Physical and Mental Health Status of Adults with Serious Mental Illness Participating in a Jail Diversion Intervention

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Physical and Mental Health Status of Adults with Serious Mental Illness Participating in a Jail Diversion Intervention

by

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy
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Keywords: Comorbidity, Criminal Justice, Missing Data, Longitudinal, Biopsychosocial

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DEDICATION

This dissertation is dedicated to a very important role model in my life, my step-father Frank. You played a huge part in my success and I miss you every day.
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This research would not have been possible without the support of many people. First, I would like to thank the incredible group of people who work in Miami-Dade with the 11th Judicial Criminal Mental Health Project. Without their support and steadfast dedication to improving behavioral health services this research would not have been possible. Second, I would like to thank my co-chairs, Drs. Bruce Lubotsky Levin and Julie Baldwin, who have mentored me and provided with guidance and encouragement throughout my graduate program. I also want to thank Drs. Sarah Desmarais and Richard Van Dorn who were instrumental in encouraging my love of statistics, and included me as part of an amazing project. They also were unwavering in their support and encouragement. Additionally, I would like to thank my fellow cohort for allowing me to ask ridiculous questions and always standing by me.

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ABSTRACT

Adults with mental illnesses are at an increased risk to be diagnosed with one or more comorbid physical illnesses compared to the general population. Much of the disparities faced by adults with serious mental illnesses (SMI) can be attributed to medication side effects, increased risk for metabolic diseases, inability to communicate about severity and monitor physical health symptoms, poor health behaviors, high rates of smoking, and poor quality health care. The rate of physical illnesses for adults with mental illnesses are even higher among those who have been involved with the criminal justice system. In order to understand the relationship between physical and mental illnesses, longitudinal study designs are needed. Longitudinal studies can provide greater understanding of the temporal relationship of physical and mental illnesses. Despite the benefits of longitudinal studies, there also are challenges, including missing data.

The first manuscript of this dissertation explores the physical and mental health status of adults with mental illnesses. Secondary data were used from three different studies: a sample of adults with SMI enrolled in a mental health court jail diversion program ($n=91$); a sample of Medicaid enrollees with SMI in Florida ($n=688$) who were part of a larger Substance Abuse and Mental Health Services Administration (SAMHSA) study; and a sample of inpatient and outpatient adults with SMI from five different study sites ($n=969$). The samples were combined into two data sets, consisting of the jail diversion sample and the SAMHSA sample, and the jail diversion sample and the 5-site sample. Participants in these samples answered questions on the Short-Form Health Survey (SF-12), recent arrests, drug and alcohol use, socio-demographic...
information, and mental illness symptom severity (measured only in the criminal justice and 5-site samples).

Overall, the mental and physical health status scores were significantly lower for all of the participants compared to the general population mean scores. The participants reporting a recent arrest had a higher physical health score compared to those who did not have a recent arrest, and in the jail diversion and 5-site sample, had a lower mental health status score than those without a recent arrest. After taking age, drug and alcohol use, and psychiatric symptom severity into account, arrest was no longer associated with the physical health status score in either of the data sets. In the jail diversion and 5-site data set, arrest was still significantly associated with mental health status score after controlling for age, drug and alcohol use, and psychiatric symptom severity.

The second manuscript of this dissertation explores the analysis of missing data in a longitudinal study to determine the missing data mechanisms and missing data patterns, and subsequently, how to prepare the data for analysis by using multiple imputation or maximum likelihood estimation. Secondary data were drawn from the same jail diversion sample as in the first manuscript. Data were collected at baseline, three months, six months, and nine months. Only participants with the potential to have data collected at these time points were included (n=50).

Analysis revealed missing data due to missing item-level information, missing participant data at one time point but complete data at a subsequent time point, and missing participant data for those who dropped out of the study completely. The missing data mechanism for the missing item-level data were missing completely at random, whereas the participant-level missing data were missing at random. Multiple imputation was used for the item-level data and for the
participant-level missing data. Maximum likelihood estimation was also used for the participant-level missing data and compared to the multiple imputation results. Findings suggest that multiple imputation produced more accurate parameter estimates, possibly due to the small sample size.

The findings from this study indicate that more research needs to be done to fully understand the physical illnesses experienced by adults with mental illnesses who are involved with the criminal justice system. Understanding mental and physical illness comorbidity is important in public health as it dictates appropriate treatments and training for behavioral health practitioners and staff. In addition, missing data in longitudinal studies cannot be ignored, as it can bias the results, and appropriate techniques for exploring the missing data must be used. When missing data is ignored in analyses, the subsequent results can be incorrect and unable to detect treatment effects, thereby preventing effective programs from receiving necessary funding. In addition, ignoring missing data can impact funding for behavioral health services by underestimating the prevalence and severity of mental illnesses. Future research should focus on exploring how mental and physical health are related in adults with a recent arrest compared to the general population, and ways to integrate services to address both mental and physical health.
SECTION 1: INTRODUCTION

Purpose of the Study

Serious mental illness (SMI) refers to a diagnosis of at least one major mood disorder or psychotic disorder that significantly impairs a person’s ability to function (Kessler et al., 2001). Adults with SMI have increased health disparities and frequently lack appropriate mental health care (Appelbaum & Swanson, 2010; Chwastiak et al., 2006; Constantine, Petrila, et al., 2010; Harris & Edlund, 2005; D. R. Jones et al., 2004; Kessler et al., 2001; Leung, Xiong, Leamon, McCarron, & Hales, 2010; Steadman, Osher, Robbins, Case, & Steven, 2009; J. A. Swartz & Lurigio, 2007; Van Dorn, Volavka, & Johnson, 2012; Van Dorn et al., 2010). They also are more likely to have contact with the criminal justice system and to be the victims and perpetrators of violence compared to adults without SMI (Teplin, McClelland, Abram, & Weiner, 2005; Van Dorn et al., 2012).

Though in recent years there has been a major focus on reducing recidivism and improving mental health for justice-involved adults with SMI, they continue to experience physical illnesses at rates higher than the general population (Bushe, Haddad, Peveler, & Pendlebury, 2005; Chwastiak et al., 2006; Druss, Zhao, Von Esenwein, Morrato, & Marcus, 2011; Leung et al., 2010; Lord, Malone, & Mitchell, 2010; Manderscheid, 2010; Oud & Meyboom-de Jong, 2009; Sherman et al., 2013; Viron & Stern, 2010; Weber, Cowan, Millikan, & Niebuhr, 2009). The literature on how to address the physical health needs of justice-involved adults with SMI is scant. To improve the overall health of this population, it is important to gain a better understanding of the relationship between physical and mental health. In order to understand this relationship and to
make causal inferences, longitudinal studies are preferred. Despite the benefits of longitudinal studies, they can be plagued by missing data, which can severely bias the results and lead to incorrect conclusions (Diggle, Heagerty, Liang, & Zeger, 2002).

The purpose of this study was to explore the relationship between physical and mental health among justice-involved adults who have a SMI. From a biopsychosocial perspective, this study examined the mental and physical health status of adults with SMI who had a recent arrest compared to other adults with SMI who did not have a recent arrest. In addition, this study provided an example of managing missing data in longitudinal studies geared towards non-statisticians who are conducting behavioral health research. This example described, how to overcome issues with missing data for future longitudinal research with a specific focus on physical and mental health studies, although the methods are the same for research in most social and behavioral science fields. This study also provided the preliminary missing data analysis that will be used in future studies with the same data. First, the author examined the Short-Form Health Survey (SF-12; Ware, Kosinski, & Keller, 1996) scores of adults with SMI with a recent arrest to explore how their scores compared to: 1) population norms; and 2) adults with SMI who do not have a recent arrest. Second, the author provided an example on how to overcome issues caused by missing data by using the data from a study of adults with SMI in a mental health jail diversion program.

**Background and Significance**

An estimated 2.1 million adults with SMI enter jails annually in the U.S. (Steadman et al., 2009). Research suggests that adults with SMI who are male, homeless, had an involuntary psychiatric evaluation, are not medication compliant, and are not receiving outpatient mental health treatment are more likely to be arrested and to spend more days in jail compared to other
adults with SMI who were also recently arrested (Constantine, Andel, et al., 2010; Lamb, Weinberger, Marsh, & Gross, 2007; Wilper et al., 2009). Prior involvement with the criminal justice system also increases the likelihood of being arrested in the future (Case, Steadman, Dupuis, & Morris, 2009). Importantly, most adults with SMI do not receive adequate discharge planning and are, therefore, less likely to be involved in outpatient treatment services after release from jail (Morrissey, Dalton, et al., 2006). Yet, receipt of services upon release is critical to successful community reintegration; research suggests that mental health treatment following release helps to break the cycle of recidivism (McLean, Robarge, & Sherman, 2006; Osher, Steadman, & Barr, 2002).

Mental health diversion programs are intended as an alternative to incarceration for adults with mental illnesses (Draine & Solomon, 1999). Diversion programs can be defined as:

...specific programs that screen defined groups of detainees for the presence of a mental disorder; use mental health professionals to evaluate those detainees identified in screening; negotiate with prosecutors, defense attorneys, community-based mental health providers, and the courts to produce a mental health disposition as a condition of bond, in lieu of prosecution, or as a condition of a reduction in charges (whether or not a formal conviction occurs); and link the detainee directly to community-based services. (Steadman, Morris, & Dennis, 1995, p. 1630–1631)

Diversion programs have been cited as one way to decrease jail time for adults with SMI (Broner, Lattimore, Cowell, & Schlenger, 2004; Case et al., 2009; Frailing, 2010; Hiday & Ray, 2010; Ryan, Brown, & Watanabe-Galloway, 2010; Sirotich, 2009). Overall, jail diversion programs have been shown to be effective at reducing recidivism, reducing the number of days spent in jail, reducing substance use, improving mental health status, increasing service utilization,
and providing mental health and substance use treatment in a less restrictive environment (Broner et al., 2004; Case et al., 2009; Cowell, Broner, & Dupont, 2004; Draine, Blank, Kottsieper, & Solomon, 2005; Draine & Solomon, 1999; Frailing, 2010; Hiday & Ray, 2010; Hoff, Baranosky, Buchanan, Zonana, & Rosenheck, 1999; Lamberti et al., 2001; Lange, Rehm, & Popova, 2011; Rivas-Vazquez et al., 2009; Ryan et al., 2010; Shafer, Arthur, & Franczak, 2004; Sirotich, 2009; Steadman et al., 1995). Moreover, jail diversion programs may reduce the number of adults with SMI in the criminal justice system, both by diverting them to more appropriate settings following arrest and by addressing issues that may bring them into contact with the criminal justice system in the future (Broner et al., 2004; Case et al., 2009; Frailing, 2010; Hiday & Ray, 2010; Ryan et al., 2010; Sirotich, 2009).

**Mental Illness and Physical Illness Comorbidity**

Although diversion programs have been shown to improve mental health and recidivism outcomes, existing programs have yet to primarily focus on the physical health needs of adults with SMI. In general, adults with SMI are at increased risk for a multitude of physical illnesses, such as diabetes, metabolic syndrome, coronary heart disease, COPD, congestive heart failure, obesity, and hepatitis. In addition, they have a life span up to 25 years shorter than the average adult without SMI (Bushe et al., 2005; Leung et al., 2010; Manderscheid, 2010; Oud & Meyboom-de Jong, 2009; Viron & Stern, 2010; Weber et al., 2009). Adults with SMI are more likely to have a comorbid physical illness. Studies indicate that for the adults who have a diagnosis of a SMI, between 58%-90% have at least one comorbid physical illness, and they have a two to nine times increase in the odds of having asthma, chronic bronchitis, and emphysema compared to the general U.S. population (Chwastiak et al., 2006; D. R. Jones et al., 2004; Leung et al., 2010; Sokal et al., 2004).
Adults with SMI also have a two-fold increase in mortality across physical conditions compared to non-mentally ill adults (Chwastiak et al., 2006; Druss, Zhao, et al., 2011; Leung et al., 2010; B. J. Miller, Paschall, & Svendsen, 2006; Sherman et al., 2013). The increased mortality risk for adults with SMI can be attributed to earlier and more frequent death due to substance abuse, mental illness, diabetes, nervous system disease, cardiovascular disease, respiratory disease, and injury compared to adults who do not have SMI (Sherman et al., 2013). Importantly, the high rates of morbidity, mortality, and health care costs associated with comorbid mental and physical illnesses represent significant public health concerns (Chwastiak et al., 2006; Druss, Zhao, et al., 2011; Leung et al., 2010; Sherman et al., 2013).

**Illness and Incarceration**

In general, incarceration is associated with higher rates of physical health conditions such as hypertension, asthma, arthritis, hepatitis and HIV, as well as higher rates of mortality due to drugs, suicide, or homicide following release from jail (Binswanger, Krueger, & Steiner, 2009; Zlodre & Fazel, 2012). These health risks may be heightened in justice-involved adults with SMI. Indeed, research suggests that adults, not necessarily with SMI, who are incarcerated have a higher risk of mortality compared to the general population (Tiihonen et al., 2009; Wilper et al., 2009; Zlodre & Fazel, 2012). Moreover, justice-involved adults with SMI are 40% more likely to have a physical illness than non-justice-involved adults with SMI (Cuddeback, Scheyett, Pettus-Davis, & Morrissey, 2010). Due to the high rates of physical illness experienced by adults with SMI who are justice-involved, it is important to further explore the mental and physical health of this population. To date, no studies have explored how self-reported health status varies between adults with SMI who report a recent arrest versus adults with SMI who do not report a recent arrest.
Measuring Physical and Mental Health

In order to provide economical and effective services to adults who have comorbid mental and physical illnesses, it is necessary to validly measure the concepts of mental and physical health in practice and research. In order to compile appropriate guidelines for the treatment of SMI that occurs in conjunction with a physical illness, the interplay of these illnesses should be understood and measured accurately (Kane, 2009).

The Short Form Health Survey (SF-36) was developed so that researchers could understand functional health, well-being, burden of disease, and benefits of treatment in various populations (Ware & Gandek, 1998). The SF-36 consists of 36 questions designed to measure eight health domains: 1) physical functioning; 2) role limitations due to physical problems; 3) social functioning; 4) bodily pain; 5) general mental health; 6) role limitations due to emotional problems; 7) vitality; and 8) general health perceptions (Ware & Sherbourne, 1992). These eight health domains are important in understanding a patient’s well-being in order to determine the appropriate course of treatment and disease burden (Ware & Sherbourne, 1992). The SF-36 was designed to measure multidimensional health concepts through a range of health states by capturing a person’s self-reported levels of well-being and personal evaluation of health (McHorney, Ware, & Raczek, 1993). The survey was initially designed to be used for health policy evaluations, general population surveys, clinical research, in health practice, and for use with diverse populations (McHorney et al., 1993; Ware & Sherbourne, 1992).

The need for an even shorter assessment tool led to the development of the 12-item Short-Form Health Survey (SF-12). The purpose of the SF-12 is to provide a one-page instrument that can be included as part of a questionnaire and completed in less than two minutes (Ware et al., 1996). The SF-12 and the original SF-36 consist of a physical and mental health scale used to
assess patients or participants in research studies (Ware et al., 1996; Ware & Sherbourne, 1992). It is used in research involving adults with SMI as a tool for assessing changes in health status by administering the survey at different time periods (Bergmann et al., 2009; Chwastiak, et al., 2009; Perron, et al., 2010; Trivedi et al., 2004).

**Missing Data**

One of the best ways to explore the relationship between mental and physical health is through longitudinal data collection. Longitudinal data allow for better inferences about the direction of the relationship between two variables, such as mental and physical health, which can lead to conclusions of causality. In order to understand how certain diseases begin, public health researchers have found a need to further define causality (Susser, 1973). At the most basic level, causality requires the knowledge of the direction of the relationship between two variables and the time-order (taking spatio-temporal ordering into consideration) of this relationship to understand whether one variable causes the other (Susser, 1973). Determining the relationship between two variables is most easily done through longitudinal research, as it provides information on the time-order of the relationship (Shadish, Cook, & Campbell, 2002).

Despite the benefits of longitudinal data in regards to drawing conclusions of causality, longitudinal studies are frequently plagued by missing data (Diggle et al., 2002). There are multiple reasons why missing data occurs, including missed follow-up appointments, lost data, missed questions, participant refusal, or participant drop-out. Missing data in longitudinal studies can lead to difficulties in calculating accurate parameter estimates and can lead to unbalanced treatment groups in randomized trials (Diggle et al., 2002; Nakai & Ke, 2011). In addition, missing data decrease sample size and may be the result of some unexplored impact of the study (Nakai & Ke, 2011). For example, participants enrolled in a new behavioral health intervention may be
dropping out of the study because they are incarcerated or hospitalized. If data are not collected on new arrests or hospitalizations, results of the evaluation may erroneously suggest that the new intervention is ineffective. For many reasons, not the least of which is the limited funding available for behavioral health interventions, it is imperative that an effective intervention be recognized.

Increasingly, practitioners and others working in the behavioral health field are being asked to provide evidence of the effectiveness of their programs to ensure ongoing funding. Often there is no statistician on staff nor is it possible to hire a statistician to assist in the analysis; consequently, practitioners and others working in the behavioral health field are responsible for conducting the data analysis. However, there are few guidelines on how to handle missing data and on the different approaches for dealing with missing data for non-statisticians. To that end, there is a need for missing data examples targeted to non-statisticians so they can learn how to approach missing data in their analysis.

The Present Research

This study draws data from multiple sources. The main source of data for this study is from the 11th Judicial Circuit of Florida Mental Health Project (CMHP), which serves over 400 justice-involved adults with SMI per year through four different jail diversion programs. The programs are as follows: 1) Pre-booking jail diversion; 2) Post-booking, pre-trial jail diversion for adults with SMI charged with a misdemeanor offense; 3) Post-booking, pre-trial jail diversion for adults with SMI charged with a felony offense; and 4) Post-booking, state forensic hospital diversion program for adults with SMI who are found incompetent to stand trial or not guilty by reason of insanity. The post-booking mental health diversion programs in Miami-Dade County, Florida (FL) provide comprehensive diversion services to their participants, including housing.

Despite the overall success of the CMHP diversion programs, there is a subset of 97 adults who continue to cycle through the criminal justice system and acute care services. These adults represent about 5% of the clients served by the jail diversion programs, but they account for 2,200 arrest, 27,000 jail days, 13,000 days in crisis stabilization units, state hospitals, and emergency rooms, and have cost almost $13 million over the past 5 years. In general, justice-involved adults, not necessarily with SMI, tend to have more severe and chronic psychiatric symptoms, need more support to access and engage in services, and have more criminogenic risk factors such as antisocial behaviors, and procriminal attitudes, values, and beliefs (Andrews, Bonta, & Wormith, 2006). This dissertation is using data from the subset of jail diversion participants who continue to cycle through the criminal justice system and are participating in any of CMHP’s three post-booking jail diversion programs. This is referred to as the jail diversion data throughout the dissertation.

For the first part of the study, two additional sources of secondary data were used. The Substance Abuse and Mental Health Services Administration (SAMHSA) conducted a study to explore differences in Medicaid fee-for-service programs and managed behavioral health for adults with SMI across six different states (K. Jones et al., 2006; Leff et al., 2005; Shern et al., 2008). In this dissertation, data collected in Florida were used, and they are referred to as the SAMHSA data throughout this dissertation. Additional data were drawn from a study conducted at five different sites in the U.S. to explore risk behaviors and sexually transmitted diseases in patients with SMI (Mueser et al., 2004; Rosenberg et al., 2001). In this dissertation data from all sites were used and are referred to as the 5-site data throughout this dissertation.
The present research focused on addressing gaps in the literature by exploring the SF-12 scores of adults with a SMI, stratified by a recent arrest. In addition, this study used data drawn from a jail diversion program as an example of how to address missing data for researchers in behavioral health services research.

The first aim of this study was to explore the relationship between reporting a recent arrest and, in turn, the relationship to physical and mental health. Specifically, the investigator used data from an ongoing jail diversion intervention and two other quantitative studies of adults with SMI to compare the physical and mental health status of those with a recent arrest to those without a recent arrest to address the following specific aims and research questions.

