average value of the outcome for cubic change is represented by an equation similar to that of quadratic change, but including the additional parameter $\widehat{\beta}_3$ (Pretz et al., 2013; Raudenbush & Bryk, 2002).

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1(Time) + \hat{\beta}_2(Time)^2 + \hat{\beta}_3(Time)^3$$

Non-Linear Change. Finally, when outcomes are not consistently changing, but are exhibiting non-linear change characterized by floor or ceiling effects, a negative exponential model is used. A floor effect occurs when there is a rapid decrease in outcome followed by a plateau. Likewise, a ceiling effect occurs when there is a rapid increase in outcome followed by a plateau. Three parameters explain the negative exponential model; a pseudo-intercept (average starting point) (β_0), rate (β_1), and asymptote (α_0) which represents the location of the plateau or average stability point. Unlike the linear, quadratic, and cubic models, the negative exponential model never traverses the y-axis which is why the intercept is called the pseudo-intercept. The rate (β_1) in this model is not indicative of a true rate of change but the rate at which the asymptote is attained. For this model, the estimate of the time that average maximum recovery is achieved is directly related to the rate. When the rate increases, the part of the trajectory that joins the pseudo-intercept to the asymptote becomes more vertical. In the event that the rate decreases, a more gradual change results. To calculate the estimated time before reaching the asymptote, the formula below is utilized where *d* is

the distance between the function and the asymptote. This value is dependent on the units of measurement specified by the outcome (Pretz et al., 2013; Raudenbush & Bryk, 2002). Caution should be taken when assigning this value as if the value is too large, the time point will be overestimated and *vice versa*.

$$\text{Estimated Time Before Asymptote} = -\frac{\ln(\frac{d}{|(\alpha_0 - \beta_0)|}}{\beta_1}$$

Unconditional Model. In the modeling process, an unconditional model is first established to describe the best-fit average trajectory for the data of interest. Similar to other multi-level or random effects models, HLM provides fixed and random effects. The fixed effects are represented by an individual's initial status and rate of change in which the initial status is equal to the average initial status plus a random error term and the rate of change is equal to the average rate plus a random error term. Each individual's average initial status and average rate of change varies randomly about the average initial status and rate of the group. The researcher may utilize values for the fixed effects as a basis of comparison to the individual and subgroup values. Random effects in HLM define the individual variation from the group average. Three parameters define the random effects: initial status, rate, and covariance (degree to which initial statuses and rates are related). It is important to assess the level of variation of initial statuses and rates as significant variability would denote that there is a meaningful spread in initial statuses and rates of change.

Conditional Model. In assessing the random effects of the unconditional model, if there is evidence of statistical significance, further variance of growth parameters may be explained by adding additional covariates; thus producing a conditional model (conditional on particular associations between the covariate and growth parameters included). Covariates may be continuous, dichotomous, or categorical. Often, researchers will center the continuous covariates such that the difference between the mean of the covariate and each individual's value of the covariate is computed. In this way, the average of the covariate is transformed to zero; thus allowing for more accurate interpretation of growth parameters. In using dichotomous or categorical covariates, common practice is to assign a reference category. Particular to categorical variables, the assignment of a reference allows the researcher to compare the reference category to other levels of the covariate. To examine the variability explained by the addition of covariates to the model, new estimates of variability in the conditional model for initial status and rate may be compared to those from the original unconditional model. Finally, it is important to assess if the addition of covariates improves the overall model fit. This is accomplished by observing model fit statistics such as the Akaike information criterion (AIC) between the conditional and unconditional models. The model that has the smaller values is the best fit model (Koslowski et al., 2013).

There have been a number of studies that have implemented modeling of individual growth using longitudinal HLM. Pretz and Dams-O'Connor (2013) examined the temporal patterns of global outcome after TBI in the TBIMS NDB using the GOS-E as the primary outcome. The GOS-E (Glasgow Outcome Scale Extended) is a common

measure utilized for analysis in the TBIMS. It measures overall disability with responses on an 8-point scale to categorize the upper and lower levels of functioning. The levels include dead, vegetative state, lower severe disability, upper severe disability, lower moderate disability, upper moderate disability, lower good recovery, and upper good recovery (Wilson, Pettigrew, & Teasdale, 1998).

Using HLM to model individual growth, the trajectory of the GOS-E scores was best fit using a model of quadratic change. Using a quadratic model, scores initially increased and peaked at approximately 10 years after the first GOS-E assessment, followed by a decrease. Using this method, it was found that change occurred the most rapidly in the initial and final years of the timeline. Each growth parameter demonstrated significant variability, thus a reduced multi-level model was then produced including multiple additional covariates (age at first GOS-E assessment, FIM, race, sex, and rehabilitation length of stay). Using these techniques, results indicated that for the GOS_E, individuals in the TBIMS NDB as a group demonstrated an improvement followed by a plateau, and then began to decline. Covariates included in the model were found to impact baseline GOS-E scores and the rate of the improvement and decline over time.

Pretz, Malec, and Hammond (2013) completed a study in which longitudinal HLM analyses were implemented to develop a more in depth understanding of temporal change at the individual level for the Disability Rating Scale (DRS). The DRS includes 8 items with scores ranging from 0 (no disability) to 29 (vegetative state) (Hall, Cope, and Rappaport, 1985). For the DRS, it was found that the negative exponential was the best

longitudinal descriptor of the DRS. The three growth parameters that are unique to this model are the pseudo-intercept, asymptote, and rate.

Using this model, covariates including race, sex, level of education, age at admission, rehab length of stay, and cognitive and motor FIM scores at rehabilitation admission were added. Associations were examined between the covariates and growth parameters. Only significant associations were maintained; thus further reducing the conditional model. The growth parameters of the final model were found to be statistically significant indicating that variability in each growth parameter was explained by the remaining covariates. Using this information, the authors were able to describe the longitudinal trajectory of recovery on the DRS for individuals that shared similar characteristics.

Similar to the previous two studies discussed, Dams-O'Connor, Pretz, Billah, Hammond, and Harrison-Felix (2015) utilized longitudinal HLM to compare long-term functional outcome trajectories using the GOS-E and DRS of individuals with TBI that survived versus those who expired more than 5 years post-injury. In modeling the GOS-E and DRS, the quadratic model was found to be the best model for describing temporal change. Results indicated that for individuals that expire many years following injury, there was evidence of worse functional status at baseline and a steeper rate of decline over time. Because there was significant variability found for both the GOS-E and DRS growth parameters, a reduced model was constructed including all of the covariates that significantly related to the growth parameters (GOS-E; living status, age at first GOS-E assessment, Cognitive FIM at rehabilitation admission, Motor FIM at rehabilitation

admission, race, and rehabilitation length of stay, DRS; living status, Cognitive FIM at rehabilitation admission, Motor FIM at rehabilitation admission, age at injury, race, education and rehabilitation length of stay). Using the results from the final conditional model, the researchers determined that the functional trajectories for the individuals who died several years after injury were indeed different from those who survived, thus providing evidence that further health management interventions may be required to improve health and longevity following a TBI (Dams-O'Connor et al., 2015).

Finally, Cuthbert et al. (2015) recently utilized longitudinal HLM to describe the 10 year patterns of employment for individuals of working age discharged from the TBIMS center between 1995 and 2009. In the studies discussed above, the impact of payer source over time was not modeled. Although payer source was not the main variable of interest for this study, it was included in the modeling process as a covariate. The quadratic model was found to be the best model for describing temporal change in this case. Covariates that were found to be significantly associated to the growth parameters included gender, age at injury, race, pre-injury substance use, pre-injury vocation, primary payment source, education, year of injury, and PTA (post-traumatic amnesia). Results of the final conditional model demonstrated varied patterns of employment for individuals with specific characteristics. Overall, there was found to be a decline in trajectories of the probability of employment between 5 and 10 years post-injury; thus indicating that moderate to severe TBI has chronic effects or perhaps that national labor market forces impact employment (Cuthbert et al., 2015).

Research Purpose, Questions, and Hypotheses. Evidence from previous work using longitudinal HLM supports the efficacy of the methodology in describing temporal patterns of change at the individual level for a variety of outcomes. The purpose of the current study was to describe temporal change as measured by the FIM and DRS scales. The primary predictor of interest was payer source and its association with the growth parameters that influence the trajectory patterns of the FIM and DRS. The research question addressed through this research was as follows: Does payer source have an impact on initial status and growth rate over time of FIM and DRS scores when controlling for covariates including: sex, race, age, marital status, education, employment status, rehabilitation length of stay, and PTA? I hypothesize that the growth rate of an individual's FIM and DRS outcome scores will decline and/or plateau from initial status to five years post injury in association with payer source reimbursement.

Research hypotheses are:

1) Unconditional Model scores for outcome measures including FIM and DRS over at least three temporal measurements show statistically significant variability in growth parameters.
2) Payer Source has an impact on FIM and DRS individual and group initial status and growth rate trajectories after controlling for covariates including sex, race, age, marital status, education, employment status, rehabilitation length of stay, and PTA.

Chapter 2: Methods

This chapter provides an overview of the participants in the study and the instruments and variables utilized to assess change over time. Validity and reliability are discussed to support the use of the chosen dependent and independent variables. Finally, procedures for data collection and data procurement are reviewed as well as the specific approaches to be used for statistical analyses.

Participants

The sample of interest consisted of those individuals with at least three temporal measurements (Follow-up periods: 0, 0.5, and 1-13, 15, 20, and 25) as the primary purpose of the study was to model and describe multiple outcome measures longitudinally.

The TBIMS use established standards to determine eligibility for admission and participation in the TBIMS ND. All participants are individuals with TBI that have provided informed consent or consent by proxy to be enrolled in the TBIMS ND. There are explicit inclusion and exclusion criteria for identifying and recruiting potential subjects into the TBIMS ND. According to the TBIMS, the case definition of TBI for inclusion in the national database is:

> Damage to brain tissue caused by an external mechanical force as evidenced by medically documented loss of consciousness or post traumatic amnesia (PTA) due to brain trauma or by objective neurological findings that can be reasonably attributed to TBI on physical examination or mental status

examination (TBINDSC (Standardized Operating Procedure 101a), 2009, p. 1). Patients with concurrent injuries or pathologies are not excluded as long as inclusion criteria are met. According to the TBINDSC standard operating procedure (2009) for identification of subjects, participants must meet at least one of the criteria for moderate to severe TBI:

> PTA>24hrs, trauma related intracranial neuroimaging abnormalities, loss of consciousness (LOC) exceeding 30 minutes, GCS (Glasgow Coma Scale) in emergency department of less than 13, those who are age 16 and older at the time of injury, presenting to the TBIMS's acute care hospital within 72 hours of injury, received both acute hospital care and comprehensive rehabilitation in a designated brain injury inpatient rehabilitation program within the TBIMS, and who understand and provide informed consent to participate or, if unable, family or legal guardian understands and provides informed consent for the patient (p.2).

The approximate sample size for this study was dependent upon each specific outcome measure. The final sample size for each outcome was as follows: FIM Cognitive (n = 8367), FIM Mobility (n = 8360), FIM Self-Care (n = 8000), and DRS (n = 8000). Participants were described by sex, race, age, marital status, employment status, primary rehab payer, and education. Other variables that described individuals included length of stay or time from rehab admit to rehab discharge, and post-traumatic amnesia or days from injury to days spent out of post-traumatic amnesia.

Measures

Functional Independence Measure. The outcomes of specific interest for this study were the Functional Independence Measure (FIM: Wright, 2000) and Disability Rating Scale (DRS: Rappaport, Hall, Hopkins, Belleza, & Cope, 1982). The FIM is an instrument established for planning and monitoring inpatient rehabilitation services and outcomes related to functional independence (Wright, 2000). The tool was created due to

a lack of uniform measurement and data on disability and rehabilitation outcomes (Hall, Hamilton, Gordon, & Zasler, 1993). It measures independent performance in self-care, sphincter control, transfers, locomotion, communication, and social cognition. The instrument encompasses 18 items that measure cognitive (5 items) and motor functioning (13 items). Functional areas covered include: feeding, grooming, bathing, upper body dressing, lower body dressing, toileting, transfers, tub/shower transfers, comprehension, expression, social interaction, problem solving, and memory. Each item is rated on a scale of 1 to 7, with 1 indicating "total assistance" (performs less than 25% of task) and 7 indicating "complete independence" in performing tasks. Any item scores less than six suggest that the patient requires another individual for supervision or assist. To produce a total score, the ratings for all 18 items are summed; thus producing a score ranging from 18 (lowest) to 126 (highest) (Hammond et al., 2001).

Functional measures must demonstrate reliability, validity and statistical significance to be useful. Reliability of an instrument refers to its precision of measurement. Construct validity determines whether the instrument measures the characteristic it intends to measure. It is important that items work together to support a single construct and within that construct, be ordered in difficulty according to clinical experience (Heinemann, Linacre, Wright, Hamilton, & Granger, 1993). The FIM instrument has provided evidence of reliability. Specifically, interrater agreement of the seven-level FIM has been found to be high. Hamilton, Laughlin, Granger, and Kayton (1991) found that the total FIM score intra-class correlation coefficient for 263 inpatients that were assessed by pairs of clinicians at 21 hospitals was .97; sub-score correlations

.93 to .96; and item scores average Kappa value of .71. Heinemann et al. (1993) scaled the FIM with Rasch analysis to determine the similarity of scaled measures across impairment groups. Rasch analysis of a Uniform Data System (UDS) for Medical Rehabilitation patient sample (N = 27,669, 13 impairment groups) generated interval measures of motor and cognitive functions. Results indicated that the FIM is composed of two fundamental subsets of items; motor and cognitive function. Additional studies utilizing factor analysis and Rasch analyses further supported that the FIM instrument consisted of two underlying constructs; physical functioning (FIM Motor) and cognitive functioning (FIM Cognitive) (Heinemann, Linacre, Wright, Hamilton, & Granger, 1994a; Linacre, Heinemann, Wright, Granger, & Hamilton, 1994; Stineman et al., 1996).

Heinemann et al. (1993) also found that validity of the FIM instrument was supported through patterns of item difficulties across impairment groups. Items that were more difficult for some impairment groups were clinically appropriate. Likewise, clinical precision of the FIM was found to be adequate. For each of the 13 impairment groups, the FIM could be scaled as an interval measure. Item difficulty was found to vary across impairment groups thus reflecting the unique impact of various kinds of impairments. Results provided evidence that raw scores are not linear and should not be used in parametric statistical analyses (Heinemann et al., 1993). Finally, DiScala, Grant, Brooke, and Gans (1992) found the FIM total score and six subscales to significantly discriminate between three groups of patients with differing severity of injury.

Disability Rating Scale. The Disability Rating Scale (DRS) originated in a rehabilitation setting and was tested with individuals who had incurred moderate and severe TBI. It was developed to provide quantitative information to track the progress of severe head injury patients from coma to community; specifically between early arousal from coma and early conscious functioning. An instrument was needed that could indicate change:

> In levels of arousal and awareness, in cognitive ability to deal with problems of feeding, toileting, and grooming, in degree of physical dependence on others, and in psychosocial adaptability as reflected primarily in the ability to do useful work as independently as possible in a socially relevant context (Rappaport, Hall, Hopkins, Belleza, & Cope, 1982, p. 118).

The DRS includes 8 items with total scores ranging from 0 (no disability) to 29 (vegetative state). The World Health Organization categories of impairment, disability, and handicap are all addressed within the DRS. Impairment ratings make up the first three items: eye opening, communication ability, and motor response. The cognitive ability enabling feeding, toileting, and grooming embody disability. Finally, the level of functioning and employability items reflect handicap. The response scale for each item varies from 0 to 3 to 0 to 5. The response scale for each item is consistent in that highest function is scored as low as 0 and lowest function as high as 5. A total DRS score is calculated by summing the score for each of the eight items producing a score from 0 (high or no disability) to 29 (low or vegetative state) (Hall et al., 1985).

Similar to reliability testing for the FIM, Rappaport et al. (1982) performed a study in which evidence for adequate interrater reliability of the DRS was found across three raters for a sample of 88 rehabilitation inpatients. Pearson correlations ranged from

.97 to .98. Likewise, Gouvier, Blanton, LaPorte, and Nepomuceno (1987) found Spearman rho correlation coefficients of .98 across 3 raters for samples of 37 to 45 subjects. In a study performed by Novack, Bergquist, Bennett, and Gouvier (1992), comparison of DRS ratings by family members and rehabilitation professionals at rehabilitation admission and discharge demonstrated correlations of .95 at admission and .93 at discharge.

In the original study performed by Rappaport et al. (1982), convergent validity was established through a significant correlation between abnormality ratings of the auditory, visual, and somatosensory brain-evoked potentials and DRS ratings (Pearson Correlations: .35 to .78). Additional studies supported convergent validity with significant correlations between the DRS and the Glasgow Outcome Scale (GOS) (Hall, Cope, & Rappaport, 1985; Jennett & Bond, 1975; Smith, Fields, Lenox, Morris, & Nolan, 1979) at two time intervals, and the Stover-Zeiger Scale (scale classifying functional levels from persistent vegetative state to full functional recovery to pre-injury level) (Gouvier et al., 1987).

In regard to predictive validity, Novack, Kofoed, and Bennett (1988) reported that the DRS tracks recovery and had potential to predict outcome for the more severely injured. Multiple additional studies supported the predictive validity of the DRS instrument (Eliason & Topp, 1984; Fryer & Haffey, 1987; Govier et al., 1987; Rao & Kilgore, 1992; Smith et al., 1979).

Independent Variable (IV), Primary Rehab Payer. The independent variable that was utilized for this study was primary rehab payer. Primary rehab payer included "private insurance" (Blue Cross/Blue Shield, employee or privately purchased insurance) as the reference, followed by Medicare, Medicaid, and Other (Workers Compensation, HMO, PPO, Auto Insurance, Self or Private Pay). Previous studies have utilized primary rehab payer as a covariate in analyses, but not as an independent variable (Gardizi et al., 2014; Jimenez et al., 2015; Nemumaitis et al., 2015). This study specifically examined the impact that primary rehab payer had on the four outcome variables (FIM Cognitive, FIM Mobility, FIM Self-Care, and the DRS).

The payer source element in hospital encounter databases provides information for the type of payer that the hospital expects to be the source of payment for services. The data element of payer source is widely used as an important explanatory variable in health related research. Additionally, payer source is has been utilized to assess the impact of health system changes and answer policy questions. Because of problems relating to lack of uniformity in coding and data collection practices from state to state in the United States, there have been concerns about the accuracy of the data. Although this is a known fact, there have been few studies that have examined expected payer data collection practices and data quality (Barrett, Lopez, Gonzalez, Hines, Andrews, & Jiang, 2014).

There were two studies using California's discharge data from the 1990s examined the accuracy of payer source data collection practices and data quality. In these studies, the discharge data were connected to program enrollment to validate the

accuracy of the payer recorded on the discharge data. In the first study, the discharge data were linked to Medicaid enrollment files. This included patients younger than 65 years that were hospitalized for ambulatory care sensitive conditions. Study findings included a total of 10% of discharges for Medicaid enrollees that were inaccurately coded as private insurance (7%), uninsured (2%), or other (1%). Of the discharges for those Medicaid enrollees in managed care, 22% were coded as private insurance. In the second study, hospital discharge data were linked with health benefits data for a large employer in California (University of California). It was found that the coding for these privately insured patients was most accurate (greater than 80%) for those enrolled in HMO's (Health Maintenance Organization), and least accurate (28-37%) for those enrolled in PPO's (Prospective Payment Organization). It was found that discharges were miscoded as Medicare for those in group HMO's who were older than 65 years when private insurance in fact should have been considered as their primary payer. Finally, miscoding of the uninsured, Medicaid, and other State or local payers was found to be rare (less than 5%). Until further research on payer source is completed, it is the responsibility of researcher to understand the information captured by expected payer or payer source data so that the data are used appropriately in research endeavors (Barrett et al., 2014).

Covariates. Covariates that have been found through literature to be associated to the FIM and DRS were included in the modeling process. Such covariates included Sex (Graham et al., 2010; Ratcliff et al., 2007), Race (Hammond et al., 2004), Age at Injury (Brown et al., 2005; Bush et al., 2003; Graham et al., 2010; Nemumaitis et al., 2015), marital status (Arango-Lasprilla et al., 2008), years of education (Bush et al., 2003;

Connelly, Chell, Tennant, Rigby, & Airey, 2006), primary employment status (Arango-Lasprilla et al., 2009), rehabilitation length of stay or days from rehab admit to rehab discharge (Dams'O'Connor et al., 2015; Pretz, et al., 2013), and days from injury to date out of post traumatic amnesia (Bush et al., 2003). Length of rehabilitation stay and PTA were continuous variables and were measured through an interval score in days. Scores for length of rehabilitation stay ranged from 0 to 474 days and PTA 0 to 361 days.

Categorical or dichotomous covariates were assigned a reference category to allow for comparison of the reference to other levels of the covariate. Of the covariates above sex, race, marital status, years of education, and primary employment status were categorical or dichotomous in nature and thus required assignment of a reference category. Because SEX was a dichotomous variable (Male or Female), the reference of interest was "Male." For RACE, "White" was the reference utilized followed by Other (Black, Asian or Pacific Islander, Native American, Hispanic Origin, and Other). The reference that was used for marital status was "Married" followed by Not Married (Single (Never Married), Divorced, Separated, Widowed, and Other). Education was broken down into categories including: Less than high school (HS), HS or GED and More than HS with "Less than HS" the reference. The codes for employment status was dichotomized into employed and not employed, of which "employed" was the chosen reference category.

Procedure

Recruitment of all TBIMS ND patients occurs during their inpatient rehabilitation stay (or at the time of IRF admission). After obtaining informed consent, data are collected from the patients using two assessment forms. Form 1 includes a Pre-Injury History Questionnaire. The questionnaire collects information regarding socio-demographic characteristics, work and school participation, previous history of functional impairment or health conditions, and activity limitations prior to injury. In addition, brain imaging studies, medical record data, neuropsychological tests, assessment of activity limitations and health status, and ICD-9 codes from acute hospital records are included in Form 1. Form 2 shares similar data features as Form 1, however contains a number of longer term outcome measures as well (1, 2, 5, and every 5 years thereafter). Data are collected in real-time for each TBIMS center, and entered into the live web-based data management system (TBINDSC, 2009).

Procurement of the data for this study required the submission of a public use request and data use agreement form. The public use request was submitted in the form of an external notification informing the TBIMS of the purpose of use, dataset to be used, principal investigators name, position, and institution, any collaborator's names, current date, and projected start and complete date. Additionally, a summary of the proposed research was required including the following sections: title of project, key words, background or introduction, study aims, research hypotheses, and methods (study sample, outcome measures, covariates, and data analysis plan). The data use agreement outlined all of the terms pertinent to data use, confidentiality, and publishing. A signature and

date was required at the time of submission. Any breach in terms would result in termination of current and future privileges to access the TBI Model Systems Data (TBINDSC, 2009).

Following submission of the necessary forms, the TBIMS NDSC and the TBI Model Systems Research Committee reviewed all information for principal investigators (PI) affiliation, scientific purpose, and potential overlap with existing approved projects. The next step involved posting the proposal to the TBI Model Systems Notification List serve for further comment by the TBI Model Systems Project Directors. When the proposal had been posted for 10 working days, the National Institute on Disability, Independent Living, and Rehabilitation Research (NIDILRR) TBI Model Systems Centers Program Manager made the final decision regarding approval of the proposal with feedback from the National Data and Statistical Center, Research Committee and Project Directors. Once approved, it was the responsibility of the PI to work with the TBIMS NDSC in detailing the proposal so that an appropriate de-identified dataset could be released for use (TBINDSC, 2009).

Data Analytic Approach

Univariate and Descriptive Statistics. All univariate, descriptive, Rasch and longitudinal HLM analyses were conducted using SPSS 23 (IBM Corp, 2015), Winsteps (Linacre, 2014) and SAS 9.4 (SAS Statistical Software, 2015) software. The first step entailed assessing the variables through univariate or descriptive statistics. Initial descriptive statistics including correlation matrices, mean and standard deviation (SD) values of the dependent variables (1- FIM Cognitive, 2 - FIM Mobility,

3 - FIM Self-Care and 4 - DRS), independent variable (13 - primary rehab payer), and covariates (5 - sex, 6 - length of rehabilitation stay, 7 - age, 8 - post-traumatic amnesia (PTA), 9 - race, 10 – marital status, 11 – employment status, and 12 – education) which are shown in Table 1. Categorical variable descriptive statistics are shown in Table 2.

Frequency analyses were performed to assess the amount of valid data and to assess if the coding utilized was appropriate for each variable. All dependent, independent, and covariate variables that included codes of 55-Other, 66 or 666- Variable did not exist, 7 or 77- Refused, 88 or 888- Not Applicable, and 9, 99 or 999- Unknown were recoded as system missing. DRS interval scores (0.5, 1.5, 2.5, 3.5, or 4.5) were recoded as system missing as these scores are no longer used in the TBIMS and would cause inaccuracy when computing total scores of the FIM and DRS outcome variables.

Table 1

Correlation Matrix and Descriptive Statistics: Analysis Variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1 FIM Cognitive	1												
2 FIM Mobility	.67**	1											
3 FIM Self-care	.80**	.89**	1										
4 Disability Rating Scale	-.88**	-.81**	-.87**	1									
5 Sex	-.02**	.06**	.03**	.01	1								
6 Length of Rehab Stay	-.22**	-.25**	-.22**	.28**	.02**	1							
7 Age at Injury	-.07**	-.22**	-.13**	.10**	-.09**	-.04**	1						
8 Post Traumatic Amnesia	-.19**	-.13**	-.14**	.24**	.08**	.59**	-.16**	1					
9 Race	-.04**	-.05**	-.04**	.06**	.04**	.01	-.11**	.03**	1				
10 Marital Status	-.00	-.04**	-.03**	.01	.02**	.00	.37**	-.01	-.06**	1			
11 Employment Status	.04**	.01**	.01**	-.04**	.09**	-.01*	.23**	-.04**	-.04**	.18**	1		
12 Education Years	.09**	.07**	.04**	-.09**	-.04**	.02**	.13**	-.06**	-.22**	.15**	.12**	1	
13 Primary Rehab Payer	.01*	.04**	.02**	-.02**	.01*	.02**	-.13**	.03**	.05**	-.02**	-.00	-.00	1
Mean	1.60	3.08	2.18	-5.98	+	27.48	40.54	23.86	+	+	+	+	+
SD	3.19	3.57	4.07	5.26	+	26.30	19.08	22.08	+	+	+	+	+

Table 2

Descriptive Statistics: Categorical Analysis Variables

Categorical Variable	Frequency	Percent (%)
Primary Rehab Payer		
Private Insurance	31688	42%
Medicare	9154	12%
Medicaid	17958	24%
Other Rehab Payer	16426	22%
Sex		
Female	16644	26%
Male	46500	74%
Race		
White	42207	67%
Black	12140	19%
Asian/Pacific Islander	1641	3%
Native American	345	.5%
Hispanic Origin	6093	10%
Other	687	1%
Marital Status		
Married	20480	3%
Not Married	42588	67%
Education Years		
Less than High school	3682	6%
High school/GED	28353	45%
More than High school	20310	32%
Employment Status		
Employment	39183	62%
Not employed	10715	17%

FIM Rasch Transformation. Following the initial screening of the data, the FIM was divided into three separate subscales: FIM Cognitive, FIM Mobility, and FIM Self-Care. Pretz et al. (2016) performed a study in which a multi-dimensional Rasch analysis was performed on the FIM. This analysis was based on the NIDILRR TBIMS ND. Using Rasch techniques, equal interval (linear) measures of participants were computed that were not impacted by non-equal interval (nonlinear) rating scales. Furthermore, it provided an increased insight into person ability and item difficulty while organizing estimates of each on an equal interval linear continuum (Pretz et al., 2016). It was a useful technique to examine dimensionality of an instrument, was robust to missing data, and allowed for transformation of ordinal measures to interval-level scaling. One main goal of this research study was to provide a raw score to interval level transformation for the FIM instrument using a multi-dimensional Rasch modeling technique. Evidence was produced through this work that the FIM, when administered to persons with TBI using data from the TBIMS ND, was described as encompassing three dimensions measuring cognition, mobility, and self-care; thus extending previous studies that purported two subscales for the FIM.

