MODELING EMPLOYMENT OUTCOME POST BRAIN INJURY RESOURCE FACILITATION

By

Devan Parrott

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BY

Devan Parrott

Dissertation Committee:

Shankar Srinivasan PhD

Lance Trexler PhD

Suril Gohel PhD

Dan Woloszyn PsyD

Approved by the Dissertation Committee:

____ Date: __________________

____ Date: __________________

____ Date: __________________

____ Date: __________________

____ Date: __________________

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ABSTRACT

Disability following traumatic brain injury (TBI) can impact community integration as well as employment post injury. Considering the impact unemployment can have on quality of life, recovery, and the economy, several targeted interventions have been identified in the literature. One successful evidence-based intervention is called resource facilitation (RF). RF is an intervention targeted at improving employment rates in the TBI community with resulting return to work rates well above established return to work rates published in the brain injury population.

Even with the success of RF, variability in outcome in a concern. Identification of variables that contribute to positive or negative employment outcomes could help target at-risk patients earlier in the treatment protocol and influence clinical recommendations during treatment.

This project was designed to identify the complex relationship between predictor variables and return to work after participation in the RF program. Although many models exist currently in the literature, none of the published models are appropriate for the RF population. Additionally, currently published models typically involve linear regression models making the relationships between predictor variables difficult to detect. Structural equation modeling (SEM) was used to test the variables identified in the literature and identify direct and indirect predictors of outcome. SEM allows for direct testing of mediating variables as well as proposed latent variables within one prediction model. A preliminary model based on theoretical considerations as well as empirical evidence was used as a starting point.

Although the initially hypothesized model was not an appropriate fit for the current dataset, two statistically sound models were generated during post hoc testing. Upon successfully identifying the two prediction models, results indicate that brain injury survivors with childhood injuries cannot be modeled in the same sample as brain injury survivors injured as adults, suggesting a difference between rehabilitation patients and "habilitation" patients.

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Chapter 1

INTRODUCTION

Disability following traumatic brain injury (TBI) can result in poor employment outcomes and community integration. In fact, unemployment rates following traumatic brain injury are estimated to be between 48 and 78 percent.[1-5] Considering the impact unemployment can have on quality of life, recovery, and the economy, several targeted interventions have been identified in the literature. One successful evidence-based intervention is called resource facilitation (RF). RF is an intervention targeted at improving employment rates in the TBI community with resulting return to work rates ranging from 64 to 69 percent.[6-7]

Even with the success of RF, variability in outcome in a concern. Identification of variables that contribute to positive or negative employment outcomes could help target at-risk patients earlier in the treatment protocol and influence clinical recommendations during treatment. No work has been published to date on modeling outcome after RF, but several papers have attempted to identify individual predictors of return to work success post TBI irrespective of intervention. Results indicate that few variables directly predict outcome, instead many predictors are actually mediating variables impacting outcome indirectly. This project is designed to test a comprehensive model that includes testing these mediating relationships as well as identify direct relationships. The major objective of this research is to identify the complex relationship between hypothesized predictor variables and return to work rates after participation in the RF program. A structural equation model (SEM) will be designed and tested allowing for prediction of outcome post treatment. The resulting algorithm will be built into a Clinical Decision Support (CDS) system. This system will allow for further identification of "at-risk" patients who may need more attention, special staff assignments, or additional interventions. Further, a CDS for RF could improve the efficiency of service delivery, and potentially serve to identify essential ingredients in the RF intervention allowing for improved outcomes.

1.1 Background of the problem

Most moderate and severe TBIs, as well as many mild TBIs, can cause chronic impairments lasting throughout the lifetime.[8] Additionally, disability following traumatic brain injury can result in poor employment outcomes due to consequences of including cognitive, neurobehavioral, and/or mood changes.[9-11] In fact, Sigurdardottir studied neuropsychological functioning in 105 patients with severe TBI and found that 67% of the sample showed significant cognitive impairments.[10] Andelic and colleagues found that patients with cognitive impairments following TBI were 82% less likely to be employed one year post injury.[12]

Historically, unemployment rates following traumatic brain injury are estimated to be between 48 and 78 percent.[1-5] More recently, Cuthbert and colleagues studied employment rates two years post injury in 7,373 patients in the Traumatic Brain Injury Model Systems (TBIMS) database and found that just over 60 percent of the sample was unemployed.[13]

RF is an evidence- based intervention targeted at improving return to work rates post brain injury. The RF intervention is an individualized treatment for brain injury survivors specializing in connecting patients and caregivers with community-based resources and services with a goal of returning the patient to work. The first randomized controlled trial of resource facilitation was published in 2010 and showed a successful return to work rate of 64 percent compared to 36 percent in the control group.[6] In addition to an increased rate of employment, participation in the community also improved significantly more in the treatment group than the control group. More recently, the results of this study were replicated with a larger sample size. Upon completion of the study, 69 percent of the treatment group returned to previous employment compared to 50 percent in the control group.[7] In addition, it was estimated that resource facilitation participants were seven times more likely to be vocationally successful than survivors not receiving services.

In addition to vocational and adaptation advantages to the treatment group, RF is believed to have a significant impact on the economy as well. In 2011, researchers at Ball State University estimated the economic impact of RF in Indiana to be just over 30 million dollars in lost wages alone (without including additional considerations such as fringe benefits, Medicare/Medicaid costs, and state-level taxes).[14]

Further refinement of resource facilitation involves identification of at-risk patients earlier in the resource facilitation treatment protocol. Employment after brain injury is not simply predicted clinically. In fact, researchers in Germany attempted to predict employment stability based on impairment level and work history information gathered during a structured interview. After the interview, clinicians were asked to predict employment outcome and the researchers found that their hypotheses were not supported.[15]

Despite the challenges, it is still important to identify significant predictors of employability after TBI in order to target specific patients.[16] Identifying outcome predictors can help identify which consequences of brain injury are modifiable or easily attended to with early intervention in addition to identifying those who are at a greater risk.[8]

Several papers have attempted to identify individual predictors of return to work post brain injury. Although many demographic variables and injury characteristics have been identified as potential predictors of employment outcome for brain injury survivors, the relationship between the predictors and weighting of various predictors is unknown. Results of structural equation modeling indicate that few predictors directly predict outcome, instead many predictors are actually mediating variables indirectly impacting outcome.[17] In Australia, Schonberger and colleagues built a structural equation model to show the dynamic interplay of variables and variable levels when predicting outcome after TBI in Australia. This structural equation model allows for general group estimates, but does not assign a specific prediction for individual group membership assignments. In addition, this model does not extend to the US employment environment nor the RF population.

In addition to the statistical disadvantages of the published models, none of the provided models are appropriate for a resource facilitation intervention. Although some models were taken from outpatient rehabilitation settings or vocational training settings, none of the samples focused on resource facilitation treatments or similar evidence-based interventions.

1.2 Significance of the study

This project allows for systematic identification of "at-risk" patients within the resource facilitation treatment protocol. Modeling outcome is not only important for our current resource facilitation program, but other resource facilitation programs across the country. Many papers exist in the literature for predicting employment outcome post TBI. However, few utilize complex multi-level modeling to allow for mediating and moderating relationships. Investigating indirect relationships is critical in order to understand the brain injury population and variables impacting treatment outcomes.

In addition, modeling outcome predictors will also provide the opportunity to provide patients with an evidence-based prognosis.[17-18] Implementation of a prediction model and resulting "risk-index" within a CDS system will allow for immediate identification of "high risk" patients allowing for utilization of more appropriate interventions as well as resource triaging.[19-20]

Currently the range of interventions are split into primary, secondary, and tertiary intervention[21] with most interventions in brain injury providing tertiary levels of prevention. This protocol aims to improve secondary prevention by allowing mitigation of the burden associated with chronicity of TBI. In addition, preventative care is considered a high-value service in terms of "value-based" care.[22, 23] Therefore, identification of "at-risk" patients and risk assessment allows for more prudent use of healthcare and state funding to be distributed based on level of need to achieve the identified outcome.

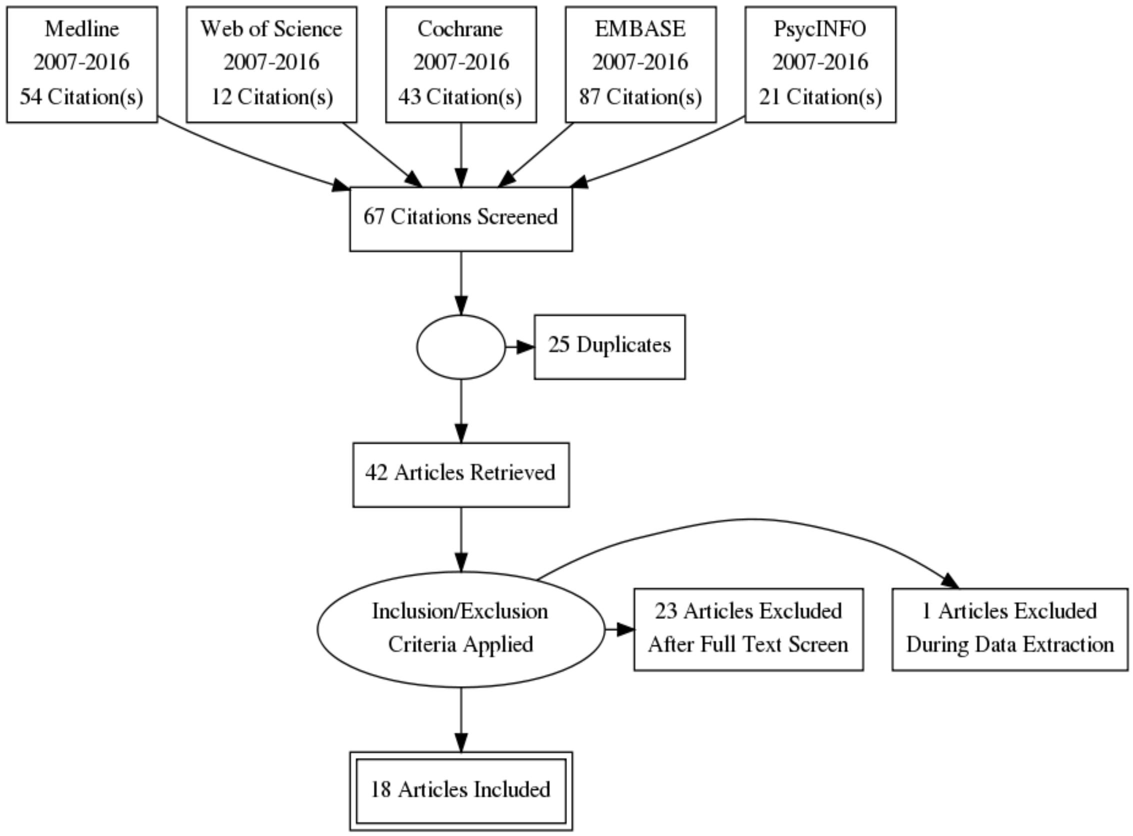
Chapter II

REVIEW OF LITERATURE

Several papers have attempted to identify individual predictors of return to work post brain injury. Many demographic variables as well as injury characteristics have been identified as potential predictors of employment outcome for brain injury survivors. The literature clearly demonstrates that individuals who sustain a moderate to severe brain injury are at risk for developing cognitive, emotional, and neurobehavioral difficulties that can impede their ability to effectively reintegrate into the community and obtain and maintain employment. Therefore, this review of literature sought to identify statistical models and individual predictors of employment after brain injury further allowing for systematic identification of variables that are attributed to “higher-risk” patients.

Results from the literature search are provided in Figure 1. The search within Medline resulted in 54 articles meeting initial inclusion/exclusion criteria, Web of Science resulted in 12, Cochrane found 43, EMBASE provided 87, and PsycINFO resulted in 21 citations. Abstract review searching for US samples eliminated some of these results leaving 67 articles to be reviewed further. Twenty-five of the 67 articles were duplicates and ultimately, 42 articles were retrieved for full-text review. After applying inclusion/exclusion criteria to the full-text articles, 23 were excluded. One additional article was excluded during data extraction leaving 18 articles to be included in the full review.

Figure 1. Flow diagram for literature search



Note, although any type of brain injury was accepted within the inclusion/exclusion criteria, only papers with TBI were among the results.

2.1 Quality Review

Quality of the articles was assessed using the Checklist for Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modeling Studies (CHARMS).[24] The CHARMS checklist was designed to evaluate the quality of, and extract data from, prediction modeling studies. The checklist contains two parts. Part 1 aids in forming the search strategy, primary aim of the review, and inclusion/exclusion criteria. Part 2, used in this study, provides targeted questions to help a reviewer rate the quality of a prediction model published in a paper. The individual items can be broken into three categories: Risk of bias, Applicability, and General. Risk of bias items help assess the level of bias and quality in the paper. Applicability items detect how applicable the paper is to the research question. The general items are for data extraction.

Many of the reported studies focused on more than one outcome variable and included more than one prediction model. Therefore, only prediction models using employment as the independent variable were assessed for quality and data extraction. Several trends were identified during the review of the 18 included articles. As mentioned earlier, all studies only included TBI samples although any brain injury would have been acceptable with the established inclusion criteria. Another trend identified within the quality review was the use of logistic regression. Seventeen of the 18 studies used logistic regression to predict employment. However, this finding is not surprising with the binary nature of the outcome variable.

In terms of concerning trends, 17 of the 18 articles were based on registry data. Although registry data typically allows for much larger sample sizes and therefore inclusion of more predictor variables, use of registry data introduces substantial amounts of bias.[24] Primarily, the registry itself is typically biased because not all patients have access to be included. For example, one registry used in 11 of the 17 studies, the Traumatic Brain Injury Model Systems (TBIMS) program data registry, only includes participants with treatment received within 24 hours of injury from an affiliated level 1 trauma center.[25] In addition, they must also have entered an affiliated inpatient rehabilitation unit with 72 hours of discharge of acute care. This makes generalizing findings from prediction models unreliable as this is not the treatment trajectory of the majority of brain injury survivors. In addition, many papers did not include the study dates for their data. This is particularly important for registry studies. It is impossible to detect overlapping samples of participants if the dates are not included. In this review, six of the studies failed to include the study dates.