**Specific Aim 1**

This study explored the health status scores of a sample of adults with SMI who have a recent arrest to a sample of adults with SMI who do not have a recent arrest, as measured by the SF-12, and to the population norms of the SF-12.

**Research question 1a.** How do the SF-12 physical health and mental health component scores of a sample of adults with SMI with a recent arrest compare to population norms of the SF-12?

*Hypothesis 1a.* Adults with SMI who have a recent arrest will have lower physical health and mental health component scores compared to the population norms of the SF-12.

**Research question 1b.** How do the SF-12 physical health and mental health component scores of a sample of adults with SMI and a recent arrest compare to a sample of adults with SMI who do not have a recent arrest?

*Hypotheses 1b.* Adults with SMI who have a recent arrest will have lower physical health and mental health component scores compared to adults with SMI who do not have a recent arrest.
Research question 1c: Are drug and alcohol use and psychiatric symptom severity significantly related to self-reported physical and mental health status as measured by the SF-12 in a sample of adults with SMI?

Hypothesis 1c. Drug and alcohol use and psychiatric symptom severity will mediate the self-reported physical and mental health status of adults with SMI.

The second aim of this study was to provide non-statisticians with a missing data example that can be used to inform their own research. This was accomplished by using data from a longitudinal study of justice-involved adults with SMI who are enrolled in one of three jail diversion programs.

Specific Aim 2

This study examined the reason(s) for missing data, the missing data mechanism, the missing data pattern, and the statistical method to determine how to model the missing data in a sample of adults with SMI in a jail diversion program.

Research question 2a: What are the reasons for missing data?

Hypothesis 2a. Data are missing due to research assistant error, participant refusal, participant inpatient treatment, and participants’ ongoing legal trouble.

Research question 2b: What is the missing data mechanism for the item missing data and for the unit missing data?

Hypothesis 2b. The item data are missing completely at random due to research assistant error and the unit missing data are missing at random because information on the reason for missing an assessment was collected as part of the study.

Research question 2c: Do methods for data missing at random work for modeling the missing data?
**Hypothesis 2c.** Multiple imputation and maximum likelihood estimation are both valid methods for modeling the missing data.

**Research Design**

This study used data from multiple sources. For the first manuscript, data were drawn from three sources. Specifically, secondary data analysis was conducted on data collected in two different studies. These secondary data were combined with primary quantitative data that were collected using an experimental, equivalent comparison group design. The primary data collected for this study came from an evaluation of an intervention being implemented by CMHP as part of two of their post-booking jail diversion programs. The intervention targeted high-risk users who continue to cycle through the criminal justice system despite receiving jail diversion assistance in the past. All of the participants were diagnosed with SMI. Additional inclusion criteria included: 1) three or more jail bookings in the past three years or seven or more lifetime jail bookings; 2) a diagnosis of schizophrenia, schizoaffective disorder, bipolar disorder, or psychotic disorder NOS; 3) voluntary participation in the jail diversion program; and 4) a rating of moderate or high on at least one of the following items on the Short-Term Assessment of Risk and Treatability (START): violence; self-harm; suicide; self-neglect; or general offending (Webster, Martin, Brink, Nicholls, & Desmarais, 2009); and 5) speak English or Spanish.

**Procedures Data Collection**

**Primary data.** Once participants agreed to be in the study, they were block randomized into one of two treatment groups: 1) Treatment as Usual (TAU); or 2) Care Coordinator (TX). All participants were interviewed using a battery of questionnaires at baseline, three-months, six-months, nine-months, 12-months, and 18-months. This study was an interim evaluation and used
data from the baseline, three-month, six-month, and nine-month interviews. Interviews typically lasted between 60-120 minutes.

**Secondary data.** The secondary data came from two sources: 1) the SAMHSA data that explored service utilization, quality of care, and health outcomes; and 2) satisfaction of care for adults with SMI through longitudinal data (K. Jones et al., 2006; Leff et al., 2005; Shern et al., 2008). Only baseline data were used in this dissertation study. The 5-site data were collected to explore risk behaviors and sexually transmitted diseases in patients with SMI who were receiving inpatient or outpatient treatment (Mueser et al., 2004; Rosenberg et al., 2001). The 5-site study was a cross-sectional study.

**Analytic Plan**

In the first manuscript, data were combined from the two secondary data sources and the primary data that were collected. Two new data sets were created, one consisting of the primary jail diversion data and the secondary data collected as part of the SAMHSA study, the other consisting again of the same primary jail diversion data and the secondary data collected as part of the 5-site study. Analysis for the first manuscript consisted of t-tests to compare mean scores and Analysis of Covariance (ANCOVA) and Factorial Analysis of Covariance to compare mean scores while controlling for the effects of covariates.

The second manuscript was based solely on the primary jail diversion data collected. The author used survival analysis to examine the relationship between participant study drop-out, SF-12 scores, and mental illness symptom severity. In addition, the author used multiple imputation and mixed effects regression to model the data while accounting for missing values.
Operational Definitions

Serious Mental Illness

In this dissertation study the definition of SMI refers to a DSM-IV axis 1 diagnosis of schizophrenia, psychotic disorder NOS, bipolar disorder, or major depressive disorder (Constantine, Petrila, et al., 2010; Kessler et al., 2001; Steadman et al., 2009). The definition of SMI for the specific sample data varies. In the jail diversion study, SMI refers to a DSM-IV axis 1 diagnosis of schizophrenia, psychotic disorder NOS, or bipolar disorder (American Psychiatric Association, 2000). This definition was devised to reflect the study inclusion criteria, but also is consistent with the definition used in prior research (Constantine, Petrila, et al., 2010; Kessler et al., 2001; Steadman et al., 2009; Van Dorn et al., 2011). In the SAMHSA study, SMI refers to a diagnosis of mental illness that impaired the participant enough that they qualified and received Social Security Income benefits (K. Jones et al., 2006; Leff et al., 2005; Shern et al., 2008). The Social Security Administration includes the following as potential diagnoses that qualify a person for benefits: organic mental disorders; schizophrenia; psychotic disorder NOS; affective disorders; intellectual disability; anxiety-related disorders; somatoform disorders; and personality disorders, along with severe impairment in daily tasks such as working or personal care (the U.S. Social Security Administration, 2013). The majority of mental illness claims approved by the Social Security Administration across the U.S. are for applicants with an organic mental disorder, schizophrenia or psychotic disorder, affective/mood disorders, anxiety disorders, and mental retardation (Meseguer, 2013). Finally, in the 5-site study, SMI refers to a DSM-IV axis 1 diagnosis of schizophrenia, psychotic disorder NOS, or a major mood disorder (American Psychiatric Association, 2000; Mueser et al., 2004; Rosenberg et al., 2001).
Mental and Physical Health Status

The term health status refers to physical health symptoms and mental health symptoms, as measured using the SF-12, Version 2. The SF-12 is a one- to two-page instrument that can be completed in less than two minutes (Ware et al., 1996). The SF-12 is a generic health survey that measures the following eight health scales: 1) physical functioning; 2) role limitations due to physical problems; 3) bodily pain; 4) general health perceptions; 5) vitality; 6) social functioning; 7) role limitations due to emotional problems; and 8) general mental health (Ware et al., 1996). The SF-12 has been used in prior research in adults with SMI to measure changes in health status over time (Bergmann et al., 2009; Chwastiak et al., 2009; Perron, Fries, Kilbourne, Vaughn, & Bauer, 2010; Trivedi et al., 2004). The SF-12 has been shown to have good test-retest reliability and convergent and divergent validity in a population of adults with SMI, although they were not criminal justice-involved (Salyers, Bosworth, Swanson, Lamb-Pagone, & Osher, 2000). There are two total scores calculated using the responses on the SF-12 that form the mental health status (MCS) and the physical health status (PCS) component scores.

Justice-Involved

In the jail diversion sample, or primary data sample, all of the participants were considered justice-involved. The post-booking jail diversion participants were arrested and arraigned at the jail. All participants in the jail diversion sample were arrested within the past six months, because arrest was required for inclusion in the jail diversion intervention. In the SAMHSA data set, justice-involved participants were those who reported having been arrested in the past six months. In the 5-site sample, justice-involved participants were those participants who reported having been arrested in the past year. None of the participants in any of the studies were currently involved with the prison system, although they may have been in the past.
Missing Data

Missing data in this study refers to both data missing at the item level and at the subject level. The difference between data missing at the item level and data missing at the subject level are discussed in detail in Section 3, Second Manuscript. Briefly, data missing at the item level are data missing for specific questions of the assessments, but not for the entire questionnaire. Item data are typically missing if the research assistant skipped a question or if the participant refused to answer that question. Data missing at the subject level occurs when the entire questionnaire is missing for a participant at the specified time point. Typically, subject-level data is missing because the person dropped out of the study or because a subject was unable to meet or refused to meet for the specific follow-up time. The definitions for the different missing data mechanisms: 1) Missing at Random; 2) Missing Completely at Random; and 3) Not Missing at Random, are based on the seminal book by Little and Rubin (2002).

Missing At Random (MAR)

Data are MAR if the probability of having a value missing is related to the other variables, but is not related to the would-be value of the incomplete variable. In other words, MAR refers to a missing value that is related to the other variables, but not the likelihood of drop-out, and is not related to current or future responses to the variable (Enders, 2011; Hedeker, 1997; Nakai & Ke, 2011). The missing-ness depends only on observed variables, and is not related to some unobserved, or unmeasured variable (Little & Rubin, 2002). Data MAR are sometimes considered “ignorable,” as there are different analysis mechanisms that will continue to result in asymptotically unbiased estimation (Raudenbush & Bryk, 2002). MAR data are fairly common in longitudinal studies that collect data on many aspects of the outcome of interests, and keep detailed information about why data are missing.
**Missing Completely At Random (MCAR)**

Data are MCAR if the probability of having a missing value for a specified variable is not related to the potential values for that variable, or any of the other observed data for the other variables (Enders, 2011; Nakai & Ke, 2011). In longitudinal studies, the missing data are a random sample of all the time points or of all the drop-out participants (Raudenbush & Bryk, 2002). Data MCAR occur at random and are not related to the study outcome. For example, a participant may move out of the area or miss their appointment because their car broke down. This is the least likely situation to occur and essentially implies that the participants with missing data are not different from participants with complete data. Data that are MCAR allow for the most choices for statistical methods to analyze the data, as the missing-ness is considered ignorable (Burzykowski et al., 2010). Since the majority of the research conducted in social sciences focuses on human participants, this is not a useful taxonomy of missing data as it is unlikely that the reason for participant drop-out is unrelated to the study (Enders, 2011).

**Not Missing At Random (NMAR)**

Data are NMAR (MNAR) when the probability of having a missing value for a particular variable is related to the would-be value of that variable. These values depend both on the observed responses and the would-be missing value (Enders, 2011: Nakai & Ke, 2011). Unlike data MAR, when data are NMAR the missing-ness of the data is related to some unobserved value or variable. NMAR data are often referred to as non-ignorable missing data, which means that the missing-ness needs to be taken into consideration in the statistical model, as future responses cannot be predicted based on the past responses. This type of missing data requires more sophisticated consideration of the appropriate way to model the data for analysis. Much of the current research deals with the optimal way to deal with NMAR data (Enders, 2011; Nakai & Ke, 2011).
Conceptual Framework

It is well-documented that physical and mental health are related and that overall health depends on both aspects of physical and mental health (Druss et al., 2009). To understand the relationship between physical and mental health, a theoretical foundation is needed to guide the research questions and place the results into context.

The Biopsychosocial Model

It is important to use a model that can help explain the relationship between SMI and co-morbid physical illness. The biopsychosocial model was introduced by Engel (1977) as a way to conceptualize health from a multi-dimensional lens. It is made up of three levels that impact health: 1) biological; 2) psychological; and 3) social. The interaction of determinants at each level is what determines the disease outcome and presentation (Engel, 1977). This interaction points out the importance of treating multiple diseases and levels of health to achieve overall health (Engel, 1977).

Health status is based on the notion that a person’s functioning and well-being related to their illness needs to be considered when planning appropriate treatment (Ware & Sherbourne, 1992). Furthermore, mental illness and physical illness are interrelated, and improvement in one area impacts the other (Druss et al., 2009). In order to measure health status, multiple dimensions of health must be considered. Understanding a person’s health status allows for improvement in their outcomes through interventions or clinical care (Ware & Sherbourne, 1992). Specifically in this research, the biopsychosocial model was used to explore the relationship between different determinants of health, physical health and mental health, to understand the relationship between the determinants and how they are related to each other. The greater understanding of how these
determinants interact will allow for an increased understanding of how disease interactions can impact a person’s health.

The biopsychosocial model provided the basis for the hypotheses in this research. In the first manuscript, the author hypothesized that at the psychological level, the mental and physical health status of participants will be lower for those who have a SMI and a recent arrest due to the social level effects of a recent arrest, in conjunction with the psychological and biological effects of the high rate of physical illnesses that adults with SMI experience. In the second manuscript, the author hypothesized that health status and mental health symptoms at the psychological level may interact with the support of a care coordinator at the social and psychological level and be related to study drop-out. The role of the care coordinator was to help the participants navigate the health care system to get the services they need, along with organizing housing and financial benefits.

The biopsychosocial model provided the base theory for the research questions and why certain outcomes may be plausible. Using a biopsychosocial model allowed this researcher to examine the relationship between different determinants of physical and mental health status, drug and alcohol use, and the support of a care coordinator at both the interpersonal or social and intrapersonal or psychological levels. Specifically, the study looked at mental illness (psychological level), the impact of a care coordinator (social level), and the participant’s health status (psychological level) on mental and physical health (Engel, 1978).

It is known that mental illness has a biological basis, but this study was not able to measure this outcome due to the complexity of the issue (Cross-Disorder Group of the Psychiatric Genomics Consortium, 2013). Thus, the study design focused on looking more closely at the psychosocial levels of the participant by using their self-reported health status, mental illness
severity, and information on drug and alcohol use rather than the biological aspects of disease. It was beyond this study to obtain biological samples from these persons to look at their physical health due to the costs and infeasibility of asking the participants to undergo additional medical testing beyond the requirements of the intervention (Moon et al., 2012).

**Manuscripts**

This research was focused on the relationship between mental health and physical health status, and the relationship between health status and study dropout. In order to address these issues, the author proposed two manuscripts (that follow in sections 2-3):

1. **Manuscript 1: Mental and Physical Health Status of Justice-Involved Adults with Serious Mental Illness.** Manuscript 1 addressed specific aim 1 and the associated research questions using multiple data sets and mean comparison data analysis in section 2.

2. **Manuscript 2: An Example of Missing Data Analysis Using a Sample of Adults with Serious Mental Illness enrolled in a Jail Diversion Intervention.** Manuscript 2 addressed specific aim 2 and the associated research questions by determining the types of missing data, the missing data mechanisms, and exploring the differences in multiple imputation and maximum likelihood estimation in section 3.
SECTION 2: FIRST MANUSCRIPT


Mental and Physical Health Status of Justice-Involved Adults with Serious Mental Illness

Background

There are an estimated 2.1 million adults with serious mental illness (SMI) entering jails annually in the U.S., not including prisons (Steadman et al., 2009). The majority of adults who are released from jail do not receive adequate discharge planning, making them less likely to seek outpatient treatment services (Morrissey, Steadman, et al., 2006). Jail diversion programs have been noted as one way to increase services provided to adults with SMI who are released from jail (Draine & Solomon, 1999; Osher et al., 2002; Steadman, Cocozza, & Veysey, 1999). Receipt of services upon release results in adults with SMI receiving more treatment and benefits, helping to break the cycle of recidivism (McLean et al., 2006; Osher et al., 2002). Moreover, these services help to improve mental health, yet we do not know much about the physical health needs of adults with SMI who are justice-involved (Cosden, Ellens, Schnell, & Yamini-Diouf, 2005; Draine et al., 2005; Ferguson, McAuley, Hornby, & Zeller, 2008; Lange et al., 2011; Steadman et al., 1995).

Rationale and Justification for Diversion Programs

Mental health jail diversion programs are unique compared to traditional forms of release from jail, such as parole or probation, because they focus on keeping adults with SMI out of the criminal justice system by providing them with mental health and substance abuse services (Draine & Solomon, 1999). Lack of available or sufficient mental health treatment is a contributing factor
to the large number of adults with SMI in the criminal justice system (Thompson, Reuland, & Souweine, 2003). Most jails are unable to provide basic mental health screenings and services to adults with SMI (Anno, 2001; Ditton, 1998; Redlich, Liu, Steadman, Callahan, & Robbins, 2012). Law enforcement, the courts, and corrections have expressed frustration at the inability to appropriately respond and assist adults with SMI (Thompson et al., 2003). As a response to these frustrations and to provide more adequate treatment, jail diversion programs have become more widespread; they are effective at reducing recidivism and improving mental health symptoms (Draine et al., 2005; Draine & Solomon, 1999; Lange et al., 2011; Steadman et al., 1995).

**Mental Illness and Physical Illness**

Mental illness has been shown to be the most burdensome disease, accounting for approximately one-third of all disabilities in the United States (Druss et al., 2000; Druss, Marcus, Olfson, & Pincus, 2002). Mental illnesses are more impairing to a person’s ability to maintain their home life, social life, work, and close relationships than chronic physical illnesses (Druss et al., 2009). Impairment is compounded for those adults who experience co-morbid mental and physical illnesses due to the synergistic relationship between mental and physical health (Druss et al., 2009).

Adults with SMI are at increased risk for physical illnesses, including diabetes, metabolic syndrome, coronary heart disease, COPD, congestive heart failure, obesity, and hepatitis (Bushe et al., 2005; Leung et al., 2010; Lord et al., 2010; Oud & Meyboom-de Jong, 2009; Weber et al., 2009). They have a shorter life span than the average adult without a mental illness (Manderscheid et al., 2010; Viron & Stern, 2010) and they have high rates of comorbid physical conditions (Chwastiak et al., 2006; Leung et al., 2010). There is a two-fold increase in the risk of mortality across physical conditions for adults with SMI compared to adults without any mental illness due
to risky health behaviors (e.g., such as smoking and not exercising) substance abuse, decreased preventative screening, lack of access to healthcare services, low quality of healthcare, low socioeconomic status, and an increased risk of injuries leading to death (Druss, Zhao, et al., 2011; Sherman et al., 2013).

**Illness and Incarceration**

People who are incarcerated have high rates of mortality upon release from jail (Zlodre & Fazel, 2012). Rates of physical illness are up to four times higher for adults in jail compared with the non-incarcerated population (Binswanger et al., 2009). Adults with SMI experience increased mortality rates that are compounded for incarcerated adults with SMI who do not receive psychiatric medication (Tiihonen et al., 2009; Wilper et al., 2009; Zlodre & Fazel, 2012). Adults with SMI who have an incarceration history are 40% more likely to have any physical illness and 30% more likely to have multiple physical illnesses compared with adults with SMI who do not have an incarceration history (Cuddeback et al., 2010). This may be due, in part, to the increased prevalence of substance use and mental health symptom severity of justice-involved adults with SMI (both in jail and released from jail) compared to other justice-involved adults who do not have SMI and other adults with SMI who are not justice-involved. For example, approximately 75% of justice-involved adults with SMI have a co-occurring substance use disorder (Abram, Teplin, & McClelland, 2003; Abram & Teplin, 1991). Furthermore, substance use disorders are associated with worse physical health outcomes and almost a five-fold increase in the risk of death due to substance abuse compared to adults without SMI (Sherman et al., 2013).

**Integration of Mental Health and Physical Health**

Adults with SMI have an increased burden of comorbid physical illnesses and experience increased impairment (Chwastiak et al., 2006), requiring greater focus on physical illnesses in
treatment (Druss et al., 2009). To improve mental health for adults with SMI they need integrative behavioral health and primary care services (Butler et al., 2008). However, current standards of treatment in correctional settings focus on treating an incarcerated person’s mental illnesses, despite the disproportionate number of physical illnesses experienced in this population. Consequently, adults with SMI experience increased mortality and morbidity compared to the general population of adults without SMI and adults with SMI who are not justice-involved (Chwastiak et al., 2006; Perry, Presley-Cantrell, & Dhingra, 2010; Viron & Stern, 2010; Weber et al., 2009). It is important that research focuses on the relationship between mental and physical health so that treatment models can be updated to reflect the state of science and practice.