Specific FIM items that were found to constitute each subscale were: FIM Cognitive- comprehension, expression, social interaction, problem solving, and memory; FIM Mobility- bed transfers, toilet transfers, tub shower transfers, stairs, and locomotion (walking or wheelchair); and FIM Self-Care- grooming, bathing, dressing upper body, dressing Lower Body, and Toileting. Pretz et al. (2016) discussed several advantages that this scoring approach provided over the traditional combined motor subscale. In

particular was that the separate mobility and self-care subscales were more useful for rehabilitation practitioners, as they corresponded to the practices of both physical and occupational therapy. This current study was designed to aim at rehabilitation practitioners working in the TBI field (psychologists, speech-language pathologists, occupational therapists, and physical therapists); thus use of the Rasch transformed logit scores was appropriate for analysis for this TBI sample. Specific raw score to logit score transformations and associated standard errors that were utilized for data analysis for FIM Cognitive, FIM Mobility, and FIM Self-Care Subscales can be found in Table 3. These scores were used in parametric statistical analyses to increase the accuracy of results.

Table 3

Raw Score to Logit Transformation: FIM Subscales

Raw Score	**Logits FIM Cognitive**	**SE FIM Cognitive**	**Logits FIM Self-care**	**SE FIM Self-care**	**Logits FIM Mobility**	**SE FIM Mobility**
5	-5.99	1.58	-	-	-	-
6	-4.71	0.96	-	-	-	-
7	-4.02	0.78	-	-	-	-
8	-3.51	0.69	-6.44	1.60	-	-
9	-3.09	0.63	-5.05	0.99	-	-
10	-2.73	0.59	-4.31	0.80	-	-
11	-2.40	0.57	-3.78	0.70	-	-
12	-2.10	0.54	-3.36	0.64	-	-
13	-1.82	0.53	-2.99	0.60	-6.12	1.53
14	-1.56	0.51	-2.66	0.58	-4.94	0.96
15	-1.30	0.50	-2.34	0.57	-4.28	0.81
16	-1.05	0.50	-2.03	0.56	-3.74	0.75
17	-0.811	0.50	-1.73	0.56	-3.22	0.73
18	-0.572	0.49	-1.42	0.57	-2.70	0.71
19	-0.332	0.50	-1.10	0.57	-2.20	0.70
20	-0.088	0.50	-0.77	0.59	-1.71	0.68
21	0.16	0.50	-0.42	0.60	-1.26	0.65
22	0.411	0.51	-0.05	0.61	-0.86	0.63

23	0.670	0.51	0.34	0.63	-0.49	0.61
24	0.932	0.52	0.76	0.64	-0.14	0.60
25	1.21	0.53	1.19	0.64	0.21	0.60
26	1.49	0.54	1.61	0.63	0.57	0.62
27	1.78	0.55	2.00	0.62	0.95	0.63
28	2.09	0.57	2.37	0.61	1.36	0.66
29	2.42	0.59	2.72	0.61	1.81	0.68
30	2.78	0.62	3.07	0.62	2.30	0.72
31	3.17	0.66	3.44	0.64	2.83	0.76
32	3.63	0.72	3.85	0.69	3.43	0.82
33	4.18	0.82	4.34	0.77	4.16	0.93
34	4.96	1.01	5.00	0.94	5.14	1.13
35	6.38	1.66	6.24	1.55	6.80	1.80

SE, standard error

DRS Rasch Analyses. Consistent with the FIM instrument, Rasch transformed logit scores were utilized for the DRS instrument when completing longitudinal analyses for this study. In contrast to the FIM instrument, no Rasch transformation had been completed for the DRS up to this date within the TBIMS. Winsteps software was utilized to complete Rasch analyses to compute the raw score to logit score transformation for the DRS instrument. Using Rasch analyses, specific attributes that were assessed for the DRS included: dimensionality, person and item reliability, scale use and function, and construct validity including person-item fit statistics.

Dimensionality. Dimensionality of the DRS was examined using Principal Components Analysis of Residuals (PCAR), including evaluation of the raw variance explained by measure (raw variance explained by Rasch item difficulties, person abilities, and rating scale model) and the unexplained variance in the first contrast (variance not explained in the Rasch model). The percent rule of thumb utilized for this study to define dimensionality was raw variance explained by the measure greater than 40% (Linacre, 2006) and an eigenvalue for unexplained variance in the first contrast less than 2.

Person and Item Reliability. Person reliability or the replicability of person ordering that would be expected if the sample were given another set of items that measured the same construct, was assessed to determine the spread of person locations across this TBI sample. Like person reliability, item reliability was examined to demonstrate the replicability of item locations if the same items were given to another sample with similar position levels. High person reliability indicated that some participants scored higher and some lower and high item reliability that some items were difficult and some easy. Devellis (2012) reports ranges for internal consistency reliability as follows: "below. 60, unacceptable; between .60 and .65, undesirable; between .65 and .70, minimally acceptable; between .70 and .80, respectable; and between .80 and .90, very good" (p. 109). For this study, the ranges proposed by Devellis (2012) were used to determine acceptable ranges of person, item, and internal consistency reliability.

Scale Use and Function. Scale use and function of the DRS was explored to ensure that the response structure worked for the study sample. To assess the function of the response scale of the DRS, the probability of a particular response category selected was observed. This was accomplished through observation of probability curves and category structure statistics (observed count for each item). Observation of probability curves demonstrated where a person measure minus an item measure was most probable.

Overall and Item fit. Finally overall fit was measured by infit and outfit mean square (MNSQ) values. Infit is a weighted fit statistic that is more sensitive to unexpected behavior affecting response to items near the person's measure. In contrast, the outfit is unweighted and is sensitive to outliers or unexpected behavior affecting

responses to items far from the person's measure. A MNSQ value of 1.0 was used as a reference to demonstrate adequate overall fit for this study (Linacre, 2014). MNSQ values that were below 1.0 indicated dependency in the data. MNSQ values found to be over 1.0 demonstrated noise. Like overall fit of the model, item fit was assessed by MNSQ infit and outfit values. Item infit measures responses near a given item difficulty or person ability while outfit is more impacted by the behavior of persons on items that are far from the persons measure level. MNSQ infit statistics less than 1.50 were used for this study to demonstrate adequate fit between the data and the model (Linacre, 2014).

Missing Data Analysis. An analysis of missing data was conducted following Rasch analyses and transformations of the FIM and DRS outcome variables. Missing data is a universal problem that occurs in data analysis. The problem of missing data occurs, for instance, when equipment malfunctions, respondents become unmanageable, or someone makes an error. The seriousness of missing data is dependent on the pattern of missing data, how much is missing, and why it is missing. The pattern of missing data is more important than the amount of missingness. Missing values that are random throughout a data set will unlikely cause serious problems, however non-randomly missing values are a threat to the generalizability of results and thereby pose a more serious problem (Rubin, 1976; Tabachnick & Fidell, 2013).

There are three major types of missing data. These include missing completely at random (MCAR), missing at random (MAR), and missing not at random or not ignorable (MNAR) (Rubin, 1976; Tabachnich & Fidell, 2013). MCAR is the best of all possible worlds if data must be missing. The missingness is unrelated to all variables or

unsystematic; therefore missingness found on one variable is unrelated to the missingness of another variable. This type of missingness may occur as a result of a participant missing a session because of sickness. MAR or missing at random takes place when the missingness is unrelated to a variable when controlling for other variables. In this case the pattern of missing data is predictable from other variables in the data set. This may happen when participants from lower income families do not report SES or total income. Missingness in this case may be predictable by another variable other than the dependent variable (DV). Missingness due to MNAR results when missingness is related to variables and therefore cannot be ignored. Often times in this case there is selection bias present. MNAR will yield unreliable results. This type of missingness may be found for instance when lower income families do not report SES and have more mental health issues. In this case the missingness for SES is related to other variables (Rubin, 1976; Tabachnick & Fidell, 2013). Using SPSS software, a missing values analysis and Little's MCAR test was implemented to assess the degree and pattern of missingness for this TBI sample so that the best method for correction could be chosen.

FIM and DRS Temporal Trajectories. It has been found through previous research (Pretz et al., 2013) that the negative exponential was the mathematical function best suited to describe the relationship between the FIM and DRS and time using the TBIMS NDB. Using generalized linear mixed modeling, Pretz et al. (2013) produced patterns of FIM and DRS outcomes that were then transferred into temporal trajectories of probability of FIM and DRS outcomes (linear, quadratic, cubic, or negative exponential). The data were analyzed graphically using plots of individual response

patterns (IRC). The trend of response patterns indicated the negative exponential function was the best equation to describe the FIM and DRS scores due to the evidence of ceiling and floor effects (Figures 1 and 2). In this case, the FIM was found to demonstrate ceiling effects or a rapid increase in outcome followed by a plateau, whereas the DRS was found to demonstrate floor effects or a rapid decrease in outcome followed by a plateau. Additionally, Pretz et al. (2013) evaluated the adequacy of the models through the use of the Akaike Information Criterion (AIC) fit indices. The models with the smallest AIC values were chosen because they were found to best fit the data; in this case the negative exponential for the FIM Cognitive, FIM Motor, and DRS outcome variables (Table 4). Using this study to model the FIM and DRS outcome variables, the negative exponential was utilized as the mathematical function to describe the data in the current study as the sample was drawn from a similar TBIMS ND sample and over the same time periods.

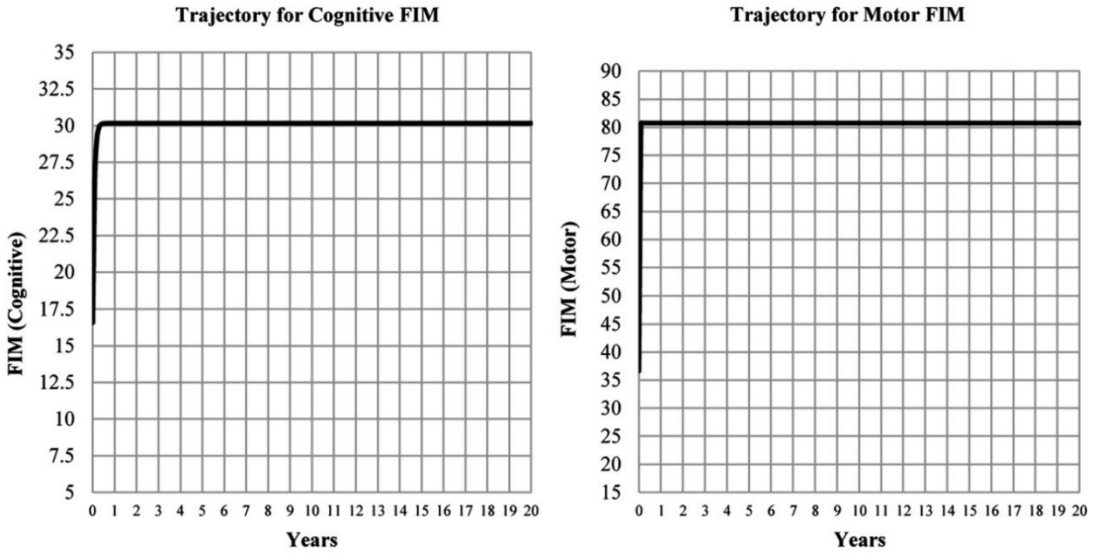

Figure 1. Average trajectory for FIM Cognitive and FIM Motor (Pretz et al., 2013)

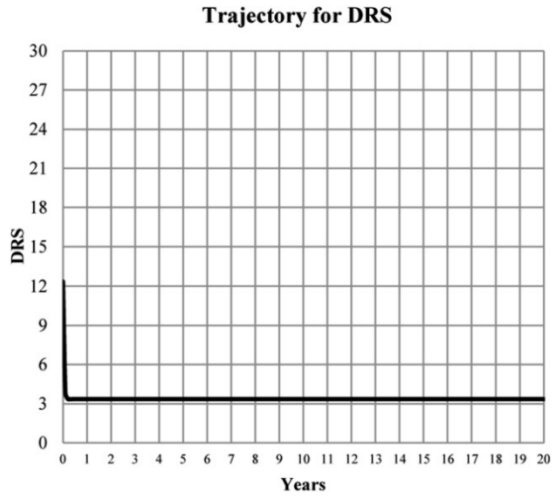

Figure 2. Average Trajectory for DRS (Pretz et al., 2013)

Table 4

AIC Values by Outcome: All Mathematical Functions

Outcome	Linear Change	Quadratic Change	Cubic Change	Negative Exponential
FIM Cognitive (n= 9157)	289,723 (CS)	284,270 (CS)	278,643 (CS)	275,438 (VC)
FIM Motor (n = 8995)	367,414 (CS)	361,708 (CS)	356,140 (CS)	345,427 (VC)
DRS (n = 9101)	257,869 (CS)	252,083 (CS)	246,685 (CS)	243,845 (VC)

Abbreviations: AIC, Akaike information criterion; CS, compound symmetry; SP, spatial; VC, variance components (Pretz et al., 2013)

Unconditional and Conditional Models. Using the negative exponential; an unconditional model was created in which no covariates were included. Because there was evidence of sufficient variability (statistical significance) across initial statuses and growth rates; covariates were included to explain variance of the growth parameters, thus producing models that were conditional on the associations between the covariates and growth parameters included. The continuous covariates were grand-mean centered such

that the grand mean of the level-1 predictor was subtracted from each level-1 case (i.e., χ_{ij} -$\chi_{..}$ where $\chi_{..}$ was the grand mean ofχ_{ij}. In this case, the intercept term takes on a different meaning. In raw metric scaling, an intercept equal to the expected value of Y_{ij} when χ_{ij} is zero. By grand-mean centering, the intercept is equal to the expected value of Y_{ij} for an individual with an average level ofχ_{ij}. For example, the expected value for Y_{ij} for a person with a score on χ is equal to the mean across all individuals in the sample. (Raudenbush & Bryk, 2002). Additionally, by grand-mean centering the continuous predictors, the correlation between the intercept and slope estimates across groups are reduced. In reducing the covariation between the random intercepts and slopes, the potential for level-2 estimation issues due to multicollinearity are alleviated (Hofmann & Gavin, 1998; Raudenbush, 1989a; Raudenbush, 1989b).

Chapter 3: Results

The analytical components of the research study are found in this chapter. Post-secondary data from the TBIMS NDSC were used to address the primary research questions formulated for this study.

Statistical data analyses comprised first assessing the variables through univariate or descriptive statistics. This portion of analyses was completed using SPSS Statistics 23 and SAS 9.4 software. The second series of analyses involved separating the FIM into three independent subscales using SPSS Statistic 23 software and then transforming raw scores to logit scores through Rasch analyses using Winsteps software. Similar to the FIM, Rasch analyses were utilized to confirm unidimensionality and complete raw score to logit score transformations for the DRS. Following the Rasch transformation of the FIM and DRS outcome variables, the dataset was examined for missingness. The fourth series of statistical analyses encompassed assessing the mathematical function that best fit the TBIMS ND dataset that was chosen for this study through a series of descriptive analyses using SAS 9.4 software. Finally, through the use of longitudinal HLM analyses, unconditional and conditional models were developed using the four outcomes of interest to describe individual growth trajectories and patterns.

Examination of trajectories and patterns in this TBIMS dataset allowed for assessment of the impact that primary rehab payer had on functional outcomes including FIM and DRS. Statistical controls used in each analysis including a set of the following variables: sex, age, race, marital status, education years, employment, length of rehab stay, and post-traumatic amnesia.

Univariate and Descriptive Statistics. The first series of statistical analyses included exploring the variables and accompanying data in the TBIMS ND. Using SPSS, frequencies, univariate, and descriptive statistics were computed for all of the variables to be included in primary analyses. Dependent variables examined were the FIM (FIM Cognitive, FIM Mobility, and FIM Self-Care) and DRS (items and total scores). Independent variable assessment included primary rehab payer. Covariates observed included sex, age, race, marital status, education years, illegal drug use, alcohol use, length of rehab stay, and post-traumatic amnesia. Initial descriptive statistics are provided in Table 1. For all of the continuous variables, normality was examined through observation of skewness. There were no issues of skew noted for all of the continuous variables with the exception of the DRS. Violations of assumptions of normality and HOV (heterogeneity of variance) were deemed robust due to the large sample size of the TBIMS ND (>75,000 observations, approximately 15,000 cases) supporting an ample sample for this study.

FIM Rasch Transformation. Following initial frequency, univariate, and descriptive analyses, the FIM was separated into three separate subscales; FIM Cognitive, FIM Mobility, and FIM Self-care. New variables were computed for each subscale and

total score. Each subscale score was recoded using the Rasch raw score to logit score transformations that were derived by Pretz et al. (2016). This same procedure was applied to the DRS outcome variable; however a DRS Rasch transformation had never been completed, therefore Rasch analyses were required to derive the raw to logit score transformations for the DRS.

DRS Rasch Analysis. Rasch methodology was utilized to examine dimensionality, person and item reliability, scale use and function, and construct validity including person-item fit statistics for the DRS.

Dimensionality. Using Winsteps, dimensionality was first evaluated through principal components analysis of residuals (PCAR). Raw variance explained by the measure was found to be greater than 40% indicating a measurement dimension for the DRS (raw variance – measure = 92.9%). Additional support for uni-dimensionality of the DRS instrument included an eigenvalue less than 2.0 for unexplained variance in the first contrast of residuals (DRS = 1.4).

Person and Item Reliability. Reliability of person separation was addressed to determine the spread of position across this particular TBI sample. Likewise, reliability of item separation was observed to determine the replicability of item placements if the same items were given to another sample with similar position levels to this TBI sample. Results indicated the DRS to contain adequate person and item reliability. (Person reliability = .92, Item Reliability => .99). Internal consistency of the DRS was measured through Cronbach's alpha and was found to be well within the ranges proposed by Devellis (2012) (Cronbach's alpha = .87).

Scale Use and Function. Scale use and function was tested to confirm that the response structure was appropriate. There were three primary groupings that were analyzed in regards to category structure. The first grouping contained items on the DRS that contained a response structure of 0 to 3 (1- Eye Opening, 4-Feeding, 5- Toileting, 6-Grooming, and 8- Employability). The second grouping encompassed those items with a 0 to 4 response structure (2- Communication Ability). Finally, the third and final grouping contained items with a 0 to 5 response structure (3- Motor Response and 7-Level of Functioning). Infit MNSQ values for category structure for each grouping was less than the recommendation of 1.5 (Linacre, 2012) except category 5 for the 3rd grouping. This may indicate that the fifth category can perhaps be collapsed into another category to improve the overall category structure (Table 5). Probability of a particular response category was explored through representation of probability curves for each grouping. The "hills" of numbers for each scale grouping demonstrated where a person measure minus an item measure was most probable (Figure 3, Figure 4, and Figure 5). The curves for each of the three groupings showed combinations of all response categories and indicated that the response structure utilized in the DRS instrument would work for future samples (Appendix A).

Table 5

Summary of DRS Category Structure

Category Label	Observed Count		Infit MNSQ	Andrich Threshold
	Count	%		
DRS Group 1 (Items 1, 4-6, & 8)				
0	178328	70	.83	None
1	23645	9	.72	-2.45
2	15643	6	.76	.31
3	36676	14	1.10	2.14
DRS Group 2 (Item 2)				
0	40546	75	1.46	None
1	9910	18	1.19	-4.75
2	1253	2	1.32	.99
3	1005	2	1.41	1.36
4	1332	2	1.23	2.41
DRS Group 3 (Items 3 & 7)				
0	63930	65	.70	None
1	6050	6	.71	-4.56
2	6220	6	.77	-2.85
3	10466	11	.86	-1.31
4	6888	7	1.19	2.53
5	5443	5	2.57	6.19

Overall and Item fit. Finally results of average fit (mean infit MNSQ) for the DRS scale was just above the reference value of 1.00 indicating some noise in the data (Infit MNSQ = 1.11). Item fit statistics were assessed to ascertain how well the data fit the model. Item infit MNSQ was found to be within the acceptable range of 1.50 with the exception of Item 1 (Eye Opening = 2.02) (Table 6). This indicated that there was generally adequate fit of the data to the model. The misfit Eye Opening item may need to be carefully researched in future analyses to determine the specific etiology for its misfit. No items were removed from analysis as dimensionality was maintained despite the misfit of this one item.

Table 6

DRS Item Statistics, Misfit Order

DRS Scale Items	Infit MNSQ	PTMEASURE Correlation
1- Eye Opening	2.02	.35
2- Communication Ability	1.30	.73
3- Motor Response	1.50	.43
4- Feeding	.84	.77
5- Toileting	.94	.79
6- Grooming	.76	.81
7- Level of Functioning	.87	.93
8- Employability	.66	.83

DRS Rasch Transformation. Following Rasch analyses of the DRS and confirmation that the DRS was in fact measuring one dimension, a SPSS data file was obtained from Winsteps containing the logit for each DRS raw score. Table 7 provides the DRS raw score to logit score transformations. Similar to the FIM, Rasch analyses provided equal interval (linear) measures of participants that were not impacted by non-equal interval (nonlinear) rating scales such as the DRS. Additionally, as with the FIM; the transformation of raw scores to logit scores allowed for increased understanding of person ability and item difficulty while organizing estimates of each on an equal interval linear continuum (Pretz et al., 2016).

Table 7

Raw Score to Logit Transformation: DRS

Raw Score	**Logits DRS**	**SE DRS**
0	-13.00	2.00
1	-11.31	1.31
2	-9.93	1.08
3	-8.89	.98
4	-7.94	.97
5	-6.92	1.07
6	-5.61	1.90
7	-4.38	1.00
8	-3.53	.72
9	-2.84	.81
10	-2.19	.81
11	-1.53	.81
12	-.89	.79
13	-.29	.81
14	.27	.74
15	.81	.73
16	1.34	.73
17	1.87	.73
18	2.39	.72
19	2.90	.71
20	3.40	.72
21	3.95	.76
22	4.57	.82
23	5.30	.89
24	6.17	.98
25	7.23	1.08
26	8.52	1.18
27	10.05	1.32
28	12.49	1.87
29	15.03	2.14

Missing Values Analyses. Missing values analyses indicated that all variables had evidence of incomplete data (100%), 80.13% of the cases included incomplete data, and 16.17% of overall values for the variables of interest for this study had incomplete data. Further univariate statistics provided by the program indicated significant missingness for the Rasch transformed FIM (FIM Cognitive (20.6%), FIM Mobility (39.4%), and FIM Self-Care (22%)) and DRS (50.5%) outcome variables. A large percentage of missing values was observed for covariates including post-traumatic amnesia (24.0%), employment (30.5%), alcohol use (21.6%), and education years (26.1%). (Table 8)

Table 8

Missing Values Analysis: Analysis Variables

Variables	N	Missing	
		Count	Percent
Rasch-Transformed FIM Cognitive	60253	15599	20.6
Rasch-Transformed FIM Mobility	45989	29863	39.4
Rasch-Transformed FIM Self-Care	59185	16667	22.0
Rasch-Transformed DRS	37569	38283	50.5
Length of Stay	75756	96	.1
Age	75775	77	.1
Post-traumatic Amnesia	57643	18209	24.0
Sex	75795	57	.1
Marital Status	75714	138	.2
Race	75765	87	.1
Employment	52752	23100	30.5
Illegal Drug Use	70805	5047	6.7
Alcohol Use	59492	16360	21.6
Education Years	56066	19786	26.1
Primary Rehab Payer	75226	626	.8

Missing data occurred in this data set at two levels; the unit level and at the item level. A unit-level non-response was the result of no information collected from a participant at multiple time points. An item non-response occurred when there was

incomplete information collected from a participant. The first level of missingness; the unit level was investigated further. In the TBIMS ND, there is a high level of attrition. This occurs for a number of reasons, one of which was the data were just not collected for an individual at a particular time point. Another potential cause is that the patient achieved functional independence and did not wish to continue to be involved in the TBIMS or on the other hand, the patient may have a history of mental illness or depression and was not motivated to participate from the beginning. Finally, attrition is at times due to the poor medical status or mortality of the patient. To determine the level of attrition or non-response in this sample of data, the longitudinal dataset was restructured and follow-up period frequencies were assessed. Frequency analyses of the 18 follow-up periods (0, 0.5, and 1-13, 15, 20, and 25) revealed missingness that ranged from 64% to over 99% from follow-up periods 6-18. Missing data for these time points was primarily due to no data being collected across all variables for a particular case.

It was important at this stage to determine the pattern of missingness in the dataset, as different methods for handling missing data are dependent on the pattern of missingness found. It should be noted that this particular sample of TBIMS data was found not to be MCAR, as the results of Little's MCAR test was statistically significant ($\chi^2 = 32350.995$, $df = 75$, $p < .001$). A statistically non-significant result is required to infer MCAR or the probability that the pattern of missingness deviates from randomness at greater than a .05 level.

There are no formal tests to infer MAR versus MNAR; however several tests were performed using SPSS Missing Values Analyses (MVA) to examine the patterns of missingness in the data. Initial analysis included examination of the missing value patterns chart (Figure 6). Each pattern (row) reflected a group of cases that encompassed the same pattern of missing values. The variables along the x-axis were arranged by the number of missing values each contained. This chart allowed for observation of whether monotonicity was present (pattern or rigid decreasing or increasing of missingness across a sequence). If there was a large concentration of missingness in the upper left corner and lower right corner, this would have indicated monotonicity or a systematic pattern of missingness. Figure 6 provides the Missing Value Patterns chart for the TBIMS data used for this analysis. As shown, a large cluster of missingness was found in the right hand corner, but not in the upper left corner. Additionally, there were patches of non-missing data strewn throughout. Using this chart, it was assumed that the data were MAR and did not demonstrate a systematic pattern of missingness.