Several trends were also present specific to the methodology and reporting of modeling. Only four of the 18 articles reported the variance explained by the full model and only presented the contribution of the individual predictors. Also concerning is the lack of model validation within the reviewed studies. Only one study showed evidence of model validation. In this particular study, the model was validated with cross-validation from a random half of the study sample. This method is not considered high quality as a random half of the data should, in terms of probability, produce a very similar model leading to a false sense of model validity.[24] Finally, seven papers failed to pass the Events per Variable (EPV) criterion. The EPV criterion is a well-established ratio that ensures the appropriate number of events in a sample per predictor variable. Specifically, it states that the total number of events in the dependent variable of a model divided by the number of predictor variables must be greater than ten. In logistic regression, the number of events is defined as the smaller of the two binary outcomes. This item is critical for overall paper quality as failing this item leads to over-fitting and potentially meaningless results. One exception to the CHARMS guidelines was made for the missing data item. According to Moons and colleagues, complete-case analysis should be marked as poor quality. Since most of the studies included were based on registry data, most sample selections were taken with complete-case analysis in mind. Credit was given for this item if the authors provided a comparison to the excluded cases and were able to show that the two samples were similar on key variables.

2.1.1 Quality guidelines for data extraction

To be included in the predictor analysis, articles had to pass minimal quality criteria. First, the article had to use an EPV ratio of ten or more. In addition, out of the 21 'Risk of bias' and 'Applicability' items on the CHARMS checklist, the paper had to pass 17 or more items (80%). This resulted in data extraction from seven high quality articles.

2.1.2 Data extraction

Data was only extracted from papers meeting minimum quality standards specified above. During this review, several individual significant predictors of outcome were identified: length of stay in acute care (LOS), cause of injury (violent vs. non-violent), payer group, vocational services provided to state Vocational Rehabilitation Services (VRS) clients, and expense per VRS case were all significant in all of the models they were entered into. However, note that payer group, vocational services, and expense per case were only tested in one study. Next, age was significant 83% of the time with level of education significant in 80% of the studies it was entered into. Race was significant 75% of the time and pre-injury employment and marital status were significant 66% of the time. Sex, duration of post-traumatic amnesia (PTA), and delirium severity were each significant in half of the models they were entered into while the Functional Independence Measure (FIM) was significant 33% of the time. See table 1.

Table 1. Summary of significant predictors

	Number of studies with this predictor out of 7	Number of studies finding significance	Percent significant
Pre-injury/Demographic			
Age	6	5	83%
Race	4	3	75%
Sex	4	2	50%
education	5	4	80%
employment	3	2	66%
marital status	3	2	66%
Time of Injury			
payer group	1	1	100%
LOS	3	3	100%
GCS	3	0	0%
PTA duration	4	2	50%
AIS	1	0	0%
CT	1	0	0%
Delirium	4	2	50%
Cause of Injury	2	2	100%
FIM	3	1	33%
Post-injury			
Vocational Services	1	1	100%
Case expenditure	1	1	100%
Disability	1	0	0%

If a predictor was included in the final model and contributed to a significant interaction, it is listed as a significant predictor in the table. However, in the explanation of significant predictors, only the significant interaction will be discussed as significant predictors also contributing to an interaction are not statistically meaningful and do not represent a truly significant main effect.

2.2 Literature results by predictor

2.2.1 Age at injury

Five out of six articles found age to be a significant predictor of return to work after brain injury.[8, 26-30] Nakase-Richardson and colleagues found that younger participants were three times more likely to be employed at follow-up than older participants.[26] Similarly, Gary and colleagues as well as Nakase-Richardson and team found that younger participants had greater odds of employment than older participants.[27-28] In fact, when studied ten years after injury, Gary and colleagues found the same result.[29] Interestingly, Corrigan and colleagues found a significant interaction between age and sex. As women in the sample increased in age, the impact on employment change declined.[30] More specifically, all ages of women were more likely to stop working after their injury until age 55. At this point, men were more likely to stop working.

2.2.2 Race

Four articles used race to predict employment outcome with three finding race to be a significant predictor.[27, 29, 30] Corrigan and colleagues found that whites were more likely to continue working while all other races were more likely to decline or stop working at one year post injury.[30] Gary and colleagues found that blacks were significantly less likely to be employed than whites at one year, two years, and five years post injury.[29] In 2010, Gary and colleagues continued to see this trend when looking at a cohort of brain injury survivors ten years post injury. Again, they found that whites were more likely to be employed than minorities.

2.2.3 Sex

Two of the four articles investigating sex as a predictor of employment outcome found sex to be significant.[29, 30] Gary and colleagues found that men showed higher odds of being employed post injury while Corrigan and colleagues found two significant interactions including sex. As discussed previously, women were less likely to be employed after their injury for all age groups except ages above 55. At age 55, men were more likely to decrease employment. In addition, an interaction between sex and marital status was also present. In general, women had a higher risk of unemployment or decrease in hours, but the interaction with marital status showed this risk was significantly higher for married women. The two interactions were independent of each other meaning a three-way interaction between the variables was not found to be significant.

2.2.4 Education

Five studies examined level of education and employment outcome. Four of the five studies, found education to be a significant predictor.[26, 29-31] All four studies found that higher levels of education were predictive of successful employment outcome. Corrigan and colleagues as well as Gary and colleagues found that education levels of high school graduate and above were significantly associated with better employment outcomes. Nakase-Richardson and colleagues used the 25th percentile, 10 years of education, compared to the 75th percentile, 13 years of education, and also found that increased education levels improved the odds of employment. Tamez used education as a continuous variable and found that with each year of education, the odds of employment increased by 1.12.[31]

2.2.5 Pre-injury Employment

Two of the three studies looking at employment pre-injury as a predictor of employment post-injury found significance.[27, 29] In 2009, Gary and colleagues found that subjects who were employed prior to injury were more likely to be employed post injury. In addition, in 2010, Gary and colleagues found that this was true in a cohort ten years post injury as well.

2.2.6 Marital Status

Two out of three studies found marital status to contribute to employment post injury.[29, 30] Gary and colleagues found that brain injury survivors who were married prior to injury were more likely to be employed post injury.[29] As mentioned previously, a significant interaction between marital status pre-injury and sex was present.[30] Corrigan and colleagues found that women had a higher risk of unemployment or decrease in working hours, however, this risk was significantly higher for married women. However, divorced women showed higher odds of stopping or decreasing work than divorced men.[30]

2.2.7 Payer group

One study looked at payer group and found significance.[30] They found that patients with private insurance were more likely to be employed post injury than patients with no insurance, worker's comp, or Medicaid.

2.2.8 Length of Stay

All three studies testing the effect of Length of Stay (LOS) on employment found significance[27, 29, 30] Corrigan and colleagues as well as Gary and colleagues found that a shorter length of stay in acute care was predictive of better employment rates. In 2010, Gary and colleagues found this to also be true in a sample of brain injury survivors ten years post injury.

2.2.9 Post-traumatic amnesia duration

*F*our studies examined the predictive power of duration of post-traumatic amnesia (PTA) on return to productivity one year post injury and two studies found the variable to be significant.[25, 28] Nakase-Richardson and colleagues found that every additional week a patient experienced PTA, their odds of employment decreased by 14%. Brown and colleagues found that PTA lasting between 22 and 27.5 days was the most predictive of employment outcome.

2.2.10 Delirium

Four studies used the DelRS-R98 [26] to measure delirium severity, or severity of confusion and two of the studies found delirium severity to be predictive of employment outcome.[26, 29] Both studies found that increased severity of confusion during acute stay was predictive of decreased likelihood of employment.

2.2.11 Cause of Injury

Both studies looking at cause of injury as a predictor of employment post-injury found significance.[27, 29] In 2009, Gary and colleagues found that subjects with a violent cause of injury were less likely to be employed post injury than subjects with a non-violent cause of injury. In addition, in 2010, the same research team found that this was true in a cohort ten years post injury as well.

2.2.12 Functional Independence Measure

Three studies looked at the Functional Independence Measure (FIM) as a predictor of employment outcome. Only one of the three studies found this measure to be predictive and they found that decrease in function was significantly predictive of employment.[28] The authors did not discuss this unexpected finding in the paper and the result was only presented briefly in a table as part of the model description.

2.2.13 Vocational Rehabilitation Services

One study looked at various vocational services provided by state Vocational Rehabilitation Services (VRS) and found significant relationships to employment.[31] More specifically, Tamez found the following services to be associated with better odds of employment at case closure: job placement, on-the-job supports, maintenance (monetary support for those with extended evaluation services), occupation/vocational training, counseling/guidance in addition to routine vocational counseling (more in-depth).

2.2.14 Case expenditure

Tamez (2016) also looked at total case expenditure and found a significant relationship with employment post injury. Increased case expenditure was predictive of increased odds of employment. In fact, for every unit increase in expense, odds of employment increased by 1.26.

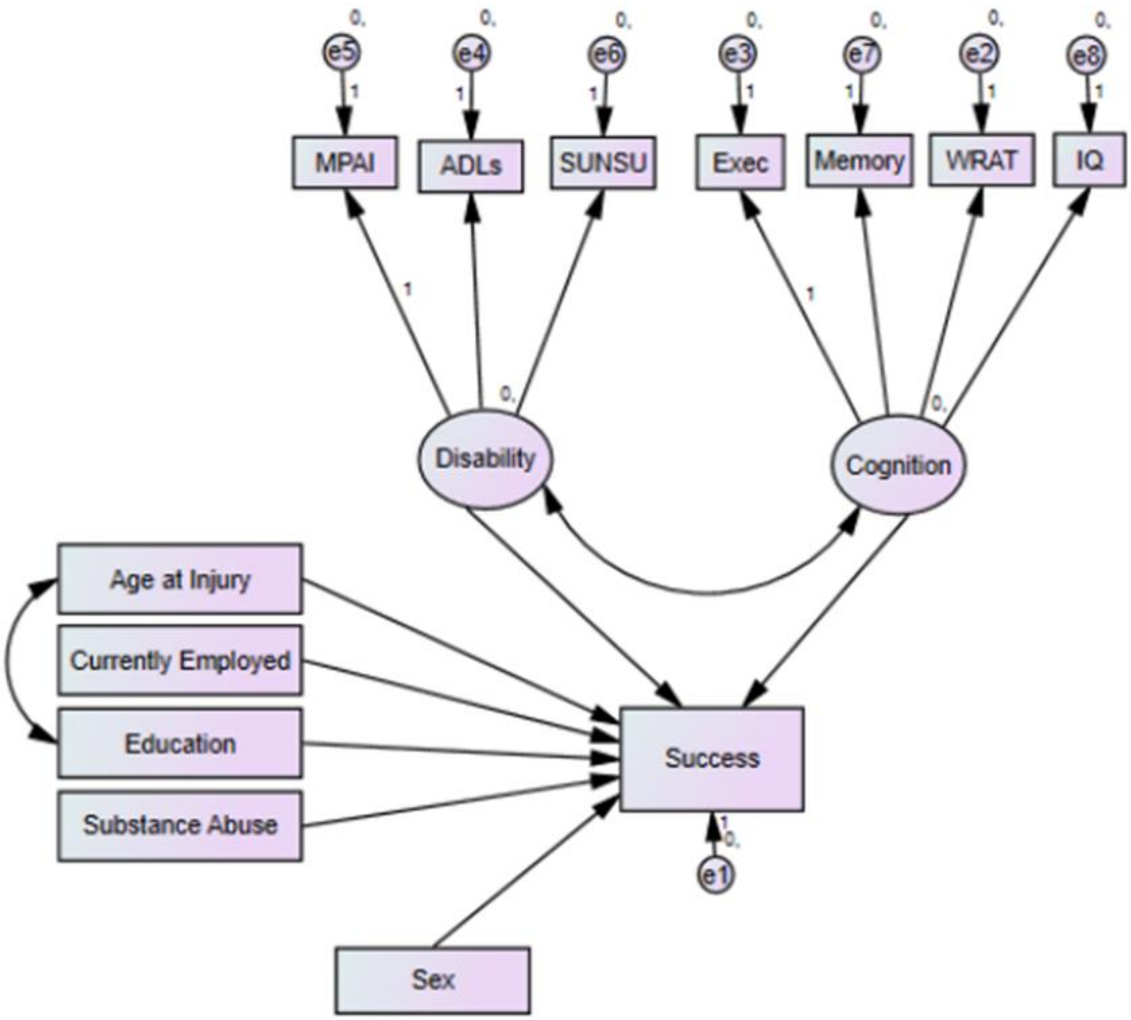
2.2.15 Summary of findings from individual predictors

Results show that the odds of returning to work may be higher in those with younger age, white race, male sex, higher education, pre-injury employment, married prior to injury, private insurance, less LOS in acute care facility, decreased length of PTA, decreased severity of confusion during acute care stay, and/or a non-violent cause of injury. In addition, those clients working with their state Vocational Rehabilitation Services, show better odds of returning to work if they receive the following services: job placement, on the job supports, maintenance, occupation/vocational training, and counseling/guidance. Finally, those within the VRS system with higher case expenditures are more likely to obtain employment. However, note that the results of the presented variables can only be interpreted independent of each other as this is not a final, comprehensive model being presented.

2.3 Hypotheses and research question

This project is designed to identify the complex relationship between predictor variables and return to work after participation in the RF program. Structural equation modeling (SEM) will be used to test the variables identified in the literature and identify direct and indirect predictors of outcome. The algorithm obtained from the analysis will be built into a program database as a Clinical Decision Support (CDS) system.[19, 20] A preliminary model based on theoretical considerations as well as empirical evidence is displayed in figure 2 as a starting point. It is hypothesized that it is possible to optimize a statistically valid model for return to work success in the RF treatment sample resulting in identification of both direct and indirect predictors of outcome.

Figure 2. Initial hypothesized model based on evidence and clinical recommendations



This model shows how several baseline variables and subject characteristics are hypothesized to impact the dependent variable, success. Success in the RF program, and this model, is defined as paid employment. Specifically, this model contains two latent variables, hypothesized to represent disability and cognition, as well as five additional exogenous variables: Age at injury, current employment, education level, history of substance abuse, and sex. It is further hypothesized that age at injury and education will be correlated within this model.

Chapter III

METHODOLOGY

3.1 Objectives

The objectives presented were met through structural equation modeling which allows for detection of both direct and indirect relationships. Additionally, the latent variables were tested using confirmatory factor analysis within the SEM protocol. Upon successful identification of predictor variables, a CDS system was built into the current program database to allow for immediate knowledge translation from research to clinical practice in addition to providing a more preventative approach to treating survivors with brain injury.