**Purpose**

Although there has been a focus on reducing recidivism and improving the mental health of justice-involved adults with SMI, less is known about the physical health of this population and how their physical health status is related to substance use and mental health symptom severity. Thus, the purpose of this study was to explore the mental and physical health status of adults with SMI who had a recent arrest. The specific aim was to compare the health status scores of a sample of adults with serious mental illness who had a recent arrest to a sample of adults with serious mental illness who did not have a recent arrest, as measured by the Short Form Health Survey (SF-12), and to the population norms of the SF-12.

**Research Question 1a**

How do the SF-12 physical health and mental health component scores of a sample of adults with SMI with a recent arrest compare to population norms of the SF-12?

**Hypothesis 1a.** Adults with SMI who have had a recent arrest will have lower physical health and mental health component scores compared to the population norms of the SF-12.
Research Question 1b.

How do the SF-12 physical health and mental health component scores of a sample of adults with SMI and a recent arrest compare to a sample of adults with SMI who do not have a recent arrest?

Hypotheses 1b. Adults with SMI who have had a recent arrest will have lower physical health and mental health component scores compared to adults with SMI who do not have a recent arrest.

Research Question 1c.

Are drug and alcohol use and psychiatric symptom severity significantly related to self-reported physical and mental health status as measured by the SF-12 in a sample of adults with SMI?

Hypothesis 1c. Drug and alcohol use and psychiatric symptom severity will mediate the self-reported physical and mental health status of adults with SMI.

Methods

Samples

The data for this study came from three different research studies.

Jail diversion sample. Data for the first sample, the jail diversion sample, were collected from two post-booking pre-trial diversion programs being conducted in Miami, Florida. The post-booking diversion programs provide justice-involved adults with SMI who were arrested for non-violent misdemeanors or less serious felony charges, with linkages to community services, treatment, and support (Eleventh Judicial Circuit of Florida, 2010).

From July 2012 to October 2013, potential participants were screened and identified by diversion staff. All participants were currently involved with the criminal justice system and were
recently arrested as part of the criteria for study inclusion. Inclusion criteria included: 1) a diagnosis of schizophrenia, schizoaffective disorder, bipolar disorder, or psychotic disorder NOS; 2) voluntary participation in the jail diversion program; 3) a rating of moderate or high on at least one of the items on the Short-Term Assessment of Risk and Treatability (START; Webster et al., 2009): violence, self-harm, suicide, self-neglect, or general offending; 4) speak English or Spanish; and 5) have either three or more jail bookings in the past three years, or seven or more lifetime jail bookings.

Eligible adults were approached by a research assistant who explained the study and obtained consent. All research staff members were trained and followed the informed consent procedures set forth by the two reviewing IRBs at the University of South Florida and North Carolina State University. Participants (n=91) were interviewed at baseline using a questionnaire that took approximately 60-90 minutes to administer.

**SAMHSA sample.** Data for the second sample were collected as part of a managed care study of Medicaid enrollees in Florida (K. Jones et al., 2006; Leff et al., 2005; Shern et al., 2008). The purpose of the study was to explore service utilization, quality of care, health outcomes, and satisfaction of care for adults with SMI who were enrolled in either a Medicaid fee-for-service program or a managed behavioral health program. The enrollment options resulted from a Medicaid waiver, thereby providing a natural research experiment. All participants chose the type of health care plan in which to enroll (i.e., managed care or fee-for-service condition). The data came from a larger Substance Abuse and Mental Health Services Administration (SAMHSA) project that was conducted in five states; only data from Florida were used in the current analysis. The data will be referred to as the SAMHSA data (n=688) throughout the study.
Information on SMI diagnosis was not collected in the SAMHSA study, and instead SMI is based on the participants qualifying for Social Security Income because of their mental illness, as determined by the Social Security Administration (the U.S. Social Security Administration, 2013). Most commonly, applications that were approved were for claimants who have a diagnosis of an organic mental disorder, schizophrenia or psychotic disorder, affective/mood disorders, anxiety disorders, and mental retardation (Meseguer, 2013). These diagnoses are representative of the entire U.S. population, and are not necessarily representative of Social Security applicants in Florida that we recruited for the SAMHSA study. All research procedures were approved by the University of South Florida IRB. Eligible participants were randomly selected from a mail screening procedure of adults ages 21-65 with SMI. From October 1997 to November 1999, participants were interviewed bimonthly for 12 months.

**5-site sample.** Data for the third sample were collected as part of a multi-site investigation of risk behaviors and sexually transmitted disease in patients with SMI, who were receiving either inpatient or outpatient mental health treatment (Mueser et al., 2004; Rosenberg et al., 2001). These data were collected as part of a 5-site study, conducted in four states, and therefore is referred to as the 5-site data \((n=969)\) throughout the study. All participants were over the age of 18, spoke English, and had a diagnosis of schizophrenia, other psychotic disorder or a major mood disorder (Mueser et al., 2004; Rosenberg et al., 2001).

Participant recruitment differed based on location. In New Hampshire and North Carolina, inpatient participants were consecutive patients admitted to hospital or psychiatric unit who consented to participate. Outpatient participants were randomly selected from the list of different community health centers in New Hampshire and Maryland. The outpatient participants in Connecticut were previously enrolled in a study, and in North Carolina they were part of an
involuntary outpatient program. All research procedures were approved by the appropriate IRB. Interviews lasted approximately one hour and additional blood and urine samples were collected.

**Parallel Analysis**

Analysis of data from multiple studies has the benefit of increased statistical power over analysis based on a single study. The jail diversion sample has an N=91 and because of the small sample size, a Type II error will occur if the effect size is small. To avoid Type II errors, the jail diversion data were combined with the SAMHSA data and the 5-site data. There are two different types of analyses that can be conducted when the raw data are present: 1) parallel analysis; and 2) integrative data analysis (IDA).

Parallel analysis is used when raw data are available, and the same analyses are run on multiple data sets that cannot be combined. For example, in this study, it is very difficult to combine all three data sets. Instead, two new data sets—in this case, the jail diversion data combined with the SAMHSA data and the jail diversion data combined with the 5-site data—were created. These data sets were then analyzed separately and discussion about generalizations from the results were made. In IDA, the raw data from all of the data sets are combined into a single data set, so the jail diversion data, SAMHSA data, and 5-site data would be combined into a single data set that is then analyzed (Curran & Hussong, 2009). There are benefits to both types of data analysis. IDA allows for an increase in sample size and more accurate conclusions based on the data analysis (Curran & Hussong, 2009; Curran et al., 2008). Although IDA might appear to be the ideal way to analyze data, it is not always practical.

There are many measurement instruments available in the behavioral health field; however, they are not used consistently across studies. When combining two studies the scaling of measurement instruments can be overcome fairly easily. For example, in the SAMHSA data, arrest
data from the past six months was measured, and in order to be a part of the jail diversion sample, the participant had a recent arrest. When information is combined from three different studies, it becomes much harder to scale the measurement instruments to be consistent across samples. Keeping with the same example, in the 5-site study, past year arrests were measured. Whereas we can assume that the participants in the SAMHSA study who responded “yes” to past six month arrest would also qualify for past year arrest, there is a subsample of participants who were not arrested in the past six months, but may have been arrested in the past year. These values therefore are incompatible, and scaling of these measurements becomes exponentially more complicated (Curran et al., 2008). Therefore, in this study, parallel analysis was used. The jail diversion data has similarities with both of the other data sets, and therefore two new data sets were created: the jail diversion and SAMHSA data, and the jail diversion and 5-site data.

**Measurement**

**Short Form Health Survey (SF-12).** The SF-12 is a shortened version of the original SF-36 and consists of 12 self-report questions that measure health and well-being. The survey is an intentionally generic instrument that can be used with any age group or disease group (Ware & Sherbourne, 1992). The SF-12 consists of two components: 1) the physical health component scale (PCS); and 2) the mental health component scale (MCS) (Ware et al., 1996). The SF-12 is scored using a predetermined algorithm with range=1-100, mean=50 and SD=10 for the general U.S. population (Quality Metric, 2013). The norm score for respondents with depression is lower, with the mean PCS=45.55 and the mean MCS=37.40 (Ware, Kosinski, Turner-Bowker, & Gandek, 2004). A score lower than 50 indicates below-average functioning for that health component or for the total score (Quality Metric, 2013). Both the general population norms and depression norms were compared to the scores obtained in this study. In the SAMHSA and 5-site studies, the SF-12
version 1 was used, whereas the SF-12 version 2 was used in the jail diversion study. To ensure comparability between scores, the 1998 constant was used to score all versions. The 1998 constant is more representative of the samples in these studies compared to the 1990 constant and allows for direct comparison between the different versions of the SF-12 (Ware, Kosinski, & Dewey, 2000; Ware et al., 2004).

**Addiction Severity Index-Alcohol and Drug subscales (ASI).** The Addiction Severity Index (ASI) drug and alcohol subscales were used in both the jail diversion and SAMHSA samples. The ASI was designed to be used as a clinical research tool to determine drug and alcohol addiction severity (McLellan, Luborsky, Woody, & O’Brien, 1980). For this study, only the Drug and Alcohol Subscales were used. These scales can be used to determine the treatment need of the participant and their functioning compared to other participants (McLellan et al., 1980). The instrument consists of 27 questions about drug and alcohol use, drug and alcohol treatment, and the perceived impact of drug and alcohol use on the participant’s functioning (McLellan et al., 1980). In the jail diversion study, the reference period was the past 90 days, whereas in the SAMHSA study the reference period was the past 30 days. To compute the composite score, the variables were added and then divided by the reference time period multiplied by the number of variables used to form the score. The composite score ranges from 0.00-1.00 (McGahan, Griffith, Parente, & McLellan, 1986).

**Brief Psychiatric Rating Scale (BPRS).** The Brief Psychiatric Rating Scale (BPRS) was used in both the jail diversion and 5-site study samples. The BPRS was first developed as a 16-item scale to assess change in symptoms of psychiatric patients to understand if treatment works (Overall & Gorham, 1962). It was later expanded to a 24-item scale to be used in research studies that involved adults with psychotic symptoms (Lukoff, Liberman, & Nuechterlein, 1986). Each of
the items assesses a different behavior that is indicative of improvement or deterioration of the adult’s mental illness. The items are rated on a scale from 1-7, with 1 indicating the symptom is not present and 7 that the symptom is extremely severe. The scores from all of the items are added together to form a total score (Overall & Gorham, 1962). The jail diversion study used the full 24-item scale, and the 5-site study used a shorter 10-item scale. The 10-item scale is on the items that are based on the interviewer’s observations; the other 14 items not included are based on the participant’s self-report of symptoms. Mean BPRS scores (total score divided by number of items) were calculated for both studies. In addition, the 10 items used in the 5-site study were pulled from the jail diversion study to create a total score for the shorter scale. The short scale total score was used throughout the analysis because it provided greater variability than the mean scores and included the same constructs.

Other Covariates.

Arrest. As mentioned above, the arrest variable differed in the three samples. In the jail diversion and SAMHSA sample, arrest was indicated by self-report of being arrested in the past six months for the SAMHSA participants and for the jail diversion participants (all of which had been arrested in the past six months per the requirements of participating in the study). In the jail diversion and 5-site study, arrest was indicated by self-report of being arrested in the past year for the 5-site participants; and also, for the jail diversion participants who had all been arrested. In both data sets this was a dichotomous variable with 0=no arrest, and 1=yes arrested at least once in the reference period.

Socio-demographics. In both data sets, information on age, sex, race, education level, and marital status were collected. In the jail diversion and SAMHSA data, dummy codes were also created for income, current employment (0=no, 1=yes), and being the victim of violence in the
past three or six months (0=no, 1=yes). The victimization variable was only used in descriptive statistics, as the reference periods were not the same; therefore, we could not use it in further analyses.

In the jail diversion and 5-site data, dummy codes were constructed for past year arrest (0=no, 1=yes). Data was also available regarding the number of times the participants had been arrested in their life. Lifetime arrests in the jail diversion sample and the 5-site study was based on self-report. In the 5-site study the Conflict Tactic Scale (Straus, Hamby, Boney-McCoyY, & Sugarman, 1996) was used to measure victimization, and in the jail diversion study the MacArthur Community Violence Screening Instrument (Monahan et al., 2000) was used to measure victimization. A dummy variable was created for victimization to try to compare across samples, but was subsequently dropped from the analysis due to issues with scaling. Scaling issues occur when the way a variable was measured, like victimization in this example, differs based on the study and there is no way to reconcile the measurements between the two studies. Both of these instruments measure victimization differently, and there was no way to scale the measurements to make them equivalent. An additional dummy variable for substance use was created. In the 5-site study, the Dartmouth Assessment of Lifestyle Instrument was used (Rosenberg et al., 1998; 2001) to measure substance use, and in the jail diversion study a cut-off score for the ASI was used, where if the Alcohol composite was ≥0.06, and/or the drug composite was ≥0.11 (Peters et al., 2000), the participant was scored as having a substance use disorder.

Data Analysis

All data analyses were conducted using SAS 9.3. Analyses for both of the created data sets, the jail diversion and SAMHSA data and the jail diversion and 5-site risk data, were identical. Univariate descriptive statistics were calculated to explore the average scores and frequencies of
all the measures based on both of the created data sets. Pearson moment correlations and Spearman rank correlations were calculated to account for the continuous and categorical variables present in the data sets.

The first part of the analysis was an overall exploration of the physical health and mental health component scores and how they relate to population norms. Previous research has found that adults with SMI have lower overall scores compared to other physically ill populations (Lempp et al., 2009; Tunis, Croghan, Heilman, Johnstone, & Obenchain, 1999). SF-12 scores were compared to the population norms using t-tests. Three different sets of t-tests were calculated: 1) SF-12 scores of the jail diversion sample compared to the population norms; 2) SF-12 scores of the new combined data sets compared to the population norms; and 3) SF-12 scores of those who were arrested, either in the past six months (jail diversion and SAMHSA data) or the past year (jail diversion and 5-site risk data), compared to the population norms. We additionally ran the same sets of t-tests using the norm scores from the SF-12 depression norm sample instead of the general population norm scores.

The second part of the analysis focused on exploring the SF-12 scores of those who reported being arrested versus those who were not arrested using t-tests. The reference period was those arrested either in the past six months (jail diversion and SAMHSA data) or the past year (jail diversion and 5-site risk data). T-tests were also calculated for ASI composite scores, BPRS scores, and age in both of the data sets. Additionally, chi-square analysis was conducted for the categorical variables to compare those who were arrested versus those who were not arrested.

The third part of the analysis was focused on whether or not the SF-12 component scores varied by criminal justice status taking covariates into account. Two different sets of Analysis of Covariance (ANCOVA) were conducted for each data set (parallel analysis), with MCS as the
dependent variable and with PCS as the dependent variable. ANCOVA is used when there is at least one continuous covariate that is significantly related to the dependent variable (Stevens, 2007). The continuous covariate must be included in the analysis, otherwise the analysis is subject to systematic bias (Stevens, 2007). The ACNOVAs included potential covariates that may be related to changes in PCS and MCS, including age, ASI drug and alcohol composites (in the jail diversion and SAMHSA sample), BPRS (in the jail diversion and 5-site sample), and number of lifetime arrests (in the jail diversion and 5-site sample). These covariates were selected based on the results from the correlation analysis. The correlation analysis showed that the jail diversion and SAMHSA sample, PCS scores were significantly related to the age, ASI drug composite, and being arrested in the past six months, whereas the MCS scores were significantly related to ASI drug composite. In the jail diversion and 5-site sample, PCS scores were significantly related to age, and being arrested in the past year, whereas the MCS scores were significantly related to age, number of lifetime arrests, psychiatric symptom severity, being arrested in the past year, and a substance use disorder. These associations are discussed in more detail in the results section.

Results

Basic descriptive information about the jail diversion and SAMHSA data set can be found in Table 1. The jail diversion participants had the youngest mean age ($M=36.26$) compared to both the SAMHSA participants ($M=44.10$) and the 5-site risk participants ($M=42.29$). The mean PCS scores were better among the jail diversion participants ($M=49.05$), followed by the 5-site risk participants ($M=48.28$), and then the SAMHSA participants ($M=39.43$). The mean MCS scores among the jail diversion participants ($M=36.39$) and the SAMHSA participants ($M=36.85$) were similar, but was notably higher in the 5-site risk participants ($M=42.29$). Overall, the mean ASI alcohol and drug composite scores were fairly low for the SAMHSA participants ($M=0.03$ and
but higher for the jail diversion participants \(M=0.10\) and \(M=0.20\) respectively. The jail diversion participants had lower mean BPRS scores, indicating better psychiatric symptom severity \(M=15.94\) than the 5-site risk participants \(M=17.43\). Jail diversion participants had a much higher number of lifetime arrests \(M=13.19\) compared to the 5-site risk participants \(M=0.52\).

Both the jail diversion sample \((81.3\%, n=74)\) and 5-site risk sample \((64.9\%, n=629)\) were mostly comprised of males, whereas the SAMHSA sample \((72.2\%, n=496)\) was mostly comprised of females. In all of the samples, the majority of the participants were Caucasian \((jail\ diversion, 52.2\%, n=47; \text{SAMHSA}, 54.5\%, n=372; 5\text{-site risk} 47.5\%, n=459)\), or African American \((jail\ diversion, 46.7\%, n=42; \text{SAMHSA}, 34.4\%, n=235; 5\text{-site risk} 44.3\%, n=428)\). Approximately half of the jail diversion sample reported Hispanic ethnicity \((53.3\%, n=48)\), but the SAMHSA sample had a lot lower report of Hispanic ethnicity \((11.2\%, n=77)\). In all of the samples there was a small number of participants that reported being married \((jail\ diversion, 7.8\%, n=7; \text{SAMHSA}, 11.2\%, n=77; 5\text{-site risk} 13.4\%, n=129)\). About half of the jail diversion sample \((51.6\%, n=47)\) and the SAMHSA sample \((53.0\%, n=359)\) graduated from high school; the 5-site risk study was comprised of a larger amount of high school graduates \((65.3\%, n=630)\). Both the jail diversion and SAMHSA participants all reported an annual income under $25,000.

In the jail diversion sample the majority of participants qualified for a substance use disorder \((88.6\%, n=78)\), compared to less than half of the 5-site risk sample \((42.5\%, n=410)\). About a third of the SAMHSA \((33.3\%, n=229)\) and all of the jail diversion participants had been arrested in the past 6 months. Again, a little over a third of the 5-site risk participants \((34.5\%, n=241)\) and all of the jail diversion participants had been arrested in the past year. The number of participants in the 5-site risk study that reported being arrested at any time in their life was much higher \((69.5\%,\)
than the number arrested in the past year, indicating that a large portion of the 5-site sample participants had been involved with the criminal justice system at some point in their life. All of the jail diversion participants had been arrested at some point in their life.

The first part of the analysis compared the mean MCS and PCS scores of the two data sets to the general population norms and the depression norms. Additionally, the data sets were split on the arrest indicator variable, operationalized as the past six months in the jail diversion and SAMHSA data, and the past year in the jail diversion and 5-site data (see Table 3). Compared to the general population norm of $M=50$, $SD=10$ (it is the same for the MCS and PCS), the jail diversion sample had a lower mean MCS $[(M=36.39, SD=10.99), t(79)=-11.08, p < .001]$, and the jail diversion and SAMHSA study had lower MCS $[(M=36.79, SD=12.20), t(603)=-26.59, p < .001]$ and PCS $[(M=40.71, SD=12.35), t(603)=-18.48, p < .001]$ scores. When the population norms were compared to the data for only those who reported being arrested in the past six months the mean MCS and PCS were still significantly lower $[(MCS, M=36.86, SD=11.71), t(265)=-18.27, p < .001; PCS, M=42.67, SD=12.74), t(265)=-9.37, p < .001]$. The jail diversion and 5-site data total sample had significantly lower MCS $[(M=40.58, SD=11.47), t(1026)=-26.32, p < .001]$ and PCS $[(M=48.34, SD=9.78), t(1026)=-5.43, p < .001]$ scores than the general population, but when data for only those who reported arrest in the past year were compared to the general population norms, only the MCS $[(M=37.90, SD=11.41), t(313)=-18.76, p < .001]$ score was significantly lower.