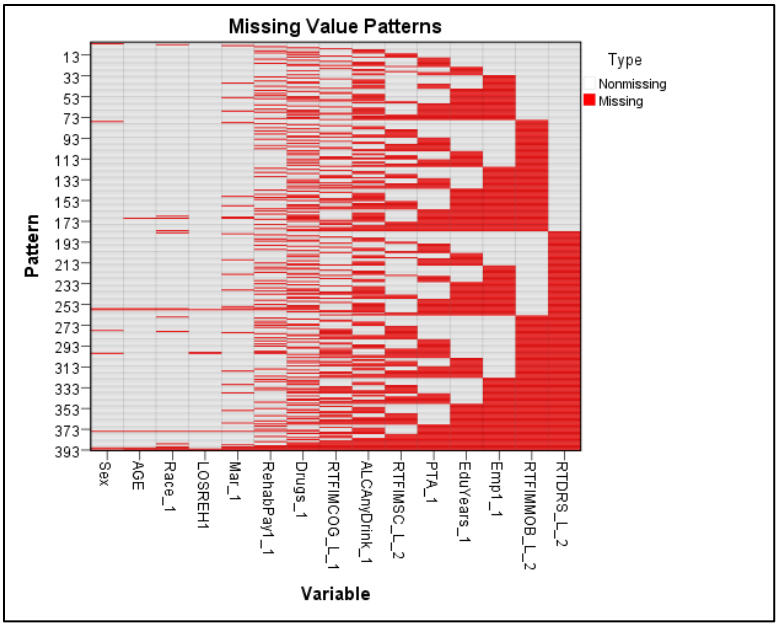

Figure 6. Missing Value Patterns Chart: Analysis Variables

Despite evidence supporting the likelihood of MAR data through the Missing Values Patterns chart, missingness that was MNAR could not be entirely excluded as there are currently no formal tests to differentiate between the two. Separate variance *t*-tests were evaluated to compare groups of cases with data on a specific variable to groups of cases without data on the same variable. Using this test, data would be found to be MAR if all of the p-values exceeded .05 or alpha. P-values that were less than .05 would indicate that systematic differences were evident in the missing outcomes and other variables. As shown in Table 9, the majority of the *t*-tests for analysis variables showed statistical significance and thus indicated that there were in fact systematic differences in the outcomes and other variables with missing data.

Table 9

Separate Variance t-Tests: Analysis Variables

Analysis Variables	FIM Cognitive	FIM Mobility	FIM Self-Care	DRS	Length of Rehab Stay	AGE	PTA
FIM Cognitive							
p(2-tail)	-	.914	< .001	<.001	< .001	< .001	< .000
# Present	60253	45797	58921	36713	60251	60248	46443
# Missing	0	192	264	856	15505	15527	11200
FIM Mobility							
p(2-tail)	< .001	-	< .001	< .001	< .001	< .001	.366
# Present	45797	45989	45919	26391	45988	45987	35510
# Missing	14456	0	13266	11178	29768	29788	22133
FIM Self-Care							
p(2-tail)	< .001	< .001	-	< .001	< .001	.001	< .001
# Present	58921	45919	59185	35815	59183	59180	45591
# Missing	1332	70	0	1754	16573	16595	12052
DRS							
p(2-tail)	< .001	< .001	< .001	-	< .001	.817	< .001
# Present	36713	26391	35815	37569	37569	37567	28748
# Missing	23540	19598	23370	0	38187	38208	28895
PTA							
p(2-tail)	< .001	< .001	< .001	< .001	< .001	< .001	-
# Present	46443	35510	45591	28748	57643	57643	57643
# Missing	13810	10479	13594	8821	18113	18132	0
Employment							
p(2-tail)	< .001	< .001	< .001	< .001	< .001	< .001	< .001
# Present	45688	34157	44530	28448	52726	52752	41363
# Missing	14565	11832	14655	9121	23030	23023	16280
Education Years							
p(2-tail)							
# Present	< .001	< .001	< .001	< .001	< .001	< .001	< .001
	48286	36248	47145	29966	56040	56066	44180
# Missing	11967	9741	12040	7603	19716	19709	13463

Systematic differences and evidence of bias in the TBIMS ND has been a topic of discussion by multiple researchers in the TBIMS. Systematic bias occurs when a characteristic associated with attrition is also associated with the dependent variable of interest. Although the TBIMS ND provides substantial information regarding traumatic brain injury for thousands of individuals across the United States, the potential for systematic bias has increased with the number of subjects lost to follow-up (Corrigan, Bogner, Mysiw, Clinchot, & Fugate, 1997; Corrigan, Harrison-Felix, Bogner, Dijkers, Terrill, & Whiteneck, 2003). It has been found that a large majority of longitudinal studies of persons with TBI have large loss to follow-up rates. In a study completed by Marquez de la Plata (2008), those that were eligible for 5 year follow-up who could not be found were determined to be younger and less educated than those that were included in analyses. These individuals were thought to perhaps be more independent, thus not allowing follow-up with the rehabilitation hospital. In this case, findings would then be underestimated. Because the disability level of those lost to follow-up was unknown, these assumptions have not been proven to be the ultimate cause of attrition.

In a previous study completed by Corrigan et al. (2012), the representativeness of the TBIMS ND was examined. Through this research it was found that the TBIMS ND was largely representative of all individuals 16 years and older admitted for rehabilitation in the U.S. with a primary diagnosis of TBI, however there was a major difference in the representativeness by age. There were not as many patients over the age of 65 in the TBIMS ND that were admitted for rehabilitation with a primary diagnosis of TBI in comparison to all those in the United States. For those 65 years and older, there were

meaningful differences in insurance type and age distribution. In fact, the proportion of patients age 70 and older that were admitted for TBI rehabilitation in the United States increased each year. This trend was not evident in the general population, TBIMS ND or for TBI patients in acute care. Cuthbert et al. (2012) completed secondary analyses of existing data sets (data set used by Corrigan et al, 2012) and previously published analyses. Results of these extended analyses were similar to results found by Corrigan and associates. Age continued to account for the largest difference between the samples (TBIMS ND and United States). Although distributional differences found between samples was markedly reduced after partitioning each dataset at age 65, the differences in the preinjury vocational status of the employed and rehabilitation length of stays between 1-9 days remained robust.

Though there are no formal tests to distinguish MAR from MNAR data, the testing and previous research discussed above attests that the current TBIMS ND likely contains some level of systematic bias and attributes of data that are MAR or MNAR. Because of the likelihood that the current dataset contains systematic bias, imputation methods were not utilized and complete case analysis was used for all statistical analyses.

Final FIM and DRS trajectories. The fourth series of statistical analyses encompassed the assessment of the mathematical function that best fit the current sample from the TBIMS ND through a series of descriptive analyses using SAS version 9.4. Because previous research indicated the negative exponential to account for floor and ceiling effects, SAS PROC NLMIXED was used to model the negative exponential for the current sample. Like Pretz et al (2013), the trend of response patterns indicated the

negative exponential function was the best equation to model the FIM and DRS scores for the current TBIMS ND sample (Figure 7, 8, 9, and 10). Similar to Pretz et al (2013) the FIM outcome variables (FIM Cognitive, FIM Mobility, and FIM Self-Care) were found to demonstrate ceiling effects or a rapid increase in outcome followed by a plateau, whereas the DRS was found to demonstrate floor effects or a rapid decrease in outcome followed by a plateau.

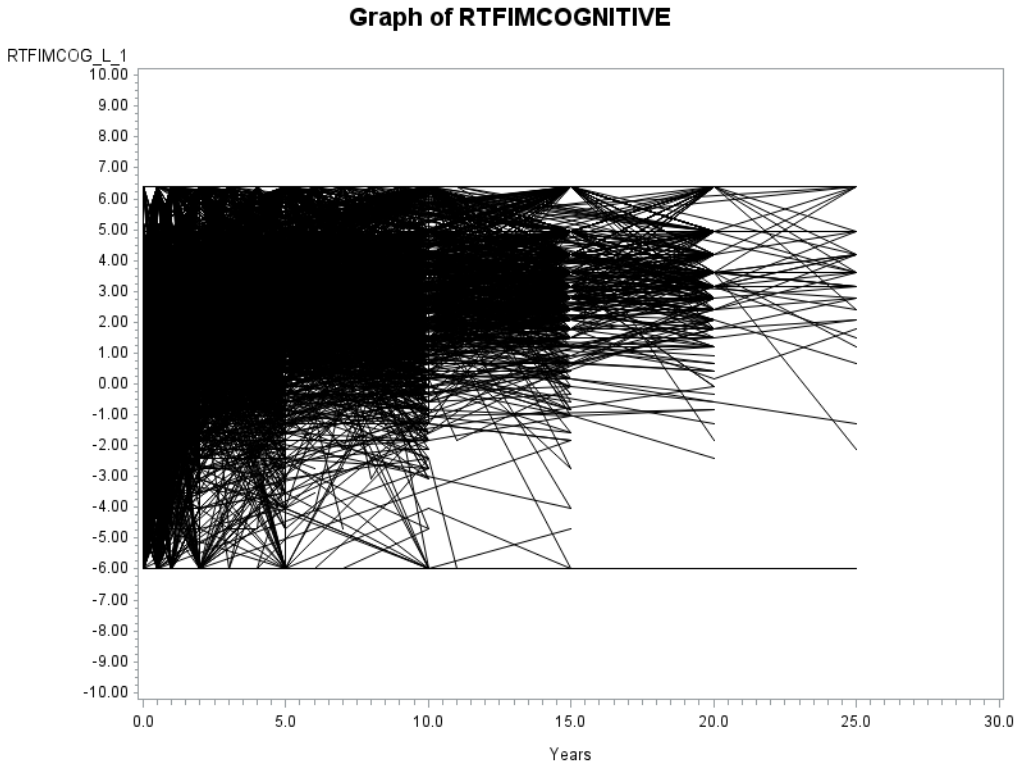

Figure 7. FIM Cognitive Response Pattern: Negative Exponential

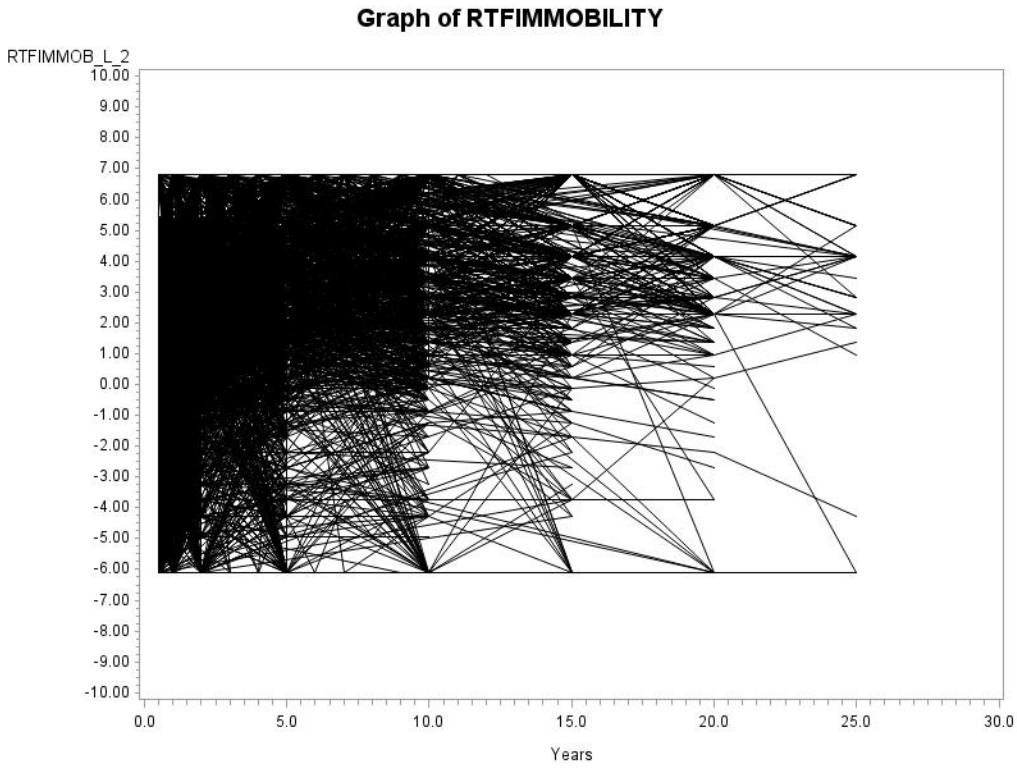

Figure 8. FIM Mobility Response Pattern: Negative Exponential

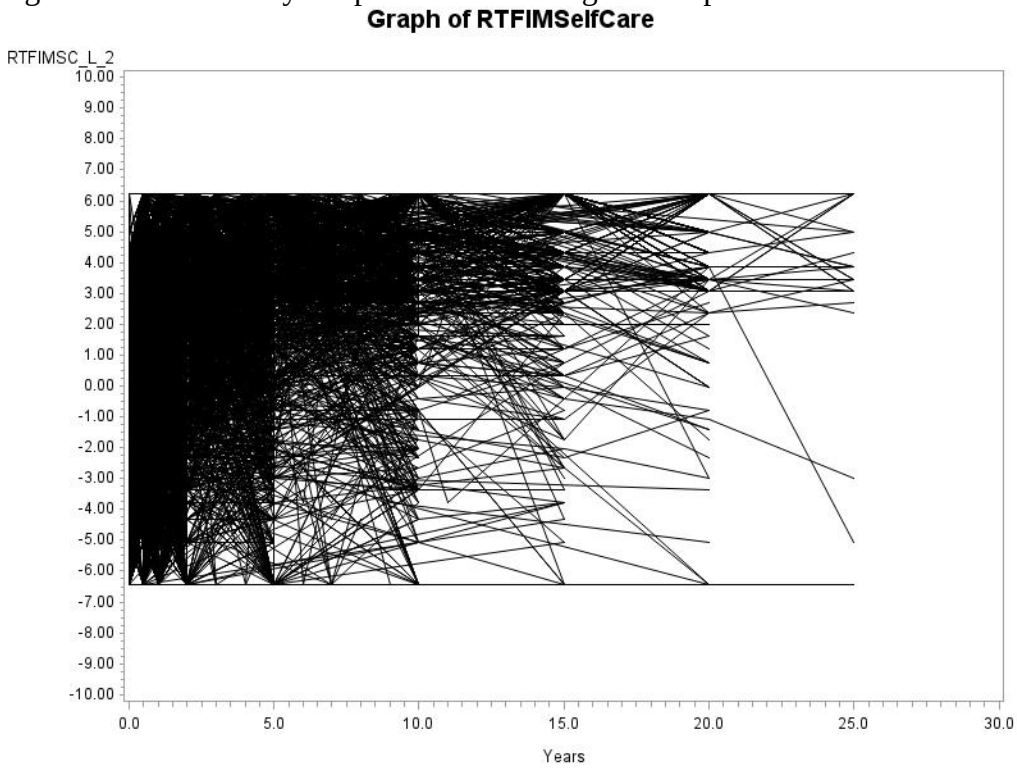

Figure 9. FIM Self-Care Response Pattern: Negative Exponential

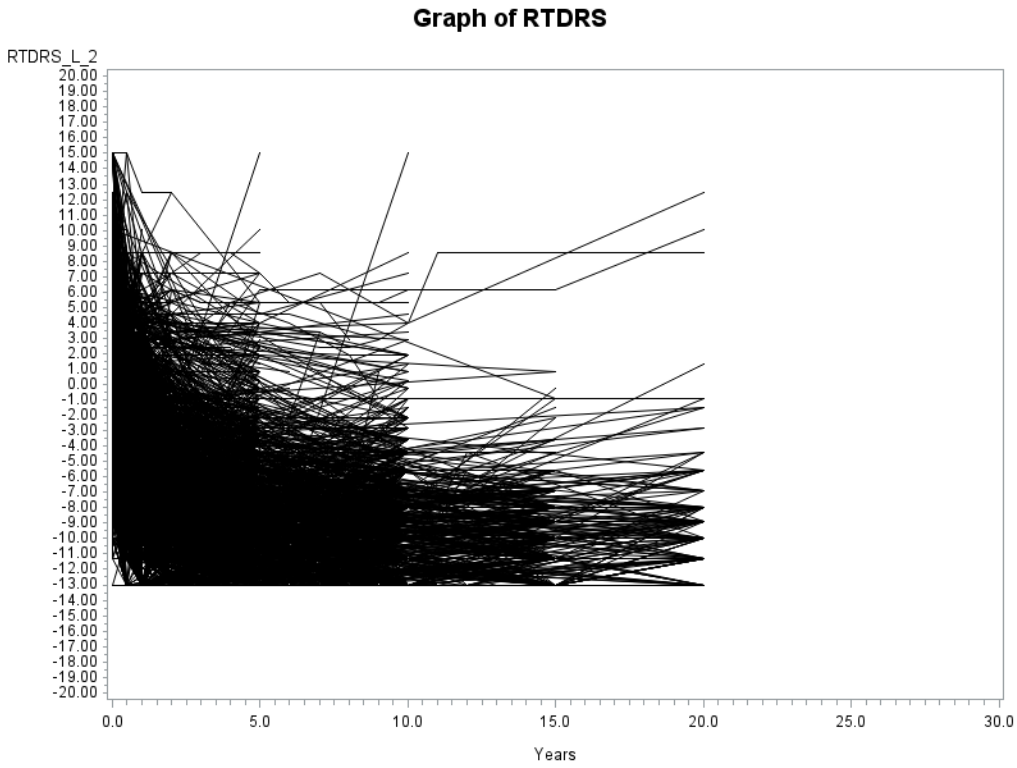

Figure 10. DRS Response Pattern: Negative Exponential

Descriptive Modeling Individual Growth Using Longitudinal HLM. Using the TBIMS ND, a longitudinal HLM approach was employed to comprehensively describe the individual growth of individuals that had sustained TBI. Specific outcomes were the FIM Cognitive, FIM Mobility, FIM Self-Care, and DRS.

Unconditional Models. Unconditional models were first implemented to describe the best-fit average trajectory for the available data. Estimates for the asymptote and pseudo-intercept showed that the average FIM Cognitive score at rehabilitation admission was -1.18, where on average; the score at which individuals reached relative stability was 4.32. FIM Mobility asymptote and pseudo-intercept estimates indicated that the average FIM Mobility score at rehabilitation admission was -3.56, and relative stability was achieved on average at a score of 5.16. The FIM Self-Care indicated that on average, the

FIM Self-Care score on admission was -2.39, and the score in which relative stability was attained was 5.49. Finally, the DRS estimates for the asymptote and pseudo-intercept suggested that the average DRS score on rehabilitation admit was -1.83, where individuals on average reached relative stability at a score of -10.90. The rate at which the asymptote was approached was on average consistent across the FIM Cognitive (1.73), FIM Mobility (1.75), FIM Self-Care (1.94), and DRS (1.69) (Tables 10-13).

Unconditional models provided the total variance in each growth parameter (Tables 14-17). For the FIM Cognitive, FIM Mobility, FIM Self-Care, and DRS outcome variables, it was found that all *p*-values were statistically significant ($p < .0001$). Statistical significance indicated a sufficient amount of variability in the growth parameters, thus providing evidence that further variability in each growth parameter may be explained by additional covariates.

Table 10

Negative exponential growth parameter estimates for the FIM Cognitive (the group trajectory)

Parameter	**Estimate**	***p***	**Lower 95% Confidence Limit**	**Upper 95% Confidence Limit**
Asymptote	4.32	<.0001	4.27	4.38
Pseudointercept	-1.18	<.0001	-1.21	-1.14
Rate	1.73	<.0001	1.69	1.76

Table 11

Negative exponential growth parameter estimates for the FIM Mobility (the group trajectory)

Parameter	Estimate	*p*	Lower 95% Confidence Limit	Upper 95% Confidence Limit
Asymptote	5.16	<.0001	5.12	5.19
Pseudointercept	-3.56	<.0001	-3.59	-3.52
Rate	1.75	<.0001	1.74	1.77

Table 12

Negative exponential growth parameter estimates for the FIM Self-Care (the group trajectory)

Parameter	Estimate	*p*	Lower 95% Confidence Limit	Upper 95% Confidence Limit
Asymptote	5.49	<.0001	5.44	5.54
Pseudointercept	-2.39	<.0001	-2.45	-2.33
Rate	1.94	<.0001	1.91	1.97

Table 13

Negative exponential growth parameter estimates for the DRS (the group trajectory)

Parameter	Estimate	*p*	Lower 95% Confidence Limit	Upper 95% Confidence Limit
Asymptote	-10.90	<.0001	-10.99	-10.82
Pseudointercept	-1.83	<.0001	-1.91	-1.74
Rate	1.69	<.0001	1.66	1.72

Table 14

Unconditional Model, FIM Cognitive: Growth Parameter Variance and Covariance Estimates

Parameter	Estimate	*p*	Lower 95% Confidence Limit	Upper 95% Confidence Limit
Variance in the asymptotes	2.10	<.0001	2.07	2.14
Variance in the pseudointercepts	4.12	<.0001	4.06	4.18
Variance in the rates	.06	<.0001	.05	.06
Residual Variance	1.79	<.0001	1.75	1.83

Table 15

Unconditional Model, FIM Mobility: Growth Parameter Variance and Covariance Estimates

Parameter	Estimate	*p*	Lower 95% Confidence Limit	Upper 95% Confidence Limit
Variance in the asymptotes	4.10	<.0001	4.05	4.15
Variance in the pseudointercepts	4.54	<.0001	4.46	4.63
Variance in the rates	0.14	<.0001	.13	.14
Residual Variance	3.06	<.0001	3.01	3.12

Table 16

Unconditional Model, FIM Self-Care: Growth Parameter Variance and Covariance Estimates

Parameter	Estimate	*p*	Lower 95% Confidence Limit	Upper 95% Confidence Limit
Variance in the asymptotes	2.24	<.0001	2.09	2.39
Variance in the pseudointercepts	4.32	<.0001	4.10	4.54
Variance in the rates	.19	<.0001	.13	.26
Residual Variance	2.29	<.0001	2.23	2.34

Table 17

Unconditional Model, DRS: Growth Parameter Variance and Covariance Estimates

Parameter	Estimate	*p*	Lower 95% Confidence Limit	Upper 95% Confidence Limit
Variance in the asymptotes	5.76	<.0001	5.36	6.17
Variance in the pseudointercepts	8.08	<.0001	7.66	8.51
Variance in the rates	.03	<.0001	.02	.05
Residual Variance	3.35	<.0001	3.24	3.46

Conditional Models. Conditional models were constructed as sufficient variability was found in the growth parameters of each unconditional model. Covariates were used in the conditional models to explain this variability and to acquire individual level trajectories. To accomplish the latter, the initial step was to examine which covariates related significantly to the growth parameters; in this case the asymptote (point at which the outcome measure reaches relative stability), pseudo-intercept (value of the outcome at admission to rehabilitation), and the rate (the rate at which the asymptote is reached). Conditional or full models were produced using the independent variable (primary payer source) and all covariates as statistical controls (age, education, employment, marital- status, length of rehabilitation stay, post traumatic amnesia, race, and sex). Using Type III sum of square analysis, parameter and covariate pairs were removed ($p > .05$). For three out of four models (FIM Cognitive, FIM Mobility and DRS), a process was implemented to ensure convergence of results. One variable at a time was removed from the analysis. If the model did not converge, the variable was placed back into the model and another removed.

This process was continued until convergence was achieved. The FIM Cognitive model required removal of the covariate marital status, the FIM Mobility model required removal of education – high school, and the DRS model required removal of race to achieve convergence.

The estimates relating payer and covariates to the growth parameters for each model tested are found in Tables 18 - 21. These were the estimates that established the associations between the covariates and growth parameters. It is these associations that are responsible for producing the individual level trajectories. Estimates that were not statistically significant were not included in the following tables, but can be found in Appendix B (Tables 22-25).

The parameter estimates for continuous covariates were interpreted as the amount of change in the outcome for a 1-unit change in the covariate. For example, the significant effect between PTA and the asymptote for each model demonstrated that for every 1 unit increase in PTA, the score at the point of relative stability (asymptote) for the outcome decreased. The FIM Cognitive decreased by -.01 logits ($p < .0001$), the FIM Mobility by -.008 logits ($p < .0001$), and the FIM Self-Care by -.003 logits ($p = .04$). Like the FIM, the asymptote for the DRS increased by .03 logits ($p < .0001$) for every 1 unit increase in PTA. Lower FIM scores demonstrated a decline in function, thus as age increased, the point of relative stability for the FIM decreased. Because higher DRS scores demonstrate a decline in function, an increase in PTA reflected a poorer or higher score on DRS when the point of relative stability was reached.

In the case of categorical covariates, a selected reference category served as the basis of comparison between itself and the other levels of the covariate. Because primary rehabilitation payer was the variable of primary interest (independent variable) for this study, results for the asymptote, pseudo-intercept and rate were interpreted for each outcome (FIM Cognitive, FIM Mobility, FIM Self-care, and DRS) using Private Insurance as the reference (Blue Cross/Blue Shield, employee, or privately purchased insurance) and all the remaining covariates as statistical controls.

In looking at the FIM Cognitive, the asymptote (point of relative stability) and primary rehab payer association was statistically significant for Medicare and Medicaid (Medicare = -.47 logits, p <.0001; Medicaid = -.58 logits, p <.0001). Results indicated that individuals with Medicare scored -.47 logits lower on the FIM Cognitive than those with Private Insurance at the point of relative stability. Individuals with Medicaid were also found to score -.58 logits lower than those with Private Insurance at the point of relative stability. The relationship between Other Rehab Payer and the asymptote was not statistically significant; therefore the asymptote of the FIM Cognitive was not impacted for those with this type of payer source (Table 18).

For the pseudo-intercept growth parameter and primary rehab payer, only Medicaid was statistically significant (Medicaid = .27 logits, p <.0001). This finding indicated that the individual value of the FIM Cognitive at admission to rehabilitation increased by .27 logits for those with Medicaid in comparison to those with Private Insurance. The association between the rate growth parameter and Medicare or Other Rehab Payer was found to be not statistically significant, thus the rate at which the asymptote was reached was not impacted by Medicare or Other Rehab Payer resources (Table 18).

Results for the FIM Mobility model indicated the relationship between the asymptote and primary rehab payer to be statistically significant for all categories of primary rehab payer (Medicare = -.98 logits, p < .0001; Medicaid = -0.90 logits, p < .0001; Other Rehab Payer = -.18 logits, p = .01). This meant that in comparison to individuals with Private Insurance, those with Medicare scored -.98 logits lower when the point of relative stability was reached, Medicaid -.90logits lower, and Other Rehab Payer -.18 logits lower (Table 19).

As noted in Table 19, the value of the individual FIM Mobility score at admission to rehabilitation or the pseudo-intercept and primary rehab payer was found to be significant only for individuals with Medicare and Medicaid as their primary insurance (Medicare = -.61 logits, p < .0001; Medicaid = .65 logits, p = < .0001). In this regard, individuals with Medicare scored -.61 logits lower on the FIM Mobility than those with Private Insurance and individuals with Medicaid scored .65 units higher on the FIM Mobility from admission to rehabilitation. Pseudo-intercept estimates for those with

Other Rehab Payer resources were found to be not statistically significant; thus had no impact on FIM Mobility scores during this time period.

Finally, the association between primary rehab payer and the rate growth parameter for the FIM Mobility model was found to be statistically significant for only Medicaid (Medicaid = .08 logits, $p = .04$). This finding suggested that the rate at which the asymptote was approached for individuals with Medicaid resources was quicker than those with Private Insurance. For individuals with Medicare or Other Rehab Payer insurance there was no impact on the rate at which the asymptote was approached as results were not statistically significant (Table 19).