3.2 Data source

Data were extracted retrospectively from a clinical database serving the resource facilitation department the rehabilitation hospital of Indiana (RHI). RHI is the largest freestanding rehabilitation provider in Indiana, offering inpatient acute care and outpatient rehabilitation services for adults with BI. Additionally, RHI is a Traumatic Brain Injury Model Systems (TBIMS) site, although none of the data for this project was extracted from the TBIMS database.

3.3 Variables of interest

In the current resource facilitation protocol, injury characteristics, pre-injury employment, and demographic information is collected during an initial intake. In addition, baseline measures of functional, neurobehavioral, mood, personality, coping, and neuro-cognitive impairment are collected during a full-day neuro-vocational evaluation. At the end of treatment, the current protocol includes program evaluation data collection including employment outcome information and functional measures. All measures are listed in table 2. Demographic variables include age, years of education, race, gender, history of substance abuse, history of psychiatric treatment, marital status, history of military service, criminal history, and whether or not the patient is currently receiving food stamps. Injury related variables include time since injury, age at injury, type of injury (TBI or acquired brain injury), independence with driving, and medical insurance type. Additionally, employment information is collected in terms of employment prior to injury as well as any current employment. However, if a client enters the program "employed currently," they are most likely on disability leave.

Table 2. Measures and variables collected

Baseline	Discharge
Demographics	
Injury Characteristics	
Pre-injury and current employment	Employment
Functional:	**Functional:**
Mayo-Portland Adaptability Inventory – 4 (MPAI)[32]	MPAI
Activities of Daily Living Questionnaire (ADLQ)[33]	ADLQ
Survey of Unmet Needs (SUNSU)[34]	SUNSU
Mood, Personality, and Coping:	
Multidimensional Scale of Perceived Social Support (MSPSS)[35]	
Neuro-Cognitive:	
Wechsler Adult Intelligence Scale - IV (WAIS-IV)[36]	
California Verbal Learning Test (CVLT-II)[37]	
Wisconsin Card Sorting Test (WCST)[38]	
Wide Range Achievement Test IV (WRAT-IV) Reading[39]	

The Mayo-Portland Adaptability Inventory (MPAI-4) is a measure for disability designed specifically for brain injury survivors. The MPAI-4 yields a total score reflecting overall disability as well as three subscale scores for the Ability Index, Adjustment Index, and Participation Index. The Ability Index covers mobility, vision and hearing, dizziness, as well as cognitive items spanning communication, concentration, memory, and executive functions. The Adjustment Index includes items for anxiety, depression, anger/aggression, social/relationship, pain, fatigue, sensitivity to awareness, and initiation. The Participation Index measures leisure and recreational activities, self-care, independent living, employment, transportation, and money management. The Participation Index alone represents the ultimate goal of most rehabilitation programs and can be used as a standalone measure psychometrically.[32] The full measure as well as the three subscales show strong internal consistency, construct validity[40-42] as well as concurrent[43] and predictive validity.[44-46] In addition, The MPAI-4 has been found to be sensitive to change in studies of rehabilitation interventions and is often used as a program evaluation tool for many rehabilitation programs and hospitals.[44,47-48] Final scores on the total measure as well as the subscales are converted to T-scores with higher scores indicating higher level of disability. In fact, the MPAI-4 alone has shown strong predictive ability in terms of predicting community participation in brain injury patients participating in community-based rehabilitation programs.[49] In a study of 642 individuals with BI, a predictive model using the MPAI participation index scores from admission was able to explain over 50 percent of the variance in discharge MPAI scores after a community-based rehabilitation treatment.

The Activities of Daily Living Questionnaire (ADLQ) was originally designed to measure functional abilities in patients with dementia.[33] However, it is used in other populations with cognitive impairments regularly to assess functional capacity. Scores range from 0 to 100 with scores below 34 indicating no to mild impairment, scores between 34 to 66 indicating moderate impairment, and scores greater than 66 indicating severe impairment.[33]

The Survey of Unmet Needs and Services Utilized (SUNSU) is a measure designed to assess both the usage of services as well as desired services within the brain injury community.[34] The measure shows strong internal consistency when compared to other needs assessments in the brain injury population and results in two scores, number of items currently received (met needs) and number of items desired, or unmet needs.

The Multidimensional Scale of Perceived Social Support (MSPSS) is a measure of the patients' perception of social support with potential scores ranging from 12 (low perception of support) to 84 (high perception of support).[35] The MSPSS shows strong internal and test re-test reliability as well as moderate construct validity. Additionally, scores on the MSPSS show strong negative correlations with depression and anxiety.[35]

The Wechsler Adult Intelligence Scale (WAIS) Verbal Comprehension Index (VCI)[36] along with the Wide Range Achievement Test (WRAT)[39] Reading subscale are accepted as proxy measures of premorbid IQ.[50-51] Premorbid IQ estimates allow for identification of potential premorbid learning disabilities. Although a full-scale IQ (FSIQ) is obtained during the neuro-vocational evaluation, the FSIQ is not part of this dataset due to the difficulty in interpreting FSIQ in brain injury patients. Since FSIQ scores are dependent on cognitive domains often impacted by brain injury, FSIQ scores should be interpreted on an individual basis. For example, a patient with a processing speed impairment resulting from brain injury will score lower on the FSIQ. FSIQ scores are also impacted by memory impairments which are common in the brain injury population. The items on the VCI subscale along with the WRAT Reading subscale are less likely to be impacted by brain injury symptoms, therefore, these measures are accepted as a proxy measure for pre-morbid IQ.

The Wisconsin Card Sorting Test (WCST) is a measure of frontal lobe damage for brain injured patients.[38] More specifically, the WCST measures the patient's ability to figure out a set of underlying card sorting rules based on limited feedback from a testing technician. This test is administered to get an idea of the impact of the brain injury on the frontal lobes of the brain which are responsible for executive functions, planning, and organizing.

The California Verbal Learning Test – Second Edition (CVLT-II) is a measure of learning and recall.[37] Although many subscales exist for this measure, the subscale reported in this sample is the standardized score for list learning. This score reflects a patient's ability to learn a list of words read to them and repeat them back. This score is used as an estimate of the patient's verbal memory.

Additionally, based on previous research on predictors of return to work after brain injury, these measures provide the relevant scope and domain to serve the structural equation model proposed in Figure 2.

3.4 Inclusion/Exclusion

All patients in the RF clinical database discharged from resource facilitation were included in the analysis. To become a participant in resource facilitation, patients need authorization from Indiana Vocational Rehabilitation Services. This authorization requires history of brain injury and a desire to return to work or school.

3.5 Treatment details

All participants participated in the resource facilitation model established in our previous work.[6-7] Table 3 shows the roles and functions of the RF team including the

Resource Facilitators, the Local Support Network Leaders, and the clinical management team.

Table 3. Roles and functions of the resource facilitation team

Roles	**Functions**
Resource Facilitator	• Initial Resource Facilitation Intake evaluation • Initiates and documents mutually agreed upon goals and service/resource needs based on initial evaluation • Patient and family education on brain injury and applicable community resources • Facilitate access to community resources through advocacy and referral. • Proactively monitor the status of the plan every two weeks with the patient and family • Coordinate services from multiple providers • Coordination and communication with IVRS counselor
Local Support Network Leader	• Identify various public and private sector brain injury resources in the community (medical, psychological, social, vocational) to support the needs of individuals with brain injury

	• Promote awareness and coordination between brain injury resources and providers • Promote access for resource facilitation services at hospitals, clinics, and community-based services and navigate to appropriate IVRS offices • Provide or facilitate brain injury education to community resources • Assess the community resources needed to assist each individual in returning to work • Ensure that community supports have a plan for sustainability of employment outcomes
Clinical Management Team	• Comprehensive assessment of cognitive, psychological, and social functioning, vocational and environmental barriers from which to develop resource facilitation plan • Lead monthly case conferences with Resource Facilitator, Local Support Network Leader and IVRS counselor • Resource facilitation program leadership • Quality assurance and program evaluation

3.6 Statistical Analysis

Structural equation modeling (SEM), also known as covariance structure analysis, causal modeling, and path analysis with latent variables, is a comprehensive statistical procedure that tests hypotheses about relationships between variables. SEM is a comprehensive procedure as it takes a traditional path analysis model and adds confirmatory factor analysis to test latent variables while also subsuming other statistical procedures like multiple regression/ logistic regression and analysis of variance (ANOVA). More specifically, SEM takes a specified model with an explicitly stated covariance matrix and tries to reproduce the specified model with supplied data. As a result, parameter estimates and model fit data show how well the data fit the specified/hypothesized model. An additional benefit of SEM is that multiple dependent variables can be used as well as explicitly stating mediating and moderating variables. SEM was used to test the hypothesized model in figure 2. Non-significant paths were removed and new paths were tested by observing the impact to the overall model fit indices using maximum likelihood estimates. The latent constructs included cognition, indexed with executive functions (WCST), memory (CVLT), and pre-morbid IQ (WRAT and WAIS VCI), and disability, indexed with MPAI-4, ADLQ, and unmet needs (SUNSU). Employment success, the dependent variable, was measured as a dichotomous variable (employed vs. not employed at discharge). It was hypothesized that the two latent variables, disability and cognition, are correlated. Additionally, five exogenous variables (age at injury, current employment, years of education, history of substance abuse, and sex) were also included with a hypothesized correlation between years of education and age at injury. Confirmatory Factor Analysis was completed prior to testing the full hypothesized model to test the stability of the latent constructs. During post hoc analyses of adjusted SEMs, moderating relationships were tested using multiple regression. All models were estimated with AMOS in SPSS.

Chapter IV

RESULTS

4.1 Sample Characteristics

Between 2014 and 2016, a total of 285 patients were discharged from Resource Facilitation. All demographic and injury related baseline variables are presented in table 4.

Table 4. Demographic variables for the full sample at baseline

Demographics		
	Mean (SD)	**Min-Max**
Age	39.48 (13.44)	17-68
Years of Education	13.34 (2.48)	5-20
WAIS VCI	95.40 (16.25)	50-145
WRAT Reading	91.10 (14.35)	45-126
	Count	**Frequency**
Race		
American Indian or Alaskan Native	1	0.35%
Asian	0	0.00%
Black or African American	30	10.53%
Hispanic or Latino	4	1.40%
Native Hawaiian/Pacific Islander	0	0.00%
White	244	85.61%
unknown/not willing to answer	6	2.11%
Gender		
Female	107	37.5%
Male	175	62.5%
History of Substance Abuse		
Yes	53	18.6%
No	232	81.4%
History of Psychiatric Treatment		
Yes	153	53.7%

No	132	46.3%
Marital Status		
Married/Partnered	68	23.86%
Single/Divorced/Widowed/Separated	212	74.39%
Other/No response	5	1.75%
History of Military Service		
Yes	17	5.96%
No	268	94.04%
Criminal History		
Yes	65	22.81%
No	220	77.19%
Receiving Food Stamps		
Yes	67	23.51%
No	218	76.49%

Table. 5. Injury related variables for the full sample at baseline

	Mean(SD)	Min-Max
ADLQ	27.06 (15.76)	0-88
TSI (years unless specified)	8.56 (10.59)	52 days – 53 years
Age at injury	31.51 (16.18)	0-67
SUNSU (services currently using)	5.89 (5.16)	0-27
SUNSU (services requested)	8.81 (4.33)	0-27
MPAI Total	42.68 (7.96)	23-70
MPAI Abilities	42.52 (8.53)	12-68
MPAI Adjustment	48.51 (9.35)	19-73
MPAI Participation	40.92 (7.79)	7-74
WCST Set fails	1.07 (1.25)	0-5
CVLT LDFR	41.4 (12.80)	3-79
MSPSS	61.42 (17.83)	12-143
	Count	**Frequency**
Type of Injury		
TBI	197	69.12%
ABI	88	30.88%
Transportation		
Independent Driver	124	43.51%
Assisted (Public or Caregiver)	161	56.49%
Employed Prior to injury		
Yes	199	69.82%
No	86	30.18%
Employed at enrollment		
Yes	55	19.30%
No	230	80.70%
Medical Insurance		
Medicaid	123	43.16%
Private/Other	111	38.95%
No Insurance	51	17.89%
Workers Compensation		
Yes	3	1.05%
No	282	98.95%

The average age was 39 years and the sample ranged from 17 to 70 years. See Figure 3. The distribution for age was bimodal with peaks between ages 18 to 28 and 42 to 52 years. Although 70 seems like an outlier for a return to work study, the data point was verified and confirmed accurate. In addition, several participants were found to be over the age of 60. In terms of educational achievement, the majority of the sample had a high school degree or more (85.5%) and showed average estimates for pre-morbid IQ. See Figures 4-6.