Next, all of the samples were compared to the depression norms where MCS scores have $M=37.40$ and PCS scores have $M=45.55$. The jail diversion sample no longer had a significantly different mean MCS, but did have a higher mean PCS $[(M=49.05, SD=12.23), t(79)=2.56, p < .05]$. The jail diversion and SAMHSA data still had significantly lower mean PCS, $t(602)=-9.63.$
Those who reported an arrest in the past six months also had a significantly lower mean PCS, \( t(264) = -3.68, p < .001 \), but not mean MCS, \( t(264) = -0.75, p = .46 \). The jail diversion and 5-site data had significantly higher mean MCS, \([t(1025) = 8.87, p < .001]\), and PCS \([t(1025) = 9.14, p < .001]\) than the depression norm. When only those who reported an arrest in the past year were compared, the mean PCS \((M=49.46, SD=10.55)\), was significantly higher \([t(312) = 6.56, p < .001]\), but the mean MCS was not significantly different \([t(312) = 0.78, p = 0.44]\) than the depression norms.

The second part of the analysis focused on splitting each of the samples by those who were arrested in the reference time period versus those who were not. The jail diversion and SAMHSA data and the jail diversion and 5-site data results are displayed in Table 4., and show that those who were married were less likely to report being arrested \([\chi^2(1, N=774) = 11.30, p < .001]\) (jail diversion & SAMHSA), \(\chi^2(1, N=784) = 4.56, p < .05\) (jail diversion & 5-Site)). Additionally, in the jail diversion and SAMHSA data, males were more likely than females to report being arrested \(\chi^2 (1, N=777) = 68.59, p < .001\) as were those who also reported being the victim of a crime (nonviolent or violent) \(\chi^2 (1, N=777) = 68.75, p < .001\) compared to those who were not the victim of a crime. In the jail diversion and 5-site data, those who reported ever being arrested in their life \(\chi^2 (1, N=786) = 8.89, p < .01\), and those who had a substance use disorder \(\chi^2 (1, N=788) = 35.29, p < .001\) were more likely to report being arrested in the past year.

The t-tests based on the arrest dummy variable appear in Table 5. The data were split based on whether or not the participant reported a recent arrest to explore any differences in the covariates. In both data sets, there were significant differences with those who were arrested reporting lower age \([\text{jail diversion & SAMHSA } t(773) = 7.56, p < .001]\); \([\text{jail diversion & 5-Site } t(784) = 6.94, p < .001]\), and better PCS scores \([\text{jail diversion & SAMHSA } t(600) = -3.44, p < .001]\)
.001]; [jail diversion & 5-Site, \( t(762) = -2.28, p < .05 \)] compared to those who were not arrested in the reference period. In the jail diversion and SAMHSA data, those who were arrested reported higher ASI drug \( t(743) = -6.78, p < .001 \) and alcohol composite scores \( t(748) = -7.88, p < .001 \) compared to those who were not arrested in the reference period. In the jail diversion and 5-site, those who were arrested reported worse MCS scores \( t(762) = 4.48, p < .001 \), lower BPRS scores (indicating lower severity of mental health symptoms \( t(753) = 3.04, p < .01 \)), and a higher number of mean arrests in their life \( t(649) = -7.68, p < .001 \) compared to those who were not arrested in the reference period.

The third part of the analysis allowed for a further look into the relationships between reported arrest, MCS and PCS scores, and the other covariates. The correlation results in Table 6. and Table 7. show that all of the continuous variables are related to the PCS and MCS scores, and therefore must be treated as covariates in the subsequent mean difference analysis. In Table 6. the continuous variables are age, ASI drug composite, and ASI alcohol composite, whereas in Table 7. the continuous variables are age, number of arrests in lifetime, and BPRS.

Four separate ANCOVAs were conducted to further explore the significant relationships we found earlier in the t-tests and correlations. The ANCOVAs results for the PCS and MCS scores as dependent variables based on the jail diversion and SAMHSA data are presented in Table 8. In the MCS analysis, the ASI drug composite score was the only significant variable \( [F(1, 564) = 16.27, p < .001] \) and the relationship between MCS and being arrested in the previous six months was not significant \( [F(1, 564) = 0.89, p = .35] \), similar to the t-test results. In the PCS analysis, both age \( [F(1, 564) = 51.69, p < .001] \), ASI drug \( [F(1, 564) = 20.44, p < .001] \), and alcohol \( [F(1, 564) = 7.65, p < .01] \) composite scores were significant, and mediated the relationship between PCS score and being arrested in the previous six months \( [F(1, 564) = 0.85, p = 36] \).
The ANCOVAs results for the PCS and MCS scores as dependent variables based on the jail diversion and 5-site data are presented in Table 9. In the MCS analysis, both PCS scores \( F(1, 731) = 26.70, p < .001 \) and BPRS scores \( F(1, 731) = 9.32, p < .01 \) were significant, as were having been arrested in the past year \( F(1, 731) = 9.33, p < .01 \) and having a substance use disorder \( F(1, 731) = 5.86, p < .05 \). In the PCS analysis, age \( F(1, 731) = 36.03, p < .001 \), MCS \( F(1, 731) = 26.70, p < .001 \), and BPRS score \( F(1, 731) = 3.91, p < .05 \) were all statistically significant. Being arrested in the past year \( F(1, 731) = 0.01, p = .92 \) was no longer significant, and neither was having a substance use disorder \( F(1, 731) = 0.65, p = .42 \), both of these variables were mediated by the other relationships.

**Discussion**

The purpose of this study was to explore the physical health and mental health status of adults with SMI as a function of recent criminal justice involvement. The results from both of the data sets revealed lower mean MCS and PCS scores in adults with SMI compared to the general population. This finding is consistent with previous research and addresses the first research question of whether or not adults with SMI have lower MCS and PCS scores than the general population (Ware et al., 2004). The jail diversion sample had lower MCS than the general population but not lower PCS scores. This was also found for those who were recently arrested in the jail diversion and 5-site sample, but not the jail diversion and SAMHSA sample. When compared to the depression norm scores, the MCS scores were more similar to the depression norm than the general population norm, and they were actually higher for the jail diversion and 5-site sample. The mental health status portion of the SF-12 was designed using a sample of adults with depression, not other types of mental illnesses and may be more discriminant for depression symptoms. Therefore, it is not surprising that the scores were higher for the jail diversion and 5-
site study, because the majority of respondents in both of the samples had a diagnosis other than major depression (Rosenberg et al., 2001; Ware et al., 2004). The PCS scores were lower than the depression norm in the jail diversion and SAMHSA sample, but higher in the jail diversion and 5-site sample. MCS and PCS scores did vary by sex and the lower scores may represent the different demographics in these two data sets. Additionally, the SAMHSA participants had the oldest mean age, so the difference in PCS scores might be attributable to the decreasing PCS scores that are found as age increases (Ware et al., 2004). The mean age for the jail diversion participants was approximately eight years younger than the SAMHSA participants.

The second research question focused on differences in the MCS and PCS scores of adults with SMI based on whether or not they reported a recent arrest. The MCS and PCS scores of those who reported arrest were different than those who were not arrested. In both data sets, those who were arrested had higher PCS scores, and in the jail diversion and 5-site data, they also had lower MCS scores. One interesting finding in the jail diversion and 5-site data was that those who reported a recent arrest had worse MCS scores and better psychiatric symptom severity scores. To further explore this relationship, the 5-site data was analyzed separately (all of the jail diversion participants had a recent arrest, therefore this data were not analyzed separately). This relationship held when the jail diversion participants were not included. Unfortunately, based on the available data there was not a good explanation for this finding indicating a strong need for future analyses to explore this relationship, to see whether it is a true relationship, or instead, represents the different ways mental illness symptoms are measured in the two instruments.

When other covariates were controlled for in the ANCOVA analysis, which addressed the third research question, the MCS score remained significantly lower for the arrest group in the jail diversion and 5-site data, and there still was no difference in the jail diversion and SAMHSA data.
Once other covariates were controlled for in the ANCOVA analysis, the PCS scores of those who were arrested were no longer significantly different from those who were not arrested in either of the data sets. Instead, in the jail diversion and SAMHSA data age, ASI drug composite score, and ASI alcohol composite score were significant predictors of PCS. This result may be tapping into the nuanced relationship that drug and alcohol use can play on physical health, and supports the conclusion that those with a younger age have better physical health. In the ANCOVA for the jail diversion and 5-site data, substance use was not a significant predictor, instead age, MCS, and mental illness symptom severity were related to PCS. The 5-site risk sample did include participants who were either inpatients or involuntary outpatients. The better PCS and MCS scores of these participants compared to the SAMHSA participants may be related to their level of treatment, which was more intensive than other adults with SMI living in the community.

The correlation between PCS and MCS scores and past six month arrest was only significant for the PCS in the jail diversion and SAMHSA data, whereas both of the MCS and PCS were significantly related to past year arrest in the jail diversion and 5-site data. In both cases, a recent arrest correlated with higher PCS score, again this relationship most likely occurred because those with a recent arrest are younger, and therefore have a higher propensity towards crime (Constantine, Andel, et al., 2010). Future analysis should focus on using regression to explore this relationship further so that additional independent categorical variables—such as sex, gender, and race—can be included.

Based on the current state of the literature, this author expected that both the MCS and PCS scores would be lower for those who reported recent arrest. In fact, the PCS scores were significantly higher in both data sets. One study found that those with more frequent arrests may have better health due to access to prison health care (Curtis, 2011). However, after taking into
consideration other covariates, including age and drug use, the PCS scores were no longer significantly different based on whether or not the participant had been arrested, meaning that other factors (covariates) are accounting for the difference in PCS scores between the participants with and without a recent arrest. Thus, although the PCS scores first appeared to be better for those adults with SMI with a recent arrest, they actually are not different than other adults with SMI who do not have a recent arrest.

Those who reported arrest were significantly younger than those who did not have a recent arrest. Mean PCS scores steadily decrease based on age groups in the population norms. This finding suggests that young age is a risk factor for arrest but protective against health problems. Consistent with this suggestion, other studies of adults with SMI involved with the criminal justice system show that those who are younger are more likely to get arrested (Constantine, Andel, et al., 2010). Similarly, extant research on physical health status shows that better physical health may result in increased propensity to commit a crime (Schroeder, Hill, Haynes, & Bradley, 2011). Age was significantly related to PCS scores in the ANCOVAs and was a mediating factor between arrest and PCS scores.

Additionally, it has been documented that those who have fewer negative mental illness symptoms, such as emotional withdrawal, social withdrawal, and difficulty showing emotions in facial expressions, and more positive psychotic symptoms, which include hostility, suspiciousness, hallucinations, excitement, and grandiose thinking, are more likely to involved with the criminal justice system (Swanson et al., 2006). At a certain point, if a person’s physical health status is bad, they are not going to be able to commit a crime. For example, if a person is unable to walk unassisted, they are limited in the type of crimes they can commit. Thus, better mental health and
physical health may result in increased criminal activity in adults with SMI, and similarly for adults without SMI (Schroeder et al., 2011).

**Limitations**

Although this study maximized sample size by merging data from different studies, there are limitations in this study. The demographic information was measured differently in each study, although some items, including age and sex, are uniform across all three samples. Race, education, income, and marital status questions and responses varied by study. The responses were collapsed to provide common answers, but this led to a decrease in information because the variation in responses was reduced. Additionally, victimization was measured differently in each study and therefore could not be included in the subsequent ANCOVA analysis. Also, the jail diversion and SAMHSA study had information about drug and alcohol use that was collected using the same instrument, the ASI, but the author was not able to scale the mental health symptom instruments to make inferences across samples. Similarly, had mental health symptom information in the jail diversion and 5-site study, but the author was not able to scale the drug and alcohol instruments to make them compatible, and instead the author had to use a dummy variable indicating substance use. Ideally, the author would have been able to look at drug and alcohol use along with mental health symptom severity, because they are interrelated. The SF-12 has been used widely, but it may not be sensitive to adults with SMI. Additionally, the weighting of the total scores and the general population norms are both based on the 1998 standards (Ware et al., 2004). The health of the population has changed, and these weights may not reflect current health issues (National Center for Health Statistics, 2011; Remington & Brownson, 2011). In addition to the issues of scaling, the measures were administered at different time frames, and different sampling
techniques were used across the different samples. Some of the results may reflect the differences in the samples versus true population differences.

Additional limitations were present with the arrest variable. The jail diversion sample consisted of participants who have frequent arrests, and therefore may be different than other participants who were arrested in the past six months or year, but do not have as extensive of a criminal history as the jail diversion sample, as indicated by the mean lifetime arrests. Also, participants in the jail diversion sample were involved in jail diversion programs, whereas we only know that the other participants were arrested, not whether they were involved in any jail diversion services. Finally, this study used cross-sectional data, which limits the inferences that can be made about any of the relationships. As a next step, analysis should focus on obtaining a larger sample of participants with SMI who report a recent arrest and obtain data on substance use, mental health symptom severity, age, and other demographic information to further explore the relationship between mental and physical health in justice-involved adults with SMI.

**Conclusion**

The mental health and physical health status scores of adults with mental illness who are involved with the criminal justice system are lower than the general population. The direct mechanisms that moderate these associations are not known. This study found a relationship between MCS and PCS and age, alcohol and drug use, and mental health symptom severity. Future research needs to explore how these constructs interact and the impact they have on criminal justice involvement over time.

**Implications**

The results of this study support the hypothesis that, in general, adults with SMI have worse physical and mental health status compared to the general population (Ware et al., 2004). When
the samples were split based on recent arrest, the relationship between mental and physical health status was more complicated. There was limited evidence that the mental health status of those who reported arrest may be lower, but this was only found in one sample. Additionally, the physical health status of those who were arrested was higher prior to controlling for covariates. This evidence suggests that although adults with SMI who are involved with the justice system have more physical illnesses, they may not perceive these illnesses to be as debilitating (Cuddeback et al., 2010). Another explanation is that those who are arrested are younger and therefore have better physical health status. Further research is needed to tease out this relationship. Currently, this research does not support targeting physical illnesses at the jail diversion intercept as the most valuable use of resources. Despite these findings, there is a continued need to increase access and utilization of physical health services for adults with SMI, as they still experience physical illness at a disproportionately high rate compared to those without SMI (Chwastiak et al., 2006; Cuddeback et al., 2010).

More research is needed to fully understand the relationship between mental and physical health among justice-involved adults with SMI. Future studies should focus on collecting data on multiple aspects of the participants’ health, including substance use and diagnosis, and how the interaction between these variables may influence physical health. Additionally, longitudinal data analysis is warranted to explore the relationship between physical and mental health among adults with SMI who are justice-involved to explore how both mental health and physical health treatment play a role.
SECTION 3: SECOND MANUSCRIPT

Potential Journal: 1. *Statistics in Medicine*; or 2. *Community Mental Health*; or 3. *Health Services and Outcome Research Methodology*

An Example of Missing Data Analysis Using a Sample of Adults with Serious Mental Illness enrolled in a Jail Diversion Intervention

**Background**

Missing data are common in longitudinal studies and occur when an intended measurement is not taken, is lost, or is unavailable at any time point (Diggle et al., 2002). Missing data are the result of a multitude of causes, such as drop-out, illness, or the participant moving. The likelihood of experiencing missing data, and more specifically dropout, is particularly high in populations with serious mental illnesses (SMI) and criminal justice involvement (Diggle et al., 2002). When data are missing, the resulting available data are unbalanced, and can lead to issues with subsequent data analysis (Diggle et al., 2002).

There are multiple implications for the subsequent analysis of the data when missing data are present. First, because the data set is unbalanced, not all participants in the study will have the same amount of data, or data at the same time points. Second, because data are missing, there is a loss of information, which may be related to the reason for the missing data or may be random measurement error. Third, because of the missing data, the information available may result in biased parameter estimates (Nakai & Ke, 2011). Fourth, missing data can result in a loss of statistical power (Palmer & Royall, 2010). Fifth, there could be a reason that the data are missing, including attrition (drop-out) due to ineffective treatment in the study. In drug treatment studies
for adults with schizophrenia, the participants who drop out are typically those who are not receiving the intended benefits of the medication. If the information is used from only the participants who remained in the study, the positive benefits of the medication may be inflated (Mazumdar et al., 2007; Shortreed & Moodie, 2012). It is important in these situations to understand the reason why attrition is occurring (Diggle et al., 2002).

Missing data are a frequent occurrence in longitudinal studies of adults with SMI as well as other longitudinal studies that are interested in piloting new drug and behavioral treatments (Diggle et al., 2002; Shortreed & Moodie, 2012). The Clinical Antipsychotics Trials in Intervention Effectiveness (CATIE) study is an example of a longitudinal study that was plagued by missing item data and participant drop-out (Shortreed & Moodie, 2012). The Behavioral Risk Factor Surveillance System (BRFSS) study is one of the largest ongoing studies in behavioral health, but consistently has missing data (Frankel, Battaglia, Balluz, & Strine, 2012; National Center for Chronic Disease Prevention and Health Promotion, 2013). There is evidence that certain missing data techniques used in previous BRFSS analyses have resulted in underestimates of the prevalence of severe depression (Frankel et al., 2012).

Longitudinal studies are conducted in the social sciences to measure change over time, including assessing the effectiveness of behavioral health interventions. Many researchers use statistical methods, like Analysis of Variance (ANOVA) for mean comparisons, to determine whether or not the intervention is working (Mazumdar et al., 2007). Findings of these analyses are then used as a way to apply for additional funding, or to ensure ongoing funding. Additionally, many federal grants now require evaluators to provide evidence on the effectiveness of interventions to justify funding for the study by conducting an evaluation. Despite the expectations that those working in the behavioral health field will evaluate their programs and interventions,
there are few clear guidelines on how to handle missing data targeted towards non-statisticians (Mazumdar et al., 2007). Sometimes researchers may apply a missing data technique, like using the last observation from a subject, without understanding how the technique may impact their results. When conducting intervention research to evaluate risk comparisons between service programs, evaluators must understand the implications of missing data.

The purpose of this study is to provide an example of how to approach missing data in behavioral health research, including the benefits and limitations of various statistical approaches. This study used data from a sample of justice-involved adults with SMI to provide a clear and easy-to-understand approach to missing data that evaluators can use as a guide for their own behavioral health intervention evaluations.

Research Objective: Determine the reasons for missing data, the missing data mechanism, and the statistical method to determine how to properly model the missing data in a sample of adults with serious mental illness in a jail diversion program.

As a first step, the author discussed missing data mechanisms and missing data patterns in the sample data. Next, the author addressed the missing item data using multiple imputation. Then the author used survival analysis to help decide on the missing data mechanism. Next, multiple imputation and maximum likelihood estimation techniques were used to account for the missing data. Finally, a short discussion on options for data not missing at random, including the benefits and limitations was presented.

Sample Data Methods

Sample

The sample data for this study came from clients participating in two post-booking jail diversion programs implementing a new intervention designed to target the needs of high-risk
users with SMI who continue to cycle through the criminal justice system. Potential participants were referred to the research team by the jail diversion staff. The research team ensured they met the eligibility criteria of: 1) a diagnosis of schizophrenia, schizoaffective disorder, bipolar disorder, or psychotic disorder NOS; 2) speak English or Spanish; 3) voluntary participation in the diversion program and the research study; 4) have three or more jail bookings in the past three years or seven or more lifetime jail bookings; and 5) scored by the jail diversion staff as moderate or high risk on one of the following items on the Short Term Assessment of Risk and Treatability (START): violence; self-harm; suicide; self-neglect; or general offending (Webster et al., 2009).