In examining results for the FIM Self-Care model, it was found that the association between the asymptote and pseudo-intercept growth parameters and primary rehab payer was statistically significant for all categories (Asymptote Medicare =-.73 logits, $p < .0001$, Asymptote Medicaid = -.49 logits, $p < .0001$, Asymptote Other Rehab Payer = -.14 logits, $p = .01$ and Pseudo-Intercept Medicare = -.39 logits, $p < .0001$, Pseudo-Intercept Medicaid = -.49 logits, $p < .0001$., Pseudo-Intercept Other Rehab Payer = .15 logits, $p = .02$). The significant association found between the Asymptote and all levels of primary rehab payer signified that at the point at which relative stability was reached, FIM Self-Care scores were -.73 logits lower for individuals with Medicare, -.49 logits lower for those with Medicaid, and -.14 logits lower for those with Other Rehab Payer resources than those with Private Insurance. The statistically significant relationship between the pseudo-intercept and Medicare and Medicaid indicated that the value of scores for the FIM Self-Care at the time point from admission to rehabilitation

was -.39 logits lower for those with Medicare and -.49 logits lower for those with Medicaid than those with Private Insurance. Interestingly, those with Other Rehab Payer resources were found to score .15 logits higher than individuals with Private Insurance from admission to rehabilitation (Table 20). The association between the rate at which the asymptote was approached for the FIM Self-Care and primary rehab payer was statistically significant for individuals with only Medicare insurance (Medicare = -0.11 logits, $p = .02$). The association between the rate growth parameter and Medicaid or Other Rehab Payer was not statistically significant. For individuals with Medicare as their primary insurance, the rate at which the asymptote was approached was longer than those with Private Insurance (Table 20).

Finally, results for the DRS model as portrayed in Table 21, showed there to be a statistically significant association between the asymptote growth parameter and primary rehab payer (Asymptote Medicare = 1.36 logits, $p < .0001$, Asymptote Medicaid = 1.31 logits, $p < .0001$, and Asymptote Other Rehab Payer = .65 logits, $p < .0001$) and the pseudo-intercept growth parameter and primary rehab payer (Pseudo-Intercept Medicare = .28 logits, $p = .04$, Pseudo-Intercept Medicaid = -.50 logits, $p < .0001$, and Pseudo-Intercept Other Rehab Payer = -.32 logits, $p = .0007$). The significant association between the asymptote and primary rehab payer indicated that DRS score was found to be 1.36 logits higher (worse) for those with Medicare versus those with Private Insurance, 1.31 logits higher (worse) for individuals with Medicaid versus Private Insurance and 0.65 logits higher (worse) for those with Other Rehab Payer resources versus Private Insurance. Similar to the association between the asymptote and primary

rehab payer, the association between the pseudo-intercept and individuals with Medicare insurance demonstrated that scores from admission to rehabilitation were .28 logits higher (worse) for those with Medicare insurance versus those with Private Insurance. On the other hand, individuals with Medicaid or Other Rehab Payer resources scored -.50 and -.32 logits lower (better) than those with Private Insurance from admit to rehabilitation.

Finally, the DRS rate growth parameter and primary rehab payer demonstrated a statistically significant association for individuals with Medicare (Rate = .17 logits, p = .02) and Medicaid (Rate = .15 logits, p =.0009) insurance resources (Table 17). This meant that the rate at which individuals approached the asymptote was quicker for those with Medicare or Medicaid insurance than for individuals with Private Insurance. There was no statistically significant relationship found between the rate growth parameter and Other Rehab Payer (Table 21).

For each model covariates that were used as statistical controls varied in statistical significance. Statistical controls that were found to be statistically significant in relation to their association to the asymptote growth parameter for the FIM Cognitive included: age, high school education, post high school education, employment, length of rehabilitation stay, post traumatic amnesia, race, and sex. With the exception of high school and post high school education and sex, the point of relative stability was met at a lower FIM Cognitive score. Individuals who were female and had at least a high school education were found to score higher on the FIM Cognitive than males with less than a high school education.

The admit to rehabilitation scores or the pseudo-intercept score was only statistically significant for employment, length of rehab stay and post- traumatic amnesia covariates and logit scores on the FIM Cognitive were found to be lower at this period of time. The sole covariate that was found to be associated to the rate growth parameter was PTA; therefore as time in post-traumatic amnesia increased the rate in which the asymptote was met was slower (Table 18).

Covariates that were found to indicate a statistically significant association to the asymptote growth parameter in modelling the FIM Mobility outcome included: age, post high school education, employment, length of rehabilitation stay, PTA, race, and sex. For a 1 logit increase in the continuous covariates length of rehabilitation stay, PTA, or age, FIM Mobility logits decreased. FIM Mobility logit scores for individuals that were unemployed and not white were found to be lower than their employed and white counterparts. Individuals with education greater than high school were found to have higher FIM Mobility logit scores than those individuals that did not have a high school education. The association between the pseudo-intercept and age, length of rehabilitation stay, PTA, race, and sex were found to be statistically significant. For continuous variables age, length of rehabilitation stay and PTA, FIM Mobility logit scores at time of rehabilitation admit decreased with increased age, length of rehabilitation stay, or time in post-traumatic amnesia. Individuals with race other than white were found to demonstrate lower FIM Mobility logit scores at admit than individuals who were white. Females scored greater FIM Mobility logit scores at admit than their male counterparts.

The rate at which the asymptote was achieved was dependent on an individual's age, length of rehabilitation stay, and time in post-traumatic amnesia. As age and length of rehabilitation stay increased, the rate at which the asymptote was met was faster. As PTA increased, the rate at which the asymptote was met was slower (Table 19).

In modelling the FIM Self-Care there were more covariates found to be associated with each growth parameter. Age, education, length of rehabilitation stay, race, sex, and PTA were all significantly associated with the asymptote. As age, length of rehab stay, and PTA increased FIM Self-Care logit scores at asymptote decreased. In contrast, FIM Self-Care logit scores increased at the asymptote for females with education greater than high school. For individuals with only a high school education, FIM Self-Care logit scores were lower at the point of relative stability. Like the asymptote growth parameter, logit scores at rehab admit were found to be lower for individuals as age, length of rehab stay, and PTA increased. Individuals that were classified "other race" demonstrated lower FIM Self-Care logit scores at admit than their white counterparts. Finally, individuals that were female or had an education greater than high school were found to present with higher logit scores on the FIM Self-Care at admit than males or individuals with less than a high school education. The rate in which the asymptote was achieved for FIM Self-Care was found to be slower for those that were female and required a longer length of rehabilitation stay. As age or PTA increased, the rate in which the asymptote was achieved was shorter. Finally, the rate in which white individuals achieved asymptote was slower than their non-white counterparts (Table 20).

In the final DRS model, covariates including: age, education, employment, length of rehabilitation stay, PTA, and sex were found to be significantly associated with the asymptote growth parameter. As age, length of stay and PTA increased, DRS logit scores at the asymptote increased (worse), as did DRS logit scores for the unemployed versus the employed. Individuals that were female or educated (high school or greater than high school) were found to have lower (better) DRS logit scores at asymptote. DRS logits at admit were found to be lower (better) for those with increased age, whereas individuals with extended length of rehabilitation stay or PTA were found to have higher (worse) DRS logit score at admit. It was established that individuals that were highly educated (more than high school) or not married presented with lower (better) DRS logit scores at admit. Individuals that were unemployed prior to admit were found to have higher (worse) DRS logit scores than individuals that were employed prior to admit. Finally, the association between the rate in which the asymptote was achieved and age, education, and length of rehabilitation stay was found to be statistically significant. As age and length of rehabilitation stay increased, the rate in which the asymptote was achieved was slower. In contrast, individuals that were highly educated (more than high school) were found to achieve the asymptote faster than those with little education (less than high school) (Table 21).

Table 18

FIM Cognitive: Estimates of the relationships between growth parameters and covariates (N=8364)

Growth Parameter/Covariate	**Estimate**	***p***	**Lower 95% Confidence Limit**	**Upper 95% Confidence Limit**
Asymptote/Age	-.01	< .0001	-.02	-.01
Asymptote/Education/High School (Ref = Less than High School)	.22	.007	.06	.39
Asymptote/Education/More than High School (Ref=Less than High School)	.73	< .0001	.56	.89
Asymptote/Employment (Ref = Employed)	-.23	< .0001	-.33	-.12
Pseudointercept/Employment (Ref = Employment)	-.16	.008	-.27	-.04
Asymptote/Length of Rehab Stay	> -.01	< .0001	-.01	> -.01
Pseudointercept/Length of Rehab Stay	< .01	< .0001	< .01	.01
Asymptote/PTA	-.01	< .0001	-.02	-.01
Pseudointercept/PTA	-.05	< .0001	-.06	-.05
Rate/PTA	< .01	< .0001	< .01	.01
Asymptote/Race (Ref=White)	-.26	< .0001	-.35	-.16
Asymptote/Sex (Ref=Male)	.17	.0002	.08	.26
Asymptote/Primary Rehab Payer/Medicare (Ref = Private)	-.47	< .0001	-.62	-.32
Asymptote/Primary Rehab Payer/Medicaid (Ref=Private)	-.58	< .0001	-.69	-.47
Pseudointercept/Primary Rehab Payer/Medicaid (Ref=Private)	.27	< .0001	.15	.39

Table 19

FIM Mobility: Estimates of the relationships between growth parameters and covariates (N=8360)

Growth Parameter/Covariate	**Estimate**	***p***	**Lower 95% Confidence Limit**	**Upper 95% Confidence Limit**
Asymptote/Age	-.04	< .0001	-.05	-.04
Pseudointercept/Age	-.01	.0001	.08	.26
Rate/Age	< .01	.02	< .01	< .01
Asymptote/Education/More than High School (Ref=Less than High School)	.51	< .0001	.40	.62
Asymptote/Employment (Ref = Employed)	-.18	< .0001	-.32	-.05
Asymptote/Length of Rehab Stay	-.03	< .0001	-.03	-.02
Pseudointercept/Length of Rehab Stay	-.03	< .0001	-.04	-.03
Rate/Length of Rehab Stay	.02	< .0001	.01	.02
Asymptote/PTA	-.01	< .0001	-.01	-.01
Pseudointercept/PTA	.11	.006	.03	.18
Rate/PTA	-.01	< .0001	-.01	> -.01
Asymptote/Race (Ref=White)	-.52	< .0001	-.64	-.40
Pseudointercept/Race (Ref=White)	-.17	.05	-.35	> -.01
Asymptote/Sex (Ref=Male)	.49	< .0001	.36	.60
Pseudointercept/Sex (Ref=Male)	.72	< .0001	.55	.90
Asymptote/Primary Rehab Payer/Medicare (Ref = Private)	-.98	< .0001	-1.18	-.78
Pseudointercept/Primary Rehab Payer/Medicare (Ref=Private)	-.61	< .0001	-.88	-.34
Asymptote/Primary Rehab Payer/Medicaid (Ref=Private)	-.90	< .0001	-1.04	-.75
Pseudointercept/Primary Rehab Payer/Medicaid (Ref=Private)	.65	< .0001	.44	.85
Rate/Primary Rehab Payer/Medicaid (Ref=Private)	.08	.04	< .01	.15
Asymptote/Primary Rehab Payer/Other (Ref=Private)	-.18	.01	-.32	-.04

Table 20

FIM Self-Care: Estimates of the relationships between growth parameters and covariates (N=8363)

Growth Parameter/Covariate	**Estimate**	***p***	**Lower 95% Confidence Limit**	**Upper 95% Confidence Limit**
Asymptote/Age	-.02	< .0001	-.03	-.02
Pseudointercept/Age	-.01	.004	-.01	-.001
Rate/Age	> -.01	< .0001	-.01	> -.01
Asymptote/Education/High School (Ref = Less than High School)	.17	.05	.001	.34
Asymptote/Education/More than High School (Ref=Less than High School)	.43	< .0001	.25	.60
Asymptote/Employment (Ref = Employed)	-.11	.03	-.22	-.01
Asymptote/Length of Rehab Stay	-.02	< .0001	-.02	-.02
Pseudointercept/Length of Rehab Stay	-.03	< .0001	-.03	-.02
Rate/Length of Rehab Stay	.01	< .0001	.003	.01
Pseudointercept/Marital Status (Ref=Married)	.19	.001	.01	.31
Asymptote/PTA	> -.01	.04	-.01	> -.01
Pseudointercept/PTA	-.04	< .0001	-.04	-.04
Rate/PTA	-.01	< .0001	-.01	> -.01
Asymptote/Race (Ref=White)	-.36	< .0001	-.45	-.27
Pseudointercept/Race (Ref=White)	-.12	.04	-.23	-.01
Rate/Race (Ref=White)	-.10	.0005	-.16	-.04
Asymptote/Sex (Ref=Male)	.19	< .0001	.10	.29
Pseudointercept/Sex (Ref=Male)	.38	< .0001	.27	.50
Rate/Sex (Ref=Male)	.08	.002	.03	.14
Asymptote/Primary Rehab Payer/Medicare (Ref = Private)	-.73	< .0001	-.90	-.57
Pseudointercept/Primary Rehab Payer/Medicare (Ref = Private)	-.39	< .0001	-.58	-.21
Rate/Primary Rehab Payer/Medicare (Ref = Private)	-.12	.02	-.21	-.02
Asymptote/Primary Rehab Payer/Medicaid (Ref=Private)	-.49	< .0001	-.61	-.38
Pseudointercept/Primary Rehab Payer/Medicaid (Ref=Private)	.32	< .0001	.18	.46

Asymptote/Primary Rehab Payer/Other (Ref=Private)	-.14	.01	-.25	-.03
Pseudointercept/Primary Rehab Payer/Other (Ref=Private)	.16	.02	.03	.29

Table 21

DRS: Estimates of the relationships between growth parameters and covariates

(N=8009)

Growth Parameter/Covariate	**Estimate**	***p***	**Lower 95% Confidence Limit**	**Upper 95% Confidence Limit**
Asymptote/Age	.05	<.0001	.04	.05
Pseudointercept/Age	-.01	.0003	-.01	-.004
Rate/Age	< .01	.01	< .01	.01
Asymptote/Education/High School (Ref = Less than High School)	-.63	.0001	-.95	-.30
Asymptote/Education/More than High School (Ref=Less than High School)	-1.51	<.0001	-1.84	-1.17
Pseudointercept/Education/More than High School (Ref=Less than High School)	-.49	.0007	-.77	-.21
Rate/Education/More than High School (Ref=Less than High School)	-.19	.02	-.35	-.03
Asymptote/Employment (Ref = Employed)	.28	.005	.09	.48
Pseudointercept/Employment (Ref = Employed)	.21	.02	.03	.39
Asymptote/Length of Rehab Stay	.02	<.0001	.01	.02
Pseudointercept/Length of Rehab Stay	.03	<.0001	.02	.03
Rate/Length of Rehab Stay	.01	<.0001	.01	.01
Pseudointercept/Marital Status (Ref=Married)	-.32	.0002	-.48	-.15
Asymptote/PTA	.02	<.0001	.02	.03
Pseudointercept/PTA	.06	<.0001	.06	.07
Asymptote/Sex (Ref=Male)	-.26	.003	-.44	-.09
Asymptote/Primary Rehab Payer/Medicare (Ref = Private)	1.36	<.0001	1.06	1.67

Pseudointercept/Primary Rehab Payer/Medicare (Ref = Private)	.28	.04	.01	.54
Rate/Primary Rehab Payer/Medicare (Ref = Private)	.17	.02	.02	.31
Asymptote/Primary Rehab Payer/Medicaid (Ref=Private)	1.31	<.0001	1.09	1.52
Pseudointercept/Primary Rehab Payer/Medicaid (Ref=Private)	-.50	<.0001	-.70	-.30
Rate/Primary Rehab Payer/Medicaid (Ref=Private)	.15	.0009	.06	.24
Asymptote/Primary Rehab Payer/Other (Ref=Private)	.65	<.0001	.45	.86
Pseudointercept/Primary Rehab Payer/Other (Ref=Private)	-.32	.0007	-.51	-.14

Percent Variance Explained and Model Fit. In addition to reporting the association amongst the covariates and growth parameters, the variability in the growth parameters that was explained by the covariates was also examined. This was determined by assessing the level at which the variability in the growth parameters decreased upon inclusion of covariates. For each model, Table 26 demonstrates the change in average asymptote, pseudo-intercept, and rate growth parameters with the inclusion of covariates as well as the percent of variance explained for each specific growth parameter. The model fit was assessed between the unconditional model and the conditional models with the inclusion of covariates. The Akaike information criterion (AIC) was used as the fit statistic to model fit. The smaller the AIC, the better the model fit. Table 27 shows the results of model fit for the unconditional and conditional models for the FIM Cognitive, FIM Mobility, FIM Self-Care, and DRS models. Results indicated the model fit to improve with the addition of covariates to each model as AIC values were notably smaller for conditional versus unconditional models.

Table 26

Variance Estimates of Growth Parameters: Conditional Models

Growth Parameter	Estimate of the Variance After Covariate Inclusion	*p*	Percent of Variability Explained by Independent Variable & Covariates
FIM Cognitive:			
Asymptote	1.74	<.0001	17%
PseudoIntercept	2.87	<.0001	30%
Rate	0.06	<.0001	0%
FIM Mobility:			
Asymptote	2.55	<.0001	38%
PseudoIntercept	2.99	<.0001	34%
Rate	0.12	<.0001	14%
FIM Self-Care:			
Asymptote	1.52	<.0001	32%
PseudoIntercept	2.82	<.0001	35%
Rate	0.19	<.0001	0%
DRS:			
Asymptote	3.89	<.0001	32%
PseudoIntercept	4.59	<.0001	43%
Rate	0.02	<.0001	33%

Table 27

Model Fit, Unconditional and Conditional Models

Model	Unconditional Model AIC Value	Conditional Model AIC Value
FIM Cognitive:		
(N = 8271 Unconditional)	137537	136051
(N = 8367 Conditional)		
FIM Mobility:		
(N = 8271 Unconditional)	133527	131688
(N = 8367 Conditional)		
FIM Self-Care:		
(N = 8271 Unconditional)	142913	140960
(N = 8367 Conditional)		
DRS:		
(N = 8271 Unconditional)	99195	96517
(N = 8367 Conditional)		

Covariance and Growth Parameters. In addition to the associations between the growth parameters and covariates, the final results of the analysis denoted the covariance between the growth parameters. Table 28 illustrates the covariances between growth parameters for the FIM Cognitive, FIM Mobility, FIM Self-Care, and DRS models were all statistically significant with the exception of the association between the asymptote and pseudo-intercept of FIM Cognitive (p = .06) and FIM Self-Care (p = .54) models. The covariance between the asymptotes and the pseudo-intercepts for the DRS indicated that those with higher (worse) scores on the DRS at admit tended to have higher (worse) DRS scores at the point of relative stability. Because the covariance was negative for the asymptote and pseudo-intercept for the FIM Mobility, high scores at admit were coupled with lower scores at the point of relative stability. For the covariances between the asymptote and rate, the FIM Mobility, Self-Care and DRS were positive. This indicated that higher scores on the FIM outcomes and low (better) scores on the DRS when relative stability was achieved was coupled with increased or faster rates. The FIM Cognitive covariance was negative, and thus indicated that the rate in which higher scores achieved relative stability was decreased or slower. The covariance between the pseudo-intercept and rate was positive for the FIM Cognitive, FIM Self-Care and DRS. This suggested that higher FIM or lower (better) DRS scores at admit were coupled with quicker rates. The negative covariance between the pseudo-intercept and rate found for the FIM Mobility indicated that high scores at admit were associated with decreased or slower rates.

Table 28

Covariance between growth parameters: All Analysis Models

Growth Parameters	**Estimate**	***P***	**Lower 95% Confidence Limit**	**Upper 95% Confidence Limit**
FIM Cognitive:				
Asymptote and pseudo-intercept	.08	.06	< -.01	.17
Asymptote and rate	-.29	< .0001	-.36	-.23
Pseudo-intercept and rate	.17	< .0001	.12	.22
FIM Mobility:				
Asymptote and pseudo-intercept	.38	.0001	.19	.58
Asymptote and rate	-.03	.36	-.10	.04
Pseudo-intercept and rate	.60	< .0001	.53	.67
FIM Self-Care:				
Asymptote and pseudo-intercept	.03	.54	-.07	.13
Asymptote and rate	.10	.001	.04	.16
Pseudo-intercept and rate	.65	< .0001	.58	.72
DRS:				
Asymptote and pseudo-intercept	.32	.02	.54	.58
Asymptote and rate	.26	< .0001	.16	.36
Pseudo-intercept and rate	.16	.002	.06	.26

Chapter 4: Discussion

Summary of the Study

The primary purpose of this study was to comprehensively describe individual growth patterns of patients that had sustained TBI utilizing a longitudinal HLM procedure. Of specific interest was the association between the growth parameters and the outcomes and the association between the growth parameters and covariates. Of particular interest for this study was the association between primary payer source and the growth parameters.

Major Findings

The main emphasis for the study was to answer one primary research question: Does payer source have an impact on initial status and growth rate over time of FIM and DRS scores when controlling for covariates including: sex, race, age, marital status, education, employment status, rehabilitation length of stay, and PTA. The findings suggest that the answer to this question is yes. Hypotheses were: Scores for outcome measures including FIM and DRS over at least three temporal measurements show a statistically significant change related to payer source benefits and payer source has an impact on FIM and DRS individual and group initial status and growth rate trajectories after controlling for covariates including sex, race, age, marital status, education, employment status, rehabilitation length of stay, and PTA. Both of the research

hypotheses listed above were supported, thus the null hypothesis was rejected that payer source did not have an impact on FIM and DRS scores for growth parameters including the asymptote, pseudo-intercept, and rate. Additionally, results indicated that up to 65% and 73% of the variance in outcome was explained by the addition of the covariates for the DRS and FIM Mobility respectively. This result mirrors that found by Cuthbert et al. (2015) in which longitudinal HLM was utilized to describe the 10 year patterns of employment for individuals of working age discharged from the TBIMS center between 1995 and 2009. Payer source was utilized by Cuthbert and associates as a covariate or statistical control and was found to be significantly associated to the quadratic growth parameters utilized to model the employment outcome variable. Although payer source was not a primary variable of interest, it nonetheless returned similar results to this current study using a similar TBIMS sample drawn from the same TBIMS ND.

In examining each growth parameter, it was found for the most part that insurance type did contribute to successful rehabilitation outcomes. The scores for the asymptote or point of relative stability on average was lower for individuals that had Medicare, Medicaid, or Other payer source benefits versus those who had Private Insurance. This means that those with Private Insurance had higher FIM or DRS scores at the location in which they reached a plateau or average stability point in function. Lower score for the asymptote for Medicare, Medicaid, and Other payer source may have been due to a number of reasons. First, those with Medicare as their primary source of payment were over the age of 65. Age was found to be a significant factor in determining ones score at the asymptote as well. For individuals over the age of 65, scores on average decrease for

the FIM and increase (worse) for the DRS due to additional comorbidities and complications of increased age in conjunction with their current TBI injury. Lower DRS scores by age were supported by Marquez de la Plata et al. (2008) in which Marquez de la Plata and associates researched the impact of age on long-term recovery from TBI. Results from this study indicated that the oldest group (> 40) was slightly more disabled at discharge from rehabilitation despite having an injury severity that was less severe than their younger counterparts. These results are also consistent with the findings from a smaller TBIMS database study that involved 182 TBI survivors and found age to be an independent predictor of cognitive decline five years post-injury (Millis et al., 2001). Other retrospective and shorter-term longitudinal studies have suggested that the risk for dementia and continued functional decline are more prevalent in older individuals (Corrada, Costa, & Kawas, 1997; Mayeux et al., 1993; Mosenthal et al., 2004; Rasmusson, Brandt, Martin, & Folstein, 1995). The mechanism of functional decline in older adults has also been explained by other researchers as stemming from decreased synaptic plasticity and cortical volume of the brain (Ge, Grossman, Babb, Rabin, Mannon, & Kolson, 2002; Kempermann, Gast, & Gage, 2002). Furthermore this notion is supported by a recent study that found that patients older than 55 years of age report more problems with headaches, body temperature changes, communication disorders, sleep disorders, and back and neck dysfunction and pain (Breed, Flanagan, & Watson, 2004).

Those individuals with Medicaid fared slightly better than individuals on Medicare; however they too saw declines in outcome scores at asymptote. The problem with Medicaid insurance is not that resources are not covered, but more so the fact that most rehabilitation facilities do not accept this insurance as a form of payment. It is likely that individuals with Medicaid will discharge to subacute facilities versus acute rehabilitation facilities. Individuals that receive subacute rehabilitation versus acute rehabilitation do not receive the same intensity of rehabilitation services. Those individuals that are able to go to acute rehabilitation will demonstrate better overall outcome scores solely because the level of care is higher and the resources more plentiful.

Finally, patients who were classified in the "Other" category are individuals that are paying for rehabilitation services out of pocket, patients on worker's compensation, or receiving free hospital and rehabilitation care. These individuals fared best against private insurance although scores also decreased at the relative point of stability. Individuals that were classified as "self-pay" may have had ample resources to pay for their care, thus outcome scores would show that they received ample rehabilitation resources. Individuals that received free hospital or rehabilitation care did not receive any less resources than those with Private Insurance, thus their outcome scores should reflect improvement. These may have been patients that were younger, but had more serious injuries; thus necessitating the need for more intensive rehabilitation services versus subacute care. Previous research has supported the notion that younger patients that have suffered a TBI injury do in fact demonstrate better functional outcomes than

older individuals with similar injury. Marquez de la Plata and associates (2008) found that even with increased injury severity, the younger groups in their study improved significantly from year 1 to year 5 and that the despite having a less severe injury, the older groups were slightly more disabled. In fact, the greatest magnitude in improvement in disability was found amongst those in the youngest group (16-26 years).

Overall, outcome scores on the FIM Self-Care and DRS at admit decreased by insurance type. Similar to the asymptote growth parameter, scores were lower on average for individuals with Medicare or Medicaid insurance. Surprisingly, individuals with "Other" rehabilitation payer source benefits scored higher on average for the FIM Self-Care and DRS than even those individuals with Private Insurance. This was most likely due to their functional status and health prior to the TBI injury. It's likely that individuals that received free care were healthy young adults prior to injury and their course of recovery was more rapid and promising. Individuals with private insurance were likely employed adults that had more resources to maintain adequate health prior to injury.

Finally, the rate at which the asymptote or relative stability was achieved for outcome scores generally was longer for those that contained Medicare or Medicaid insurance benefits. This was likely due to increased age, poor overall health status prior to TBI injury, additional medical comorbidities in addition to the TBI, and severity of injury. Nemunaitis et al. (2015) has completed research supporting this notion. Using the FIM, Nemunaitis and associates found that older patients with government insurance (Medicaid and Medicare) demonstrated poorer discharge score than patients with private

insurance. Disparities in FIM score were explained by factors including more severe injuries for those on Medicaid due to violence or mental illness (Wei et al., 2005) and the presence of greater comorbidities among the elderly (Gardizi et al., 2014).

Limitations

The primary limitation of this work was the fact that results derived from analyses could not be generalized to the larger TBI population; thus the final reduced models presented were only applicable to future studies in which an identical dataset would be used. The intent of this study was to describe participants within the TBIMS ND in great detail, not make statistical inferences about individuals who have sustained TBI outside of the TBIMS ND. Although covariates were chosen *apriori*, the associations that were found between the covariates and the growth parameters do not denote causality. Another limitation regarding the covariates chosen was that some of the covariates were not included in analyses in order to achieve convergence, thus models differed across outcome measures.