Figure 3. Age distribution

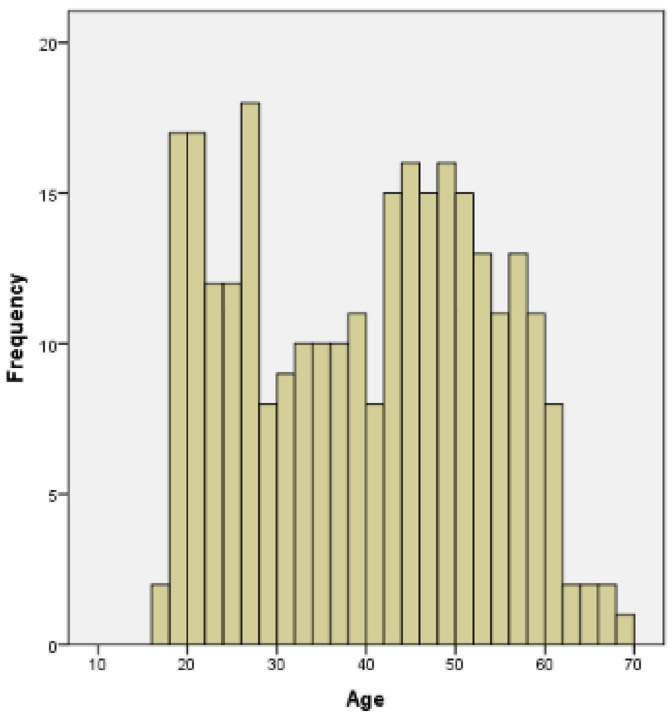


Figure 4. Years of education distribution

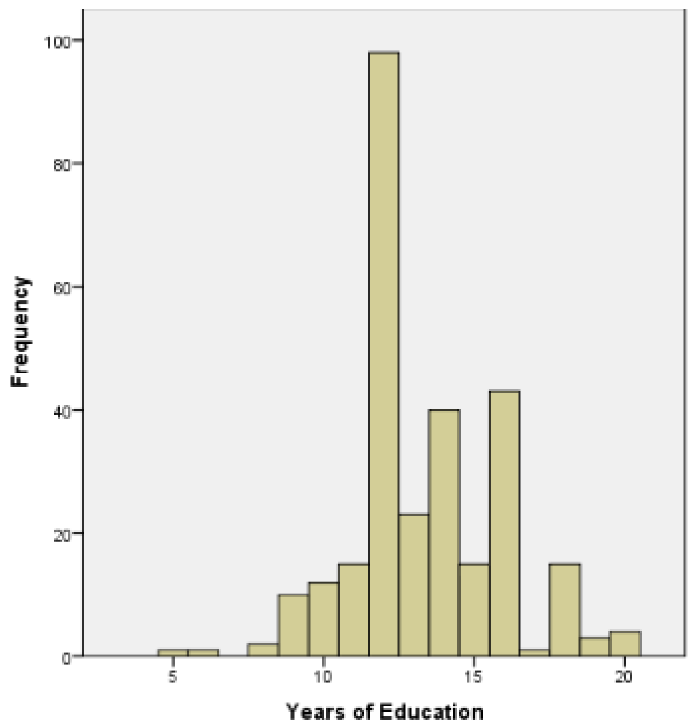


Figure 5. WAIS VCI distribution

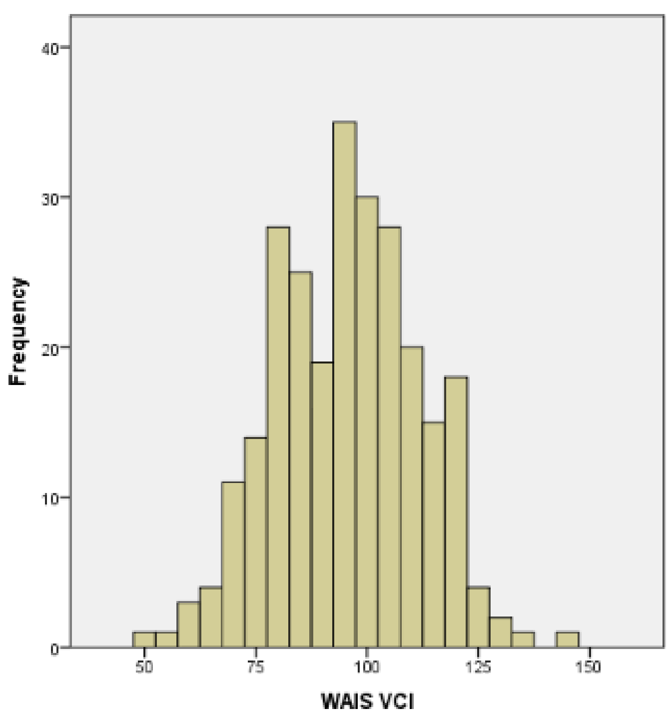
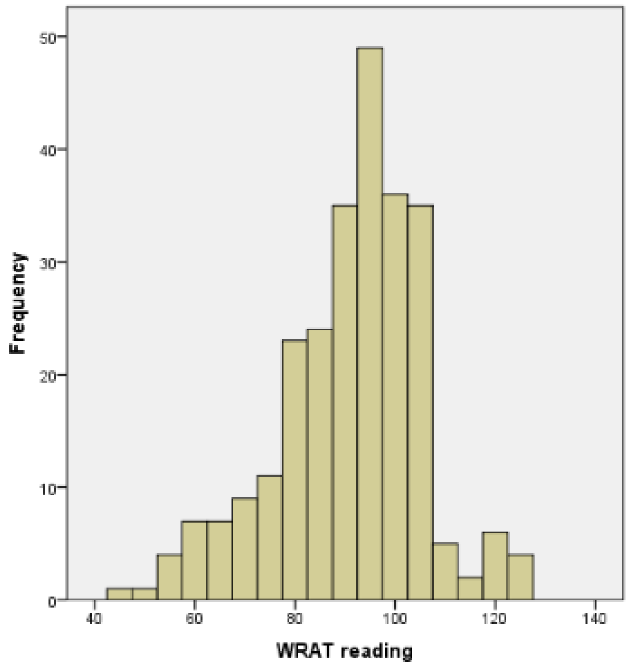


Figure 6. WRAT reading distribution



The sample was also primarily white and male. This is not surprising as this matches the racial/ethnic mix of the Indiana population and males are more likely to sustain brain injuries than females.[30] The high rate of psychiatric treatment in this sample is also not surprising as psychiatric comorbidities are found in the literature both prior and after head injury.[8-9] In addition, this sample had a low rate of prior military service (6%), and moderate rates of criminal history (23%), substance abuse (19%), and food stamps (24%).

In terms of injury related variables, the sample was over eight years post injury on average with time since injury ranging from 52 days to 53 years. However, this variable is positively skewed with 25 percent of the sample having a time since injury less than a year and a half. See Figure 7. Age at injury also varied with an average age of 32 years ranging from birth to 67 years. However, this variable was more uniform and no skewness was present in either direction. See Figure 8. The sample showed a mild to moderate disability level in terms of their ADLQ, SUNSU, and MPAI-4 subscales. More specifically, a 27 on the ADLQ is categorized as mild impairment,[33] The results of the SUNSU show that, on average, this sample was receiving 5.89 total services, yet they could identify 8.81 services they were unable to access resulting in a 33% discrepancy. In addition, all MPAI-4 subscales scored in the mild to moderate range.[49] Cognitively, the sample showed below average scores on measures of executive functions (WCST) and memory (CVLT).[37-38] On average, the patients felt moderate levels of support as indicated by the MSPSS.[35]

Figure 7. Time since injury

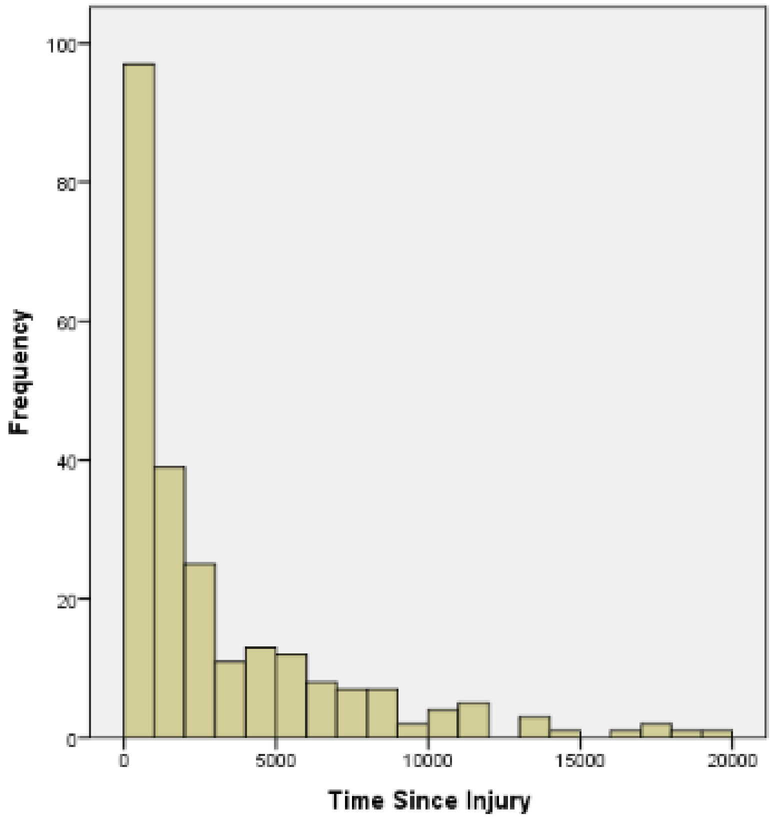
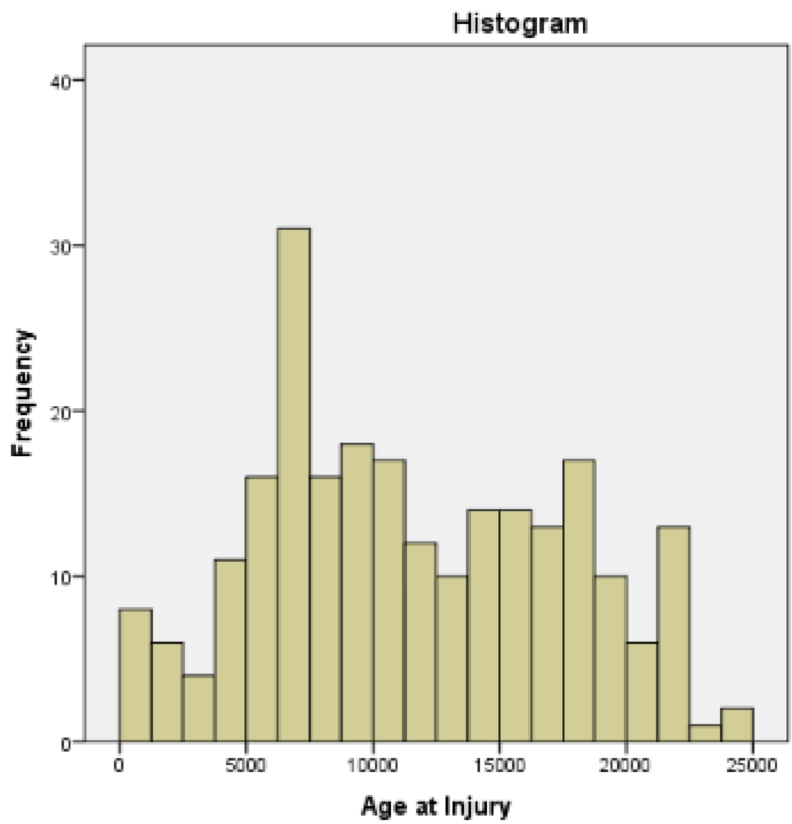


Figure 8. Age at injury



Type of injury was split into two categories, TBI and acquired brain injury (ABI). TBIs occur when an external force injures the brain (for example, car accident, fight, fall, or sports-related injury to the head) whereas an ABI is a brain injury from non-forceful source that still causes brain damage from lack of oxygen or bleeding on the brain. ABIs can be the result of strokes, chemotherapy, electrocution, ruptured aneurysms, etc. The sample consisted mostly of TBI, though 30 percent were ABI. Nearly 44 percent of the patients were independent with driving, 70 percent were employed prior to injury, and 20 percent were employed at enrollment. Since patients come into the program seeking help with returning to work, some enter the program with jobs to return to after they are released medically. Therefore, these patients are considered “employed” at enrollment as they are either on disability or their employer is holding their position for them. These patients still need resource facilitation in order to return successfully as the program provides brain injury education to the employer as well as co-workers and resource facilitators can help work with graduated work schedules and/or modifications to responsibilities. The majority of the sample reported having insurance and very few (less than two percent) were workers compensation cases.

4.2 Program Outcomes

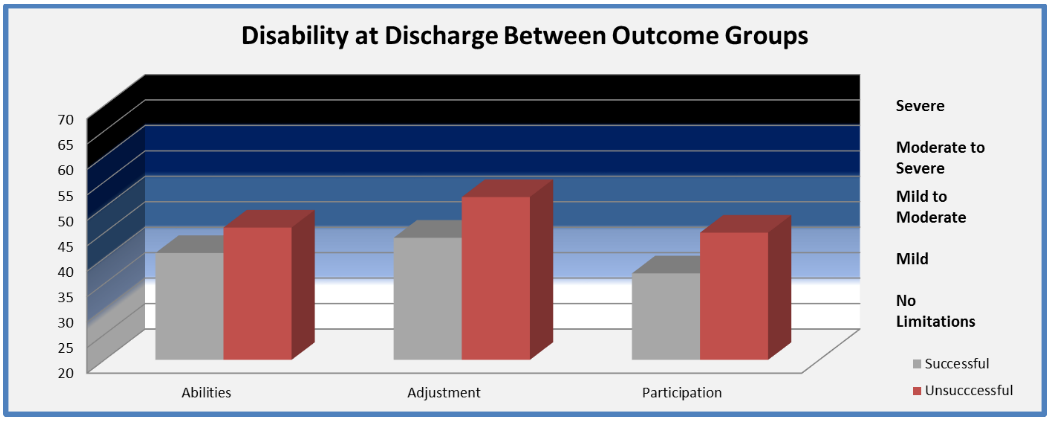
The resource facilitation program is designed to improve employment outcomes after brain injury. Therefore, the primary outcome measure of resource facilitation is a dichotomous variable indicating whether or not the patient was employed at discharge. Employment could be part-time or full-time, but did need to be a paid position, therefore excluding volunteer positions. Upon discharge, 165 of the 285 patients were employed resulting in a success rate of 58%. However, a secondary outcome of RF is level of disability. Therefore, the MPAI-4 is also collected at discharge as part of the program evaluation protocol. See table 6.

Table 6. MPAI-4 scores at discharge

	Total Sample *n=285*	*Successful* *n=165*	*Unsuccessful* *n=120*
MPAI-4 Total Score	38.64 (12.32)	34.84 (11.56)	43.88 (11.43)
MPAI-4 Participation	37.53 (9.39)	34.16 (9.02)	42.16 (7.80)
MPAI-4 Abilities	40.15 (12.05)	37.99 (11.47)	43.12 (12.24)
MPAI-4 Adjustment	44.67 (12.46)	41.32 (12.24)	49.27 (11.22)

As a whole, the sample at discharge scored in the mild disability range on participation and the total score. However, the sample scored in the mild to moderate range on the abilities and adjustment subscales. When looking at the sample by outcome, the successful group scored in the mild range on the total score as well as the participation and abilities subscales compared to the unsuccessful group scoring in the mild to moderate range on all subscales and the total. In fact, the successfully employed group showed significantly lower disability levels than the unsuccessful group on the MPAI-4 on all subscales as well as the total at discharge (abilities $t = -3.62$, $p=.000$; adjustment $t = -5.59$, $p=.000$; participation $t = -7.82$, $p = .000$; MPAI total $t = -6.549$, $p = .000$). See Figure 9.