Once participants agreed to be in the study \( (n=50) \), they were randomized to the treatment as the usual (TAU, \( n=16 \)) group or the treatment group (TX, \( n=34 \)). Typically, differences in group sizes can result in power issues, but inferences about the effectiveness of the study groups will not be made in this study. Additionally, oversampling of new TX group can increase power to detect differences, therefore no statistical adjustments or re-randomization was done (Shadish et al., 2002). TAU was provided by the jail diversion staff and included crisis stabilization, service linkages to outpatient or residential treatment, peer specialist support, housing assistance, medication assistance, transportation, and financial assistance to obtain benefits. The TX group received these services, with the addition of a staff person who was a care coordinator and a peer support specialist who were responsible for coordinating care across the different service providers and community linkages. The care coordinator was responsible for going beyond the standard of just referring the participant, and instead was involved in all aspects of the participants’ care to ensure they received the services they need.
Data Collection

Data were collected in 60-90 minute interviews conducted by one of four research assistants. All of the questions were verbally asked of the participant. Interviews were conducted at baseline, three months, six months, and nine months. The questionnaire consisted of a battery of instruments including socio-demographic information, service use information, criminal justice and arrest information, the Short Form Health Survey version 2 (SF-12; Ware et al., 1996), and the Brief Psychiatric Rating Scale (BPRS, Lukoff et al., 1986; Overall & Gorham, 1962). The main outcome of the model was the SF-12 total scores. Additional covariates in the model included age, race, gender, lifetime jail bookings, and mental illness symptom severity measured with the BPRS. All data analyses were conducted using SAS 9.3 (see Appendix B for a copy of the code).

Measurement

The SF-12 was designed as a shortened version of the SF-36 to assess functioning and well-being (Ware et al., 1996). The SF-12 is an intentionally general health status measure that can be used with different age and disease groups (Ware et al., 1996). The scoring is norm based, with a mean=50. A lower score indicates poorer health status (Ware et al., 1996).

The BPRS is an expanded 24-item scale that was designed to assess change in the symptoms of psychiatric patients over time to understand how a treatment is working (Lukoff et al., 1986; Overall & Gorham, 1962). The 24 items measure different behaviors and attributes that are related to improvement or deterioration in mental health (Lukoff et al., 1986). All of the items are rated on the same scale, from 1-7, with 1 indicating the symptom is not present and 7 that the symptom is extremely severe. The item ratings were summed to create a total score (Overall & Gorham, 1962).
Missing Data Overview

The most important issue in dealing with missing data involves identifying the prevalence of missing data by the variable of interest. To begin, the author calculated the percent of missing SF-12 items and SF-12 total scores and BPRS total scores data at each time point. At baseline, 14% of the data were missing, at three months 34% of the data were missing, at six months 56% of the data were missing, and at nine months 62% of the data were missing (these are the percentages for both measures, as they are frequently missing at the same time). The other covariates were not included because they were only measured at baseline and the data were complete, except for sex, which was missing for one participant. The high rate of missing data cannot be ignored in this study, and therefore, it is necessary to explore further.

Missing Data Mechanisms

Once the prevalence of missing data has been established, the missing data mechanisms must be identified. There are three missing data mechanism classification categories: 1) Missing at Random (MAR); 2) Missing Completely at Random (MCAR); and 3) Not Missing at Random (NMAR or MNAR) (Enders, 2011; Little & Rubin, 2002; Nakai & Ke, 2011). This classification system is based on the principle that each participant has a score for a variable and a probability for having a missing value on that variable (Enders, 2011). For all instances of missing data, the first step is to explore the data to understand why they are missing. To deal with the statistical issues of missing data, the mechanism of missing data must be determined because it provides the underlying reason why the data are missing, which is then used to decide on an analytic technique (Little & Rubin, 2002). Most of the analyses that are conducted on missing data are to determine the missing data mechanism.
**Missing At Random (MAR)**

Data are MAR if the probability of having a value missing is related to the other variables, but is not related to the would-be value of the incomplete variable. In other words, MAR refers to a missing value that is related to the other variables, but not the likelihood of drop-out, and is not related to current or future responses to the variable (Enders, 2011; Hedeker, 1997; Nakai & Ke, 2011). The missing-ness depends only on observed variables, and is not related to some unobserved, or unmeasured variable (Little & Rubin, 2002). Data MAR are sometimes considered “ignorable,” as there are different analysis mechanisms that will continue to result in asymptotically unbiased estimation (Raudenbush & Bryk, 2002). MAR data are fairly common in longitudinal studies that collect data on many aspects of the outcome of interest, and keep detailed information about why data are missing. For example, data can be considered MAR if the participant dropped out of the study because they were re-arrested or hospitalized, and data were collected on these variables. This information can then be incorporated into the analysis.

**Missing Completely At Random (MCAR)**

Data are MCAR if the probability of having a missing value for a specified variable is not related to the potential values for that variable, or any of the other observed data for the other variables (Enders, 2011; Nakai & Ke, 2011). In longitudinal studies, the missing data are a random sample of all the time points or the drop-out participants are a random sample of all participants (Raudenbush & Bryk, 2002). Data MCAR occur at random and are not related to the study outcome. For example, a participant may move out of the area or miss their appointment because their car broke down. This is the least likely situation to occur and essentially implies that the persons with missing data are not different from persons with complete data. Data that are MCAR allow for the most choices for statistical methods to analyze the data, as the missing-ness is
ignorable (Burzykowski et al., 2010). Given the majority of the research conducted in social sciences focuses on human participants, this is not a useful taxonomy of missing data as it is unlikely that the reason for participant drop-out is unrelated to the study (Enders, 2011).

**Not Missing At Random (NMAR)**

Data are NMAR (MNAR) when the probability of having a missing value for a particular variable is related to the would-be value of that variable. These values depend both on the observed responses and the would-be missing value (Enders, 2011: Nakai & Ke, 2011). Unlike data MAR, when data are NMAR the missing-ness of the data is related to some unobserved value or variable. For instance, in the MAR example, if a participant was re-arrested or hospitalized and data were not collected on the reason why the participant dropped out of the study, the missing data mechanism would be changed to NMAR. NMAR data are often referred to as non-ignorable missing data, meaning that the missing-ness needs to be taken into consideration in the statistical model, through advanced analytic procedures, as future responses cannot be predicted based on the past responses. This type of missing data requires more sophisticated consideration of the appropriate way to model the data for analysis that go beyond many of the basic regression models used in behavioral health research. Much of the current research deals with the optimal way to deal with NMAR data (Enders, 2011; Nakai & Ke, 2011).

One of the most significant issues with the above classification system is the difficulty of determining whether data are MAR. It may not be an apparent variable that is causing the participants to drop out and could be a covariate that was not measured. Many studies include multiple covariates during data collection to ensure that, to the best of their ability, the data that they have are MAR, which are easier to handle for analysis (Gelman & Hill, 2007). Due to the assumptions of NMAR where the variable is related to the unobserved values (or would-be scores),
it is impossible to definitely decide which mechanism matches the data. The observed data cannot be used to decide the type of missing data due to the untestable relationship of the missing data to unobserved values (Enders, 2011).

**Missing Data Pattern**

The pattern of missing data can help to understand the missing data mechanism (Little & Rubin, 2002). There are two different types of patterns that occur: 1) monotone and 2) non-monotone (or arbitrary). Data have a monotone pattern if a participant misses a measurement time period and he/she is not observed at any future time periods. Monotone missing data is a term typically reserved for data missing due to dropout (Ibrahim & Molenberghs, 2009). Data have a non-monotone pattern if a participant misses a measurement time period, but they have an observed value at a future measurement (“Statistical Computing Seminars: Multiple Imputation in SAS, Part 1,” 2013). Intermittent missing data are usually represented by arbitrary missing data patterns, as these participants miss one time period but then participate at a later time period. Both dropout and intermittent missing data are referred to as unit nonresponse, because there is no information from the participant on any of the items for that time period (Rubin, 1987). When a participant completes the survey or questionnaire, but either skips or refuses to answer specific items, it is referred to as item nonresponse (Rubin, 1987). It is important to begin the analysis by exploring all instances of missing data to determine whether or not the missing data are due to item nonresponse or unit nonresponse.

**Missing Data Basics**

There were multiple types of missing data in this sample, including SF-12 total scores that were missing due to an item on the SF-12 being missed (item non-response), participants who missed one time period but returned at the next time period (intermittent missing), and participants
who dropped out of the study (see Table 10). The author also explored the types of missing data by study group to see whether or not the missing-ness varied by study group (see Table 10). To understand the dropout occurring at each time point by study group, a chi square analysis was conducted. At the nine-month time period, the TAU group had significantly more participants dropout compared to the TX group ($\chi^2=5.88, P<.05$). Although this is an interesting finding, it is premature to draw conclusions, as there is a need to look further at the data to determine the missing data mechanism.

The first step in determining the missing data mechanism is to conduct basic descriptive statistics to compare the mean and standard deviation of participants who had complete data compared to those with complete data that dropped out after that data collection time, and also those who had complete data versus those with missing item data. This analysis was done by treatment group, as treatment or lack of treatment has been shown to impact study dropout (Diggle, 2002; Shortreed & Moodie, 2012). Mean values revealed that at baseline, those who continued in the study and those who subsequently dropped out had statistically different PCS scores in the TX group, with those dropping out reporting better health status (see Table 11). This is an important finding, as physical health status could potentially be a predictor of dropout. The mental health status in the TAU group was slightly lower for those who dropped out after the six month follow-up. Although interesting, we cannot draw any conclusions due to the small sample size. None of the other results were statistically significant.

**Item Nonresponse**

The first step to handle the missing-ness of the data is to focus on the missing items. The scoring algorithm for the SF-12 does not allow for any missing items. If there is missing item data, the total score will also be missing. In this data set, there were seven baseline interviews
missing due to a missing item, one three-month, three six-month, and zero nine-month interviews. The easiest way to understand missing item data is to have data coding options specific to missing and refused items. During the data cleaning phase, the person conducting the analysis can explore the items to see whether or not they were missed due to participant or interviewer error, or if the participant refused to answer. The former leads to an easy conclusion of data MCAR, because the missing-ness is random and due to error, whereas the latter results in more complicated analysis to understand why participants did not want to answer a specific item. When participants refuse to answer, it could represent an item that is upsetting or related to their current situation. Without further information, the missing-ness is no longer random. Exploration of the SF-12 scores of participants with missing items was not necessary in this study. Documentation of any items that were refused by the participant was made by the research assistant, and after exploring the data it was clear that the reason participants had a missing item was due to research assistant error, not because the item was related to any other measured or unmeasured construct. Therefore, in this study, item missing-ness was considered random, or MCAR, and easy to deal with statistically.

**Statistical Solutions: Approaches for Data MAR or MCAR**

Many of the simple techniques that are used to deal with missing data can result in biased parameters estimates because they ignore the missing data and they require the missing data to be MCAR. Some examples include list-wise deletion, where any case that has missing data is dropped; complete case analysis, where only complete cases are included in the analysis; and last observation carried forward, where the previous measurement is used for the current time point. List-wise deletion and complete case analysis result in a loss in power (Nakai & Ke, 2011). Complete case analysis leads to unbalanced sample size across variables. An example of a complete case analysis procedure is ANOVA (Nakai & Ke, 2011). When the missing data are
completely ignored, it will cause the results to be biased given only data from participants who continued in the study and ignoring those who may have dropped out due to worsening symptoms (Palmer & Royall, 2010). The last observation carried forward is a type of single imputation. The underlying assumption of carrying forward the last observation is that if the participant had continued in the study, they would not have changed at all for the duration of the study. This is not a valid method to use even for data that are MCAR, as continuity throughout the duration of the study is counterintuitive to the majority of research studies no matter the type of missing data, especially in human subjects research (Burzykowski et al., 2010; Grittner, Gmel, Ripatti, Bloomfield, & Wicki, 2011; Mazumdar et al., 2007). Using the last observation results in incorrect estimates for variance and standard errors, and underestimates within-subject variation. In general, the research field no longer views this as a valid way to deal with missing data (Grittner et al., 2011).

Another similar single imputation technique is to calculate a composite score based on the mean of the previously observed scores. In this technique, the non-missing values for the variable are averaged; this number is then used in place of the missing values. When a mean value is substituted for a missing value, it ignores any trend—whether positive or negative—that the participant with missing data was experiencing up until that time point and thus “washes out” any true trend that exists. It also results in incorrect distributions of the variable and underestimation of the standard deviation. As an alternative, sometimes the median value is used, which has the same issues. This method for dealing with missing data is also reliant on MCAR data assumptions and is not a viable option for missing data (Nakai & Ke, 2011).

In this example, all of the missing data at the item level are the result of the research assistant missing the question. Even though we know the data are MCAR, the above methods
either result in a loss of power or would bias the results given we are interested in the treatment effect over time. Therefore, it is necessary to use a method that incorporates previous information but also allows us to model the potential for a treatment effect.

**Multiple Imputation**

Multiple imputation methods for missing values have received considerable attention in the longitudinal literature, and experts agree it is an appropriate technique to use when data are MAR (Burzykowski et al., 2010). Multiple imputation is used to fill in the missing values prior to analysis and has three phases: 1) an imputation phase; 2) an analysis phase; and 3) a pooling phase. The imputation phase creates multiple sets of data, all of which are plausible replacements for the missing data (Enders, 2011). The analysis phase consists of the statistical analysis method specified by the researcher, such as linear regression. This is then followed by a pooling phase, during which the parameter estimates and standard errors are aggregated into a single set of results (Enders, 2011). In SAS, the first phase is conducted using PROC MI; the second and third phases are done using PROC MIANALYZE, which pools and analyzes the data (SAS Institute Inc., 2014a, 2014b).

The imputation stage begins by grouping participants based on characteristics related to their missing values. If the missing data patterns are monotone, regression methods or propensity score methods can be used. Regression methods fit each variable using the previous observed variables as covariates (Diggle et al., 2002). Although regression multiple imputation is the most common, it is not always the most appropriate method. Regression multiple imputation is only appropriate when the data have a monotone missing data pattern, such as when there is only data missing due to drop-out. Regression multiple imputation would be appropriate if participants dropped out of the study and information is collected on the reason for the drop-out. There are
different methods for imputing values that can be chosen based on the missing data patterns. For arbitrary missing data patterns, the Markov chain Monte Carlo method is most frequently used (Schafer, 1997).

During the imputation stage, the number of imputations that need to be used should be calculated. Previous research found that five imputations was enough to achieve relative efficiency, but in most social science research the focus is on obtaining stable parameter estimates and $p$ values, not on relative efficiency (Bodner, 2008; Graham, Olchowski, & Gilreath, 2007; Schafer, 1997; White, Royston, & Wood, 2011). Bodner (2008) provides a user-friendly way to estimate the fraction of missing data, or $\lambda$, for variables in a data set. Specifically, an estimate of the fraction of missing data, or $\hat{\lambda}_L$, can be obtained by using the number of observations available after list-wise deletion, or $n_L$, and the total number of cases, or $n$. The formula is:

$$\hat{\lambda}_L = 1 - \frac{n_L}{n}$$

The result of this formula is then used to calculate the number of imputations needed. Bodner (2008) also provides an estimate of the number of imputations needed to achieve 95% confidence interval half-widths. One of the main reasons multiple imputation is done is to prevent power issues (Graham et al., 2007). Graham et al. (2007) also provide an estimate of the number of imputations needed based on the fraction of missing data to prevent power falloff, which can be thought of as a dramatic decrease in power that occurs at a certain point as the number of imputations is decreased.

SAS provides examples and guidance on the different imputation techniques available based on the pattern of missing data (SAS Institute Inc., 2014b). After imputation, multiple data sets are created, which contain the new values. Each data set is analyzed separately during the analysis phase and multiple sets of parameter estimates and standard errors are produced (Enders,
During the pooling stage, the multiple parameters and standard errors obtained in the analysis stage are aggregated (Enders, 2011). Again, these stages are combined in the PROC MIANALYZE procedure in SAS (SAS Institute Inc., 2014a).

Multiple imputation methods can result in correlated data sets, which cause the between-imputation standard error to be underestimated. There are statistical methods to avoid this, but they are situation-specific depending on sample size, number of variables, missing data rates, and correlations among the variables (Enders, 2011). Issues are also encountered in longitudinal data when all the data are not collected at the same interval, resulting in different imputation algorithms (Enders, 2011). One of the other major issues with multiple imputation is it operates under the assumption that the missing data are MAR, which can be a difficult assumption to defend in longitudinal studies (Siddiqui, 2011).

**Missing Item Analysis**

In this study, the item nonresponse missing data were MCAR because information was collected on why data were missing and the missing data could be attributed to research assistant error. Therefore, multiple imputation was an appropriate statistical technique to handle the missing item data. Whenever multiple imputation is used, SAS provides the missing data pattern. In this study, the missing data patterns were calculated by time point, because the non-missing values for the PCS and MCS do vary by time (see Table 12). The missing data pattern produced by SAS was informative about how the data were missing. At baseline, approximately 86% of the information was complete as represented by the first row with all x’s. The o symbol represents missing data. The last row, which contains approximately 6% of the observations, were missing data for all of the SF-12 items; these were the cases where the entire assessment was missing either due to intermittent drop-out or study drop-out, and are considered unit nonresponse. The other three
groups were the situations where either one or two items were missing a response; these were the data that were imputed with multiple imputation for the missing item analysis. Both the three-month and six-month data had similar missing data patterns. There was no missing data pattern for the nine-month follow-ups; all of the items were either complete or all of them were missing, so for this portion of the analysis, the nine-month data was omitted.

The item values of the SF-12 were not for prediction or inferences; instead they were used to calculate the SF-12 composite score. The values were imputed two different ways, the first was using multiple imputations and the second was using a single iteration to impute the value for each missing item, or single imputation. In both situations, restrictions were specified about the minimum and maximum values of the items, and the values were rounded to the nearest whole number. These restrictions can bias the results, but in this situation were necessary because the item values were used to calculate the total scores (“Statistical Computing Seminars: Multiple Imputation in SAS, Part 1,” 2013). If the item values are not within the acceptable range, or a whole number, they would be excluded from the total score calculations, and the item data would still be considered missing. For the multiple imputations the fraction of missing data was calculated first to determine the number of imputations. There were 10 cases of missing item data across all of the time points. There were a total of 50 participants, and 9 had an item missing at any time point (one participant had items missing at two time points). Listwise deletion drops all of the participants with any missing data and only keeps the complete cases, $n_L = 41$ for this data. According to the formula Bodner (2008) presented, the fraction of missing data was $(1 - (41/50)) = 0.18$. The fraction of missing data were between .10 and .20, which were used to calculate the number of imputations needed. According to Bodner (2008), ten imputations would be sufficient for this data (see page 671 for more information on the formula used to calculate this result).
Graham et al. (2007) suggest 20 imputations to avoid power falloff, but we were not interested in using the SF-12 item variables for inferences, so power was not a concern.

Once the values were imputed for the items, the total scores were calculated for the MCS and PCS scales. To determine whether it was acceptable to only impute a single value for each missing item, the means and standard deviations of the item values for the single imputation were compared to the values of the multiple imputed values. There were no differences in item values or in total score values for these items. These results support the assumption made that these data were in fact MCAR, and although multiple imputation could be used, single imputation was also a valid, and easier to use, form of imputation. After dealing with the missing item level data, the next step was to focus on the unit level missing data.

**Missing Data Mechanism Analysis**

**Survival Analysis**

The data for this study represent a common occurrence in studies with drop-out and intermittent missing data; the reason for the missing data was related to the study outcomes and therefore was considered informative. This relationship can be inferred from information that was collected throughout the study; in this study there were participants who were hospitalized, which was related to MCS scores, one of the outcomes of interest. In addition, the large amount of data that were missing indicates the data were not missing completely at random. Survival analysis is useful when there is reason to suspect that the missing data are informative and provides a better understanding of the relationship between the study groups and drop-out (Allison, 2010). The advantage of survival analysis is it provides information not only on whether a person dropped out of the study, but also when they dropped out (Allison, 2010). By using this information, the researcher is able to understand how different factors can predict dropout, which can then be used
in subsequent data analysis. Because the data used in this study did not have continuous time and multiple participants dropped out at the same time period, it was necessary to use a discrete method for calculating the partial likelihoods (Allison, 2010).