An additional potential limiting factor was the fact that outcomes were modelled using the complete timeline of available data for this particular TBIMS ND sample. Individual data had to include data for at least three follow-up periods to be included in analyses. While this was useful to measuring individual trajectories, it also reduced the overall sample and potentially excluded individuals with valuable data. Other inclusion or exclusion criteria may warrant the use of different modeling procedures for other time periods or groups.

For this particular study, the negative exponential was appropriate to model trajectories of early recovery; however the modelling technique used for studies examining trajectories over a longer time period may vary significantly. The asymptote or point of relative stability does not indicate the final level of recovery. The FIM and DRS outcome variables were modelled over the full range of available data to current time, thus the sensitivity of the modelling may not have been strong enough to measure change after the asymptote is reached.

Because the TBIMS ND is evolving over time, both outcomes and patients are always changing; thus analyses now may encompass specific outcomes and patients that may not be the same over the next 1 to 5 years. A limitation specific to the TBIMS ND is that no intervention variables are currently in place to measure the association between outcome score and current treatment modalities used by model system facilities. Finally, there may have been an impact on the accuracy of estimates due to the unbalanced nature of nominal or categorical variables used in this study. Variables such as primary rehab payer may require restructuring of categories for future studies to improve accuracy of estimates as percentages were not balanced amongst groups (Medicare 12%, Medicaid 24%, Private 42%, and Other 22%). Likewise, other nominal or categorical variables utilized for this study demonstrated similar disparities in regards to the percent balance amongst groups (Race: White 67%, Other 33%; Education: Less than High School 6%, High School 45%, and Greater than High School 32%; Employment: Employed 62%, Unemployed 17%; Marital Status: Married 3%, Not married 67%; Sex: Female 26%, Male 74%).

Recommendations for Future Study

The relationship between the covariates and growth parameters allow for investigation of temporal patterns that are expressed by individuals sharing equivalent values on a set of covariates. Although this study reported all of the significant associations between covariates and growth parameters, it did not include an interactive tool. Pretz and associates have utilized an interactive tool in previous research studies to display an individual trajectory for each combination of covariate values created. Visualization of individual trajectories is most useful to clinicians in rehabilitation as it allows them to see anticipated temporal change in a number of different individual situations. Furthermore, clinicians can use an interactive tool to describe the recovery path for individuals with specific values on the covariates given. Although results cannot be transferred to future groups, the interactive tools allows for a very comprehensive description of the current rehabilitation situation to be more informative to make future rehabilitation decisions for individuals with TBI. For instance, using the FIM Cognitive or the DRS, individual trajectories can be described for individuals with varying characteristics for covariates that were found to be significant for each growth parameter. For the FIM Cognitive, trajectories would be based on the significant covariates including: age, education, employment, length of rehabilitation stay, PTA, race, sec, and primary rehab payer. For the DRS, projected individual trajectories would be influenced by age, education, employment, length of rehabilitation stay, marital status, PTA, sex and primary rehab payer.

The TBIMS ND is currently in the process of implementing population-based weighting procedures to the database. In this way, researchers will be able to generalize analysis results to the overall TBI population versus just the TBIMS ND sample. Replication of this study with a population-based weighting mechanism would be beneficial so that results could be generalized to the overall TBI population, but also to TBI rehabilitation practitioners to utilize in clinical practice and to influence reimbursement decisions.

Conclusion

The findings of the current study are most useful to practitioners and clinicians in the rehabilitation field. In the rehabilitation field, patient populations have a tendency to demonstrate change during and after intervention. There are a number of factors that influence outcomes at the individual level. The analysis of individual growth portrayed through this study allows for a more thorough understanding of how such factors influence individual variability over time. As practitioners, we can utilize this methodology to evaluate the effectiveness of the current rehabilitation interventions on patient outcomes. Furthermore, we as practitioners are able to better understand how our patients recover and live with disability over time.

The primary goal for any practitioner in the rehabilitation field that treats TBI is to maximize functional outcomes over time. Through the use of individual growth modelling, clinicians are able to apply research findings to compare individuals or subgroups with each other or with the overall group. Knowledge of patient outcome trends at the individual, subgroup, or group levels provide the clinician with a wealth of

information; particularly what interventions and treatments are the most useful to the achievement of successful patient outcomes. Trajectories for new patients could be predicted based on individual growth models that have been developed from existing patient data simply by exchanging the new patients demographic and injury characteristic values into the equations for the growth parameters. Clinicians can use the predicted trajectory as a point of reference in evaluating the recovery of the new patient.

In reference to primary payer source, evidence of actual patient trajectories of recovery over time can provide the impetus for change in reimbursement patterns. Individual patient trajectories would provide a model of recovery in which large insurance holders such as Medicare and Medicaid can utilize to optimize the use of the resources they provide for post TBI rehabilitation care. Further rehabilitation resources that were once unavailable to specific patient populations may become available; as primary payers will want to maximize the effects of the financial support provided. Primary payers such as Medicare and Medicaid would actually have more resources available as resources would be more appropriately allocated across the TBI spectrum and individuals would receive adequate benefits for their specific stage of recovery. Providing the appropriate services and resources at specific phases of recovery would allow patients to achieve the asymptote or relative stability in a timeframe that allows individuals to continue to further their rehabilitation goals and require less financial support over their lifetime from primary payers such as Medicare and Medicaid. In fact, patients would have access to more resources from these insurance payers as the resources that were allocated would be distributed more appropriately over the lifetime of

their injury. Less capital would be spent as practitioners will have the knowledge of specific treatments and interventions that will maximize patient performance within the smallest time frame over the course of an individual's specific traumatic brain injury.

References

Alban, R.F., Berry, C., Ley, E., Mirocha, J., Margulies, D.R., Tillou, A., & Salim, A. (2010). Does health care insurance affect outcomes after traumatic brain injury? *The American Surgeon*, 76 (10), 1108-1111.

American Psychiatric Association. (2000). *Diagnostic and statistical manual of mental disorders* (4th ed., Text Rev.). Washington, DC: American Psychiatric Association.

Arango-Lasprilla, J. C., Ketchum, J. M., Dezfulian, T., Kreutzer, J. S., O'Neil-Pirozzi, T. M., Hammond, F., & Jha, A. (2008). Predictors of marital stability 2 years following traumatic brain injury. *Brain Injury, 22*(7-8), 565-574.

Arango-Lasprilla, J. C., Ketchum, J. M., Gary, K. W., Kreutzer, J. S., O'Neil-Pirozzi, T. M., Wehman, P.,. Jha, A. (2009). The influence of minority status on job stability after traumatic brain injury. *American Academy of Physical Medicine and Rehabilitation, 1*(1), 41-49.

Arango-Lasprilla, J. C., Ketchum, J. M., Cifu, D., Hammond, F., Castillo, C., Nicholls, E., . . Deng, X. (2010). Predictors of extended rehabilitation length of stay after traumatic brain injury. *Archives of Physical Medicine and Rehabilitation, 91*, 1495-1504.

Asemota, A.O., George, B.P., Cumpsty-Fowler, C.J., Haider, A.H, & Schneider, E.B (2013). Race and insurance disparities in discharge to rehabilitation for patients with traumatic brain injury. *Journal of Neurotrauma,* 2057-2065.

Baker, D. W., Parker, R. M., Williams, M.V., Pitkin, K, Parikh, N. S., Coates, W., & Imara, M. (1996). The health care experience of patients with low literacy. *Archives of Family Medicine, 5* (6) 329- 334.

Barrett, M., Lopez-Gonzalez, L., Hines, A., Andrews, R., and Jiang, J. *An examination of expected payer coding in HCUP databases*. 2014. HCUPMethods Series Report # 2014-03 ONLINE. December 17, 2014. U.S. Agency for Healthcare Research and Quality. Available:http://www.hcupus.ahrq.gov/reports/methods/methods.jsp.

Bereiter, C. (1963). Some persisting dilemmas in the measurement of change. In C. W. Harris (Ed.), *Problems in measuring change* (pp. 3-20). Madison, WI: University of Wisconsin Press.

Bleakley, C. M., O'Connor, S. R., Tully, M.A., Rocke, L. G., MacAuley, D. C., Bradbury, I., . McDonough, S. M. (2010). Effect of accelerated rehabilitation on function after ankle sprain: Randomized controlled trial. *BMJ, 340*, c1964. *doi: http://dx.doi.org/10.1136/bmj.c1964 (Published 10 May 2010)*

Bond, T. G. & Fox, C. M. (2001). *Applying the Rasch model: Fundamental measurement in the human sciences.* Mahwah, New Jersey: Lawrence Erlbaum.

Breed, S. T., Flanagan, S. R., & Watson, K. R. (2004). The relationship between age and the self-report of health symptoms in persons with traumatic brain injury. *Archives of Physical Medicine and Rehabilitation, 85,* S61-S67.

Brown, A. W., Malec, J. F., McClelland, R. L., Diehl, N. N., Englander, J., & Cifu, D. X. (2005). Clinical elements that predict outcome after traumatic brain injury: a

prospective multicenter recursive partitioning (decision tree) analysis. *Journal of Neurotrauma, 22,* 1040-1051.

Bryk, A. S. & Raudenbush, S. W. (1987). Application of hierarchical linear models to assessing change. *Psychological Bulletin, 101,* 147-158.

Bush, B. A., Novack, T. A., Malec, J. F., Stringer, A. Y., Millis, S. R., & Madan, A. (2003). Validation of a model for evaluating outcome after traumatic brain injury. *Archives of Physical Medicine and Rehabilitation, 84,* 1803-1807.

Centers for Disease Control and Prevention. (2014). *Report to congress on traumatic brain injury in the United States: Epidemiology and rehabilitation.* National Center for Injury Prevention and Control; Division of Unintentional Injury Prevention. Atlanta, GA.

Chan, L., Doctor, J., Temkin, N., MacLehose, R. F., Esselman, P., Bell, K., & Dikmen, S. (2001). Discharge disposition from acute care after traumatic brain injury: The effect of insurance type. *Archives of Physical Medicine and Rehabilitation, 82,* 1151-1154.

Chikani, V., Brophy, M., Vossbrink, A., Hussaini, K., Salvino, C., Skubic, J., & Martinez, R. (2015). Association of insurance status with health outcomes following traumatic injury: Statewide multicenter analysis. *Western Journal of Emergency Medicine, 16*(3), 408-413.

Connelly, J., Chell, S., Tennant, A., Rigby, A. S., & Airey, C. M. (2006). Modelling 5-year functional outcome in a major traumatic injury survivor cohort. *Disability Rehabilitation, 28,* 629-636.

Consensus conference. (1999). Rehabilitation of persons with traumatic brain injury. NIH consensus development panel on rehabilitation of persons with traumatic brain injury. *Journal of the American Medical Association, 282,* 974-983.

Coronado, V. G., Xu, L., Basavaraju, S. V., McGuire, L. C., Wald, M. M., Faul, M. D., Guzman, B. R., & Hemphill, J. D. (2011). Surviellance for traumatic brain injury-related deaths- United States, 1997-2007. *MMWR Surveill. Summ.* 60, 1-32.

Coronado, V. G., McGuire, L. C., Faul, M. F., Sugerman, D. E, & Pearson, W. S. (2012). *Traumatic brain injury epidemiology and public health issues.* In Brain InjuryMedicine: Principles and Practice, 2nd ed., eds. N. D. Zasler, D. I., Katz, R. D Zafonte. Demos Medical Publishing, New York, 84-100.

Corrada, M. M., Costa, P.T., & Kawas, C.H. (1997). Head injury and the risk of developing Alzheimer's disease. *Neurology, 48,* A301.

Corrigan, J. D., Bogner, J. A., Mysiw, W. J., Clinchot, D., & Fugate, L. (1997). Systematic bias in outcome studies of persons with traumatic brain injury. *Archives of Physical Medicine and Rehabilitation, 78,* 132-137.

Corrigan, J. D., Harrison-Felix, C, Bogner, J., Dijkers, M., Terrill, M. S., & Whiteneck, G. (2003). Systematic bias in traumatic brain injury outcome studies because of loss to follow-up. *Archives of Physical Medicine and Rehabilitation, 84,* 153-160.

Corrigan, J. D., Cuthbert, J. P., Whiteneck, G. G., Dijkers, M. P., Coronado, V., Heinemann, A. W., ., Graham, J. E. (2012). Representativeness of the traumatic brain injury model systems national database. *Journal of Head Trauma Rehabilitation, 27*(6), 391-403.

Corrigan, J. D., Horn, S. D., Barrett, R. S., Smout, R. J., Bogner, J., Hammond, F. M., . Majercik, S. (2015). Effects of patient preinjury and injury characteristics on acute rehabilitation outcomes for traumatic brain injury. *Archives of Physical Medicine and Rehabilitation, 96*(8), S209-S221.

Cronbach, L. J., & Furby, L. (1970). How should we measure "change" or should we? *Psychological Bulletin, 74*, 68-80.

Cuthbert, J.P., Corrigan, J.D., Harrison-Felix, C., Coronado, V., Dijkers, M.P., Heinemann, A. W., & Whiteneck, G.G. (2011). Factors that predict acute hospitalization discharge disposition for adults with moderate to severe traumatic brain injury. *Archives of Physical Medicine and Rehabilitation. 92,* 721–730.

Cuthbert, J. P., Corrigan, J. D., Whiteneck, G. G., Harrison-Felix, C., Graham, J. E., Bell, J. M, & Coronado, V. G. (2012). Extension of the representativeness of the traumatic brain injury model systems national database: 2001 to 2010. *Journal of Head Trauma and Rehabilitation, 27*(6), E15-27.

Cuthbert, J. P., Pretz, C, R., Bushnik, T, Fraser, R. T., Hart, T., Kolakowsky-Hayner, S. A., . . Sherer, M. (2015). Ten-year employment patterns of working age individuals after moderate to severe traumatic brain injury: A national institute on disability and rehabilitation research traumatic brain injury model systems study. *Archives of Physical Medicine and Rehabilitation, 96*(12), 2128-2136.

Dams-O'Connor, K., Pretz, C., Billah, T., Hammond, F. M., & Harrison-Felix, C. (2015). Global outcome trajectories after TBI among survivors and non-survivors: A

national institute on disability and rehabilitation research traumatic brain injury model systems study. *Journal of Head Trauma Rehabilitation, 30*(4), E1-E10.

DeGuise, E., LeBlanc, J., Feyz, M., Meyer, K., Duplantie, J., Thomas, H., ... Roger, E. (2008). Long-term outcome after severe traumatic brain injury: The McGill interdisciplinary prospective study. *Journal of Head Trauma Rehabilitation, 23*(5), 294-303.

DeVellis, R. F. (2012). Scale development: Theory and applications (3rded.). Thousand Oaks, CA: Sage Publications, Inc.

Di Scala, C., Grant, C. C., Brooke, M. M., & Gans, B. M. (1992). Functional outcome in children with traumatic brain injury. Agreement between clinical judgment and the functional independence measure. *American Journal of Physical Medicine and Rehabilitation, 71*(3), 145-148.

Dunlop, D. D. (1994). Regression for longitudinal data: a bridge from least squares regression. *Journal of the American Statistical Association, 48*, 299-303.

Eliason M. R & Topp B. W. (1984). Predictive validity of Rappaport's disability rating scale in subjects with acute brain dysfunction. *Physical Therapy, 64*, 1357–1363.

Englum, B. R., Villegas, C., Bolorunduro, O., Haut, E. R., Cornwell, E. E., Efron, D., & Haider, A. H. (2011). Racial, ethnic, and insurance status disparities in use of post hospitalization care after trauma. *Journal of the American College of Surgeons, 213*(6), 699-708.

Fitzmaurice, G., Laird, M., & Ware, J. (2011). *Applied longitudinal analysis* (2nd ed.). Hoboken: John Wiley & Sons.

Francis, D. J., Fletcher, J. M., Stuebing, K. K., Davidson, K. C., & Thompson, N. M. (1991). Analysis of change: Modeling individual growth. *Journal of Consulting and Clinical Psychology*, *59*(1), 27-37.

Fryer, L. J. & Haffey, W. J. (1987). Cognitive rehabilitation and community readaptation: Outcomes from two program models. *Journal of Head Trauma Rehabilitation, 2*, 51–63.

Gardizi, M. A., Hanks, R. A., Millis, S. R., & Figueroa, M. J. (2014). Comorbidity and insurance as predictors of disability after traumatic brain injury. *Archives of Physical Medicine and Rehabilitation, 95,* 2396-2401.

Gary, K. W., Arango-Lasprilla, J. C., & Stevens, L. F. (2009). Do racial/ethnic differences exist in post-injury outcomes after TBI? A comprehensive review of the literature. *Brain Injury, 23,* 775-789.

Ge, Y., Grossman, R., Babb, J. S., Rabin, M. L., Mannon, L. J., & Kolson, D. L. (2002). Age-related total gray matter and white matter changes in normal adult brain. Part I: volumetric MR imaging analysis. *American Journal of Neurologic Radiology, 23,* 1327-1333.

Goldstein, H. (1987). *Multilevel models in educational and social research.* London: Oxford University Press.

Gouvier, W. D., Blanton, P. D., Laporte, K. K., & Nepomuceno, C. (1987). Reliability and validity of the disability rating scale and the levels of cognitive functioning

scale in monitoring recovery from severe head injury. *Archives of Physical Medicine and Rehabilitation, 68*(2), 94-97.

Graham, J. E., Radice-Neumann, D. M., Reistetter, T. A., Hammond, F. M., Dijkers, M., & Granger, C. V. (2010). Influence of sex and age on inpatient rehabilitation outcomes among older adults with traumatic brain injury. *Archives of Physical Medicine and Rehabilitation, 91,* 43-50.

Green, W. R., Oyetunji, T. A., Bowers, U., Haider, A. H., Mellman, T. A., Cornwell, E. E., Siram, S. M., & Chang, D. C. (2010). Insurance status is a potent predictor of outcomes in both blunt and penetrating trauma. *The American Journal of Surgery, 199,* 554-557.

Haas, J. S. & Goldman, L. (1994). Acutely injured patients with trauma in Massachusetts: Differences in care and mortality, by insurance status. *American Journal of Public Health, 84,* 1605-1608.

Haider, A. H., Chang, D. C., Efron, D. T., Haut, E. R., Crandall, M., & Cornwell III, E. E. (2008). Race and Insurance status as risk factors for trauma mortality. *Archives of Surgery, 143*(10), 945-949.

Hall, K., Cope, D. N., & Rappaport, M. (1985). Glasgow outcome scale and disability rating scale: Comparative usefulness in following recovery in traumatic head injury. *Archives of Physical Medicine and Rehabilitation, 66,* 35-37.

Hall, K. M., Hamilton, B. B., Gordon, W. A., & Zasler, N. D. (1993). Characteristics and comparisons of functional assessment indices: Disability rating scale,

functional independence measure, and functional assessment measure. *Journal of Head Trauma Rehabilitation, 8*, 60-74.

Hamilton, B. B., Laughlin, J. A., Granger, C. V. & Kayton, R. M. (1991). Interrater agreement of the seven level Functional Independence Measure (FIM) [Abstract]. *Archives of Physical Medicine and Rehabilitation, 72*, 790.

Hammond, F. M., Grattan, K. D., Sasser, H., Corrigan, J. D., Bushnik, T., & Zafonte, R. D. (2001). Long-term recovery course after traumatic brain injury: A comparison of the functional independence measure and disability rating scale. *Journal of Head Trauma Rehabilitation, 16*(4), 318-329.

Hammond, F. M., Grattan, K. D., Sasser, H., Corrigan, J. D., Rosenthal, M., Bushnik, T., & Shull, W. (2004). Five years after traumatic brain injury: A study of individual outcomes and predictors of change in function. *Neurorehabilitation, 19*, 25-35.

Hammond, F. M., Hart, T., Bushnik, T., Corrigan, J. D., & Sasser, H. (2004). Change and predictors of change in communication, cognition, and social function between 1 and 5 years after traumatic brain injury. *Journal of Head Trauma Rehabilitation, 19*(4), 314-328.

Hedeker, D. G. & Gibbons, R. D. (2006). *Longitudinal data analysis.* Hoboken: John Wiley & Sons.

Heinemann, A. W., Linacre, J. M., Wright, B. D., Hamilton, B. B., & Granger, C. V. (1993). Relationships between impairment and physical disability as measured by

the Functional Independence Measure. *Archives of Physical Medicine and Rehabilitation, 74*(6), 566-573.

Heinemann, A. W., Linacre, J. W., Wright, B. D., Hamilton, B. B., & Granger, C. (1994a). Measurement characteristics of the functional independence measure. *Top Stroke Rehabilitation, 1*, 1-15.

Hekmeh, W., Barker, J., Szpunar, S. M., Fox, J. M., & Irvin, C. B. (2010). Effect of race and insurance on outcome of pediatric trauma. *Academic Emergency Medicine, 17*, 809-812.

HLM-7 statistical software for hierarchical linear modeling. Version 7. Lincolnwood: Scientific Software International; 2012.

Hoffman, J. M., Doctor, J. N., Chan, L., Whyte, J., Jha, A., & Dikmen, S. (2003). Potential impact of the new Medicare prospective payment system on reimbursement for traumatic brain injury inpatient rehabilitation. *Archives of Physical Medicine and Rehabilitation, 84*, 1165-1172.

Hofmann, D. A. & Gavin, M. B. (1998). Centering decisions in hierarchical linear models: Implications for research in organizations. *Journal of Management, 24*(5), 623-641.

Horn, S. D., Corrigan, J. D., Beaulieu, C. L., Bogner, J., Barrett. R. S., Giuffrida, C. G., . . . Deutscher, D. (2015). Traumatic brain injury patient, injury, therapy, and ancillary treatments associated with outcomes at discharge and 9 months post discharge. *Archives of Physical Medicine and Rehabilitation, 96*(8), S304- S329.

IBM Corp. Released 2015. IBM SPSS Statistics for Windows, Version 23.0. Armonk, NY: IBM Corp.

Jennet, B. & Bond, M. (1975). Assessment of outcome after severe brain damage. *Lancet, 1*, 480-484.

Jimenez, N., Osorio, M., Ramos, J. L., Apkon, S., Ebel, B. E., & Rivara, F. P. (2015). Functional independence after inpatient rehabilitation for traumatic brain injury among minority children and adolescents. *Archives of Physical Medicine and Rehabilitation, 96*, 1255-1261.

Kempermann, G., Gast, D., & Gage, F. H. (2002). Neuroplasticity in old age: Sustained five-fold induction of hippocampal neurogenesis by long-term environmental enrichment. *Annals of Neurology, 52*, 135-143.

Khan, S., Khan, A., & Feyz, M. (2002). Decreased length of stay, cost savings and descriptive findings of enhanced patient care resulting from an integrated traumatic brain injury programme. *Brain Injury, 16*, 537-554.

Kozlowski, A. J., Pretz, C. R., Dams-O'Connor, K., Kreider, S., & Whiteneck, G. (2013). An introduction to applying individual growth curve models to evaluate change in rehabilitation: A national institute on disability and rehabilitation research traumatic brain injury model systems report. *Archives of Physical Medicine and Rehabilitation, 94*, 589-596.

Kreutzer, J. S., Kolakowsky-Hayner, S. A., Ripley, D., Cifu, D. X., Rosenthal, M., Bushnick, T., . . . High, W. (2001). Charges and lengths of stay for acute and

inpatient rehabilitation treatment of traumatic brain injury. *Brain Injury*, *9*, 763-774.

Linacre, J. M., Heinemann, A. W., Wright, B. D., Granger, C. V., & Hamilton, B. B. (1994). The structure and stability of the Functional Independence Measure. *Archives of Physical Medicine and Rehabilitation, 75*, 127-132.

Linacre, J. M. (2006). Data variance explained by measures. *Rasch Measurement Transactions, 20*, 1045.

Linacre, J. M. (2014). Winsteps® Rasch measurement computer software. Beaverton, Oregon: Winsteps.com.

Linn, R. L., & Slinde, J. A. (1977). The determination of the significance of change between pre- and post-testing periods. *Review of Educational Research, 47*, 121-150.

Lippert-Gruner, M., Lefering, R., & Svestkova, O. (2007). Functional outcome at 1 vs. 2 years after severe traumatic brain injury. *Brain Injury, 21*(10), 1001-1005.

Lord, F. M. (1956). The measurement of growth. *Educational and Psychological Measurement, 16*, 421-437.

Lord, F. M. (1963). Elementary models for measuring change. In C. W. Harris (Ed.), *Problems in measuring change.* Madison, WI: University of Wisconsin Press.

Maas, A.I., Stocchetti, N., & Bullock, R. (2008). Moderate and severe traumatic brain injury in adults. Lancet Neurology. *7*, 728-741.

Mackay, L. E., Bernstein, B. A., Chapman, P. E., Morgan, A. S., & Milazzo, L. S. (1992). Early intervention in severe head injury: Long-term benefits of a

formalized program. *Archives of Physical Medicine and Rehabilitation, 73*, 635-641.

MacKenzie, E. J. (2000). Epidemiology of injuries: Current trends and future challenges. *Epidemiological Review, 22*, 112-119.

Marquez de la Plata, C., Hart, T., Hammond, F. M., Frol, A., Hudak, A., Harper, C. R., . . ., Diaz-Arrastia, R. (2008). Impact of age on long-term recovery from traumatic brain injury. *Archives of Physical Medicine and Rehabilitation, 89*(5), 896-903.

Marr, A.L. & Coronado, V.G. (Eds.). (2002). *Central nervous system injury surveillance data submission standards—2002.* Atlanta, GA: Centers for Disease Control and Prevention, National Center for Injury Prevention and Control.

Masel, B.E. & DeWitt, D.S. (2010). TBI: A disease process not an event. *Journal of Neurotrauma, 27*(8), 1529–1540.

Mayeux, R., Ottman, R., Tang, M. X., Noboa-Bauza, L., Marder, K., Gurland, B. & Stern, Y. (1993). Genetic susceptibility and head injury as risk factors for Alzheimer's disease among community-dwelling elderly persons and their first degree relatives. *Annals of Neurology, 33*, 494–501

Max, W., Mackenzie E. J., & Rice D. P. (1991). Head injuries: cost and consequences. *Journal of Head Trauma Rehabilitation, 6*, 76-91.

McGarry L. J, Thompson D, Millham F. H, Cowell, L., Snyder, P. J., Lenderking, W. R., & Weinstein, M. C. (2002). Outcomes and cost of acute treatment of traumatic brain injury. *Journal of Trauma, 53*(6), 1152-1159.

McNemar, Q. (1958). On growth measurement. *Educational and Psychological Measurement, 18*, 47-55.

Meagher, A. D., Beadles, C. A., Doorey, J., & Charles, A. G. (2015). Racial and ethnic disparities in discharge to rehabilitation following traumatic brain injury. *Journal of Neurosurgery, 122*, 595-601.

Mellick, D., Gerhart, K. A., & Whiteneck, G. G. (2003). Understanding outcomes based on the post-acute hospitalization pathways followed by persons with traumatic brain injury. *Brain Injury, 17*(1), 55-71.