Figure 9. MPAI-4 scores at discharge



Demographic and baseline injury related characteristics were also compared by outcome group. See table 7. Differences between groups were tested using independent samples t –tests for continuous variables and Chi-square/Fischer's exact tests were used for categorical variables. Significant differences were detected between age and WRAT reading scores. More specifically, the average age in the successful group was significantly lower than the average age in the unsuccessful group (t=-2.76; p = .006) and WRAT reading scores were significantly better in the successful group than the unsuccessful group (t=2.63; p = .009). In addition, a history of substance abuse was more likely in the non-employed group (X^2 = 8.92; p = .003). See table 8.

Table 7. Demographic variables split by outcome group

Demographics		
	Employed n = 165	Not Employed n = 120
	Mean (SD)	
Age	**37.49 (13.93)**	**41.82 (12.48)**
Years of Education*	13.48 (2.45)	13.16 (2.53)
WAIS VCI	96.82 (15.47)	93.69 (17.05)
WRAT Reading*	**93.17 (13.38)**	**88.5 (15.15)**
	Count (%)	
race		
American Indian or Alaskan Native	1 (0.61%)	0 (0.00%)
Asian	0 (0.00%)	0 (0.00%)
Black or African American	13 (7.88%)	17 (14.17%)
Hispanic or Latino	2 (1.21%)	2 (1.67%)
Native Hawaiian/Pacific Islander	0 (0.00%)	0 (0.00%)
White	146 (88.48%)	98 (81.67%)
unknown/not willing to answer	3 (1.82%)	3 (2.50%)
Gender		
Female	67 (40.61%)	40 (33.33%)
Male	98 (59.39%)	80 (66.67%)
History of Substance Abuse*		
Yes	**21 (12.73%)**	**32 (26.67%)**
No	**144 (87.27%)**	**88 (73.33%)**
History of Psychiatric Treatment		
Yes	88 (53.33%)	65 (54.17%)
No	77 (46.67%)	55 (45.83%)
Marital Status		
Married/Partnered	42 (25.45%)	26 (21.67%)
Single/Divorced/Widowed/Separated	120 (72.73%)	92 (76.67%)
Other/No response	3 (1.82%)	2 (1.67%)
History of Military Service		
Yes	12 (7.27%)	5 (4.17%)
No	153 (92.73%)	115 (95.83%)
Criminal History*		
Yes	**31 (18.79%)**	**34 (28.33%)**
No	**134 (81.21%)**	**86 (71.67%)**
Receiving Food Stamps		
Yes	33 (20.00%)	34 (28.33%)
No	132 (80.00%)	86 (71.67%)

Table 8. Injury related variables split by outcome group

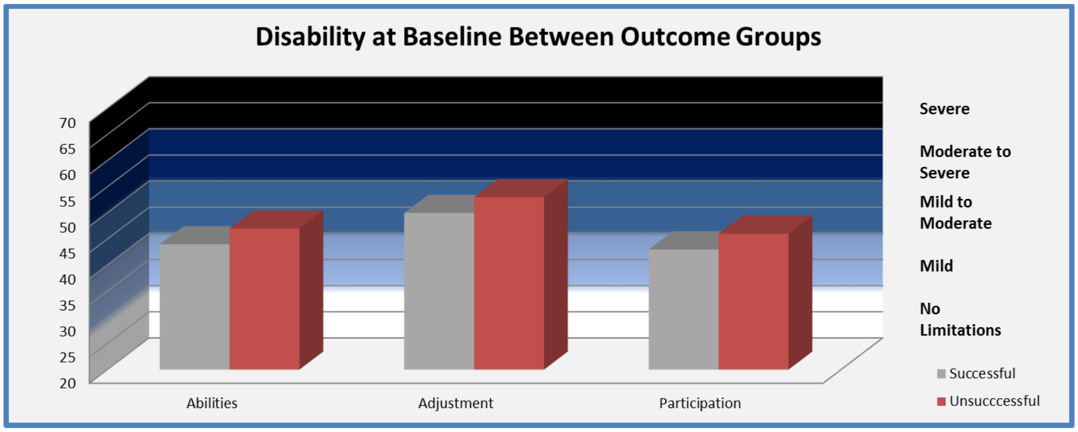
	Employed n = 165	Not Employed n = 120
	Mean (SD)	
ADLQ*	**23.54 (12.46)**	**31.22 (18.13)**
TSI (years)	9.07 (10.91)	7.87 (10.15)
Age at injury*	**28.83 (16.03)**	**35.17 (15.74)**
SUNSU (services currently using)	5359 (5.29)	6.23 (5.00)
SUNSU (services requested)*	**8.31 (4.03)**	**9.39 (4.59)**
MPAI Total*	**41.16 (8.18)**	**44.56 (7.28)**
MPAI Abilities*	**41.42 (8.65)**	**43.87 (8.23)**
MPAI Adjustment*	**47.22 (9.89)**	**50.10 (8.40)**
MPAI Participation*	**39.60 (8.23)**	**42.55 (6.90)**
WCST Set fails*	**.88 (1.19)**	**1.31 (1.30)**
CVLT LDFR	42.34 (12.52)	40.29 (13.10)
MSPSS	63.36 (17.52)	59.10 (18.00)
	Count (%)	
Type of Injury		
TBI	115 (69.70%)	82 (68.33%)
ABI	50 (30.30%)	38 (31.67%)
Transportation		
Independent Driver	77 (46.67%)	47 (39.17%)
Assisted (Public or Caregiver)	88 (53.33%)	73 (60.83%)
Employed Prior to injury		
Yes	111 (67.27%)	88 (73.33%)
No	54 (32.73%)	32 (26.67%)
Employed at enrollment*		
Yes	**44 (26.67%)**	**11 (9.17%)**
No	**121 (73.33%)**	**109 (90.83%)**
Medical Insurance		
Medicaid	63 (38.18%)	48 (40.00%)
Private/Other	73 (44.24%)	50 (41.67%)
No Insurance	29 (17.58%)	22 (18.33%)
Workers Compensation		
Yes	2 (1.21%)	1 (0.83%)
No	163 (98.79%)	119 (99.17%)

**indicates a statistically significant difference, p<.05*

To compare the race categories between the two outcome groups, race was coded as white versus non-white due to the small sample sizes in the other race categories. In addition, as mentioned in the literature review, employment outcome has been shown to be different when looking at white versus black or African American as well as comparing whites to a minority category combining other races. However, no significant differences were detected ($X^2 = 1.42$; $p = .234$).

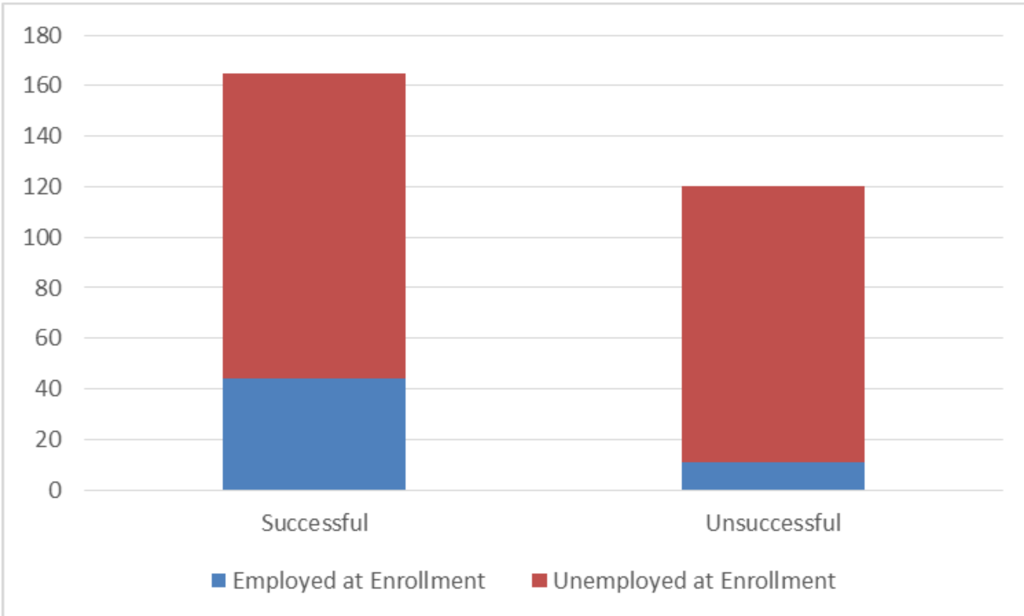
Injury characteristics between the successful and non-successful groups showed several significant differences between the groups. Age at injury was significantly lower in the successful group (t=-3.07. p=.002) as were the total number of set failures on the WCST (t = -2.77, p =.006). Looking at level of disability between the groups at baseline shows significantly lower impairment in activities of daily living (ADLQ) scores with the successful group showing a score of 23 compared to 31 in the unsuccessful group (t=-3.96; p = .000). Although this difference is significant, both groups were in the "no impairment to mild impairment" scoring range.[33] The total score on the MPAI-4 was significantly lower in the successful group (t = -3.53; p = .000) indicating lower levels of disability at baseline. This was the same with all three MPAI-4 subscales (abilities t = -2.34, p=.02; adjustment t = -2.52, p=.012; participation t = -3.12, p = .002). See figure 10.

Figure 10. Disability at baseline between outcome groups



Although both successful and unsuccessful patients at baseline reported a similar number of services currently received while completing the SUNSU, they did report different amounts of services they felt were not being met. The successful group indicated fewer unmet needs than the unsuccessful group (t=-2.04, p=.043). Finally, although employment at enrollment was relatively low for the overall sample (less than twenty percent), significantly different rates were found between the two outcome groups with the successful group having higher rates of employment at enrollment than the unsuccessful group (X^2=13.66, p=.000). See figure 11.

Figure 11. Employment rates at enrollment

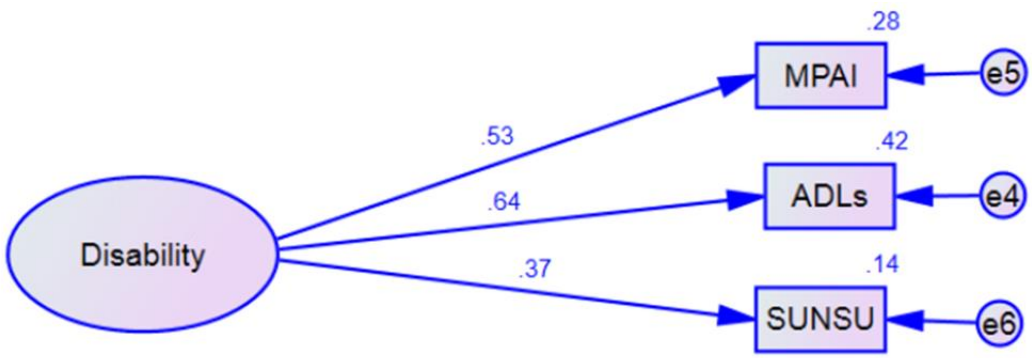


4. 3 Evaluation of the hypothesized model

Although not common in this dataset, missing data was investigated and corrected using maximum likelihood estimation. Only two variables contained any missing data, the MSPSS and the CVLT-II. Only two cases were missing MSPSS data and three cases were missing CVLT-II data. Prior to analyzing the full hypothesized model in figure 2, confirmatory factor analysis was run to check the accuracy of the hypothesized latent variables. The proposed latent variable, disability, consisted of MPAI-4 Total T score at baseline, activities of daily living measured by the ADLQ total score, and number of unmet needs reported on the SUNSU. See Figure 12.

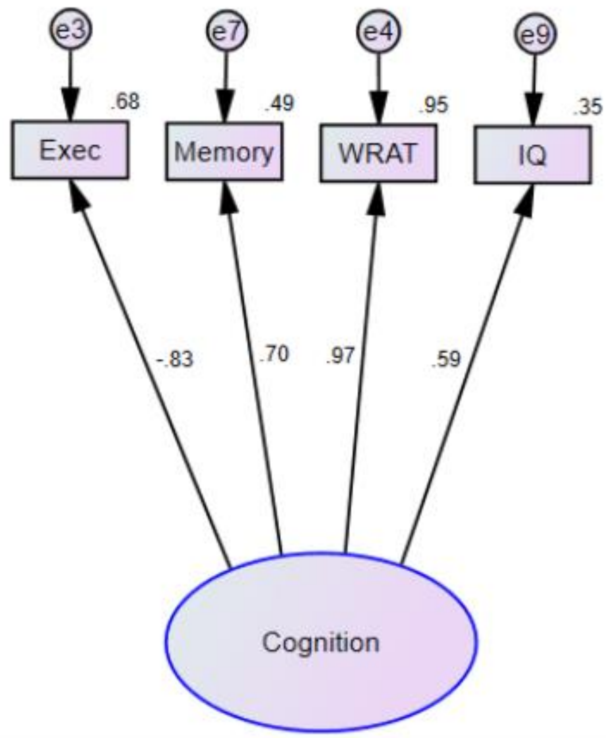
Overall, all variables fit well on the common factor, disability, with activities of daily living and the MPAI being the best indicators. In fact, the standardized regression weights are .64 and .53, respectively, with the SUNSU unmet needs resulting in a regression weight of .37. Additionally, level of disability explains 42% of the variance in activities of daily living, 28% of the variance in MPAI-4 Total Scores, and 14% of the variance in SUNSU unmet needs.

Figure 12. Confirmatory Factor Analysis for the disability latent variable



The second latent variable proposed was a cognitive factor which was hypothesized to include WCST to represent executive functions, CVLT to represent memory, and WRAT Reading and WAIS VCI to represent premorbid IQ. All variables loaded on the cognition factor well with the WRAT reading showing the highest regression weight at .97, followed by executive dysfunction at -.83 and CVLT at .70. Finally, the Verbal Comprehension Index on the WAIS resulted in a regression weight of .59, which although the lowest regression weight, was still a strong factor. Cognition explained 35 percent of the variance in VCI, 95% of the variance in WRAT reading scores, 49% of the variance in memory, and 68% of the variance in executive dysfunction. See figure 13.