The purpose of conducting survival analysis is to get a better understanding of the data. Although you cannot test for MAR versus NMAR, survival analysis allows the researcher to see if the data are MCAR. To start, Kaplan-Meier survival curves were calculated based on the study group. The survival plots and test for trends show there was no difference between the rates of drop-out for the two study groups. This was an important finding; differences in drop-out between study groups would strongly suggest that the MCAR assumption should be rejected. Earlier, results showed that a greater number of the TAU participants dropped out after the six-month assessment and before the nine-month assessment. The survival curves do not support that finding, and show that the two study groups have similar dropout patterns.

Next, multiple Cox Proportional Hazards models were calculated to explore the relationship between time to drop-out, based on treatment group, MCS, PCS, BPRS, age, race, and sex as potential predictors. Two different models were constructed, one with only baseline predictors (see Table 13), the other model included time-varying predictors, but is not included here as the results were similar. None of the variables were significant predictors of drop-out. Even though this could lead to a MCAR determination, this model was not exhaustive and excludes other potential predictors such as criminal justice history, substance abuse history, and treatment history. In addition, throughout the study, information was collected on why participants dropped-out. Many of these reasons were directly related to the study outcomes and include re-arrest, inpatient substance abuse treatment, and ongoing legal trouble resulting in a warrant for arrest being issued (Hogan, Roy, & Korkontzelou, 2004). Because of these circumstances the data cannot
be MCAR. All longitudinal studies should strive to include as much data as possible on why participants drop-out. As stated above, the awareness of why participants dropped out makes it easier to decide to treat the data as MAR. If this information was not collected, and could not be incorporated into the future models, the data would have to be treated as NMAR. Because the data were MAR, multiple imputation is a valid method for the missing data. An additional and also valid way to analyze the available data without creating artificial data is through maximum likelihood estimation.

**Other Statistical Solutions for Data MAR: Maximum Likelihood Estimation**

Maximum likelihood estimation is used to identify the population parameters that are most likely to produce the sample data (Enders, 2011). These estimates are based on all of the available data, incomplete data are not discarded, and values are not imputed. The process that is used in maximum likelihood is iterative, which allows for optimization of the parameters for the sample data. The incomplete data are used in this process, by borrowing information from the observed cases. An example of a statistical procedure that employs maximum likelihood models to deal with missing data for longitudinal data are mixed-effects models; these are also referred to as mixed effects regression models or multi-level models (Mazumdar et al., 2007; Siddiqui, 2011). In SAS, these models are analyzed using the PROC MIXED procedure (SAS Institute Inc., 2014c).

Maximum likelihood is only appropriate when the multivariate normality assumption holds for information about the missing data. In addition, if the participants who have dropped out of the study are not the same as participants who continued (data NMAR), maximum likelihood is no longer an appropriate option (Burzykowski et al., 2010). The multiple imputation method is a more statistically intense procedure than maximum likelihood estimates, although the parameter estimates from the two methods are comparable. Multiple imputation does have some advantages
over maximum likelihood estimation, in that it allows for increased complexity of variables, such as treatment withdrawals and intermittent missing-ness, to be taken into consideration. This allows for the incorporation of variables such as predictive dropouts (Burzykowski et al., 2010)

**Drop-out and Intermittent Missing Data Analysis**

In this study, there were instances of participant dropout and intermittent missing data. Intermittent missing data can occur for many reasons including hospitalizations, missed appointments, increased mental illness symptoms, and incarceration. In this study, there were a total of five instances where the data were missing intermittently, which means the data have an arbitrary data pattern (see Table 10). After calculating the missing data pattern for the total scores the intermittent missing data patterns were apparent in groups 5, 7, and 8 (see Table 14). Although it is not discussed in detail here, it is important to determine if the means are different for those who missed a subsequent time period and if possible, to collect data on why participants missed that assessment to help with determining the missing data mechanism.

For purposes of illustration, both multiple imputation and maximum likelihood estimation were used to calculate parameter estimates for the same regression equation. Instead of imputing values just for the intermittent missing data, Monte Carlo Multiple Chain (MCMC) imputation was used, because it can also impute values for the missing data due to drop-out. The MCMC imputation method can handle the complexity of an arbitrary missing data pattern (Schafer, 1997).

In order to compare parameter estimates, the same regression equation was used for the maximum likelihood estimation and for the multiple imputations. Multiple imputation can be conducted on as many variables as desired, up to the entire data set. In this example, there were over 3,500 variables, so imputing values for all of the variables was not realistic. Instead, variables that were related to drop-out and the outcome variable were included in the model. It is important
to include both the independent and dependent variables when doing imputation (Schafer, 1997). This allows for the information to be used from all of the variables to calculate the missing values. If only one variable was used for the imputation, then the resulting imputed data would be based only on the information available from that variable (Rubin, 1987; Schafer, 1997). Again, like in the missing item analysis, the fraction of missing data was calculated. In this data, 15 participants had complete data out of the total of 50 \((1-(15/50))\), so the fraction of missing data was estimated to be .70. According to Bodner (2008), 114 imputations are necessary to achieve stable parameter estimates and \(p\) values. Graham et al. (2007) recommends around 100 imputations to avoid power falloff. The author decided to be conservative, and 114 imputations were calculated.

The results for the MCS (mental health status) regression outcomes are displayed in 5 and the result for the PCS (physical health status) regression outcomes are displayed in Table 16. The MCS data revealed similar parameter estimates from the maximum likelihood estimation and the multiple imputation estimates. Most notably, the BPRS scores were no longer significant in the multiple imputation analysis, and lifetime jail bookings became marginally significant in the multiple imputation analysis. Otherwise, all of the parameter estimates were similar.

The PCS analysis was fairly consistent between the two methods. When data were imputed, the effects of race and sex on the PCS scores were decreased and no longer significant at the .05 level. This finding may indicate some bias in the results from the missing data set, as the race parameter was more conservative in the imputed data analysis. There was a change in the age parameter, with a lower parameter estimate in the multiple imputation analysis that was also approaching significance. Age is a known factor that influences PCS scores. In the maximum likelihood analysis increased age was related to better PCS, which is not consistent with the literature (Ware et al., 2004). Although the multiple imputation analysis also found that increased
age increased PCS scores, it was more conservative than the maximum likelihood estimate. Finally, there was a difference in the statistical significance of mental health severity as measured by the BPRS on PCS score between the missing data and imputed data, although the parameter estimates were similar. Deciding on the best method to use depends on the data that are present. Overall, the literature has shown that multiple imputation results in unbiased parameter estimates as long as the data are multivariate normal and MAR (Burzykowski et al., 2010; Mazumdar et al., 2007). If the data are not MAR or MCAR, neither of these methods provide accurate parameter estimates and instead, more complex models must be used (Siddiqui, 2011).

**When Data are Not Ignorable: Approaches for Data NMAR**

When data are NMAR, the missing data are considered non-ignorable. The techniques to appropriately utilize information about the missing data are more complex than the techniques used for data MAR or MCAR. If the missing data are modeled using one of the previous methods for MAR or MCAR the model will be biased. Typically for NMAR data, likelihood-based models are specified for the data and for the missing data mechanism (Ibrahim & Molenberghs, 2009). When data are NMAR, maximum likelihood estimates can no longer be used, as the parameter estimates will be biased (Xu & Blozis, 2010). Instead, it is necessary to use models specifically designed for data NMAR.

The way that the data are classified into these models depends on the relationship between the missing data and the observed data and typically is dealt with using a selection model, pattern-mixture model, or a shared parameter model. Each of these methods can utilize different types of inference paradigms, including maximum likelihood, multiple imputation, Bayesian methods, and weighted estimate equations (Ibrahim & Molenberghs, 2009). Data that are NMAR are considered to have a missing data pattern that will influence the results, rendering it non-ignorable.
Types of NMAR Models

Selection models are used to augment growth models, which are used for longitudinal data by specifying regression equations that predict missing data indicators for observed or missing data (Ibrahim & Molenberghs, 2009). Selection models can use repeated measure variables to predict the probability of missing data at a particular time point (Hogan et al., 2004). Selection models operate under strict assumptions that many times are violated in traditional longitudinal studies. Selection models assume normality for the response distribution, and linear dependence between logit and possible missing values in the model (Hogan et al., 2004). These two assumptions are critical and statistically there is no way to determine which of the two has been violated, making them untestable (Hogan et al., 2004). If there is even a moderate departure from the multivariate normality assumption, it can result in substantial bias (Enders, 2011). The accuracy of the model depends on how well the dropout process is specified, which can be difficult. Again, there is no way to test whether the drop out was properly specified (Enders, 2011), and that is why this method may be less useful to non-statisticians.

Pattern mixture models operate under the assumption that there is not a single pattern of missing data and models the different missing data patterns based on sub-groups that share similarities in their missing data patterns. This is different than selection models that assume there is only a single missing data pattern (Ibrahim & Molenberghs, 2009). Again, pattern mixture models operate under assumptions about the unobserved values that are difficult to assess. Pattern mixture models only provide information about the marginal distribution of the outcomes, which is done by making inferences by averaging over parameters. This means the individual effects of covariates cannot be examined (Ibrahim & Molenberghs, 2009).
Shared parameter models augment the growth curve analysis using regression equations that predict missing data indicators. Instead of basing the parameter model on a general growth curve, shared parameter models use the individual growth curves to predict missing data (Enders, 2011). Shared parameter models can incorporate the modeling of both the longitudinal and survival time analysis (Ibrahim & Molenberghs, 2009). This allows for better modeling of the longitudinal data while understanding the marker trajectories to identify survival. Unfortunately, the shared parameter models also require untestable assumptions. Multivariate normality of the individual intercepts and slopes is required, along with independence between the repeated measure variables and the missing data indicators (Enders, 2011). Any violation of these assumptions can result in biased parameter estimates (Enders, 2011).

Although much of the new research on missing data is focused on methods for NMAR, these methods have limitations. The biggest limitation of all these models is the need to have a good understanding of the drop-out pattern, the relationship to unobserved covariates, and how to properly model drop-out. Although this is a reasonable expectation for statisticians, those who are non-statisticians may struggle and inadvertently incorrectly specify the model. In fact, using NMAR models when it is not necessary or incorrectly specifying these models can lead to worse parameter estimates than the use of MAR methods (Siddiqui, 2011).

**Limitations**

None of the methods discussed above are perfect. It is difficult to discern the pattern of the missing data and to decide whether it is monotone or arbitrary. Additionally, one must decide on the missing data mechanism. Unfortunately, there is no way to test whether or not the data are NMAR. The missing data mechanisms rely on the unobserved data, making it impossible to measure the probability that the unobserved values are related to the observed values (Little &
Rubin, 2002). There continues to be large amounts of literature dedicated to the multitude of methods that can be used once the data mechanism is decided. Unfortunately, as the field still does not have a solid technique for deciding on the missing data mechanism, researchers are limited to educated guesses about the proper methods to use. There also continues to be limited information on the best way to model and understand data that are non-normal. Many of the techniques currently available have only been researched with normal data. Behavioral health researchers need to understand the missing data mechanisms and how one can best model and use this information to ensure that one has accurate results.

Discussion

Missing data can be problematic in any study. The only true solution to obtaining accurate results is to use both research design and training methods to prevent missing data from occurring. The ideal situation is to have no, or very little missing data. Strategies to prevent missing data should be employed at the design stage, the planning stage, and the implementation stage (Dziura, Post, Zhao, & Fu, 2013). Some examples of what to do at the design stage include limiting the number of visits, using data collection methods that aren’t face-to-face, and providing incentives (Dziura et al., 2013). Some examples of what to do at the planning stage include detailing study procedures with follow-up methods, training study personnel to avoid missing item data, and if possible, piloting the study protocols to estimate retention (Dziura et al., 2013; Little et al., 2012). Some of the examples of what to do at the implementation stage have been discussed already, such as keeping detailed records of reasons for dropout. Other examples include having procedures in place on how to contact participants and ways to intervene if they are likely to dropout (Dziura et al., 2013). If these strategies do not prove effective, then the researcher must use techniques at the data analysis stage, which was the primary focus of this manuscript.
One disadvantage of missing data analysis is there is not a single correct answer. In this study, several data analysis techniques were used to deal with the missing data. For the missing item data, multiple imputation, and sometimes single imputation were good techniques to use because the data were not used in a regression model. Most missing item data needs to be imputed so that it can be used to calculate a total score. Ignoring missing item data may not result in biased parameter estimates if the data are missing completely at random, but it does decrease sample size, which can have larger implications in evaluations of behavioral interventions since the number of participants is usually small. The decrease in sample size increases the risk that the evaluation will not find a significant result, even if one exists.

Most behavioral health interventions are costly to implement; therefore, it is important that we are able to detect differences in study groups when they actually exist. Many times, individuals working in the behavioral health field are responsible for conducting their own analyses, as hiring a statistician can be costly or not feasible. Therefore, an example of how to conduct missing data analysis specifically targeted at these individuals is warranted.

When data are missing at the subject level, the subsequent analysis becomes more complicated. One of the most important things evaluators can do is to prepare for missing data in longitudinal studies by collecting information on additional covariates that may impact a persons’ penchant to remain in the study. Additionally, many studies include a variable to account for why a participant drops out (e.g., treatment does not work, too sick, got better) which is then added as a covariate into the model. If this information is collected throughout the study, the researcher can be more confident in their assertion that the data is most likely MAR. Because most evaluators in the behavioral health field are not primarily statisticians, using techniques for data MAR are more appropriate, feasible, and easier to understand. To use techniques for data NMAR, a statistician
should be involved in the modelling process; without their expertise on these techniques, the results will be more biased than if a MAR technique had been used.

Specifically, this example presented two techniques for data MAR that are considered to be the most appropriate for non-statistician researchers—multiple imputation and maximum likelihood. Although the results in this study suggest that multiple imputation was a better option, both were valid techniques for missing data analysis. Multiple imputation creates new data based on the existing data that are not missing, which maximizes the sample size, and this is the reason it was best in this study. This does not mean that multiple imputation is the best option for all behavioral health evaluations that are studying treatment effects for a new intervention, but for most studies it can be applied.

Not only does this paper provide an example for non-statisticians who conduct evaluations in the behavioral health field, it also was the basis for future analyses that will be done with this sample. Once the data collection is complete, the author will use the data to understand the relationship between the variables over time. In order to conduct this analysis, missing data analysis will have to be done first, which is what this manuscript provides. Although having a large sample size is ideal, it was not feasible in this sample data because the participants are adults with SMI who have frequent jail bookings. The general population of adults with SMI who have frequent jail bookings is small, and therefore location-specific samples are also small. Using multiple imputation for this sample data provides the researchers with the maximum amount of available data to detect any differences in treatment group.

Most importantly, research and data analysis drive program funding and infrastructure resource allocation. As mentioned earlier, previous studies that analyzed data from the large, national Behavioral Risk Factor Surveillance System study have underestimated the prevalence of
severe depression because the missing data was ignored (Frankel et al., 2012). This example has two important implications. First, allocation of funding to treatment providers and other mental health programs are based on the findings from national studies. If these studies are underestimating the prevalence of mental illnesses, inadequate funding will be provided to the mental health system, which is already under-funded and over-burdened. Incorrect inferences that occur because missing data are ignored can have national implications in mental health treatment. Second, studies such as the BRFSS are costly to conduct, and because of the cost, are only possible through federal funding. If missing data and the data are analyzed incorrectly, as a result, large sums of money may be wasted on research that has no practical implications. Although this is an extreme example, all researchers and practitioners should be aware of the potential waste of resources attributable to ignoring missing data. This is not only an issue in the behavioral health field, but in all public health research.

Conclusions

Dealing with missing data in longitudinal studies continues to be a difficult and tedious process. This manuscript was focused on using a real-world example of how data can be missing in a longitudinal study, and how to explore the data to understand the missing data pattern. This was not meant to be an exhaustive list of the techniques to use to handle missing data, but instead an example of how social science researchers can improve the accuracy of their research by understanding why data are missing. Results were presented from both maximum likelihood estimation and multiple imputation to help the reader understand how to choose a method. Missing data will always be present in longitudinal studies involving human subjects. In order to ensure one is correctly estimating parameter estimates, one cannot ignore the missing data, and instead must delve further into why the data are missing to overcome this barrier.
SECTION 4: DISCUSSION, CONCLUSION, AND RECOMMENDATIONS

Introduction

Significance of Topic

Adults with SMI have an increased risk of physical illness compared to the general population (Bushe et al., 2005; Chwastiak et al., 2006; Druss, Zhao, et al., 2011; Leung et al., 2010; Lord et al., 2010; Manderscheid, 2010; Oud & Meyboom-de Jong, 2009; Sherman et al., 2013; Viron & Stern, 2010; Weber et al., 2009). In addition, adults with SMI have high rates of involvement with the criminal justice system (Steadman et al., 2009). Incarceration is related to an increased risk of having a physical illness and death upon release (Binswanger et al., 2009). The risk of physical illness for those who are incarcerated is increased even more for adults with SMI who are incarcerated. Justice-involvement (including incarceration) increases the risk that an adult with SMI will have a physical illness and more than one physical illness compared to those with an SMI who are not justice-involved (Binswanger et al., 2009; Cuddeback et al., 2010; Tiihonen et al., 2009; Wilper et al., 2009; Zlodre & Fazel, 2012). Efforts have been made to improve the mental health of justice-involved adults with SMI through jail diversion programs. Yet information is lacking about the number and type of physical illnesses experienced by adults with SMI in jail diversion programs, and about the relationship between mental illness and physical illness in this population (Bushe et al., 2005; Chwastiak et al., 2006; Druss, Zhao, et al., 2011; Leung et al., 2010; Lord et al., 2010; Manderscheid, 2010; Oud & Meyboom-de Jong, 2009; Sherman et al., 2013; Viron & Stern, 2010; Weber et al., 2009).
A greater understanding of the interplay between mental and physical illness has been at the forefront of the idea of greater integration of behavioral health and physical health services (Druss & Mauer, 2010; Druss, 2002; Druss et al., 2010; Druss, Rohrbaugh, Levinson, & Rosenheck, 2001; Giles & Collins, 2010; Manderscheid, 2010; Mauer & Druss, 2010; Parks, 2007; Satcher & Druss, 2010; Vreeland, 2007; Wakefield, 2011). Integration of behavioral health and physical health services leads to improved health for adults (Vreeland, 2007) and may lead to improved criminal justice outcomes, including reducing recidivism. At this time, the integration of behavioral health and physical health services in jail diversion programs has not been explored. In order to understand the relationship between integrated services and improved physical and mental health and reduced recidivism, longitudinal studies are needed to make causal inferences. Despite the benefits of longitudinal studies, they can be plagued by missing data, which can severely bias the results and lead to incorrect conclusions (Diggle et al., 2002).

The purpose of this dissertation study was two-fold. First, this study sought to gain further insight into the relationship between physical and mental illness in adults with SMI who reported a recent arrest by examining physical and mental health status of these participants compared to adults with SMI who did not report a recent arrest in the reference period, and the general population. Health status was assessed using the Short-Form Health Survey (SF-12), while accounting for other covariates such as age, mental illness symptom severity, and drug and alcohol use. Second, this study began formulating a regression model to use to examine the longitudinal data of a jail diversion sample of adults with SMI. The first step to exploring the longitudinal data was to create a plan for missing data. Specifically, this portion of the study focused on providing an example, using the jail diversion sample as an example, of the steps to take to analyze missing
data. This portion of the study provided the base analysis that will be used for the longitudinal data to explore the relationship between physical and mental health status over time.

**Research Summary**

This dissertation study began to explore data on a sample of adults with SMI who were enrolled in a jail diversion intervention. The first portion of the study was based on data from the sample of adults with SMI enrolled in a jail diversion intervention, which was then combined with a sample of adults receiving community mental health services in Florida (SAMHSA), and a sample of adults with SMI who were either receiving inpatient or outpatient mental health services at five different sites across four states (5-site study). The results from this portion of the study revealed that in all of the samples, the mental health status (MCS) and physical health status (PCS) scores of the participants were lower for adults with SMI than in the general population. Results were more complicated when the samples were split based on those who reported a recent arrest versus those who did not report a recent arrest. Initial analyses suggested that those who had a recent arrest had higher PCS scores; in the jail diversion and 5-site sample, those who had a recent arrest also had lower MCS scores. Once age, mental symptom severity, and alcohol and drug use were controlled for, the MCS and PCS scores for those who reported a recent arrest were no longer significantly different than those who did not report a recent arrest. This means that other factors, like age and alcohol and drug use, mitigated the relationship between recent arrest and MCS and PCS scores.