Millis, S. R., Rosenthal, M., Novack, T. A., Sherer, M., Nick, T. G., Kreutzer, J. S., . Ricker, J. H. (2001). Long-term neuropsychological outcome after traumatic brain injury. *Journal of Head Trauma Rehabilitation, 16*, 343–355.

Missios, S. & Bekelis, K. (2016). The association of insurance status and race with the procedural volume of traumatic brain injury patients. *Injury, 47*(1), 154-159. http://dx.doi.org/10.1016/j.injury.2015.06.037

Mosenthal, A. C, Livingston, D. H., Lavery, R.F., Knudson, M. M., Lee, S., Morabito, D., ... Coimbra, R. (2004). The effect of age on functional outcome in mild traumatic brain injury: 6-month report of a prospective multi-center trial. *Journal of Trauma, 56*, 1042–1048.

Nakase-Richardson, R., Whyte, J., Giacino, J. T., Pavawalla, S., Barnett, S. D., Yablon, S. A., ... Walker, W. C. (2012). Longitudinal outcome of patients with disordered consciousness in the NIDRR TBI model systems programs. *Journal of Neurotrauma, 29*, 59-65.

National Center for Injury Prevention and Control, Centers for Disease Control and Prevention. (2010). *National Hospital Discharge Survey.* Atlanta, GA: Centers for Disease Control and Prevention.

Nemunaitis, G., Roach, M. J., Claridge, J., & Mejia, M. (2015). Early predictors of functional outcome after trauma. *American Academy of Physical Medicine and Rehabilitation, 4*, 314-320. *http://dx.doi.org/10.1016/j.pmrj.2015.08.007*.

Nirula, R., Nirula, G., & Gentilello, L. M. (2009). Inequity of rehabilitation services after traumatic injury. *Journal of Trauma, 66*(1), 255-259.

Novack, T. A., Kofoed, B. A., & Bennett, G. (1988). *Disability rating scale scores during recovery from head injury.* Presented at the 65th annual conference of the American congress rehabilitation medicine; Seattle, Washington.

Novack, T. A., Bergquist, T. F., Bennett, G., & Gouvier, W.D. (1992). Primary caregiver distress following severe head injury. *Journal of Head Trauma Rehabilitation, 6*(4), 69-77.

Pretz, C. R., Malec, J. F., & Hammond, F. M. (2013). Longitudinal description of the disability rating scale for individuals in the national institute on disability and rehabilitation research traumatic brain injury model systems national database. *Archives of Physical Medicine and Rehabilitation, 94*, 2478-2485.

Pretz, C. R. & Dams-O'Connor, K. (2013). Longitudinal description of the Glasgow outcome scale-extended for individuals in the traumatic brain injury model systems national database: A national institute on disability and rehabilitation

research traumatic brain injury model systems study. *Archives of Physical Medicine and Rehabilitation, 94*, 2486-2493.

Pretz, C. R., Kean, J., Heinemann, A. W., Kozlowski, A. J., Bode, R. K., & Gebhardt, E. (2016). A multidimensional Rasch analysis of the Functional Independence Measure based on the national institute on disability, independent living, and rehabilitation research traumatic brain injury model systems national database. *Journal of Neurotrauma, 33,* 1-5.

Rao, N. & Kilgore, K. M. (1992). Predicting return to work in traumatic brain injury using assessment scales. *Archives of Physical Medicine and Rehabilitation, 73*, 911–916.

Rappaport, M., Hall, K. M., Hopkins, K., Belleza, T., & Cope, D. N. (1982). Disability rating scale for severe head trauma: Coma to community. *Archives of Physical Medicine and Rehabilitation, 63*, 118-123.

Rasmusson, D. X., Brandt, J., Martin, D.B., & Folstein, M. F. (1995). Head injury as a risk factor in Alzheimer's disease. *Brain Injury, 9*, 213-219.

Ratcliff, J. J., Greenspan, A. I., Goldstein, F. C., Stringer, A. Y., Bushnik, T., Hammond, F. M., . . Wright, D. W. (2007). Gender and traumatic brain injury: Do the sexes fare differently? *Brain Injury, 21*(10), 1023-1030.

Raudenbush, S. (1989a). "Centering" predictors in multilevel analysis: Choices and consequences. *Multilevel Modelling Newsletter, 1* (2): 10-12.

Raudenbush, S. (1989b). A response to Longford and Plewis. *Multilevel Modelling Newsletter, 1* (3): 8-10.

Raudenbush, S. W. & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks: Sage Publications.

Rogosa, D. R., Brandt, D., & Zimowski, M. (1982). A growth curve approach to the measurement of change. *Psychological Bulletin, 90,* 726-748.

Rogosa, D. R., & Willett, J. B. (1983). Demonstrating the reliability of the difference score in the measurement of change. *Journal of Educational Measurement, 20,* 335-343.

Rogosa, D. R., & Willett, J. B. (1985). Understanding correlates of change by modeling individual differences in growth. *Psychometrika, 50,* 203-228.

Rosen, H., Saleh, F., Lipsitz, S. R., Meara, J. G., & Rogers Jr., S. O. (2009). Lack of insurance negatively affects trauma mortality in US children. *Journal of Pediatric Surgery, 44,* 1952-1957.

Rubin, D. B. (1976) Inference and missing data. *Biometrika, 63*(3), 581–592. doi:10.1093/biomet/63.3.581

Sabharwal, S., Zhao, C., McClemons, E., & Kaufman. (2007). Pediatric orthopedic patients presenting to a university emergency department after visiting another emergency department: Demographics and health insurance status. *Journal of Pediatric Orthopaedics, 27*(6), 690-694.

Sacks, G. D., Hill, C., & Rogers, S. O. Jr. (2011). Insurance status and hospital discharge disposition after trauma: Inequities in access to post acute care. *Journal of Trauma, 71,* 1011-1015.

Sandhaug, M., Andelic, N., Berntsen, S.A., Seiler, S., & Mygland, A. (2012). Self and near relative ratings of functional level one year after traumatic brain injury. *Disability Rehabilitation, 34*, 904-909.

Sandhaug, M., Andelic, N., Langhammer, B., & Mygland, A. (2015). Functional level during the first 2 years after moderate and severe traumatic brain injury. *Brain Injury, 12*, 1431-1438.

SAS Statistical Software. Version 9.4. Released March, 2015. SAS Institute: Cary, NC.

Schiraldi, M., Patil, C. G., Mukherjee, D., Ugiliweneza, B., Nuno, M., Lad, S. P., & Boakye, M. (2015). Effect of insurance and racial disparities on outcomes in traumatic brain injury. *Journal of Neurological Surgery Part A:Central European Neurosurgery, 76*(3), 224-232.

Scholten, A. C., Haagsma, J. A., Andriessen, T. M. J. C., Vos, P. E., Steyerberg, E. W., van Beeck, E. F., & Polinder, S. (2015). Health-related quality of life after mild, moderate and severe traumatic brain injury: Patterns and predictors of suboptimal functioning during the first year after injury. *Injury, 46*, 616-624.

Shafi, S., Marquez de la Plata, C., Diaz-Arrastia, R., Shipman, K., Carlile, M., Frankel, H.,. Gentilello, L. M. (2007), Racial disparities in long-term functional outcome after traumatic brain injury. *The Journal of Trauma, Injury, Infection, and Critical Care, 63*(6), 1263-1270.

Smith, R. M., Fields, F.R.J., Lenox, J.L., Morris, H.O., & Nolan, J.J. (1979). A functional scale of recovery from severe head trauma. *Clinical Neuropsychology, 1*, 48–50.

Sorbo, A., Rydenhag, B., Sunnerhagen, K. S., Blomqvist, M., Svensson, S., & Emanuelson, I. (2005). Outcome after severe brain damage, what makes the difference? *Brain Injury, 19,* 493-503.

Stineman, M. G., Shea, J. A., Jette, A., Tassoni, C. J., Ottenbacher, K. J., Fiedler, R., & Granger, C. V. (1996). The functional independence measure: Tests of scaling assumptions, structure, and reliability across 20 diverse impairment categories. *Archives of Physical Medicine and Rehabilitation, 77*(11), 1101-1108.

Summers, C. R., Ivins, B., & Schwab, K. A. (2009). Traumatic brain injury in the United States; an epidemiologic overview. *Mt Sinai Journal of Medicine, 76,* 105-110.

Taghavi, S., Jayarajan, S. N., Duran, J. M., Gaughan, J. P., Pathak, A., Santora, T. A., Willis, A. I., & Goldberg, A. J. (2012). Does payer status matter in predicting penetrating trauma outcomes? *Surgery, 152,* 227-231.

Tabachnich, B. G. & Fidell, L. S. (2013). *Using Multivariate Statistics* (6th Ed.). United States of America: Pearson.

Tasaki, O., Shiozaki, T., Hamasaki, T., Kajino, K., Nakae, H., Tanaka, H., . Sugimoto, H. (2009). Prognostic indicators and outcome prediction model for severe traumatic brain injury. *Journal of Trauma, Injury, Infection, and Critical Care, 66*(2), 304-308.

Tepas, J. J. III, Pracht, E. E., Orban, B. L., & Flint, L. M. (2011). Insurance status, not race, is a determinant of outcomes from vehicular injury. *Journal of the American College of Surgeons, 212,* 722-729

Thurman, D.J., Alverson, C., Dunn, K.A., Guerrero, J., & Sniezek, J.E. (1999). Traumatic brain injury in the United States: A public health perspective. *Journal of Head Trauma Rehabilitation,* 14(6), 602–615.

Traumatic Brain Injury Model Systems National Database Syllabus. Traumatic Brain Injury Model Systems National Data and Statistical Center; 2009.Url: http://www.tbindsc.org.

Velopulos, C. G., Enwerem, N. Y., Obirieze, A., Hui, X., Hashmi, Z. G., Scott, V. K., . . Haider, A. H. (2013). National cost of trauma care by payer status. *Journal of Surgical Research, 184*, 444-449.

Wallace, L. S., Cassada, D. C., Rogers, E.S., Freeman, M. B., Grandas, O. H., Stevens, S. L., & Goldman, M. H. (2007). Can screening items identify surgery patients at risk of limited health literacy? *Journal of Surgical Research, 140* (2), 208- 213.

Wei, W., Sambamoorthi, U., Crystal, S., & Findley, P.A. (2005). Mental illness, traumatic brain injury, and Medicaid expenditures. *Archives of Physical Medicine and Rehabilitation, 86*(5), 905-911.

Weir, S., Salkever, D. S., Rivara, F. P., Jurkovich, G. J., Nathens, A. B., & Mackenzie, E. L. (2010). One-year treatment costs of trauma care in the USA. *Experts Reviews Pharmacoeconomics Outcomes Research, 10*(2), 187-197.

Weygandt, P. L., Losonczy, L. I., Schneider, E. B., Kisat, M. T., Licatino, L, K., Cornwell III, E. E., . . Haider, A. H. (2012). Disparities in mortality after blunt injury: Does insurance type matter? *Journal of Surgical Research, 177*, 288-294.

White, F. A., French, D., Zwerner, F. L., & Fairbanks, R. J. (2007). Care without coverage: Is there a relationship between insurance and ed care? *The Journal of Emergency Medicine, 32*(2), 159-165.

Willett, J. B. (1988). Questions and answers in the measurement of change. In E. Z. Rothkopf (Ed.), *Review of Research in Education, 15*, 345-422.

Wilson, J. T., Pettigrew, L. E., & Teasdale, G. M. (1998). Structured interviews for the Glasgow outcome scale and the extended Glasgow outcome scale: Guidelines for their use. *Journal of Neurotrauma, 15*(8), 573-585.

World Health Organization. *The world health report 2002 - Reducing risks, promoting healthy life.* Geneva, Switzerland: WHO; 2002 Jan Available from: http://www.who.int/whr/2002/en/

Wright, J. (2000). The FIM(TM). *The Center for Outcome Measurement in Brain Injury.* http://www.tbims.org/combi/FIM (accessed December 3, 2015).

Zaloshnja, E., Miller, T., Langlois, J.A., & Selassie, A.W. (2008). Prevalence of long-term disability from traumatic brain injury in the civilian population of the United States, 2005. *The Journal of Head Trauma Rehabilitation, 23*(6), 394–400.

Zimmerman, D. W. & Williams, R. H. (1982a). Gain scores in research can be highly reliable. *Journal of Educational Measurement, 19*, 149-154.

Zimmerman, D. W. & Williams, R. H. (1982b). The relative error magnitude in three measures of change. *Psychometrika, 47*, 141-147.

Appendix A

Category Probabilities, DRS Grouping 1, 2, and 3

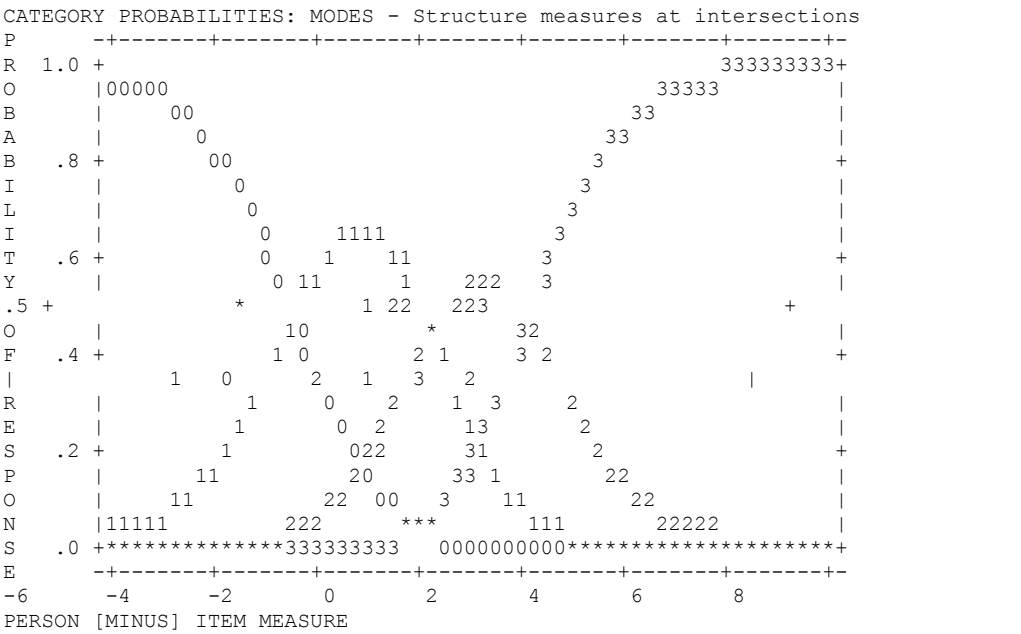

Figure 3. Category Probabilities, DRS Grouping 1 (0 to 3 Response Structure)

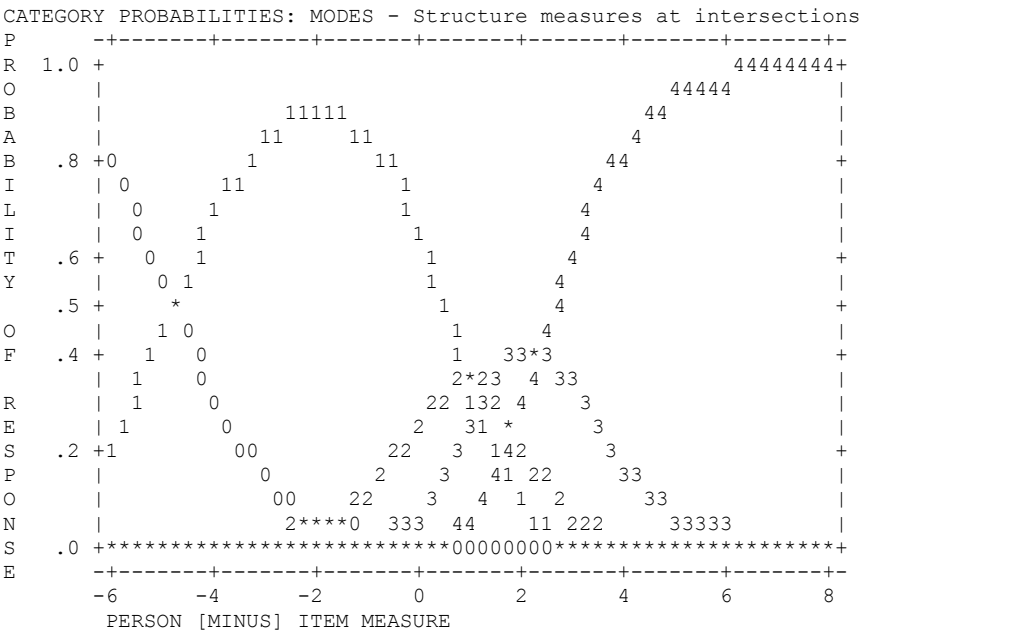

Figure 4. Category Probabilities, DRS Grouping 2 (0 to 4 Response Structure)

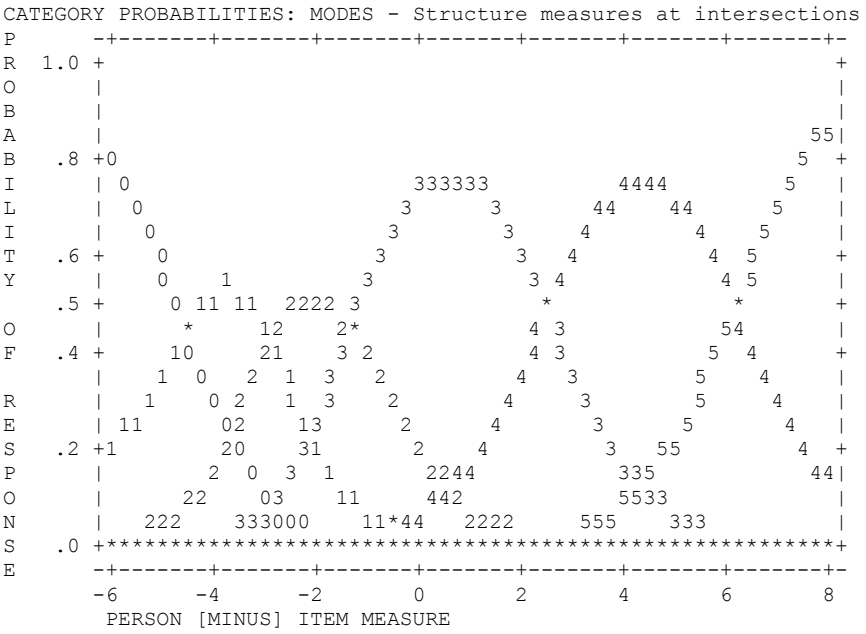

Figure 5. Category Probabilities, DRS Grouping 3 (0 to 5 Response Structure)

Appendix B

All Estimates of the Relationships Between Growth Parameters and Covariates:

FIM Cognitive, FIM Mobility, FIM Self-Care, and DRS

Table 22

FIM Cognitive: Estimates of the relationships between growth parameters and covariates (N=8364)

Growth Parameter/Covariate	**Estimate**	***p***	**Lower 95% Confidence Limit**	**Upper 95% Confidence Limit**
Asymptote/Age	-.01	< .0001	-.02	-.01
Pseudointercept/Age	> -.01	.59	> -.01	< .01
Rate/Age	> -.01	.94	> -.01	< .01
Asymptote/Education/High School (Ref = Less than High School)	.22	.007	.06	.39
Pseudointercept/Education/High School (Ref = Less than High School)	-.03	.75	-.21	.15
Rate/Education/High School (Ref = Less than High School)	-.03	.56	-.14	.08
Asymptote/Education/More than High School (Ref=Less than High School)	.73	< .0001	.56	.89
Pseudointercept/Education/More than High School (Ref=Less than High School)	.09	.37	-.10	.28
Rate/Education/More than High School (Ref=Less than High School)	-.08	.17	-.19	.03
Asymptote/Employment (Ref = Employed)	-.23	< .0001	-.33	-.12
Pseudointercept/Employment (Ref = Employment)	-.16	.008	-.27	-.04
Rate/Employment (Ref = Employment)	.02	.48	-.04	.09
Asymptote/Length of Rehab Stay	-.004	< .0001	-.01	-.002
Pseudointercept/Length of Rehab Stay	.003	< .0001	.002	.01
Rate/Length of Rehab Stay				

Asymptote/PTA	-.01	< .0001	-.02	-.01
Pseudointercept/PTA	-.05	< .0001	-.06	-.05
Rate/PTA	.003	< .0001	.002	.005
Asymptote/Race (Ref=White)	-.26	< .0001	-.35	-.16
Pseudointercept/Race (Ref=White)	.07	.22	-.04	.17
Rate/Race (Ref=White)	-.05	.11	-.10	.01
Asymptote/Sex (Ref=Male)	.17	.0002	.08	.26
Pseudointercept/Sex (Ref=Male)	-.10	.07	-.20	.01
Rate/Sex (Ref=Male)	-.05	.11	-.10	.01
Asymptote/Primary Rehab Payer/Medicare (Ref = Private)	-.47	< .0001	-.62	-.32
Pseudointercept/Primary Rehab Payer/Medicare (Ref = Private)	-.02	.77	-.19	.14
Rate/Primary Rehab Payer/Medicare (Ref = Private)	-.03	.60	-.12	.07
Asymptote/Primary Rehab Payer/Medicaid (Ref=Private)	-.58	< .0001	-.69	-.47
Pseudointercept/Primary Rehab Payer/Medicaid (Ref=Private)	.27	< .0001	.15	.39
Rate/Primary Rehab Payer/Medicaid (Ref=Private)	-.04	.31	-.10	.03
Asymptote/Primary Rehab Payer/Other Rehab Payer (Ref=Private)	-.15	.08	-.31	.02
Pseudointercept/Primary Rehab Payer/Other Rehab Payer (Ref=Private)	.12	.20	-.07	.30
Rate/Primary Rehab Payer/Other Rehab Payer (Ref=Private)	-.05	.36	-.15	.05

Table 23

FIM Mobility: Estimates of the relationships between growth parameters and covariates (N=8358)

Growth Parameter/Covariate	**Estimate**	***p***	**Lower 95% Confidence Limit**	**Upper 95% Confidence Limit**
Asymptote/Age	-.05	< .0001	-.05	-.04
Pseudointercept/Age	-.01	< .0001	-.02	-.01
Rate/Age	< .01	.02	< .01	< .01
Asymptote/Education/More than High School (Ref=Less than High School)	.51	< .0001	.40	.62
Pseudointercept/Education/More than High School (Ref=Less than High School)	.13	.12	-.03	.29
Rate/Education/More than High School (Ref=Less than High School)	.01	.70	-.04	.06
Asymptote/Employment (Ref = Employed)	-.18	.009	-.32	-.05
Pseudointercept/Employment (Ref = Employed)	.08	.46	-.12	.27
Rate/Employment (Ref = Employed)	-.04	.19	-.11	.02
Asymptote/Length of Rehab Stay	-.03	< .0001	-.03	-.02
Pseudointercept/Length of Rehab Stay	-.03	< .0001	-.04	-.03
Rate/Length of Rehab Stay	.01	< .0001	.01	.01
Asymptote/PTA	-.01	.09	-.01	<.01
Pseudointercept/PTA	-.04	< .0001	-.04	-.03
Rate/PTA	-.01	< .0001	-.01	< -.01
Asymptote/Race (Ref=White)	-.52	< .0001	-.64	-.40
Pseudointercept/Race (Ref=White)	-.17	.05	-.35	< .01
Rate/Race (Ref=White)	-.05	.07	-.11	< .01
Asymptote/Sex (Ref=Male)	.48	< .0001	.36	.60
Pseudointercept/Sex (Ref=Male)	.72	< .0001	.55	.90
Rate/Sex (Ref=Male)	< .01	.80	-.05	.07
Asymptote/Primary Rehab Payer/Medicare (Ref = Private)	-.98	< .0001	-1.18	-.78
Pseudointercept/Primary Rehab Payer/Medicare (Ref = Private)	-.61	< .0001	-.88	-.34

Rate/Primary Rehab Payer/Medicare (Ref = Private)	-.05	.33	-.15	.05
Asymptote/Primary Rehab Payer/Medicaid (Ref=Private)	-.90	< .0001	-1.04	-.75
Pseudointercept/Primary Rehab Payer/Medicaid (Ref=Private)	.65	< .0001	.44	.85
Rate/Primary Rehab Payer/Medicaid (Ref=Private)	.08	.04	< .01	.15
Asymptote/Primary Rehab Payer/Other (Ref=Private)	-.18	.01	-.32	-.04
Pseudointercept/Primary Rehab Payer/Other (Ref=Private)	.17	.10	-.03	.38
Rate/Primary Rehab Payer/Other (Ref=Private)	-.01	.87	-.07	.06

Table 24

FIM Self-Care: Estimates of the relationships between growth parameters and covariates (N=8363)

Growth Parameter/Covariate	**Estimate**	***p***	**Lower 95% Confidence Limit**	**Upper 95% Confidence Limit**
Asymptote/Age	-.02	< .0001	-.03	-.02
Pseudointercept/Age	-.01	.004	-.01	-.001
Rate/Age	-.004	< .0001	-.01	-.002
Asymptote/Education/High School (Ref = Less than High School)	.17	.05	.001	.34
Pseudointercept/Education/High School (Ref = Less than High School)	-.07	.50	-.26	.13
Rate/Education/High School (Ref = Less than High School)	-.02	.70	-.13	.09
Asymptote/Education/More than High School (Ref=Less than High School)	.43	< .0001	.25	.60
Pseudointercept/Education/More than High School (Ref=Less than High School)	.16	.13	-.05	.36
Rate/Education/More than High School (Ref=Less than High School)	< .01	.94	-.11	.12
Asymptote/Employment (Ref = Employed)	-.11	.03	-.22	-.01
Pseudointercept/Employment (Ref = Employed)	-.04	.52	-.17	.09
Rate/Employment (Ref = Employed)	-.01	.71	-.07	.05
Asymptote/Length of Rehab Stay	-.02	< .0001	-.02	-.02
Pseudointercept/Length of Rehab Stay	-.03	< .0001	-.03	-.02
Rate/Length of Rehab Stay	.01	< .0001	.003	.01
Asymptote/Marital Status (Ref=Married)	-.06	.19	-.16	.03
Pseudointercept/Marital Status (Ref=Married)	.19	.001	.01	.31
Rate/Marital Status (Ref=Married)	-.03	.30	-.10	.03
Asymptote/PTA	-.003	.04	-.01	-.0001

Pseudointercept/PTA	-.04	< .0001	-.04	-.04
Rate/PTA	-.01	< .0001	-.01	-.004
Asymptote/Race (Ref=White)	-.36	< .0001	-.45	-.27
Pseudointercept/Race (Ref=White)	-.12	.04	-.23	-.01
Rate/Race (Ref=White)	-.10	.0005	-.16	-.04
Asymptote/Sex (Ref=Male)	.19	< .0001	.10	.29
Pseudointercept/Sex (Ref=Male)	.38	< .0001	.27	.50
Rate/Sex (Ref=Male)	.08	.002	.03	.14
Asymptote/Primary Rehab Payer/Medicare (Ref = Private)	-.73	< .0001	-.90	-.57
Pseudointercept/Primary Rehab Payer/Medicare (Ref = Private)	-.39	< .0001	-.58	-.21
Rate/Primary Rehab Payer/Medicare (Ref = Private)	-.12	.02	-.21	-.02
Asymptote/Primary Rehab Payer/Medicaid (Ref=Private)	-.49	< .0001	-.61	-.38
Pseudointercept/Primary Rehab Payer/Medicaid (Ref=Private)	.32	< .0001	.18	.46
Rate/Primary Rehab Payer/Medicaid (Ref=Private)	.03	.35	-.04	.10
Asymptote/Primary Rehab Payer/Other (Ref=Private)	-.14	.01	-.25	-.03
Pseudointercept/Primary Rehab Payer/Other (Ref=Private)	.16	.02	.03	.29
Rate/Primary Rehab Payer/Other (Ref=Private)	.06	.10	-.01	.12