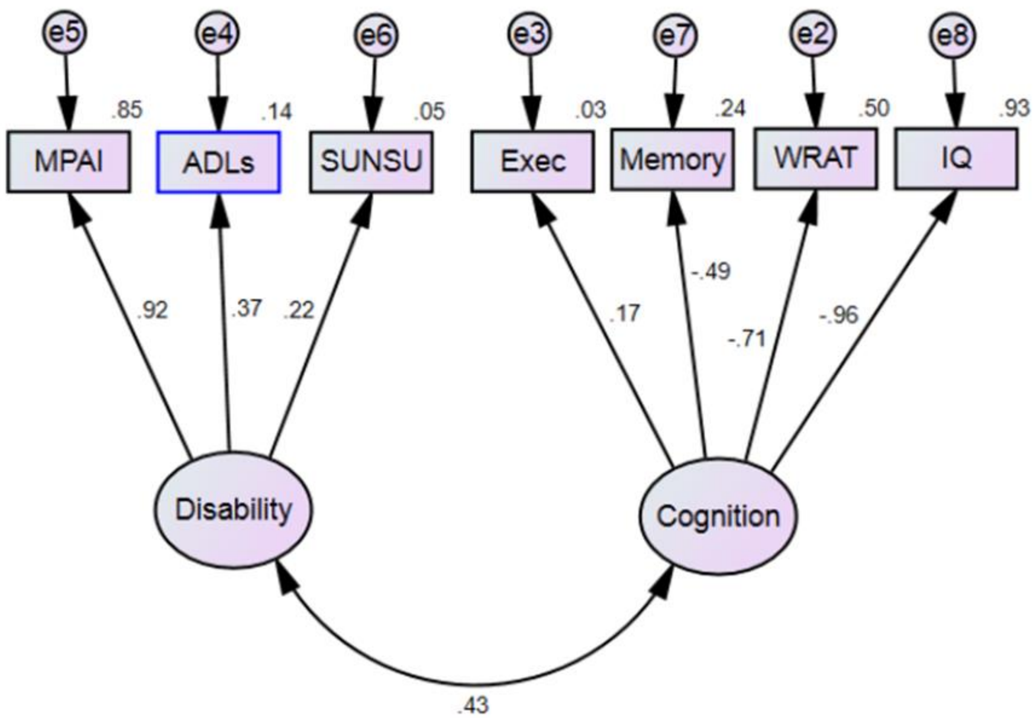
Figure 13. Confirmatory Factor Analysis for the cognition latent variable



Although the sample size was adequate for the model, analysis of the full hypothesized model in figure 2 led to an empirically under-identified model preventing any further analyses, parameter estimation, and production of model fit indices. The full hypothesized model contained 24 parameters (including variance estimates) and therefore required a minimum sample of 240 cases based on the recommendation of a parameter to case ratio of ten or more.[52-54] Considering the current sample size of 285, the under-identification is more likely due to multicollinearity.[52] Therefore, correlations between the predictor variables had to be investigated before further modification iterations could begin since correlations within the model could be indicative of repetitive information and spurious variables.[52] Repetitive information would occur if two predictor variables are highly correlated with each other and have a similar impact in terms of predicting the dependent variable. Spurious variables are variables showing a correlation because they have a common cause, not because they are actually related in a causal way. Correlation analyses would allow for identification of these potential relationships further allowing the stronger variable to be used in the next model iteration.

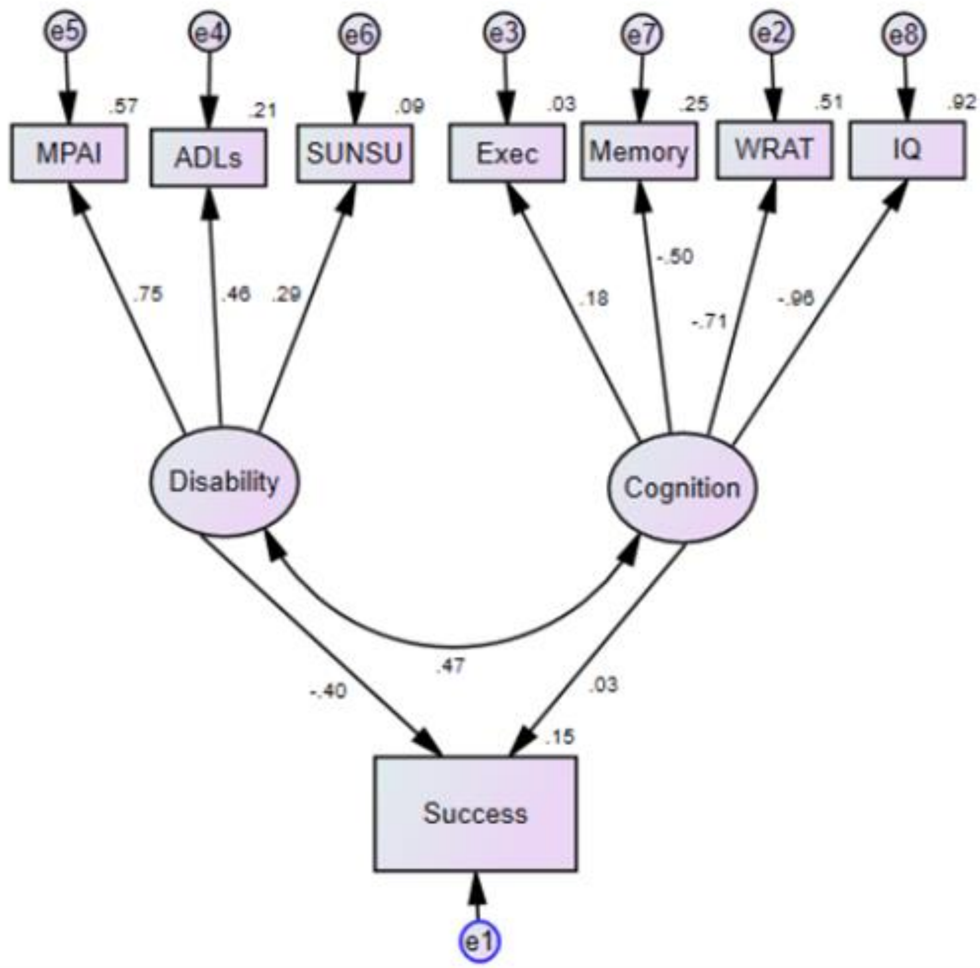
The first relationship investigated was the correlation between the two latent variables, disability and cognition with results showing a Pearson r of .43 indicating a significant correlation ($p=.018$). See figure 14. This likely means that the factors are not distinct factors.

Figure 14. Relationship between latent variables disability and cognition



Only one factor should be retained, or a single variable should be defined. To test those options, the dependent variable was added in order to determine the impact of each variable. Upon the addition of the dependent variable, it was apparent that while the CFA results were strong for both latent variables, both are not needed to explain success in this sample. While the disability factor resulted in an R-squared of -.40, the relationship between cognition and success was only .03. Due to the high correlation between the two factors, it can be assumed that the disability factor subsumed the cognition factor. See Figure 15.

Figure 15. Latent variables relating to outcome



In fact, upon removing the cognition factor, the model was no longer under identified and the parameters were estimated as well as the model fit statistics. However, the model was not a strong model for the data with a significant Chi-Square test indicating that the fit between the over identified model is worse than the fit between the just-identified model and data (X^2=25.73, p=.002). As a result, the CMIN/DF, a ratio of a Chi-square statistic comparing this model to the saturated model over the model degrees of freedom was equal to 2.86 which is above the recommended cut-off of two.[53] The normative fit index (NFI) and the Comparative Fit Index (CFI), .778 and .824, respectively, were below the recommended range which is above .90 or .95. Finally, the Root Mean Square Error of Approximation (RMSEA) was .081 which is indicative of below adequate fit (p>.05).[52]

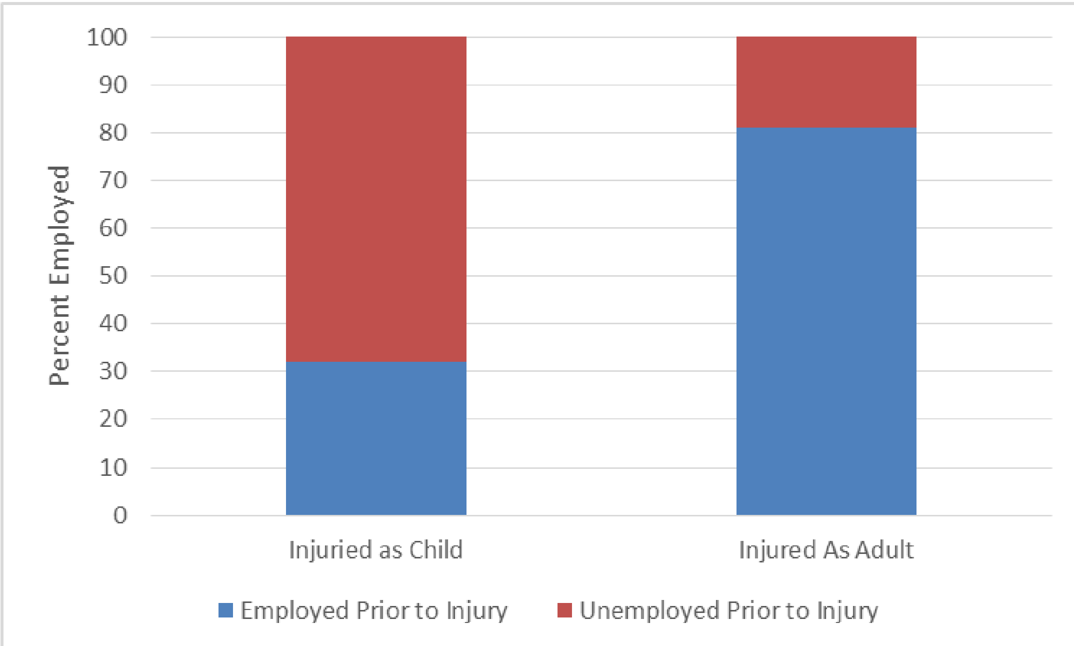
4.4 Post-hoc analyses

Due to the poor fitting model, further analyses were completed in order to understand the variability in employment outcome. Since the model was based on the current literature on return to work in brain injury, our sample was compared to the samples reported in the papers presented in the review of the literature. The primary difference between the current sample and the evidence driving the hypothesized model was the intervention. Most papers publish employment rates after brain injury regardless of intervention of specific rehabilitation programs. For example, the largest study reported results from TBIMS which includes over 7,000 patients who participated in inpatient brain injury rehabilitation and may or may not have participated in outpatient rehabilitation at all.[13]

An additional difference between this study and the published literature is the inclusion of ABI patients. Since the articles meeting quality criteria for the literature review only included TBI samples, the current sample may in fact be different from the published literature and may in fact have different predictors for outcome. However, when looking specifically at type of injury and outcome in this sample, a significant difference was not detected (X^2 =58.88, p=.000).

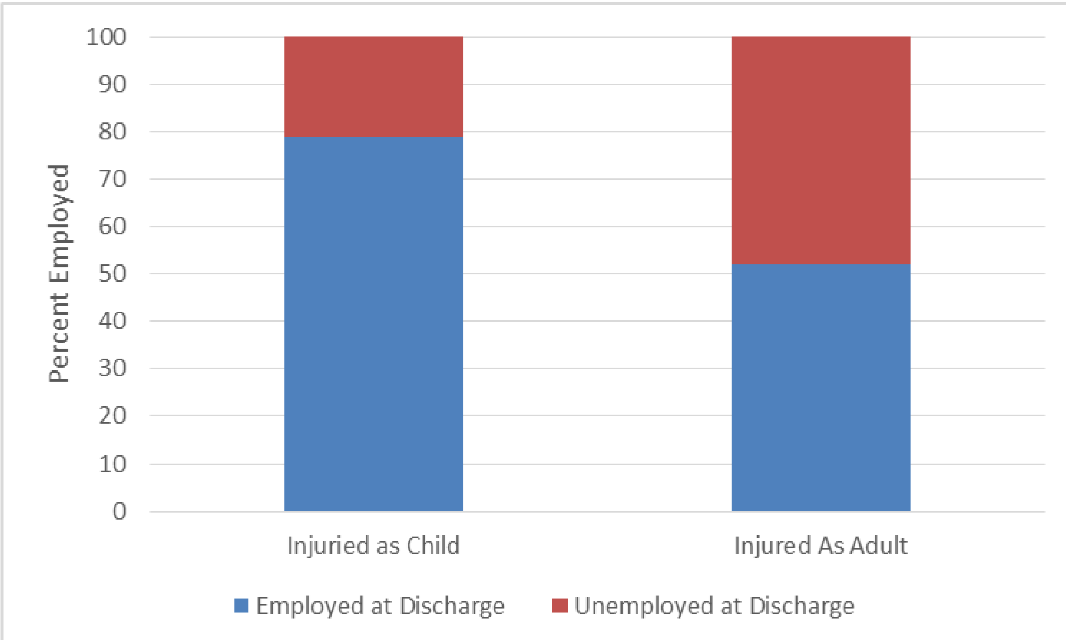
Finally, after consultation with clinicians in the resource facilitation program, it was hypothesized that patients who sustain a brain injury as an adult present differently than patients who sustained their brain injury as a child. In general, not just resource facilitation patients, but most TBI patients who sustain brain injuries as adults are seeking rehabilitation in order to return to their pre-injury level of participation in the community. Those injured as children and entering rehabilitation programs as adults are not wishing to return to their pre-injury participation, but rather gain participation in their community that they didn't have time to develop prior to their injury. In fact, comparing the rates of pre-injury employment between those injured prior to the age of 18 and those injured after 18 years of age shows that 32% of the child injury sample was employed prior to injury compared to 81% in the adult injury sample. See Figure 16. The difference in proportions between the two samples was statistically significant further indicating that one group seems to be working toward gaining employment for the first time while the other group is working toward returning to employment (X^2 =58.88, p=.000).

Figure 16. Percent employed by age at injury



Additionally, employment outcome after resource facilitation is significantly different between the two groups with the childhood injury group showing a 79% success rate compared to 52% in the adult injury group (X^2 =15.38, p=.000). See Figure 17.