This study supports the notion that adults with SMI indeed have worse physical health than the general population. But, there was limited support that those with a recent arrest may have worse physical or mental health than other adults with SMI who do not have a recent arrest. One important consideration is that the majority of the participants in these studies were living in the
community and none of them were currently incarcerated. Previous research has found that those with SMI who are incarcerated have more physical illness compared to those with SMI who are not incarcerated; but number of physical illnesses was not specifically explored in this study (Cuddeback et al., 2010).

The second portion of this study focused on missing data in longitudinal research studies. Specifically, the sample of adults with SMI enrolled in a jail diversion intervention were followed over nine months. Participants were interviewed every three months. Although missing data is present in all longitudinal studies, it was prevalent in this study due to the extenuating circumstances faced by this sample. Specifically, if the participants did not follow treatment as ordered by the court, a warrant for their arrest could be issued. Due to these impending legal troubles, the research team was no longer able to reach some of the participants. Other participants did not want participant in the study, or were in inpatient treatment. By the fourth time point, 62% of the data were missing.

The analyses proceeded as follows: first, the author calculated the missing data patterns for the item-nonresponse missing data; second, the author used multiple and single imputation to compare methods for imputing missing item data. The author concluded that they produced equivalent results because this level of data was missing completely at random; third, the author calculated the missing data pattern for the unit-nonresponse missing data; fourth, the author used multiple imputation and maximum likelihood estimation to compare the results of the two methods, the author concluded that although they are both valid methods, the multiple imputation method was more aligned with the literature and was a better method because of the small sample size (it creates data); and fifth, the author discussed missing data analysis techniques for data not missing at random, and concluded that for non-statisticians these methods should be avoided. The
final discussion for this study explored the importance of not ignoring missing data, as missing data analyses are an integral part of assuring that the results are accurate and not biased. This study provided the base for future analysis of the longitudinal data to further explore the relationship between physical and mental health status of adults with SMI who are justice-involved over time.

Both portions of this study were aimed at tackling a larger issue: understanding the interaction between mental and physical illness. This study began to explore this relationship by conducting preliminary analysis to understand how the physical and mental health status of adults with SMI in a jail diversion program, and those with a recent arrest, varies compared to the general population and adults with SMI who do not have a recent arrest. Additionally, this study used the longitudinal data available from the sample of adults with SMI in a jail diversion program to conduct preliminary missing data analysis and begin to build a regression model for future use.

**Conceptual Implications**

This study sought to further explore the relationship between mental and physical illness. The biopsychosocial model provided the basis for the hypotheses in this research. Specifically, the author hypothesized that mental and physical health status would be lower for those who had a SMI and a recent arrest, due to the high number of physical illnesses and social stress that this group experienced. In the second manuscript, the author hypothesized that health status, mental health symptoms, and support of a care coordinator may be related to study drop-out. The biopsychosocial model posits that treatment of illness must focus on the biological, psychological, and social interactions of disease within the person instead of focusing on these constructs as separate entities (Engel, 1977). Factors at each of these levels impact the presentation and outcome of disease for each person.
Biological Factors

Mental illness, mental health, and physical health are all inter-related and can impact the course of chronic disease, occurrence, and treatment (Perry et al., 2010). The genetic basis of mental illness is just beginning to be understood; therefore, the connection to other physical illnesses at a biological level is still under investigation (Cross-Disorder Group of the Psychiatric Genomics Consortium, 2013). Additional biological factors that adults with SMI experience include: medication side-effects, high rates of hypothyroidism, metabolic disorders, diabetes, and cardiovascular disease (Kane, 2009; Weber et al., 2009).

Psychological Factors

Adults with SMI may be less likely to receive a diagnosis for a co-morbid physical illness, possibly due to their inability to communicate about the physical problem, or their inability to monitor their health because of their mental illness symptoms (Kane, 2009). Adults with SMI may be disorganized, have cognitive deficits, fear the physical health care system, have impaired insight into their illnesses, lack motivation to seek care, or be unable to describe or recognize physical illness symptoms (Goff, 2007; Kane, 2009; Viron & Stern, 2010). Even when adults with SMI are diagnosed with a physical condition, their mental illness may make it difficult to adhere to the prescribed treatment (Goff, 2007). In addition, adults with SMI and a comorbid physical illness are less likely to seek treatment than a person without SMI (Druss et al., 2009).

Health behaviors of adults with SMI also play a role in the development of comorbid physical illnesses (Kane, 2009). Adults with SMI have poorer exercise and eating habits, contributing to obesity, which can lead to diabetes and heart disease (Druss, Zhao, et al., 2011; Kane, 2009; Kilbourne et al., 2009; Paton, Esop, Young, & Taylor, 2004). A high prevalence of co-occurring substance abuse in adults with SMI leads to high rates of HIV and hepatitis C that
are elevated compared to the general population (Davidson et al., 2001; Rosenberg et al., 2001; Rosenberg, Drake, Brunette, Wolford, & Marsh, 2005), a relationship that is compounded when the person has criminal justice involvement (Springer, Spaulding, Meyer, & Altice, 2011; Westergaard, Spaulding, & Flanigan, 2013). Adults with schizophrenia are more likely to smoke cigarettes and have a harder time quitting than adults without SMI (Mobascher & Winterer, 2008).

**Social Factors**

There are multiple social factors that impact increased mortality in adults with SMI including lack of access and low quality healthcare (Druss, Zhao, et al., 2011). The combination of low socioeconomic status, adverse health behaviors, and poor quality of physical care produce a cumulative effect that accounts for approximately 70% of the increased mortality risk of adults with SMI (Druss, Zhao, et al., 2011). Adults with SMI live in resource-poor areas and are less likely to complete high school, both of which are contributing factors to poorer health (Kessler, Foster, Saunders, & Stang, 1995; Link & Phelan, 1995; Weber et al., 2009). It is estimated that nearly 25% of homeless adults in the U.S. have SMI (Housing and Urban Development, 2010; Long, Rio, & Rosen, 2007). Adults with SMI have a high risk of being a victim of a violent crime, which also predisposes them to increased psychiatric and physical symptoms (Teplin et al., 2005; Viron & Stern, 2010). In addition, adults with SMI have a five-fold greater risk of being a victim of homicide compared to the non-mentally-ill population (Crump, Sundquist, Winkleby, & Sundquist, 2013).

Death after release from prison can be attributed to social factors such as drug-related causes (18%), suicide (8%), and homicide (9%) in the general population (Zlodre & Fazel, 2012). Reasons for increased physical illnesses among offenders with SMI are impacted by where they
live, lifestyle choices, and behaviors that are all associated with arrests (Cuddeback et al., 2010), which also includes psychological factors.

Health care infrastructure also contributes to comorbidity in adults with SMI. It is difficult to coordinate between the behavioral health and the primary care system, which is a barrier to receiving services (Kane, 2009). In addition, care that is received through the medical system is sub-optimal (Druss, Rosenheck, Desai, & Perlin, 2002; Levinson Miller, Druss, Dombrowski, & Rosenheck, 2003; Lord et al., 2010). Other factors that contribute to poor medical care are lack of health insurance and lack of access to health care (Goldman, 1999). In addition, the provider’s ability to deliver appropriate care that focuses on physical illnesses, not mental illnesses, is not always present. Lack of provider continuity also results in adults with SMI receiving less care proportionate to their physical illnesses (Zolnierek, 2009).

Overall, there are many factors that contribute to poorer health for adults with SMI at all levels of the biopsychosocial model. In addition, these health problems are compounded for adults with SMI who are justice-involved due to increased psychological symptomology, lifestyle choices, and lack of resources (Cuddeback et al., 2010). It is important to understand the interaction between different levels of the biopsychosocial model related to behavioral health services. Current techniques of analyzing data do not allow for causal inferences about mental health symptoms and physical health symptoms. Although medical problems are common in adults with SMI, there is a lack of understanding of how these symptoms interact. There is the need for longitudinal research that explores the relationship of factors at all levels to further explore the relationship between physical and mental health of adults with SMI and a recent arrest.

Results from this study are the preliminary information that is needed to fully support the biopsychosocial model in this sample. Specifically, those with SMI (whether or not they had a
recent arrest) had lower mental health status and physical health status than the general population, which provides support for the theory that physical and mental illness are related. From a theoretical perspective, this study furthered the support that treatment of adults with SMI should focus on multiple aspects of their health and well-being, instead of focusing solely on their mental illness. When the analysis was broken down further, there was no support that adults with SMI with a recent arrest had worse physical or mental health status compared to adults with SMI without a recent arrest. This finding does not necessarily mean that the social stress of criminal-justice involvement has no impact of physical or mental health status; instead, it represents the inability to analyze this complex relationship with the available data. The biopsychosocial model is based on systems theory and states that change at any of the levels can impact the other levels; therefore, it is necessary to take a more advanced approach by using a statistical model that represents the relationship between the different levels of the biopsychosocial model to analyze the true underlying relationship between these factors through a causal model.

Implications for Behavioral Health

The implications of this study for behavioral health are two-fold. First, the exploration into the relationship between mental health status and physical health status revealed adults with SMI have worse physical and mental health status compared to the general population. This finding provides further support that the behavioral health field needs to focus on improving mental and physical health for adults with SMI. One approach is through more integrated behavioral health and primary care services, which overcomes some of the access to care and low-quality health care issues that contribute to worse physical health in this population (Druss, Zhao, et al., 2011). Although there was no significant difference in physical or mental health status after controlling for age, drug and alcohol use, and mental health severity between adults with SMI who did and
did not have a recent arrest, there is still the need to further understand the relationship between physical and mental health in this population. These factors moderated the relationship between arrest and physical and mental health status, but they also revealed that adults who have justice involvement have more alcohol and substance use which may be contributing to the worse mental health status found in the jail diversion and 5-site sample. Additionally, these findings support the need for the integration of behavioral health and primary care services not only for adults with SMI who live in the community, but also for those who are involved with the criminal justice system.

Second, this dissertation used a real-world example of how to analyze and account for missing data in longitudinal studies. This manuscript provides a much-needed example that can be used by clinicians and other non-statistician researchers in the behavioral health field. The current literature requires a statistical background to synthesize and apply the techniques for missing data. This manuscript provides an easy-to-follow template for those without a statistical background to use in their research. Evidence of program effectiveness is becoming an increasing demand in order for continued funding. It is not always feasible for an agency to hire a statistician; therefore, they are responsible for their own data analysis. This manuscript provides agencies, researchers, and evaluators a guide so they are able to accurately analyze their data. By incorporating missing data analysis into explorations of program effectiveness, results will be more accurate and provide the evidence needed to secure continued funding and support. To ensure appropriate allocation of funding for behavioral health interventions, missing data analyses must be employed. Without accounting for missing data, treatment effects may not be apparent, and as in the case of the BRFSS, prevalence estimates can be underestimated, contributing to underestimates in the true need for funding for treatment or other programs. Additionally, this
portion of the study provides the base analysis that can be used to further the exploration into the mechanisms that impact physical and mental illness of adults with SMI who are enrolled in a jail diversion program.

Collaborative and integrated care improve physical and mental health outcomes, although the specific mechanisms behind the health improvements are not clear (Butler et al., 2008). This study began to explore these mechanisms and provided preliminary analysis needed to further explore these mechanisms. Just by introducing the notion of integrated care, adults with mental illness may receive more evidence-based treatment, and therefore experience improved health (Butler et al., 2008). There is less evidence about the success of integrating primary care services into behavioral health services, although studies conducted at the Veterans Administration show promising outcomes (Butler et al., 2008; Druss et al., 2001; Druss & von Esenwein, 2006).

One of the biggest pushes for the integration of behavioral health and public health services is the provisions in the Affordable Care Act of 2010 (ACA). Under the ACA, Medicaid will be expanded, and will allow for the provision of behavioral health services with copays comparable to other public health services (Druss, von Esenwein, Compton, Zhao, & Leslie, 2011; Garfield, Lave, & Donohue, 2010). The expansion of Medicaid through the ACA will also allow for increased access to substance abuse treatment (Busch, Meara, Huskamp, & Barry, 2013). The ACA provides a perfect financial platform for the integration of care to commence, as it overcomes many of the financial barriers that were faced in the past.

Providing more integrated care has many positive benefits for adults with SMI. Integrated care reduces costs, it provides more holistic care, it can provide care to more adults with SMI, it reduces stigma, access to care is easier, and it improves outcomes for adults with SMI (Funk & Ivbijaro, 2008). With the disproportionate health issues faced by adults with SMI, especially
justice-involved adults, a holistic approach to care should be taken in order to address both their physical and mental illnesses (Druss et al., 2009; Funk & Ivbijaro, 2008; Kane, 2009; Manderscheid, 2010).

Although research supports the integration of behavioral health services and primary care services, the focus has been on adults with SMI living in the community. Further research is warranted to explore how these services work with adults with SMI who have been recently arrested, and whether, in the future, there is evidence for more integrated jail diversion programs. Results of the present research support the notion of integrated care; specifically, adults with SMI, both with and without a recent arrest had worse physical and mental health compared to the general population norms. This finding has some practical applications for the behavioral health field. Currently, treatment is focused on improving the symptoms of mental illnesses. With this research, there is greater support for the idea that behavioral health practitioners and therapists should also be monitoring and focusing on the physical illnesses of their clients. By better understanding the relationship between physical and mental health, guidelines can be created for those who are providing treatment, and in turn, this will help to improve the overall health of adults with SMI (Butler et al., 2008). More specifically, practitioners who are providing services to adults with SMI with a recent arrest need to be aware of the potential for their clients to have even worse physical health than other adults with SMI who do not have a recent arrest, to ensure that services are addressing all aspects of the client’s health (Cuddeback et al., 2010).

**Strengths and Limitations**

**Limitations**

Although this study contributed important new knowledge to the field, it is necessary to acknowledge the limitations. The first portion of the study used parallel analysis to explore the
physical and mental health status of adults with SMI. Unfortunately, because this study was based on secondary data with measures not scalable across all three studies, we were unable to make as strong of conclusions. In addition, the first data set consisting of the jail diversion sample and the SAMHSA sample had information only available on drug and alcohol use, but did not include mental health severity. The second data set consisting of the jail diversion sample and the 5-site sample measured mental health severity, but there was not a consistent measure of alcohol and drug use between the two samples. This led to different results between these data sets. Future research should focus on evaluating all of these factors in one study for a more comprehensive understanding of how these covariates may impact physical and mental health status in relation to recent arrest.

Additionally, the author knew which participants had a recent arrest, but information about access to services and whether or not they were enrolled in a jail diversion program was not available. This additional information would have made the analysis stronger because receiving services could have mediated the relationship between recent arrest and health status, e.g., health status may have been better in adults with recent arrest because they were receiving more services as part of a jail diversion program. This information was not available and therefore this relationship was not explored.

The second part of the analysis only focused on the criminal justice sample using longitudinal data. The sample size in the missing data analysis was small, and could potentially introduce bias into the results of the analysis. Specifically, drug and alcohol use could not be included in this example because the results were unstable (i.e., the parameter estimates had very large confidence intervals) due to the small sample size. A larger sample size would have allowed
for a better model to have been used in the example, as drug and alcohol use are related to health status and therefore should be explored as potential predictors of attrition in the study.

Finally, this study focused on a minority population of adults with SMI who were involved in the criminal justice system, and who had at least three jail bookings in the past three years, or seven or more jail bookings during their lifetime. This sample represented a subset of adults with SMI who had criminal justice-involvement at some point in their life. Therefore the results from this study are not necessarily generalizable to other jail diversion samples.

**Strengths**

Despite the limitations stated above, this study has some strengths that should be emphasized. First, the jail diversion sample used was recruited as part of an evaluation of a jail diversion program that was a randomized control trial. One of the biggest benefits of a randomized control trial is the ability to control for heterogeneity between groups by assigning participants to groups randomly, which in effect allows for equality between the level of heterogeneity in each group (D’Agostino, 2007; Rosenbaum & Rubin, 1983). This allows for similarity in the groups for all of the covariates, except for the independent variable of interest that can then be intentionally manipulated (Shadish et al., 2002; Susser, 1973).

The purpose of randomization is to make the relationship between the independent and dependent variables clearer by reducing the plausibility of an alternative explanation because all participants have a nonzero probability of being assigned to a condition (Shadish et al., 2002). Randomization is important in research designs because it gives unbiased estimates of the average treatment effect (Shadish et al., 2002). Random assignment allows the researcher to know the selection process; it equates the groups on variables prior to implementation of the intervention. It distributes threats to validity across conditions, thereby reducing the plausibility, it reduces
The confounding of alternative causes with the treatment condition, and it allows for valid estimates of error variance (Shadish et al., 2002). The different treatment conditions remain equal on the distribution of covariates, which means that they only differ on the treatment variable resulting in an easier interpretation of causality (Susser, 1973). Additionally, by randomly assigning participants to treatment groups it reduces the bias of the researcher because the random assignment precedes the outcome of the study (Susser, 1973). Experimental designs allow for a clearer inference of causality, due to the nature of controlling for other potentially confounding variables, and through randomly equating the groups on covariates (D. C. Miller & Salkin, 2002; Shadish et al., 2002; Susser, 1973)

Second, this study explored the physical health status of adults with SMI who have a recent arrest, which has not been previously addressed in the literature. Currently, there is only a single study that looks at the number of physical illnesses in adults with SMI who have justice-involvement (Cuddeback et al., 2010). The current study provides an additional exploration into the physical health status of justice-involved adults with SMI, and the basis for future research into this area.

Third, missing data in longitudinal studies is an often-overlooked issue during data analysis. This study not only used the data from the jail diversion sample to conduct the missing data analysis for the longitudinal study (to provide as a base for future analysis); it also used this as an example to provide to other behavioral health evaluators. Currently, the missing data literature is geared towards statisticians and it can be confusing for those without a statistics background. This study aimed to bridge the gap by providing an example specifically geared towards behavioral health evaluators and researchers who are not trained statisticians.
Future Research

The results of this study suggest several areas for future research.

Physical Illnesses

There is a substantial gap in the literature about the physical illnesses of adults with SMI involved with the criminal justice system. As a first step, an epidemiological study of the prevalence and type of physical illness present in those with SMI who are incarcerated and those with recent arrest or justice-involvement is needed. This study provided evidence that adults with SMI with a recent arrest have lower physical health status than the general population, and previous research indicates they may have even worse physical health than other adults with SMI who do not have a recent arrest (Cuddeback et al., 2010). More jail diversion studies should include measures of both the amount and type of physical illnesses, or measures of physical health status of the enrollees in their program to begin to build the knowledge base about this population.

Longitudinal Design

In the jail diversion data used for this study, the intervention implemented represents a new approach to diversion programs by taking into consideration that participants have individual needs that cannot be treated with a “one-size-fits-all” approach (Andrews, Bonta, & Hoge, 1990; Bonta & Andrews, 2007). In order to address the unique needs of participants, the intervention used in this study focused on a care coordinator position as a new form of treatment. The care coordinator was responsible for tailoring treatment to the needs, strengths, and risks of each participant. Future research should explore the relationship between providing tailored treatment to participants and how it improves their mental health symptoms, and also their physical health symptoms. Because treatment will be tailored to the needs of each participant, and because mental and physical health are intertwined, it is realistic to expect that physical health symptoms and
physical health service usage may be impacted. There is a need for greater focus on physical health issues of adults with SMI in diversion programs, due to the high health disparities they face. The care coordinator position can be made as an extension to staff already working at the jail diversion program, by either creating a new position, or changing the responsibilities of a current staff member. Reallocation of resources to re-focus the duties of a current staff member can help to keep costs low.

To conduct research to further explore the relationship between physical and mental health status and jail diversion programs, a longitudinal study would be most appropriate. The missing data analysis in this dissertation provided the base missing data analysis that will allow for proper planning of a multi-level model to explore how the mental and physical health status of adults with SMI enrolled in a jail diversion program changes over time. As a first step, analysis should focus on analyzing the change in health status scores over time. Additional covariates, such as gender, age, and race should be included to account for their influence on health status. In this specific study, the goal would be to understand how the services of the jail diversion services can also impact mental and physical health status over time.