Table 25

DRS: Estimates of the relationships between growth parameters and covariates (N=8009)

Growth Parameter/Covariate	**Estimate**	***p***	**Lower 95% Confidence Limit**	**Upper 95% Confidence Limit**
Asymptote/Age	.05	<.0001	.04	.05
Pseudointercept/Age	-.01	.0003	-.01	-.004
Rate/Age	.003	.01	.0007	.01
Asymptote/Education/High School (Ref = Less than High School)	-.63	.0001	-.95	-.30
Pseudointercept/Education/High School (Ref = Less than High School)	-.11	.41	-.39	.16
Rate/Education/High School (Ref = Less than High School)	-.08	.31	-.24	.08
Asymptote/Education/More than High School (Ref=Less than High School)	-1.51	<.0001	-1.84	-1.17
Pseudointercept/Education/More than High School (Ref=Less than High School)	-.49	.0007	-.77	-.21
Rate/Education/More than High School (Ref=Less than High School)	-.19	.02	-.35	-.03
Asymptote/Employment (Ref = Employed)	.28	.005	.09	.48
Pseudointercept/Employment (Ref = Employed)	.21	.02	.03	.39
Rate/Employment (Ref = Employed)	-.05	.14	-.13	.02
Asymptote/Length of Rehab Stay	.02	<.0001	.01	.02
Pseudointercept/Length of Rehab Stay	.03	<.0001	.02	.03
Rate/Length of Rehab Stay	.01	<.0001	.01	.01
Asymptote/Marital Status (Ref=Married)	.12	.19	-.06	.30
Pseudointercept/Marital Status (Ref=Married)	-.32	<.01	-.48	-.15
Rate/Marital Status (Ref=Married)	-.05	.14	-.13	.02
Asymptote/PTA	.02	<.0001	.02	.03

Pseudointercept/PTA	.06	<.0001	.06	.07
Rate/PTA				
Asymptote/Sex (Ref=Male)	-.26	.003	-.44	-.09
Pseudointercept/Sex (Ref=Male)				
Rate/Sex (Ref=Male)	-.07	.053	-.14	< .01
Asymptote/Primary Rehab Payer/Medicare (Ref = Private)	1.36	<.0001	1.06	1.67
Pseudointercept/Primary Rehab Payer/Medicare (Ref = Private)	.28	.04	.01	.54
Rate/Primary Rehab Payer/Medicare (Ref = Private)	.17	.02	.02	.31
Asymptote/Primary Rehab Payer/Medicaid (Ref=Private)	1.31	<.0001	1.09	1.52
Pseudointercept/Primary Rehab Payer/Medicaid (Ref=Private)	-.50	<.0001	-.70	-.30
Rate/Primary Rehab Payer/Medicaid (Ref=Private)	.15	.0009	.06	.24
Asymptote/Primary Rehab Payer/Other (Ref=Private)	.65	<.0001	.45	.86
Pseudointercept/Primary Rehab Payer/Other (Ref=Private)	-.32	.0007	-.51	-.14
Rate/Primary Rehab Payer/Other (Ref=Private)	.05	.20	-.03	.13

Appendix C

SAS Code: FIM Cognitive, FIM Mobility, FIM Self-Care & DRS

FIM Cognitive:

```
ods html close;
ods html;
DM log 'clear';


proc contents data = TBI1;
run;
proc univariate data = TBI1;
var RTFIMCOG_L_1 RTFIMMOB_L_2 RTFIMSC_L_2 RTDRS_L_2 AGE ALCAnyDrink_1
Drugs_1 EduYears_1 Emp1_1
LOSREH1 Mar_1 PTA_1 Race_1 Sex RehabPay1_1;
run;

data Data_Set_1;
set TBI1;
usi=compress(center||subjectid);
run;
proc sort data = Data_Set_1;
by usi;
run;

proc freq data = Data_Set_1 noprint;
tables usi / out = Data_Set_2;
run;

Data Data_Set_3;
Set Data_Set_2;
run;
proc sort data = Data_Set_3;
by usi;
run;

Data Data_Set_4;
merge Data_Set_3 Data_Set_1;
by usi;
run;
proc sort data = Data_Set_4;
by usi;
run;
Data Data_Set_5;
Set Data_Set_4;
if count LE 2 then delete;
run;

proc freq data = Data_Set_5 noprint;
tables usi / out = Data_Set_6;
run;
```

```
proc sort data = Data_Set_6;
by usi;
run;
data Data_Set_7;
merge Data_Set_6 Data_Set_1;
by usi;
if count = "." then delete;
if count LE 2 then delete;
if EduYears_1 in (1 2 3 4 5 6 7 8) then EduYears_2 = "LTHS";
if EduYears_1 in (9 10 11 12) then EduYears_2 = "HS";
if EduYears_1 in (13 14 15 16 17 18 19 20) then EduYears_2 = "MTHS";
if EduYears_2 = "HS" then EduYears_HS = 1;
else EduYears_HS = 0;
if EduYears_2 = "MTHS" then EduYears_MTHS = 1;
else EduYears_MTHS = 0;
if Emp1_1 = 1 then Emp1_2 = 0;
if Emp1_1 = 0 then Emp1_2 = 1;
if Mar_1 = 1 then MAR_2 = 0;
if Mar_1 = 0 then MAR_2 = 1;
if Race_1 = 1 then Race_2 = "White";
if Race_1 in (2 3 4 5 7) then Race_2 = "Other";
if Race_2 = "Other" then Race_Other = 1;
else Race_Other = 0;
if Sex = 1 then Sex_1 = 0;
if Sex = 2 then Sex_1 = 1;
if Sex_1 = 0 then Sex_2 = "Female";
if Sex_1 = 1 then Sex_2 = "Male";
if RehabPay1_1 = 1 then RehabPay1_2 = "Medicare";
if RehabPay1_1 = 2 then RehabPay1_2 = "Medicaid";
*if RehabPay1_1 in (3 10) then RehabPay1_2 = "WC_Auto";
if RehabPay1_1 in (3 4 6 7 10 11 12) then RehabPay1_2 = "Private";
*if RehabPay1_1 = 7 then RehabPay1_2 = "Self_PP";
if RehabPay1_1 in (8 14 55 77) then RehabPay1_2 = "Other";
if RehabPay1_2 = "Medicare" then RehabPay_Medicare = 1;
else RehabPay_Medicare = 0;
if RehabPay1_2 = "Medicaid" then RehabPay_Medicaid = 1;
else RehabPay_Medicaid= 0;
*if RehabPay1_2 = "WC_Auto" then RehabPay_WC_Auto = 1;
*else RehabPay_WC_Auto = 0;
*if RehabPay1_2 = "Self_PP" then RehabPay_Self_PP = 1;
*else RehabPay_Self_PP = 0;
if RehabPay1_2 = "Other" then RehabPay_Other = 1;
else RehabPay_Other = 0;
AGE_GMC = AGE - 40.99;
LOSREH1_GMC = LOSREH1 - 27.56;
PTA_1_GMC = PTA_1 - 23.87;
run;
proc print data = Data_Set_7 (obs=200);
var usi followupperiod AGE_GMC LOSREH1_GMC PTA_1_GMC ALCAnyDrink_2
Drugs_2 EduYears_HS EduYears_MTHS Emp1_2
Mar_2 Race_Other Sex_1 RehabPay_Medicare RehabPay_Medicaid
RehabPay_WC_Auto RehabPay_Self_PP RehabPay_Other;
run;
proc univariate data = Data_Set_7;
```

```
var AGE_GMC LOSREH1_GMC PTA_1_GMC;
run;

proc sort data = Data_Set_7;
by usi followupperiod;
run;

proc freq data = Data_Set_7;
table followupperiod;
run;

proc print data = Data_Set_7 (obs=200);
var usi followupperiod;
run;


data y;
set Data_Set_7;
run;

proc sort data = y nodupkey;
by usi;
run;


goptions reset = all border;
options orientation = landscape;
symbol1 interpol = join color = black repeat = 13317;
*symbol1 interpol = join width = 5 color = red repeat = 1;
axis1 order = 0 to 30 by 5 label = ("Years");
axis2 order = -10 to 10 by 1 label = ("RTFIMCOG_L_1");
*legend1 value = ('Individual Responses') label = none;
*legend2 value = ('Fixed Effects') label = none;
title;
proc gplot data = Data_Set_7;
plot1 RTFIMCOG_L_1*FollowupPeriod = usi/ nolegend vaxis = axis2 haxis =
axis1;
title 'Graph of RTFIMCOGNITIVE';

run;


proc nlmixed data = Data_Set_7 method = FIRO maxiter = 5000;
parms fai = 4
fpi0i = -1.71
fpi1i = 2
t11= 2
t21= 0.75
t22= 2
t31= -0.07
t32= 0.25
t33= 0.0005
VarE = 2;
```

```
a0i = fai + U0i;
pi0i = fpi0i + U1i;
pi1i = fpi1i + U2i;

Var_Asymptote = t11**2;
Var_Pseudo_Int = t21**2 + t22**2;
Var_Rate = t31**2 +t32**2 + t33**2;
Cov_Asymp_PI = t11*t21;
Cov_Asymp_Rate = t11*t31;
Cov_PI_Rate = t21*t31 + t22*t32;

y = a0i - (a0i - pi0i)*exp(-pi1i*followupperiod);

Model RTFIMCOG_L_1 ~ normal (y, VarE);
Random U0i U1i U2i ~ normal ([0,0,0],
[Var_Asymptote,Cov_Asymp_PI,Var_Pseudo_Int,Cov_Asymp_Rate,Cov_PI_Rate,V
ar_Rate])
Subject = usi;


Estimate 'Var_Asymptote' t11**2;
Estimate 'Var_Pseudo_Int' t21**2 + t22**2;
Estimate 'Var_Rate' t31**2 + t32**2 + t33**2;
Estimate 'Cov_Asymp_PI' t11*t21;
Estimate 'Cov_Asymp_Rate' t11*t31;
Estimate 'Cov_PI_Rate' t21*t31 + t22*t32;

predict a0i out=out1;
predict pi0i out=out2;
predict pi1i out=out3;

Title 'Negative Exponential for RTFIMCOGNITIVE Unconditional Model';
run;
/*
proc nlmixed data = Data_Set_7 method = FIRO maxiter = 10000;
parms
Asymptote = 4
P_I = -1.6
Rate = 1.7

Asymptote_Sex = 0
P_I_Sex = 0
Rate_Sex = 0
Asymptote_Medicare = 0
P_I_Medicare = 0
Rate_Medicare = 0
Asymptote_Medicaid = 0
P_I_Medicaid = 0
Rate_Medicaid = 0
Asymptote_WC_Auto = 0
P_I_WC_Auto = 0
Rate_WC_Auto = 0
Asymptote_Self_PP = 0
P_I_Self_PP = 0
```

```
Rate_Self_PP = 0
Asymptote_RehabPay_Other = 0
P_I_RehabPay_Other = 0
Rate_RehabPay_Other = 0
t11= -5 to 5 by 1
t21= -5 to 5 by 1
t22= -5 to 5 by 1
t31= -5 to 5 by 1
t32= -5 to 5 by 1
t33= -5 to 5 by 1
VarE = 1 to 5 by 1;

a0i = Asymptote + Asymptote_Sex*Sex_1 +
Asymptote_Medicare*Rehabpay_Medicare +
Asymptote_Medicaid*RehabPay_Medicaid +
Asymptote_WC_Auto*RehabPay_WC_Auto + Asymptote_Self_PP*RehabPay_Self_PP
+ Asymptote_RehabPay_Other*RehabPay_Other + U0i;

pi0i = P_I + P_I_Sex*Sex_1 + P_I_Medicare*Rehabpay_Medicare +
P_I_Medicaid*RehabPay_Medicaid + P_I_WC_Auto*RehabPay_WC_Auto +
P_I_Self_PP*RehabPay_Self_PP + P_I_RehabPay_Other*RehabPay_Other + U1i;

pi1i = Rate + Rate_Sex*Sex_1 + Rate_Medicare*Rehabpay_Medicare +
Rate_Medicaid*RehabPay_Medicaid + Rate_WC_Auto*RehabPay_WC_Auto +
Rate_Self_PP*RehabPay_Self_PP + Rate_RehabPay_Other*RehabPay_Other +
U2i;

Var_Asymptote = t11**2;
Var_Pseudo_Int = t21**2 + t22**2;
Var_Rate = t31**2 +t32**2 + t33**2;
Cov_Asymp_PI = t11*t21;
Cov_Asymp_Rate = t11*t31;
Cov_PI_Rate = t21*t31 + t22*t32;

y = a0i - (a0i - pi0i)*exp(-pi1i*followupperiod);

Model RTFIMCOG_L_1 ~ normal (y, VarE);

Random U0i U1i U2i ~ normal ([0,0,0],
[Var_Asymptote,Cov_Asymp_PI,Var_Pseudo_Int,Cov_Asymp_Rate,Cov_PI_Rate,V
ar_Rate])
Subject = usi;


Estimate 'Var_Asymptote' t11**2;
Estimate 'Var_Pseudo_Int' t21**2 + t22**2;
Estimate 'Var_Rate' t31**2 + t32**2 + t33**2;
Estimate 'Cov_Asymp_PI' t11*t21;
Estimate 'Cov_Asymp_Rate' t11*t31;
Estimate 'Cov_PI_Rate' t21*t31 + t22*t32;

Title 'RTFIMCognitive Full Model';

predict a0i out=out1;
```

```
predict pi0i out=out2;
predict pi1i out=out3;

run;

*/

proc nlmixed data = Data_Set_7 method = FIRO maxiter = 10000;

parms
Asymptote = 4
P_I = -1.5
Rate = 2
Asymptote_Age = 0
P_I_Age = 0
Rate_Age = 0
Asymptote_HS = 0
P_I_HS = 0
Rate_HS = 0
Asymptote_MTHS = 0
P_I_MTHS = 0
Rate_MTHS = 0
Asymptote_Emp = 0
P_I_Emp = 0
Rate_Emp = 0
Asymptote_LOSREH = 0
P_I_LOSREH = 0
Rate_LOSREH = 0
Asymptote_PTA = 0
P_I_PTA = 0
Rate_PTA = 0
Asymptote_Race = 0
P_I_Race = 0
Rate_Race = 0
Asymptote_Sex = 0
P_I_Sex = 0
Rate_Sex = 0
Asymptote_Medicare = 0
P_I_Medicare = 0
Rate_Medicare = 0
Asymptote_Medicaid = 0
P_I_Medicaid = 0
Rate_Medicaid = 0
Asymptote_Otherpay = 0
P_I_Otherpay = 0
Rate_Otherpay = 0
t11= 1.3
t21= 0.07
t22= 1.5
t31= -0.25
t32= 0.1
t33= -0.0005
VarE = 2;
```

```
a0i = Asymptote + Asymptote_Age*AGE_GMC + Asymptote_HS*EduYears_HS +
Asymptote_MTHS*EduYears_MTHS + Asymptote_Emp*Emp1_2 +
Asymptote_LOSREH*LOSREH1_GMC + Asymptote_PTA*PTA_1_GMC +
Asymptote_Race*Race_Other + Asymptote_Sex*Sex_1 +
Asymptote_Medicare*Rehabpay_Medicare +
Asymptote_Medicaid*RehabPay_Medicaid +
Asymptote_Otherpay*RehabPay_Other + U0i;

pi0i = P_I + P_I_Age*AGE_GMC + P_I_HS*EduYears_HS +
P_I_MTHS*EduYears_MTHS + P_I_Emp*Emp1_2 + P_I_LOSREH*LOSREH1_GMC +
P_I_PTA*PTA_1_GMC +
P_I_Race*Race_Other + P_I_Sex*Sex_1 + P_I_Medicare*Rehabpay_Medicare +
P_I_Medicaid*RehabPay_Medicaid +
P_I_Otherpay*RehabPay_Other + U1i;

pi1i = Rate + Rate_Age*AGE_GMC + Rate_HS*EduYears_HS +
Rate_MTHS*EduYears_MTHS + Rate_Emp*Emp1_2 + Rate_LOSREH*LOSREH1_GMC +
Rate_PTA*PTA_1_GMC +
Rate_Race*Race_Other + Rate_Sex*Sex_1 + Rate_Medicare*Rehabpay_Medicare
+ Rate_Medicaid*RehabPay_Medicaid + Rate_Otherpay*RehabPay_Other + U2i;


Var_Asymptote = t11**2;
Var_Pseudo_Int = t21**2 + t22**2;
Var_Rate = t31**2 +t32**2 + t33**2;
Cov_Asymp_PI = t11*t21;
Cov_Asymp_Rate = t11*t31;
Cov_PI_Rate = t21*t31 + t22*t32;

y = a0i - (a0i - pi0i)*exp(-pi1i*followupperiod);

Model RTFIMCOG_L_1 ~ normal (y, VarE);

Random U0i U1i U2i ~ normal ([0,0,0],
[Var_Asymptote,Cov_Asymp_PI,Var_Pseudo_Int,Cov_Asymp_Rate,Cov_PI_Rate,V
ar_Rate])
Subject = usi;


Estimate 'Var_Asymptote' t11**2;
Estimate 'Var_Pseudo_Int' t21**2 + t22**2;
Estimate 'Var_Rate' t31**2 + t32**2 + t33**2;
Estimate 'Cov_Asymp_PI' t11*t21;
Estimate 'Cov_Asymp_Rate' t11*t31;
Estimate 'Cov_PI_Rate' t21*t31 + t22*t32;

Title 'RTFIMCognitive Full Model';

predict a0i out=out1;
predict pi0i out=out2;
predict pi1i out=out3;

run;
```

FIM Mobility:

```
ods html close;
ods html;
DM log 'clear';


proc contents data = TBI1;
run;
proc univariate data = TBI1;
var RTFIMCOG_L_1 RTFIMMOB_L_2 RTFIMSC_L_2 RTDRS_L_2 AGE ALCAnyDrink_1
Drugs_1 EduYears_1 Emp1_1
LOSREH1 Mar_1 PTA_1 Race_1 Sex RehabPay1_1;
run;

data Data_Set_1;
set TBI1;
usi=compress(center||subjectid);
run;
proc sort data = Data_Set_1;
by usi;
run;

proc freq data = Data_Set_1 noprint;
tables usi / out = Data_Set_2;
run;

Data Data_Set_3;
Set Data_Set_2;
run;
proc sort data = Data_Set_3;
by usi;
run;

Data Data_Set_4;
merge Data_Set_3 Data_Set_1;
```

```
by usi;
run;
proc sort data = Data_Set_4;
by usi;
run;
Data Data_Set_5;
Set Data_Set_4;
if count LE 2 then delete;
run;

proc freq data = Data_Set_5 noprint;
tables usi / out = Data_Set_6;
run;
proc sort data = Data_Set_6;
by usi;
run;
data Data_Set_7;
merge Data_Set_6 Data_Set_1;
by usi;
if count = "." then delete;
if count LE 2 then delete;
*if ALCAnyDrink_1 = 1 then ALCAnyDrink_2 = 0;
*if ALCAnyDrink_1 = 2 then ALCAnyDrink_2 = 1;
*if Drugs_1 = 1 then Drugs_2 = 0;
*if Drugs_1 = 2 then Drugs_2 = 1;
if EduYears_1 in (1 2 3 4 5 6 7 8) then EduYears_2 = "LTHS";
if EduYears_1 in (9 10 11 12) then EduYears_2 = "HS";
if EduYears_1 in (13 14 15 16 17 18 19 20) then EduYears_2 = "MTHS";
if EduYears_2 = "HS" then EduYears_HS = 1;
else EduYears_HS = 0;
if EduYears_2 = "MTHS" then EduYears_MTHS = 1;
else EduYears_MTHS = 0;
if Emp1_1 = 1 then Emp1_2 = 0;
if Emp1_1 = 0 then Emp1_2 = 1;
if Mar_1 = 1 then MAR_2 = 0;
if Mar_1 = 0 then MAR_2 = 1;
if Race_1 = 1 then Race_2 = "White";
if Race_1 in (2 3 4 5 7) then Race_2 = "Other";
if Race_2 = "Other" then Race_Other = 1;
else Race_Other = 0;
if Sex = 1 then Sex_1 = 0;
if Sex = 2 then Sex_1 = 1;
if Sex_1 = 0 then Sex_2 = "Female";
if Sex_1 = 1 then Sex_2 = "Male";
if RehabPay1_1 = 1 then RehabPay1_2 = "Medicare";
if RehabPay1_1 = 2 then RehabPay1_2 = "Medicaid";
*if RehabPay1_1 in (3 10) then RehabPay1_2 = "WC_Auto";
if RehabPay1_1 in (4 6 11 12) then RehabPay1_2 = "Private";
*if RehabPay1_1 = 7 then RehabPay1_2 = "Self_PP";
if RehabPay1_1 in (3 7 8 10 14 55 77) then RehabPay1_2 = "Other";
if RehabPay1_2 = "Medicare" then RehabPay_Medicare = 1;
else RehabPay_Medicare = 0;
if RehabPay1_2 = "Medicaid" then RehabPay_Medicaid = 1;
else RehabPay_Medicaid= 0;
```

```
*if RehabPay1_2 = "WC_Auto" then RehabPay_WC_Auto = 1;
*else RehabPay_WC_Auto = 0;
*if RehabPay1_2 = "Self_PP" then RehabPay_Self_PP = 1;
*else RehabPay_Self_PP = 0;
if RehabPay1_2 = "Other" then RehabPay_Other = 1;
else RehabPay_Other = 0;
AGE_GMC = AGE - 40.99;
LOSREH1_GMC = LOSREH1 - 27.56;
PTA_1_GMC = PTA_1 - 23.87;
run;

proc univariate data = Data_Set_7;
var AGE_GMC LOSREH1_GMC PTA_1_GMC;
run;

proc sort data = Data_Set_7;
by usi followupperiod;
run;

proc freq data = Data_Set_7;
table followupperiod;
run;

proc print data = Data_Set_7 (obs=200);
var usi followupperiod;
run;


data y;
set Data_Set_7;
run;

proc sort data = y nodupkey;
by usi;
run;
proc univariate data = y;
var AGE PTA_1 LOSREH1;
run;
proc univariate data = y;
var AGE_GMC PTA_1_GMC LOSREH1_GMC;
run;
goptions reset = all border;
options orientation = landscape;
symbol1 interpol = join color = black repeat = 13317;
*symbol1 interpol = join width = 5 color = red repeat = 1;
axis1 order = 0 to 30 by 5 label = ("Years");
axis2 order = -10 to 10 by 1 label = ("RTFIMMOB_TS");
*legend1 value = ('Individual Responses') label = none;
*legend2 value = ('Fixed Effects') label = none;
title;
proc gplot data = Data_Set_7;
plot1 RTFIMMOB_TS*FollowupPeriod = usi/ nolegend vaxis = axis2 haxis =
axis1;
title 'Graph of RTFIMMOBILITY';
```

```
run;
proc univariate data = Data_Set_7;
var RTFIMMOB_L_2 ALCAnyDrink_2 Drugs_2 EduYears_HS EduYears_MTHS Emp1_2
MAR_2
Race_Other Sex_1 RehabPay_Medicare RehabPay_Medicaid RehabPay_WC_Auto
RehabPay_Self_PP
RehabPay_Other AGE_GMC LOSREH1_GMC PTA_1_GMC;
run;
proc freq data = Data_Set_7;
tables EduYears_2 MAR_2 Emp1_2 Race_2 Sex_1 RehabPay1_2 AGE_GMC
LOSREH1_GMC PTA_1_GMC;
run;

proc nlmixed data = Data_Set_7 method = FIRO maxiter = 2000;
parms fai = 4.7
fpi0i = -3.76
fpi1i = 1.75
t11= 2.57
t21= .72
t22= 1.96
t31= .02
t32= .50
t33= 0.004
VarE = 3.5;

a0i = fai + U0i;
pi0i = fpi0i + U1i;
pi1i = fpi1i + U2i;

Var_Asymptote = t11**2;
Var_Pseudo_Int = t21**2 + t22**2;
Var_Rate = t31**2 +t32**2 + t33**2;
Cov_Asymp_PI = t11*t21;
Cov_Asymp_Rate = t11*t31;
Cov_PI_Rate = t21*t31 + t22*t32;


y = a0i - (a0i - pi0i)*exp(-pi1i*followupperiod);

Model RTFIMMOB_TS ~ normal (y, VarE);
Random U0i U1i U2i ~ normal ([0,0,0],
[Var_Asymptote,Cov_Asymp_PI,Var_Pseudo_Int,Cov_Asymp_Rate,Cov_PI_Rate,V
ar_Rate])
Subject = usi;

Estimate 'Var_Asymptote' t11**2;
Estimate 'Var_Pseudo_Int' t21**2 + t22**2;
Estimate 'Var_Rate' t31**2 + t32**2 + t33**2;
Estimate 'Cov_Asymp_PI' t11*t21;
Estimate 'Cov_Asymp_Rate' t11*t31;
Estimate 'Cov_PI_Rate' t21*t31 + t22*t32;

predict a0i out=out1;
```

```
predict pi0i out=out2;
predict pi1i out=out3;

Title 'Negative Exponential for RTFIMMOBILITY Unconditional Model';
run;

proc nlmixed data = Data_Set_7 method = FIRO maxiter = 10000;

parms
Asymptote = 4
P_I = -50
Rate = 5
Asymptote_Sex = 0
P_I_Sex = 0
Rate_Sex = 0
Asymptote_Medicare = 0
P_I_Medicare = 0
Rate_Medicare = 0
Asymptote_Medicaid = 0
P_I_Medicaid = 0
Rate_Medicaid = 0
Asymptote_Otherpay = 0
P_I_Otherpay = 0
Rate_Otherpay = 0
t11= 2.5
t21= -35
t22= 15
t31= 0.5
t32= -1.5
t33= -0.05
VarE = 2;

a0i = Asymptote + Asymptote_Sex*Sex_1 +
Asymptote_Medicare*Rehabpay_Medicare +
Asymptote_Medicaid*RehabPay_Medicaid +
Asymptote_Otherpay*RehabPay_Other + U0i;

pi0i = P_I + P_I_Sex*Sex_1 + P_I_Medicare*Rehabpay_Medicare +
P_I_Medicaid*RehabPay_Medicaid +
P_I_Otherpay*RehabPay_Other + U1i;

pi1i = Rate + Rate_Sex*Sex_1 + Rate_Medicare*Rehabpay_Medicare +
Rate_Medicaid*RehabPay_Medicaid + Rate_Otherpay*RehabPay_Other + U2i;

Var_Asymptote = t11**2;
Var_Pseudo_Int = t21**2 + t22**2;
Var_Rate = t31**2 +t32**2 + t33**2;
Cov_Asymp_PI = t11*t21;
Cov_Asymp_Rate = t11*t31;
Cov_PI_Rate = t21*t31 + t22*t32;

y = a0i - (a0i - pi0i)*exp(-pi1i*followupperiod);

Model RTFIMMOB_L_2 ~ normal (y, VarE);
```

```
Random U0i U1i U2i ~ normal ([0,0,0],
[Var_Asymptote,Cov_Asymp_PI,Var_Pseudo_Int,Cov_Asymp_Rate,Cov_PI_Rate,V
ar_Rate])
Subject = usi;


Estimate 'Var_Asymptote' t11**2;
Estimate 'Var_Pseudo_Int' t21**2 + t22**2;
Estimate 'Var_Rate' t31**2 + t32**2 + t33**2;
Estimate 'Cov_Asymp_PI' t11*t21;
Estimate 'Cov_Asymp_Rate' t11*t31;
Estimate 'Cov_PI_Rate' t21*t31 + t22*t32;

Title 'RTFIMMOBILITY Full Model';

predict a0i out=out1;
predict pi0i out=out2;
predict pi1i out=out3;

run;

proc nlmixed data = Data_Set_7 method = FIRO maxiter= 10000;

parms
Asymptote = 5.5
P_I = -3.8
Rate = 2
Asymptote_Age = 0
P_I_Age = 0
Rate_Age = 0
Asymptote_MTHS = 0
P_I_MTHS = 0
Rate_MTHS = 0
Asymptote_Emp = 0
P_I_Emp = 0
Rate_Emp = 0
Asymptote_LOSREH = 0
P_I_LOSREH = 0
Rate_LOSREH = 0
Asymptote_PTA = 0
P_I_PTA = 0
Rate_PTA = 0
Asymptote_Race = 0
P_I_Race = 0
Rate_Race = 0
Asymptote_Sex = 0
P_I_Sex = 0
Rate_Sex = 0
Asymptote_Medicare = 0
P_I_Medicare = 0
Rate_Medicare = 0
Asymptote_Medicaid = 0
P_I_Medicaid = 0
```

```
Rate_Medicaid = 0
Asymptote_Otherpay = 0
P_I_Otherpay = 0
Rate_Otherpay = 0
t11= 1.60
t21= .28
t22= 1.75
t31= -.02
t32= .35
t33= -0.001
VarE = 3.5;

a0i = Asymptote + Asymptote_Age*AGE_GMC + Asymptote_MTHS*EduYears_MTHS
+ Asymptote_Emp*Emp1_2 +
Asymptote_LOSREH*LOSREH1_GMC + Asymptote_PTA*PTA_1_GMC +
Asymptote_Race*Race_Other + Asymptote_Sex*Sex_1 +
Asymptote_Medicare*RehabPay_Medicare +
Asymptote_Medicaid*RehabPay_Medicaid +
Asymptote_Otherpay*RehabPay_Other + U0i;

pi0i = P_I + P_I_Age*AGE_GMC + P_I_MTHS*EduYears_MTHS + P_I_Emp*Emp1_2
+ P_I_LOSREH*LOSREH1_GMC +
P_I_PTA*PTA_1_GMC + P_I_Race*Race_Other + P_I_Sex*Sex_1 +
P_I_Medicare*RehabPay_Medicare + P_I_Medicaid*RehabPay_Medicaid +
P_I_Otherpay*RehabPay_Other + U1i;

pi1i = Rate + Rate_Age*AGE_GMC + Rate_MTHS*EduYears_MTHS +
Rate_Emp*Emp1_2 + Rate_LOSREH*LOSREH1_GMC +
Rate_PTA*PTA_1_GMC + Rate_Race*Race_Other + Rate_Sex*Sex_1 +
Rate_Medicare*RehabPay_Medicare + Rate_Medicaid*RehabPay_Medicaid +
Rate_Otherpay*RehabPay_Other + U2i;


Var_Asymptote = t11**2;
Var_Pseudo_Int = t21**2 + t22**2;
Var_Rate = t31**2 +t32**2 + t33**2;
Cov_Asymp_PI = t11*t21;
Cov_Asymp_Rate = t11*t31;
Cov_PI_Rate = t21*t31 + t22*t32;

y = a0i - (a0i - pi0i)*exp(-pi1i*followupperiod);

Model RTFIMMOB_TS ~ normal (y, VarE);

Random U0i U1i U2i ~ normal ([0,0,0],
[Var_Asymptote,Cov_Asymp_PI,Var_Pseudo_Int,Cov_Asymp_Rate,Cov_PI_Rate,V
ar_Rate])
Subject = usi;


Estimate 'Var_Asymptote' t11**2;
Estimate 'Var_Pseudo_Int' t21**2 + t22**2;
Estimate 'Var_Rate' t31**2 + t32**2 + t33**2;
Estimate 'Cov_Asymp_PI' t11*t21;
```

```
Estimate 'Cov_Asymp_Rate' t11*t31;
Estimate 'Cov_PI_Rate' t21*t31 + t22*t32;

Title 'RTFIMMOBILITY Full Model';

predict a0i out=out1;
predict pi0i out=out2;
predict pi1i out=out3;

run;
```