Figure 17. Percent successfully employed at discharge by age at injury



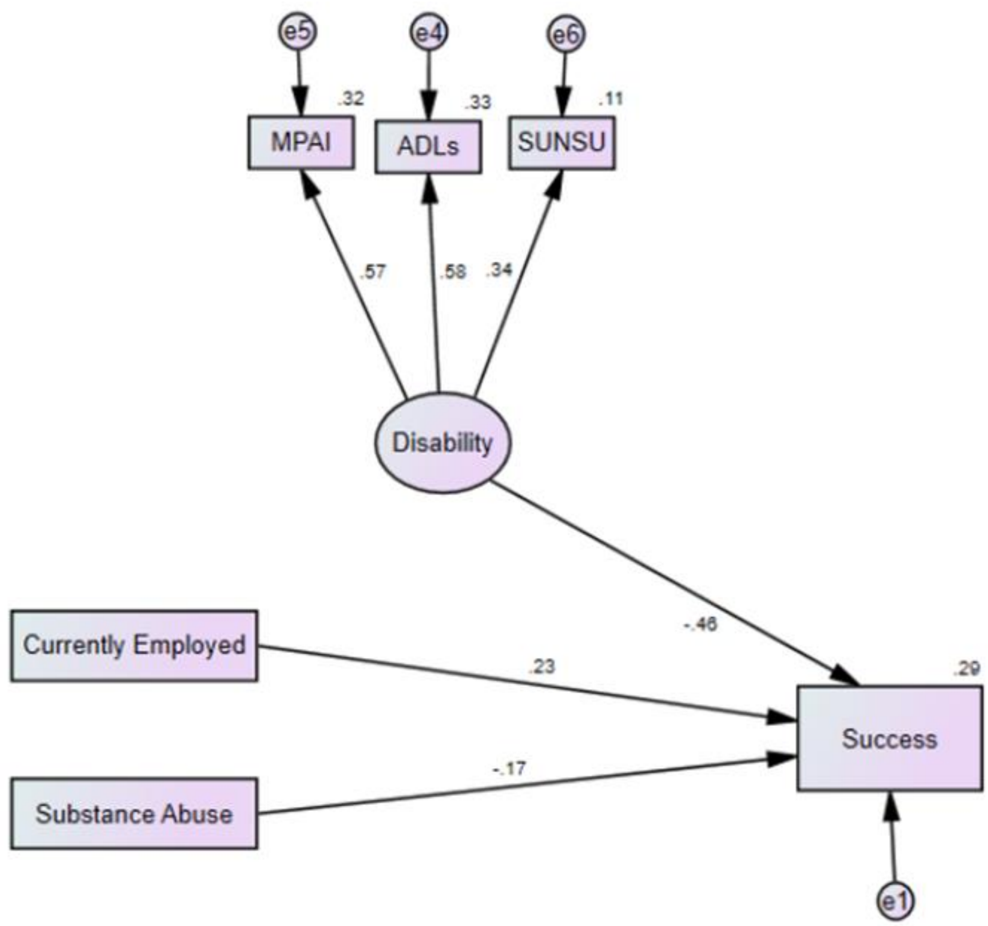
4.4.1 Post hoc models

As a result, post hoc analyses were completed to test the differences between the two samples and outcome. Post hoc modelling involved two different models, one for those injured prior to the age of 18 and one for those injured as an adult as different sets of predictor variables produced significant prediction models.

4.4.2 Predicting outcome for patients injured as an adult

Post hoc modelling resulted in a significant model predicting outcome for the 219 patients sustaining a brain injury after the age of 18. The final model consists of one latent variable representing overall disability and other exogenous variables including employment status at enrollment and history of substance abuse. See Figure 18. The overall model fit is supported significantly with several measures. First, the non-significant Chi-Square test indicates that the fit between this over-identified model and the data is not significantly worse than the fit between the saturated model and the data (X^2=10.02, p=.349) and the CMIN/DF is 1.11 meaning that important paths were not removed. Due to the reduced sample size in this cohort, the comparative fit index (CFI) was used instead of the Normed Fit Index to compare the model to the independence model resulting in a CFI of .985 which is above the recommended .95 cut-point for models demonstrating a good fit. Finally, the RMSEA was .023 showing good fit (p>.05).[53] Additionally, sample size was adequate for this model as the final model had ten total parameters (including the four variance estimates) and a sample size of 219 resulting in a case per parameter ratio of 21.9, which is well above the recommended ten indicating model stability.[54]

Figure 18. Final model predicting outcome for brain injury survivors injured as adults



Maximum likelihood Estimates resulted in significant relationships between all predictors and outcome and these direct effects are listed below in table 7. In addition, the resulting standardized coefficients show moderate to large effect sizes. A moderate effect size is defined as a standardized estimate between .1 and .25 whereas a large effect size is greater than .25.[53] The final model for the adult injury cohort does not contain any mediating variables nor correlations between predictors and therefore, no indirect effects on outcome need to be taken into account when interpreting the main effects.

Table 7. Standardized regression weights for adult injuries

	ESTIMATE	EFFECT SIZE
MPAI ← DISABILITY	.566	large
ADLQ ← DISABILITY	.577	large
SUNSU ← DISABILITY	.338	large
SUCCESS ← DISABILITY	-.460	large
SUCCESS ←CURRENTLY EMPLOYED	.226	moderate
SUCCESS ← SUBSTANCE ABUSE	-.171	moderate

4.4.3 Model validation for adult injuries

When predicting success for an incoming patient, patient variables can be entered into the logit equation derived from the unstandardized regression weights, intercepts, and squared multiple correlations calculated during the SEM procedure. See Table 8 for unstandardized weights and table 9 for Intercepts and Squared Multiple Correlations. Figure 19 shows the prediction equation.

Table 8. Unstandardized regression weights for adult injuries

	Estimate
MPAI ← Disability	1.00
ADLQ ← Disability	2.23
SUNSU ← Disability	.350
Success ← Disability	-.053
Success ←Currently Employed	.299
Success ← Substance Abuse	-.206

Table 9. Intercepts and squared multiple correlations for adult injuries

	Intercepts	*Squared Multiple Correlations*
MPAI	42.89	.321
ADLQ	27.98	.332
SUNSU	8.96	.114
Success	0.51	.292

Figure 19. Prediction equation for adult injury sample

$$\pi_i = P(Y_i = 1|X_i = x_i) = \frac{\exp(B_0 + B_1x_i + \cdots B_kx_i)}{1 + \exp(B_0 + B_1x_i + \cdots B_kx_i)}$$

$$\pi_i = \frac{\exp(.51 + .3(Employed) - .21\ (SubAbuseHx) - [0.053(disability)])}{1 + \exp(.51 + .3(Employed) - .21\ (SubAbuseHx) - [0.053(disability)])}$$

Where $disability = (MPAI - 43) + \frac{ADLQ-28}{2.23} + \frac{SUNSU-8.96}{0.35}$

Therefore the probability of an entering patient obtaining employment at the end of treatment can be computed by entering the patient's specific scores on baseline measures MPAI, ADLQ, and SUNSU into the equation as well as indicating whether they are currently employed and/or have a history of substance abuse. Some hypothetical scenarios are presented in table 12 below to show the applicability of the equation in a clinical setting.

Table 12. Hypothetical patients with adult injuries and their probability of success

	Probability
Patient A has a mild to moderate level of disability with an MPAI total T score of 42, an ADLQ of 28, and she reported 5 unmet needs on the SUNSU. She is not currently employed and does not have a history of substance abuse.	**76%**
Patient B has a moderate level of disability with an MPAI total T score of 45, ADLQ of 30, and reported 7 unmet needs. He is not currently employed and has a history of substance abuse.	**61%**
***Best Scenario:** Patient C has a mild level of disability with an MPAI total T score of 20, ADLQ of 25, and reported 3 unmet needs. He is currently employed and does not have a history of substance abuse.*	**95%**
***Worst Scenario:** Patient D has a severe level of disability with an MPAI total T score of 50, ADLQ of 34, and reports 9 unmet needs. She is not currently employed and has a history of substance abuse.*	**45%**

To validate the algorithm identified in figure 19, data from all patients injured as adults and discharged from resource facilitation in 2017 was collected and entered into the model to test the model's ability to fit the new data. The initial model was built on discharges through 2016, therefore this new test set is an independent sample of cases.

In 2017, 48 total patients injured as adults were discharged from resource facilitation. Overall, the sample replicated the training set described earlier on model variables. See Table 13 for key variables between the training and 2017 test dataset. No significant differences were detected between the two groups (p>.05).

Table 13. Comparison between the training and test adult injury datasets

	Mean (SD)	
	Training Data Set n=219	Test Dataset from 2017 n=48
MPAI-4 Total T score at baseline	42.85 (7.54)	43.23 (7.28)
ADLQ	27.91 (16.52)	30.35 (15.21)
SUNSU unmet needs	8.96 (4.44)	8.98 (4.21)
	Count (%)	
Employed at enrollment **Yes** **No**	 37 (16.9%) 182 (83.1%)	 4 (8.3%) 44 (91.7%)
Substance Abuse History **Yes** **No**	 47 (21.5%) 172 (78.5%)	 12 (25%) 36 (75%)
Employed at discharge **Yes** **No**	 114 (52%) 105 (48%)	 15 (31%) 33 (69%)

Upon testing the new data set in the established model, the overall model fit was sustained indicating a valid model (X^2=11.16, p=.265). The RMSEA was .07 showing adequate fit (p>.05).[53] However, the number of parameters in this model exceeds the recommended ten cases per parameter recommendation so results should be interpreted with caution.[54] Finally, the test data was entered into the equation to test the classification accuracy. See Table 14. Those who were not successful at discharge showed success probabilities ranging from 20 to 76% compared to a range of 40 to 90% in the successful group. This data leads to a potential assumption that patients scoring less than 40% can be considered “high-risk” and those scoring above 76% can be considered “low-risk.”

Table 14. Test sample validation results for the adult injury model

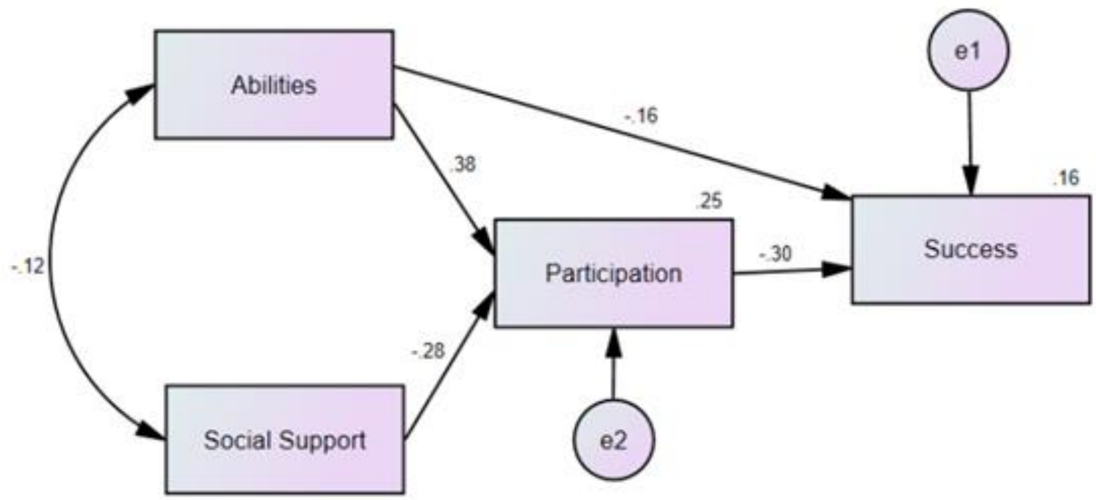
MPAI	ADLQ	SUNSU	Employed at Admission?	History of Substance Abuse?	Probability of success	Employment outcome
44	36	20	No	No	20%	**No**
46	28	20	No	No	21%	**No**
47	62	14	No	No	22%	**No**
43	56	14	No	Yes	24%	**No**
49	48	14	No	No	26%	**No**
47	41	14	No	No	32%	**No**
44	37	14	No	No	37%	**No**
44	35	14	No	No	38%	**No**
60	45	7	No	No	38%	**No**
40	18	16	No	Yes	41%	**No**
46	39	12	No	No	41%	**No**
41	51	8	No	No	55%	**No**
49	28	9	No	No	55%	**No**
65	15	4	No	Yes	55%	**No**
47	49	6	No	No	56%	**No**
43	42	8	No	No	58%	**No**
49	35	7	No	No	58%	**No**
37	28	12	No	No	59%	**No**
45	28	9	No	No	60%	**No**
41	28	10	No	No	61%	**No**
45	43	5	No	Yes	61%	**No**
43	28	9	No	No	62%	**No**
43	21	10	No	No	63%	**No**
40	35	7	No	Yes	64%	**No**
41	43	6	No	No	67%	**No**
37	26	9	No	No	70%	**No**
43	35	5	No	No	72%	**No**
34	14	10	No	Yes	72%	**No**
43	13	9	Yes	Yes	72%	**No**
46	35	4	No	No	72%	**No**
43	35	4	No	No	75%	**No**
39	25	7	No	No	75%	**No**
53	10	4	No	No	76%	**No**
53	51	8	No	No	40%	**Yes**
43	19	13	Yes	Yes	55%	**Yes**
43	28	9	No	No	62%	**Yes**
49	51	5	Yes	No	63%	**Yes**
43	28	8	No	No	66%	**Yes**
41	27	8	No	No	69%	**Yes**

32	15	11	No	Yes	71%	**Yes**
43	7	7	No	Yes	75%	**Yes**
39	17	8	No	No	76%	**Yes**
37	10	7	No	Yes	79%	**Yes**
37	15	7	No	No	81%	**Yes**
39	15	4	No	No	86%	**Yes**
37	18	6	Yes	No	86%	**Yes**
28	6	6	No	Yes	89%	**Yes**
32	19	3	No	No	90%	**Yes**

4.4.4 Predicting outcome for patients injured as children

When looking at the portion of the sample with childhood injuries, fewer parameters could be estimated as the sample was relatively small (n=66). However, the final model consisted of two correlated exogenous variables, MPAI-4 Abilities Index and Perceived Social Support (MSPSS), as well as a mediating endogenous variable, MPAI-4 Participation Index at discharge. See Figure 20. This model proposes that baseline scores on abilities and perceived social support predict discharge participation levels which in turn predicts employment outcome. Despite the small sample size, the overall model fit was supported significantly with several measures. First, the non-significant Chi-Square test indicates that the fit between this over-identified model and the data is not significantly worse than the fit between the saturated model and the data (X^2=1.47,p=.226) and the CMIN/DF is 1.47 meaning that important paths were not removed. Due to the reduced sample size in this cohort, the comparative fit index (CFI) was used instead of the Normed Fit Index to compare the model to the independence model resulting in a CFI of .983 which is above the recommended .95 cut-point for models demonstrating a good fit. Finally, the RMSEA was .075 indicating adequate fit (p>.05).[53] However, model stability is questionable as the sample size produced a case per parameter ratio of 9.43 which is slightly below the recommendation of ten.[54]

Figure 20. Final model predicting outcome for brain injury survivors injured as children



Maximum likelihood Estimates resulted in significant parameters for all predictors and the direct, indirect, and total effects are listed below in table 15. In addition, the resulting direct effects show moderate to large effect sizes. See Table 16 for unstandardized weights and table 17 for intercepts and squared multiple correlations.

Table 15. Standardized direct, indirect, and total effects for patients injured as children

	Direct Effect	*Indirect Effect*	*Total Effect*	*Effect Size*
Participation ← Abilities	.382	----	.382	large
Participation ← MSPSS	-.284	----	-.284	large
Success ← Participation	-.300	----	-.300	large
Success ← Abilities	-.164	-.115	-0.279	large
Success ← MSPSS	----	.085	.085	small

4.4.5 Model validation for childhood injuries

Predicting success for incoming patients in this cohort is different than the adult injury model in two ways. Primarily, there is not a latent variable in the model. In addition, two dependent variables need to be estimated upon admission, MPAI-4 Participation Index scores at discharge as well as the probability of success. Therefore, baseline MSPSS and MPAI-4 Abilities Index scores need to be entered in a linear equation to estimate discharge Participation scores allowing for the ultimate logit model to contain both this participation estimate and the baseline ratings for MSPSS and Abilities. See Figure 21.

Table 16. Unstandardized regression weights for childhood injuries

	Direct Effect	*Indirect Effect*	*Total Effect*
Participation ← Abilities	.336	----	.336
Participation ← MSPSS	-.145	----	-.145
Success ← Participation	-.013	----	-.130
Success ← Abilities	-.006	-.004	-.010
Success ← MSPSS	----	.002	.002

Table 17. Intercepts and squared multiple correlations

	Intercepts	*Squared Multiple Correlations*
Participation	32.27	.253
Success	1.54	.158

Figure 21. Prediction equation for childhood injury sample

$$\pi_i = P(Y_i = 1|X_i = x_i) = \frac{\exp(B_0 + B_1x_i + \cdots B_kx_i)}{1 + \exp(B_0 + B_1x_i + \cdots B_kx_i)}$$

$$\pi_i = \frac{\exp(1.54 - .36(Abilities) - .013([Participation]))}{1 + \exp(1.54 - .36(Abilities) - .013([Participation]))}$$

Where $Participation = 32.27 + .336\ (Abilities) - .145(MSPSS)$

Therefore the probability of an entering patient obtaining employment at the end of treatment can be computed by entering the patient's specific scores on baseline measures of MPAI-4 Abilities Index and the MSPSS. This model will then estimate participation index discharge scores as well as the probability of obtaining employment. Some hypothetical scenarios are presented in table 18 below to show the clinical applicability of the derived equation.

Table 18. Hypothetical patients with childhood injuries and their probability of success

	Estimated Participation Index at Discharge	**Probability of Obtaining Employment**
Patient A has a mild to moderate level of disability on the abilities subscale of the MPAI with a T score of 42 and an average perception of social support resulting in an MSPSS score of 61.	37.54	69%
Patient B has a severe level of disability upon admission and has an abilities score of 62. He also has a low perceived level of social support resulting in a score of 12 on the MSPSS.	51.36	62%

Results from the hypothetical scenarios highlight a potential weakness of this model. Since the participants in this equation had such a high employment rate (79%), predicting low success rates is not reliable. Ultimately, a larger sample with a higher number of unsuccessfully closed cases is needed to improve the parameter defining the relationship between participation and employment outcome.

Another solution is using a bootstrap approximation to estimate a 95% confidence interval for the parameter. Bootstrapping is a methodology used for estimating standard errors further allowing for confidence intervals to be applied to parameters. This method resulted in a 95% confidence interval of [-.005, -.026] (p=.002) indicating that the true parameter value is estimated to be between -.005 and .026. As a result, the hypothetical scenarios in table 18 are replicated in table 19 below now showing the estimated ranges for probability of success.

Table 19. Bootstrap corrected hypothetical scenarios for childhood injuries

	Estimated Participation Index at Discharge	Probability of Obtaining Employment
Patient A has a mild to moderate level of disability on the abilities subscale of the MPAI with a T score of 42 and an average perception of social support resulting in an MSPSS score of 61.	37.54	58% to 75%
Patient B has a severe level of disability upon admission and has an abilities score of 62. He also has a low perceived level of social support resulting in a score of 12 on the MSPSS.	51.36	46% to 71%

To validate the algorithm identified in figure 21, data from all patients injured as children and discharged from resource facilitation in 2017 was collected and entered into the model to test the model's ability to fit the new data. The initial model was built on discharges through 2016, therefore this new test set is an independent sample of cases.

In 2017, only 15 total patients who were injured as children were discharged from resource facilitation. Therefore results should be interpreted cautiously. Overall, the sample replicated the training set described earlier on model variables. See Table 20 for key variables between the training and 2017 test dataset for those with injuries prior to the age of 18. No significant differences were detected between the two groups (p>.05).

Table 20. Comparison between the training and test childhood injury datasets

	Mean (SD)	
	Training Data Set n=65	Test Dataset from 2017 n=15
MPAI-4 Abilities at baseline	41.68 (10.76)	40.80 (10.07)
MSPSS	61.78 (17.38)	62.53 (19.58)
MPAI-4 Participation at discharge	37.32 (9.47)	40.40 (8.54)
	Count (%)	
Employed at discharge		
Yes	51 (78.5%)	9 (60%)
No	14 (21.5%)	6 (40%)

Bootstrapping methods were used to test the model fit in the test sample due to the limited sample size. Upon testing the new data set in the established model, the overall model fit was sustained indicating a valid model (X^2=.802, p=.371) despite the sample size. The RMSEA was .000 showing good fit (p>.05).[53]

To further investigate the test sample's fit to the model, all MPAI-4 Abilities and MSPSS scores were entered into the equation and the equation results were compared to the actual outcomes. See table 21. This table shows estimation errors (residuals) ranging from zero to ten points on the MPAI-4 Participation Index with an average difference of 5.3 points with a standard deviation of 3.43. The probabilities produced range from 51 to 78 percent suggesting that it would be difficult for a patient to enter the program and receive less than a fifty percent chance of obtaining employment. Considering the high overall success rate in this sample, this implies that all patients entering resource facilitation with a childhood injury have a strong chance of obtaining employment. Therefore, in order to identify higher risk patients in this sample, it is important to interpret their probability of success on a different scale than the typical zero to 100 scale assigned to percentages. It is recommended that clinicians compare the patient's percentage to the percentage of success in that group. For example, probabilities calculated for patients in this cohort should be compared to 78 percent. In other words, the closer the patient's probability is to 78, the more likely they will be successful. In this cohort, a patient with a probability of success equal to 66% is well below the sample's success rate and therefore should be considered "high-risk." However, determining where to apply cut-offs for specific risk categories will require a larger sample and further validation of the model.

Table 21. Test sample validation results for the childhood injury model

Abilities actual score	MSPSS actual score	Predicted Discharge Participation Score	Actual Participation Score at discharge	Residual	Probability of Success bootstrap range	Probability non-bootstrap	Actual Employment Outcome
21	54	32	25	-7	64-78%	73%	Yes
35	74	33	25	-8	61-76%	71%	Yes
25	82	34	34	0	62-77%	73%	Yes
45	84	35	34	-1	59-75%	69%	Yes
31	52	35	37	2	61-76%	71%	Yes
39	84	33	37	4	61-76%	71%	Yes
31	54	35	41	6	61-76%	71%	No
52	75	39	41	2	55-74%	67%	Yes
45	48	40	42	2	55-74%	68%	Yes
42	79	35	43	8	59-75%	70%	Yes
48	66	39	46	7	56-74%	68%	No
50	70	39	48	9	56-74%	68%	No
47	57	40	50	10	56-74%	68%	No
47	10	47	50	3	51-74%	66%	No
54	49	43	53	10	52-73%	66%	No

Chapter V

DISCUSSION

5.1 Interpretation of main findings

Several conclusions can be drawn from the work completed within this project. Primarily, it can be concluded that the resource facilitation sample in this clinic does not match the samples cited in the available literature. Many of the variables in the published literature that show strong predictive power with employment outcome, failed to show a relationship with employment outcome in this sample. For example, gender, race, age, years of education, marital status, and payer source were all significant predictors in the literature and none of these variables were significant in this sample. In addition, the one study from the literature review that looked at level of disability failed to show a significant relationship with outcome, while this study found level of disability to be a critical predictor. This could be due to the difference in samples themselves, the inability to accurately and consistently predict outcome in this population, or the RF intervention. Perhaps the intervention's success lies in the ability to address the barriers unique to gender, race, age, years of education, marital status, and payer source.

Another conclusion from this study is that modeling outcome after brain injury should be a thorough process and all potential variables should be considered. For example, many significant univariate results were found prior to modeling. However, upon entering multiple variables into the model, it was apparent that some variables subsumed others. For example, although the cognitive factor and disability factor both independently predicted outcome, when they were entered together, the disability factor explained most of the variance in outcome and the cognitive factor was entirely subsumed.

Perhaps the most significant finding from this project is the difference between those injured before the age of 18 and those injured after the age of 18. Not only is this particular data point critical for predicting outcome, but it also determines the other variables required to predict outcome. Although different prediction models exist in the literature for children with brain injury and adults with brain injury, this is the first paper to propose two entirely different prediction models for adults depending on when their injury occurred.

These findings suggest that brain injury patients can react to rehabilitation differently depending on when their injury occurred. More specifically, showing that patients injured at a younger age are different than those injured as adults. When a child sustains a brain injury and lives with the associated consequences into adulthood, their journey to employment is different than a patient who sustains a brain injury as an adult. Adult brain injury patients seek rehabilitation to return to the productive life they had prior to their injury whereas childhood brain injury patients do not have a “pre-injury productive lifestyle” in which to return. Interestingly, it was possible to model outcome for the adult injury sample using employment as the only dependent variable. However, it was not possible to model outcome for the childhood injury sample without including post-treatment productivity (MPAI Participation Index) as a mediating factor. Therefore, it appears that the RF intervention provides patients with childhood injuries an opportunity to be productive and participate in the community, which in turn, leads to better employability for these patients.

5.2 Interpretation of significant adult injury model

The adult injury model shows that level of disability is the largest predictor of outcome for patients sustaining brain injuries after the age of 18. The model shows that in addition to level of disability, if a patient enters the program employed, they are more likely to be employed at discharge. Although this finding is not surprising, it is important clinically. A patient is considered employed at admission if they are on disability, worker's comp, or working in a position that they do not feel is a match with their potential. In order to be considered a "success" in this program, they have to successfully return to the position if on disability/worker's comp, or obtain a different position that meets the goals set during intake. Finally, patients with a history of substance abuse were less likely to return to work. This variable was interesting in that it directly predicted outcome. Regardless of the level of disability or current employment, patients with a history of substance abuse are expected to have a lower probability of success. This variable is important because it is an area to look for clinical intervention leading to additional questions in terms of the cause. For example, "What about these substance abuse patients makes them less employable? Would it be beneficial for RF to require substance abuse treatment prior to enrollment in RF?"

5.3 Interpretation of significant childhood injury model

Predicting outcome for those injured as children is a more dynamic model with results suggesting that RF impacts participation, which in turn predicts outcome. In addition, patients at baseline displaying lower levels of perceived social support have higher levels of disability and are also less participatory in their community (including work and social engagement). Through RF, it appears they gain increased social support (potentially due to engagement with the resource facilitator, Vocational Rehabilitation Counselor). RF also helps to increase their involvement in social activities through referral to mental health services, brain injury support group, family education, etc. As a result, becoming more participatory in their community and increased social engagement makes them more likely to experience a positive outcome, including employment.

Although the model is significant, there are a few caveats. First, the training and test data sets were very small. A model resulting from such a small data set should be interpreted cautiously. In addition, the algorithm derived from the model is not able to predict low probabilities of success. Since the model was based on a sample with a high success rate, the model is not able to predict failure reliably. Finally, the model estimates two dependent variables. If the model incorrectly estimates participation at discharge, it will no longer be an accurate predictor for employment outcome. Unlike the first model, this mediating relationship in this particular model allows for additional error when predicting outcome.

Chapter VI

CONCLUSION

6.1 Limitations

Results of this study provided two equations for estimating outcome after participation in the resource facilitation program as well as a better understanding of the resource facilitation population. The equations were built into the clinic's electronic database and now, upon admission to the program, staff are able to see the probability of success for each client. However, several limitations should be taken into account.

Although the final models presented showed great model fit on all statistical tests, the results should be interpreted with caution. Primarily, the statistically significant models were fit to the dataset specifically therefore risking the generalizability of the models. The validation method used was a strategic choice based on programmatic changes, instead of the traditional k-fold cross-validation. Recent programmatic changes occurring January 2017 led to the decision to exclude those patients from the modeling. However, it was decided that the 2017 sample would be used to validate the models and test the generalizability. In addition, the sample size for the childhood injury test data set is below the recommended minimum of ten subjects per parameter.

6.2 Future directions

Primarily, data should be collected over the next several years to continue to validate and refine the models. Data should be collected on the probability of success estimated at baseline and the actual outcome for each patient discharging the RF program. This data should be collected so that the percentages from the prediction models can be calibrated into categories based on risk.

In addition, it was discovered during this project that patients sustaining brain injuries as children may not need rehabilitation in the traditional sense. Rehabilitation implies that they are striving to return to a former level of functioning. Instead, these patients need to "habilitate," or work toward a new level of functioning they have not experienced before. Although RF patients in this sample show great improvements in community participation, further work investigating this relationship is needed, especially comparing those needing rehabilitation to those needing "habilitation."

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