FIM Self-Care:

```
ods html close;
ods html;
DM log 'clear';


proc contents data = TBI1;
run;
proc univariate data = TBI1;
var RTFIMCOG_L_1 RTFIMMOB_L_2 RTFIMSC_L_2 RTDRS_L_2 AGE ALCAnyDrink_1
Drugs_1 EduYears_1 Emp1_1
LOSREH1 Mar_1 PTA_1 Race_1 Sex RehabPay1_1;
run;
```

```
data Data_Set_1;
set TBI1;
usi=compress(center||subjectid);
run;
proc sort data = Data_Set_1;
by usi;
run;

proc freq data = Data_Set_1 noprint;
tables usi / out = Data_Set_2;
run;

Data Data_Set_3;
Set Data_Set_2;
run;
proc sort data = Data_Set_3;
by usi;
run;

Data Data_Set_4;
merge Data_Set_3 Data_Set_1;
by usi;
run;
proc sort data = Data_Set_4;
by usi;
run;
Data Data_Set_5;
Set Data_Set_4;
if count LE 2 then delete;
run;

proc freq data = Data_Set_5 noprint;
tables usi / out = Data_Set_6;
run;
proc sort data = Data_Set_6;
by usi;
run;
data Data_Set_7;
merge Data_Set_6 Data_Set_1;
by usi;
if count = "." then delete;
if count LE 2 then delete;
*if ALCAnyDrink_1 = 1 then ALCAnyDrink_2 = 0;
*if ALCAnyDrink_1 = 2 then ALCAnyDrink_2 = 1;
*if Drugs_1 = 1 then Drugs_2 = 0;
*if Drugs_1 = 2 then Drugs_2 = 1;
if EduYears_1 in (1 2 3 4 5 6 7 8) then EduYears_2 = "LTHS";
if EduYears_1 in (9 10 11 12) then EduYears_2 = "HS";
if EduYears_1 in (13 14 15 16 17 18 19 20) then EduYears_2 = "MTHS";
if EduYears_2 = "HS" then EduYears_HS = 1;
else EduYears_HS = 0;
if EduYears_2 = "MTHS" then EduYears_MTHS = 1;
else EduYears_MTHS = 0;
if Emp1_1 = 1 then Emp1_2 = 0;
```

```
if Emp1_1 = 0 then Emp1_2 = 1;
if Mar_1 = 1 then MAR_2 = 0;
if Mar_1 = 0 then MAR_2 = 1;
if Race_1 = 1 then Race_2 = "White";
if Race_1 in (2 3 4 5 7) then Race_2 = "Other";
if Race_2 = "Other" then Race_Other = 1;
else Race_Other = 0;
if Sex = 1 then Sex_1 = 0;
if Sex = 2 then Sex_1 = 1;
if Sex_1 = 0 then Sex_2 = "Female";
if Sex_1 = 1 then Sex_2 = "Male";
if RehabPay1_1 = 1 then RehabPay1_2 = "Medicare";
if RehabPay1_1 = 2 then RehabPay1_2 = "Medicaid";
*if RehabPay1_1 in (3 10) then RehabPay1_2 = "WC_Auto";
if RehabPay1_1 in (4 6 11 12) then RehabPay1_2 = "Private";
*if RehabPay1_1 = 7 then RehabPay1_2 = "Self_PP";
if RehabPay1_1 in (3 7 8 10 14 55 77) then RehabPay1_2 = "Other";
if RehabPay1_2 = "Medicare" then RehabPay_Medicare = 1;
else RehabPay_Medicare = 0;
if RehabPay1_2 = "Medicaid" then RehabPay_Medicaid = 1;
else RehabPay_Medicaid= 0;
*if RehabPay1_2 = "WC_Auto" then RehabPay_WC_Auto = 1;
*else RehabPay_WC_Auto = 0;
*if RehabPay1_2 = "Self_PP" then RehabPay_Self_PP = 1;
*else RehabPay_Self_PP = 0;
if RehabPay1_2 = "Other" then RehabPay_Other = 1;
else RehabPay_Other = 0;
AGE_GMC = AGE - 40.99;
LOSREH1_GMC = LOSREH1 - 27.56;
PTA_1_GMC = PTA_1 - 23.87;
run;

proc univariate data = Data_Set_7;
var AGE_GMC LOSREH1_GMC PTA_1_GMC;
run;

proc sort data = Data_Set_7;
by usi followupperiod;
run;

proc freq data = Data_Set_7;
table followupperiod;
run;

proc print data = Data_Set_7 (obs=200);
var usi followupperiod;
run;


data y;
set Data_Set_7;
run;

proc sort data = y nodupkey;
```

```
by usi;
run;


goptions reset = all border;
options orientation = landscape;
symbol1 interpol = join color = black repeat = 13317;
*symbol1 interpol = join width = 5 color = red repeat = 1;
axis1 order = 0 to 30 by 5 label = ("Years");
axis2 order = -10 to 10 by 1 label = ("RTFIMSC_L_2");
*legend1 value = ('Individual Responses') label = none;
*legend2 value = ('Fixed Effects') label = none;
title;
proc gplot data = Data_Set_7;
plot1 RTFIMSC_L_2*FollowupPeriod = usi/ nolegend vaxis = axis2 haxis =
axis1;
title 'Graph of RTFIMSelfCare';

run;


proc nlmixed data = Data_Set_7 method = FIRO maxiter = 5000;
parms fai = 5
fpi0i = -3
fpi1i = .5
t11= 6
t21= 6
t22= 6
t31= 6
t32= 6
t33= 6
VarE = 3;

a0i = fai + U0i;
pi0i = fpi0i + U1i;
pi1i = fpi1i + U2i;

Var_Asymptote = t11**2;
Var_Pseudo_Int = t21**2 + t22**2;
Var_Rate = t31**2 +t32**2 + t33**2;
Cov_Asymp_PI = t11*t21;
Cov_Asymp_Rate = t11*t31;
Cov_PI_Rate = t21*t31 + t22*t32;

y = a0i - (a0i - pi0i)*exp(-pi1i*followupperiod);

Model RTFIMSC_L_2 ~ normal (y, VarE);
Random U0i U1i U2i ~ normal ([0,0,0],
[Var_Asymptote,Cov_Asymp_PI,Var_Pseudo_Int,Cov_Asymp_Rate,Cov_PI_Rate,V
ar_Rate])
Subject = usi;


Estimate 'Var_Asymptote' t11**2;
```

```
Estimate 'Var_Pseudo_Int' t21**2 + t22**2;
Estimate 'Var_Rate' t31**2 + t32**2 + t33**2;
Estimate 'Cov_Asymp_PI' t11*t21;
Estimate 'Cov_Asymp_Rate' t11*t31;
Estimate 'Cov_PI_Rate' t21*t31 + t22*t32;

Title 'Negative Exponential for RTFIMSelfCare Unconditional Model';

predict a0i out=out1;
predict pi0i out=out2;
predict pi1i out=out3;

run;
proc nlmixed data = Data_Set_7 method = FIRO maxiter = 5000;

parms
Asymptote = 4
P_I = -1.6
Rate = 1.7
Asymptote_Age = 0
P_I_Age = 0
Rate_Age = 0
Asymptote_HS = 0
P_I_HS = 0
Rate_HS = 0
Asymptote_MTHS = 0
P_I_MTHS = 0
Rate_MTHS = 0
Asymptote_Emp1 = 0
P_I_Emp1 = 0
Rate_Emp1 = 0
Asymptote_LOSREH1 = 0
P_I_LOSREH1 = 0
Rate_LOSREH1 = 0
Asymptote_Mar = 0
P_I_Mar = 0
Rate_Mar = 0
Asymptote_PTA = 0
P_I_PTA = 0
Rate_PTA = 0
Asymptote_Race = 0
P_I_Race = 0
Rate_Race = 0
Asymptote_Sex = 0
P_I_Sex = 0
Rate_Sex = 0
Asymptote_Medicare = 0
P_I_Medicare = 0
Rate_Medicare = 0
Asymptote_Medicaid = 0
P_I_Medicaid = 0
Rate_Medicaid = 0
Asymptote_RehabPay_Other = 0
P_I_RehabPay_Other = 0
```

```
Rate_RehabPay_Other = 0
t11= 6
t21= 6
t22= 6
t31= 6
t32= 6
t33= 6
VarE = 1.5;

a0i = Asymptote + Asymptote_Age*AGE_GMC  + Asymptote_HS*EduYears_HS +
Asymptote_MTHS*EduYears_MTHS + Asymptote_Emp1*Emp1_2 +
Asymptote_LOSREH1*LOSREH1_GMC + Asymptote_Mar*MAR_2 +
Asymptote_PTA*PTA_1_GMC + Asymptote_Race*Race_Other +
Asymptote_Sex*Sex_1 +
Asymptote_Medicare*Rehabpay_Medicare +
Asymptote_Medicaid*RehabPay_Medicaid +
Asymptote_RehabPay_Other*RehabPay_Other + U0i;

pi0i = P_I + P_I_Age*AGE_GMC + P_I_HS*EduYears_HS +
P_I_MTHS*EduYears_MTHS + P_I_Emp1*Emp1_2 + P_I_LOSREH1*LOSREH1_GMC +
P_I_Mar*MAR_2 +
P_I_PTA*PTA_1_GMC + P_I_Race*Race_Other + P_I_Sex*Sex_1 +
P_I_Medicare*Rehabpay_Medicare + P_I_Medicaid*RehabPay_Medicaid +
P_I_RehabPay_Other*RehabPay_Other + U1i;

pi1i = Rate + Rate_Age*AGE_GMC + Rate_HS*EduYears_HS +
Rate_MTHS*EduYears_MTHS + Rate_Emp1*Emp1_2 + Rate_LOSREH1*LOSREH1_GMC +
Rate_Mar*MAR_2 +
Rate_PTA*PTA_1_GMC + Rate_Race*Race_Other + Rate_Sex*Sex_1 +
Rate_Medicare*Rehabpay_Medicare + Rate_Medicaid*RehabPay_Medicaid +
Rate_RehabPay_Other*RehabPay_Other + U2i;


Var_Asymptote = t11**2;
Var_Pseudo_Int = t21**2 + t22**2;
Var_Rate = t31**2 +t32**2 + t33**2;
Cov_Asymp_PI = t11*t21;
Cov_Asymp_Rate = t11*t31;
Cov_PI_Rate = t21*t31 + t22*t32;

y = a0i - (a0i - pi0i)*exp(-pi1i*followupperiod);

Model RTFIMSC_L_2 ~ normal (y, VarE);

Random U0i U1i U2i ~ normal ([0,0,0],
[Var_Asymptote,Cov_Asymp_PI,Var_Pseudo_Int,Cov_Asymp_Rate,Cov_PI_Rate,V
ar_Rate])
Subject = usi;


Estimate 'Var_Asymptote' t11**2;
Estimate 'Var_Pseudo_Int' t21**2 + t22**2;
Estimate 'Var_Rate' t31**2 + t32**2 + t33**2;
Estimate 'Cov_Asymp_PI' t11*t21;
```

```
Estimate 'Cov_Asymp_Rate' t11*t31;
Estimate 'Cov_PI_Rate' t21*t31 + t22*t32;

Title 'RTFIMSelfCare Full Model';

predict a0i out=out1;
predict pi0i out=out2;
predict pi1i out=out3;

run;
```

DRS:

```
ods html close;
ods html;
DM log 'clear';


proc contents data = TBI1;
run;
proc univariate data = TBI1;
var RTFIMCOG_L_1 RTFIMMOB_L_2 RTFIMSC_L_2 RTDRS_L_2 AGE ALCAnyDrink_1
Drugs_1 EduYears_1 Emp1_1
LOSREH1 Mar_1 PTA_1 Race_1 Sex RehabPay1_1;
run;

data Data_Set_1;
set TBI1;
usi=compress(center||subjectid);
run;
proc sort data = Data_Set_1;
by usi;
run;

proc freq data = Data_Set_1 noprint;
tables usi / out = Data_Set_2;
run;

Data Data_Set_3;
Set Data_Set_2;
run;
proc sort data = Data_Set_3;
by usi;
run;

Data Data_Set_4;
merge Data_Set_3 Data_Set_1;
by usi;
run;
proc sort data = Data_Set_4;
by usi;
run;
Data Data_Set_5;
Set Data_Set_4;
if count LE 2 then delete;
run;

proc freq data = Data_Set_5 noprint;
tables usi / out = Data_Set_6;
run;
proc sort data = Data_Set_6;
by usi;
```

```
run;
data Data_Set_7;
merge Data_Set_6 Data_Set_1;
by usi;
if count = "." then delete;
if count LE 2 then delete;
*if ALCAnyDrink_1 = 1 then ALCAnyDrink_2 = 0;
*if ALCAnyDrink_1 = 2 then ALCAnyDrink_2 = 1;
*if Drugs_1 = 1 then Drugs_2 = 0;
*if Drugs_1 = 2 then Drugs_2 = 1;
if EduYears_1 in (1 2 3 4 5 6 7 8) then EduYears_2 = "LTHS";
if EduYears_1 in (9 10 11 12) then EduYears_2 = "HS";
if EduYears_1 in (13 14 15 16 17 18 19 20) then EduYears_2 = "MTHS";
if EduYears_2 = "HS" then EduYears_HS = 1;
else EduYears_HS = 0;
if EduYears_2 = "MTHS" then EduYears_MTHS = 1;
else EduYears_MTHS = 0;
if Emp1_1 = 1 then Emp1_2 = 0;
if Emp1_1 = 0 then Emp1_2 = 1;
if Mar_1 = 1 then MAR_2 = 0;
if Mar_1 = 0 then MAR_2 = 1;
if Race_1 = 1 then Race_2 = "White";
if Race_1 in (2 3 4 5 7) then Race_2 = "Other";
if Race_2 = "Other" then Race_Other = 1;
else Race_Other = 0;
if Sex = 1 then Sex_1 = 0;
if Sex = 2 then Sex_1 = 1;
if Sex_1 = 0 then Sex_2 = "Female";
if Sex_1 = 1 then Sex_2 = "Male";
if RehabPay1_1 = 1 then RehabPay1_2 = "Medicare";
if RehabPay1_1 = 2 then RehabPay1_2 = "Medicaid";
*if RehabPay1_1 in (3 10) then RehabPay1_2 = "WC_Auto";
if RehabPay1_1 in (4 6 11 12) then RehabPay1_2 = "Private";
*if RehabPay1_1 = 7 then RehabPay1_2 = "Self_PP";
if RehabPay1_1 in (3 7 8 10 14 55 77) then RehabPay1_2 = "Other";
if RehabPay1_2 = "Medicare" then RehabPay_Medicare = 1;
else RehabPay_Medicare = 0;
if RehabPay1_2 = "Medicaid" then RehabPay_Medicaid = 1;
else RehabPay_Medicaid= 0;
*if RehabPay1_2 = "WC_Auto" then RehabPay_WC_Auto = 1;
*else RehabPay_WC_Auto = 0;
*if RehabPay1_2 = "Self_PP" then RehabPay_Self_PP = 1;
*else RehabPay_Self_PP = 0;
if RehabPay1_2 = "Other" then RehabPay_Other = 1;
else RehabPay_Other = 0;
AGE_GMC = AGE - 40.99;
LOSREH1_GMC = LOSREH1 - 27.56;
PTA_1_GMC = PTA_1 - 23.87;
run;
proc univariate data = Data_Set_7;
var AGE_GMC LOSREH1_GMC PTA_1_GMC;
run;

proc sort data = Data_Set_7;
```

```
by usi followupperiod;
run;

proc freq data = Data_Set_7;
table followupperiod;
run;

proc print data = Data_Set_7 (obs=200);
var usi followupperiod;
run;


data y;
set Data_Set_7;
run;

proc sort data = y nodupkey;
by usi;
run;


goptions reset = all border;
options orientation = landscape;
symbol1 interpol = join color = black repeat = 13317;
*symbol1 interpol = join width = 5 color = red repeat = 1;
axis1 order = 0 to 30 by 5 label = ("Years");
axis2 order = -20 to 20  by 1 label = ("RTDRS_L_2");
*legend1 value = ('Individual Responses') label = none;
*legend2 value = ('Fixed Effects') label = none;
title;
proc gplot data = Data_Set_7;
plot1 RTDRS_L_2*FollowupPeriod = usi/ nolegend vaxis = axis2 haxis =
axis1;
title 'Graph of RTDRS';

run;


proc nlmixed data = Data_Set_7 method = FIRO maxiter = 5000;
parms fai = -10
fpi0i = -.89
fpi1i = .25
t11= 2
t21= 0.2
t22= 2.5
t31= 0.1
t32= 0.06
t33= 0.0006
VarE = 3;

a0i = fai + U0i;
pi0i = fpi0i + U1i;
pi1i = fpi1i + U2i;
```

```
Var_Asymptote = t11**2;
Var_Pseudo_Int = t21**2 + t22**2;
Var_Rate = t31**2 +t32**2 + t33**2;
Cov_Asymp_PI = t11*t21;
Cov_Asymp_Rate = t11*t31;
Cov_PI_Rate = t21*t31 + t22*t32;

y = a0i - (a0i - pi0i)*exp(-pi1i*followupperiod);

Model RTDRS_L_2 ~ normal (y, VarE);
Random U0i U1i U2i ~ normal ([0,0,0],
[Var_Asymptote,Cov_Asymp_PI,Var_Pseudo_Int,Cov_Asymp_Rate,Cov_PI_Rate,V
ar_Rate])
Subject = usi;


Estimate 'Var_Asymptote' t11**2;
Estimate 'Var_Pseudo_Int' t21**2 + t22**2;
Estimate 'Var_Rate' t31**2 + t32**2 + t33**2;
Estimate 'Cov_Asymp_PI' t11*t21;
Estimate 'Cov_Asymp_Rate' t11*t31;
Estimate 'Cov_PI_Rate' t21*t31 + t22*t32;


Title 'Negative Exponential for RTDRS Unconditional Model';

predict a0i out=out1;
predict pi0i out=out2;
predict pi1i out=out3;

run;

proc nlmixed data = Data_Set_7 method = FIRO maxiter = 10000;

parms
Asymptote = -10
P_I = -0.5
Rate = 1.6
Asymptote_Age = 0
P_I_Age = 0
Rate_Age = 0
Asymptote_HS = 0
P_I_HS = 0
Rate_HS = 0
Asymptote_MTHS = 0
P_I_MTHS = 0
Rate_MTHS = 0
Asymptote_Emp1 = 0
P_I_Emp1 = 0
Rate_Emp1 = 0
Asymptote_LOSREH1 = 0
P_I_LOSREH1 = 0
Rate_LOSREH1 = 0
Asymptote_Mar = 0
```

```
P_I_Mar = 0
Rate_Mar = 0
Asymptote_PTA = 0
P_I_PTA = 0
Rate_PTA = 0
Asymptote_Sex = 0
P_I_Sex = 0
Rate_Sex = 0
Asymptote_Medicare = 0
P_I_Medicare = 0
Rate_Medicare = 0
Asymptote_Medicaid = 0
P_I_Medicaid = 0
Rate_Medicaid = 0
Asymptote_RehabPay_Other = 0
P_I_RehabPay_Other = 0
Rate_RehabPay_Other = 0
t11= 2
t21= 0.2
t22= 2.5
t31= 0.1
t32= 0.06
t33= 0.0006
VarE = 3.5;

a0i = Asymptote + Asymptote_Age*AGE_GMC + Asymptote_HS*EduYears_HS +
Asymptote_MTHS*EduYears_MTHS + Asymptote_Emp1*Emp1_2 +
Asymptote_LOSREH1*LOSREH1_GMC + Asymptote_Mar*Mar_2 +
Asymptote_PTA*PTA_1_GMC + Asymptote_Sex*Sex_1 +
Asymptote_Medicare*Rehabpay_Medicare +
Asymptote_Medicaid*RehabPay_Medicaid +
Asymptote_RehabPay_Other*RehabPay_Other + U0i;

pi0i = P_I + P_I_Age*AGE_GMC + P_I_HS*EduYears_HS +
P_I_MTHS*EduYears_MTHS + P_I_Emp1*Emp1_2 + P_I_LOSREH1*LOSREH1_GMC +
P_I_Mar*Mar_2 +
P_I_PTA*PTA_1_GMC + P_I_Sex*Sex_1 + P_I_Medicare*Rehabpay_Medicare +
P_I_Medicaid*RehabPay_Medicaid +
P_I_RehabPay_Other*RehabPay_Other + U1i;

pi1i = Rate + Rate_Age*AGE_GMC + Rate_HS*EduYears_HS +
Rate_MTHS*EduYears_MTHS + Rate_Emp1*Emp1_2 + Rate_LOSREH1*LOSREH1_GMC +
Rate_Mar*Mar_2 + Rate_PTA*PTA_1_GMC + Rate_Sex*Sex_1 +
Rate_Medicare*Rehabpay_Medicare +
Rate_Medicaid*RehabPay_Medicaid + Rate_RehabPay_Other*RehabPay_Other +
U2i;


Var_Asymptote = t11**2;
Var_Pseudo_Int = t21**2 + t22**2;
Var_Rate = t31**2 +t32**2 + t33**2;
Cov_Asymp_PI = t11*t21;
Cov_Asymp_Rate = t11*t31;
Cov_PI_Rate = t21*t31 + t22*t32;
```

```
y = a0i - (a0i - pi0i)*exp(-pi1i*followupperiod);

Model RTDRS_L_2 ~ normal (y, VarE);

Random U0i U1i U2i ~ normal ([0,0,0],
[Var_Asymptote,Cov_Asymp_PI,Var_Pseudo_Int,Cov_Asymp_Rate,Cov_PI_Rate,V
ar_Rate])
Subject = usi;


Estimate 'Var_Asymptote' t11**2;
Estimate 'Var_Pseudo_Int' t21**2 + t22**2;
Estimate 'Var_Rate' t31**2 + t32**2 + t33**2;
Estimate 'Cov_Asymp_PI' t11*t21;
Estimate 'Cov_Asymp_Rate' t11*t31;
Estimate 'Cov_PI_Rate' t21*t31 + t22*t32;

Title 'RTDRS Full Model';

predict a0i out=out1;
predict pi0i out=out2;
predict pi1i out=out3;

run;
```