**Biopsychosocial Interactions**

Studies that examine the interaction between different levels of the biopsychosocial model related to behavioral health services are needed. Current techniques of analyzing data do not allow for causal inferences about mental health symptoms and physical health symptoms. Although medical problems are common in adults with SMI, there is a lack of understanding of how these symptoms interact. Future research needs to focus on the relationship through more advanced causal models.
Specifically, the jail diversion intervention in this study focuses on the psychosocial aspects of the participants in order to improve their mental illness and reduce recidivism. It is reasonable to assume that an intervention that is targeting two levels of the biopsychosocial model may impact another dimension of health (Engel, 1978). The direct, intended, outcomes of the intervention are to reduce recidivism and improve mental health by targeting high-risk adults by providing them with tailored treatment. A potentially indirect outcome of the intervention is improved health status due to receiving more appropriate treatment and improvements in mental health. It is unknown whether it will be an indirect consequence of receiving more appropriate behavioral health treatment or if the participants may have increased access to primary care services as part of their identified needs. The biopsychosocial model should guide the understanding of how the different services interact to improve participants’ functioning at the psychosocial level.

The analysis should focus on exploring the bi-directional relationship between self-reported physical health and mental health symptoms to see how self-reported health status is related to self-reported mental illness symptomology. The interaction between mental illness and physical health is well-known, but the specific relationship between improvements in symptomology over time has not been explored using longitudinal data.

To further explore the relationship between health status, mental health severity, and drug and alcohol use over time a cross-lagged auto-regressive model should be used. When two variables, X and Y, no longer have a unidirectional relationship, the parameter estimates produced using OLS regression will be biased (Finkel, 1995). Cross-lagged analysis takes into consideration the reciprocal relationship between variables X and Y (Finkel, 1995). Cross-lagged panel analysis models the relationship between X and Y over time, while allowing for bidirectional causality (Finkel, 1995). In order to understand how these values change over time it is necessary to not
only consider the effect of the variable $X_1$ on $X_2$ but also the effect of $Y_1$ on $X_2$, $Y_1$ on $Y_2$, and $X_1$ on $Y_2$, and so on depending on the waves of data.

Autoregressive models refer to the relationship between a variable $X_i$ and the value of that variable at the previous measurement period, $X_{i, t-1}$ (Curran & Hussong, 2002). Autoregressive models state that the value at time $t$ is related to the value at time $t-1$ and has added value from time $t-1$ (Curran & Hussong, 2002). Very basically, to obtain a value for a variable at time $t$, that variable is regressed onto the same variable at time $t-1$ (Curran & Bollen, 2001). The relationship between a variable and its previous measurement must be taken into consideration in order to achieve accurate parameter estimates (Curran & Hussong, 2002). The cross-lagged autoregressive model will allow for increased understanding of the relationship between health status, mental health severity, and alcohol and drug use over time, and begin to get a greater understanding of the relationship between health status and mental health symptoms.

**Jail Diversion Intervention**

Since their inception, jail diversion programs have become widespread, with more than 500 diversion programs in the United States (Case et al., 2009). At this time, studies have mainly focused on the impact on mental illness symptoms and criminal justice recidivism. There is a need to explore physical illnesses in jail diversion studies from a more proactive approach. Specifically, future research is needed in which a joint effort is made between experts in the field of mental health jail diversion programs and experts in the medical field who work with adults recently released from incarceration to provide needed medical treatment. Further collaboration between these two fields will lead to more comprehensive diversion programs, which will provide a more holistic approach to health. Through this pilot program, a longitudinal study can be conducted to assess mental health symptom severity, drug and alcohol use, health status, biological markers of
health (i.e., saliva stress tests, blood test for diseases), measures of number of physical illnesses, types, and severity, measures of stress, medication adherence, service utilization (behavioral health and physical health), and criminal justice involvement.

Results from a study of this detail will provide greater understanding into the biopsychosocial presentation of illness and will provide guidance for future programs. Although ideal, this type of study would be very costly and therefore some of the less expensive studies proposed above should be conducted first to provide support for such a large scale and in-depth study to look at jail diversion programs and the relationship to health.

**Conclusion**

Future research needs to focus on adding to the knowledge base about the prevalence and severity of physical illnesses in adults with SMI who are justice-involved, the relationship between physical and mental health status and jail diversion programs, and the potential for more comprehensive jail diversion programs that also integrate physical health care. Adults with SMI have a high number of physical illnesses compared to the general population and high rates of criminal justice involvement (Cuddeback et al., 2010; Steadman et al., 2009). This study explored the mental and physical health status of adults with SMI who had a recent arrest and found they were significantly worse than in the general population, but after controlling for age, alcohol and drug use, and mental symptom severity they were not different than other adults with SMI who do not have a recent arrest. Longitudinal research is needed to explore the mechanisms that mediate the relationship between physical and mental health status. Missing data are common in longitudinal studies, and behavioral health researchers need to conduct missing data analysis to ensure accurate results to secure funding for future projects.
REFERENCES


Institute of Medicine Committe on Crossing the Quality Chasm: Adaptation to Mental Health and Addictive Disorders. (2006). *Improving the quality of healthcare for mental and substance use conditions*. Washington, DC.


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### Appendix A: Tables

#### Table 1. Descriptive Statistics of all Data Sets-Continuous Variables

<table>
<thead>
<tr>
<th>Participant Characteristics</th>
<th>Jail Diversion Participants</th>
<th>SAMHSA Participants</th>
<th>5-Site Risk Participants</th>
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<tbody>
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<td></td>
<td>n (%)</td>
<td>M</td>
<td>SD</td>
</tr>
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<td>Age in Years</td>
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<td>12.52</td>
</tr>
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<td>49.05</td>
<td>12.23</td>
</tr>
<tr>
<td>MCS</td>
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<td>10.99</td>
</tr>
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<td>0.11</td>
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<tr>
<td>ASI Drug</td>
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<td>0.19</td>
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<td>Number of Arrests during life</td>
<td>88</td>
<td>13.19</td>
<td>18.37</td>
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Table 2. Descriptive Statistics of all Data Sets-Categorical Variables

<table>
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<tr>
<th>Participant Characteristics</th>
<th>Jail Diversion Participants</th>
<th>SAMHSA Participants</th>
<th>5-Site Risk Participants</th>
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</thead>
<tbody>
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<td></td>
<td>n (%)</td>
<td>n (%)</td>
<td>n (%)</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>74 (81.3%)</td>
<td>191 (27.8%)</td>
<td>629 (64.9%)</td>
</tr>
<tr>
<td>Female</td>
<td>17 (18.7%)</td>
<td>496 (72.2%)</td>
<td>340 (35.1%)</td>
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<tr>
<td>Race</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Caucasian (White)</td>
<td>47 (52.2%)</td>
<td>372 (54.5%)</td>
<td>459 (47.5%)</td>
</tr>
<tr>
<td>African American (Black)</td>
<td>42 (46.7%)</td>
<td>235 (34.4%)</td>
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<td>Other</td>
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<td>76 (11.1%)</td>
<td>80 (8.3%)</td>
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<td>48 (53.3%)</td>
<td>105 (15.4%)</td>
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<td>Married (1=yes)</td>
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<td>Substance Abuse Disorder</td>
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<td></td>
</tr>
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<td>410 (42.5%)</td>
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<td>No</td>
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<td>555 (57.5%)</td>
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</tr>
<tr>
<td>Yes</td>
<td>91 (100%)</td>
<td>229 (33.3%)</td>
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</tr>
<tr>
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<td>0 (0%)</td>
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<tr>
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<td>91 (100%)</td>
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<td>241 (34.5%)</td>
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<td>0 (0%)</td>
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</tr>
<tr>
<td>Ever arrested during life</td>
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<td></td>
</tr>
<tr>
<td>Yes</td>
<td>91 (100%)</td>
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<td>666 (69.5%)</td>
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<tr>
<td>No</td>
<td>0 (0%)</td>
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<td>293 (30.5%)</td>
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Table 3. **Mean PCS and MCS Scores by Sample Compared to Population Norms and Depression Population Norms**

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<th>SD</th>
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<th>p</th>
<th>df</th>
<th>t value</th>
<th>p</th>
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<tr>
<td>MCS</td>
<td>80</td>
<td>36.39</td>
<td>10.99</td>
<td>79</td>
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<td>11.71</td>
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<td>-3.68</td>
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<tr>
<td>Jail Diversion and 5-site Sample</td>
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<td></td>
<td></td>
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<td>Arrested in Past Year</td>
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Table 4. Chi Square Analysis of Participants with a Recent Arrest versus Participants without a Recent Arrest

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<th>( p )</th>
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<td>( n )</td>
<td>( % )</td>
<td>( n )</td>
<td>( % )</td>
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<td>Jail Diversion and SAMHSA Data</td>
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<td></td>
<td></td>
<td></td>
</tr>
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<td>Sex</td>
<td>Male</td>
<td>102</td>
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<td>163</td>
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<td>Married</td>
<td>Yes</td>
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<td>Jail Diversion and 5-Site Data</td>
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<td>Sex</td>
<td>Male</td>
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<td></td>
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Table 5. Mean values of Participants with a Recent Arrest versus Participants without a Recent Arrest

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<td>M</td>
<td>SD</td>
<td>df</td>
<td>t value</td>
<td>p</td>
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<tr>
<td>Jail Diversion and SAMHSA Data</td>
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Table 6. Jail Diversion and SAMHSA Study Pearson Product Moment Correlations and Spearman Rank Correlations

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Table 7. Jail Diversion and 5-Site Study Pearson Product Moment Correlations and Spearman Rank Correlations

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Table 8. Jail Diversion and SAMHSA ANCOVA with MCS and PCS as the Outcome Variable

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Table 11. Comparison of SF-12 Component Scores by Missing Data Status

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Table 12. SF-12 Item Missing Data Pattern by Time Point

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Table 13. Cox Proportional Hazard Regression for Time to Drop-out with Baseline Predictors

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Table 14. Means of Missing Data Pattern

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Table 15. MCS Regression Parameter Estimates of Maximum Likelihood Estimation and Multiple Imputation

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<th>Multiple Imputation</th>
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<td>SE</td>
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<td>Age</td>
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<td>0.09</td>
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<tr>
<td>Race (African American=1)</td>
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</tr>
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<td>Lifetime Jail Bookings</td>
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</table>

† p<.10, * p<.05, ** p<.01, *** p<.001
<table>
<thead>
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<th>Characteristic</th>
<th>Maximum Likelihood</th>
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<th>Multiple Imputation</th>
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<td>PCS N=1026</td>
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<tr>
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<td>***</td>
<td></td>
<td>β = 71.80, SE = 10.55</td>
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<tr>
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<td></td>
<td>β = -1.22, SE = 2.72</td>
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</tr>
<tr>
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<td>β = -0.01, SE = 0.14</td>
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<tr>
<td>BPRS</td>
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<td>**</td>
<td></td>
<td>β = -0.18, SE = 0.10</td>
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<tr>
<td>Age</td>
<td>β = 7.55, SE = 3.32</td>
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<td></td>
<td>β = 1.78, SE = 3.07</td>
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<tr>
<td>Race (African American=1)</td>
<td>β = -9.12, SE = 3.91</td>
<td>*</td>
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<td>β = -6.84, SE = 3.66</td>
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<td>Sex (Female=1)</td>
<td>β = -0.23, SE = 0.09</td>
<td>*</td>
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<td>Lifetime Jail Bookings</td>
<td>β = -0.02, SE = 0.10</td>
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</tbody>
</table>

† p<.10, * p<.05, ** p<.01, *** p<.001
Appendix B: SAS Program Code

/**********************************************************************************
** This first portion of analysis focused on exploring those who dropped out, those who had data missing at one time point (intermittent), and those who were just missing an item from an assessment. The rtf command provides an output Word document.
**
* Clientid is the arbitrary id number
* MCS is the SF-12 mental health status score, the number at the end represents the time period
* BPRS is the brief psychiatric rating score
* Time is the time period
**********************************************************************************/

/*item missing*/
ods rtf file="C:\Users\Robin\Desktop\Grad school\Dissertation\Missing Data Analysis\miss data SAS output.rtf";

proc sort data=bmsf.wideformat;
by clientid;
run;
proc print data=bmsf.wideformat;
var clientid mcs1-mcs4 pcs1-pcs4 bprs1-bprs4 time1-time4;
run;
ods rtf close;
/*Based on the previous analysis and exploration those with a missing item are assigned a value to a dummy indicator variable*/
data bmsf.itemsordrop;
set bmsf.wideformat;
itemmiss4=0;
if clientid=2 then itemmiss3=1;
else if clientid=6 then itemmiss3=1;
else if clientid=45 then itemmiss3=1;
else itemmiss3=0;
if clientid=13 then itemmiss2=1;
else itemmiss2=0;
if clientid=3 then itemmiss1=1;
else if clientid=4 then itemmiss1=1;
else if clientid=8 then itemmiss1=1;
else if clientid=13 then itemmiss1=1;
else if clientid=29 then itemmiss1=1;
else if clientid=36 then itemmiss1=1;
else if clientid=44 then itemmiss1=1;
else itemmiss1=0;
run;
After assigning those with a missing item it is useful to compare the data again to make sure the categories make sense. For this portion the date of the interview (adateint), MCS, PCS BPRS scores, and indicator variables for the time period that they dropped out (dropouttime), the intermittent indicator variable (intermittent), and the missing item indicator variable created above (itemmiss) are useful.

```sas
proc print data=bmsf.itemsordrop;
var clientid dateint1 dateint2 dateint3 dateint4 mcs1-mcs4 pcs1-pcs4 bprs1-bprs4 dropouttime intermittent itemmiss1-itemmiss4;
run;
```

```sas
proc freq data=bmsf.itemsordrop;
tables clientid a1dateint a2dateint a3dateint a4dateint dropouttime intermittent itemmiss1-itemmiss4/ list missing nopercent;
run;
```

```sas
proc sort data=bmsf.transposed;
by timepoint;
run;
```

At this time it is necessary to transpose the data into the long format to look at the missing data pattern. The code is not shown here, but an array statement was used. The new data set was named "Transposed".

```sas
proc mi data=bmsf.transposed nimpute=0;
var age mcs pcs bprs sex race;
by timepoint;
run;
```

Proc MI is the statement used for multiple imputation. The nimpute= is the number of imputations. When it is set to zero it will provide the missing data pattern, but will not impute any data. This is useful for exploring your data.

```sas
proc mi data=bmsf.transposed nimpute=0;
var
```

Next we explore the missing data pattern for the items of the SF12 (sf12i1-sf12i12) and the bprs (they were named for the specific question constructs).

```sas
proc mi data=bmsf.transposed nimpute=0;
var
```
/*Missing item analysis-multiple imputation*/
proc mi data=bmsf.transposed seed=21355417 nimpute=10 out=bmsf.outitemMI round=1
minimum= 1 1 1 0 0 0 0 1 1 1 1
maximum= 5 3 3 1 1 1 1 5 5 5 5;
run;

/*missing item single imputation*/
proc mi data=bmsf.transposed nimitpute=1 seed=21355417 out=bmsf.ItemImonotone1 round=1
minimum= 1 1 1 0 0 0 0 1 1 1 1
maximum= 5 3 3 1 1 1 1 5 5 5 5;
run;

/*recombining with non imputed data. There were no imputations for the fourth time period those variables were dropped from the imputed data set and must be recombined*/
data bmsf.timepoint4;
set bmsf.transposed;
if timepoint=1 then delete;
if timepoint=2 then delete;
if timepoint=3 then delete;
run;

proc sort data=bmsf.timepoint4;
by clientid;
run;
proc sort data=bmsf.itemmimonotone1;
by clientid;
run;

data bmsf.sf12MImonotone;
set bmsf.itemmimonotone1  bmsf.timepoint4;
run;

/*recombining multiple imputation data*/
proc sort data=bmsf.outitemmi;
by clientid;
run;
data bmsf.sf12MImultiple;
set bmsf.outitemmi  bmsf.timepoint4;
run;

/*calculate sf-12 total scores */
data bmsf.sf12recode;
set bmsf.sf12mimonotone;
if sf12i2=1 then sf12i2_1=1;
else if sf12i2=. then sf12i2_1=.;
else sf12i2_1=0;
if sf12i2=2 then sf12i2_2=1;
else if sf12i2=. then sf12i2_2=.;
else sf12i2_2=0;
if sf12i3=1 then sf12i3_1=1;
else if sf12i3=. then sf12i3_1=.;
else sf12i3_1=0;
if sf12i3=2 then sf12i3_2=1;
else if sf12i3=. then sf12i3_2=.;
else sf12i3_2=0;
if sf12i4=0 then sf12i4_1=1;
else if sf12i4=. then sf12i4_1=.;
else sf12i4_1=0;
if sf12i5=0 then sf12i5_1=1;
else if sf12i5=. then sf12i5_1=.;
else sf12i5_1=0;
if sf12i6=0 then sf12i6_1=1;
else if sf12i6=. then sf12i6_1=.;
else sf12i6_1=0;
if sf12i7=0 then sf12i7_1=1;
else if sf12i7=. then sf12i7_1=.;
else sf12i7_1=0;
if sf12i8=1 then sf12i8_1=1; else if sf12i8=., then sf12i8_1=.; else sf12i8_1=0; if sf12i8=2 then sf12i8_2=1; else if sf12i8=., then sf12i8_2=.; else sf12i8_2=0; if sf12i8=3 then sf12i8_3=1; else if sf12i8=., then sf12i8_3=.; else sf12i8_3=0; if sf12i8=4 then sf12i8_4=1; else if sf12i8=., then sf12i8_4=.; else sf12i8_4=0; if sf12i1=1 then sf12i1_1=1; else if sf12i1=., then sf12i1_1=.; else sf12i1_1=0; if sf12i1=2 then sf12i1_2=1; else if sf12i1=., then sf12i1_2=.; else sf12i1_2=0; if sf12i1=3 then sf12i1_3=1; else if sf12i1=., then sf12i1_3=.; else sf12i1_3=0; if sf12i1=4 then sf12i1_4=1; else if sf12i1=., then sf12i1_4=.; else sf12i1_4=0; if sf12i10=1 then sf12i10_1=1; else if sf12i10=., then sf12i10_1=.; else sf12i10_1=0; if sf12i10=2 then sf12i10_2=1; else if sf12i10=., then sf12i10_2=.; else sf12i10_2=0; if sf12i10=3 then sf12i10_3=1; else if sf12i10=., then sf12i10_3=.; else sf12i10_3=0; if sf12i10=4 then sf12i10_4=1; else if sf12i10=., then sf12i10_4=.; else sf12i10_4=0; if sf12i10=5 then sf12i10_5=1; else if sf12i10=., then sf12i10_5=.; else sf12i10_5=0; if sf12i9=1 then sf12i9_1=1; else if sf12i9=., then sf12i9_1=.; else sf12i9_1=0; if sf12i9=2 then sf12i9_2=1; else if sf12i9=., then sf12i9_2=.; else sf12i9_2=0; if sf12i9=3 then sf12i9_3=1; else if sf12i9=., then sf12i9_3=.; else sf12i9_3=0; if sf12i9=4 then sf12i9_4=1; else if sf12i9=., then sf12i9_4=.; else sf12i9_4=0; if sf12i9=5 then sf12i9_5=1; else if sf12i9=., then sf12i9_5=.;
else sf12i9_5=0;
if sf12i11=1 then sf12i11_1=1;
else if sf12i11= then sf12i11_1=.;
else sf12i11_1=0;
if sf12i11=2 then sf12i11_2=1;
else if sf12i11= then sf12i11_2=.;
else sf12i11_2=0;
if sf12i11=3 then sf12i11_3=1;
else if sf12i11= then sf12i11_3=.;
else sf12i11_3=0;
if sf12i11=4 then sf12i11_4=1;
else if sf12i11= then sf12i11_4=.;
else sf12i11_4=0;
if sf12i11=5 then sf12i11_5=1;
else if sf12i11= then sf12i11_5=.;
else sf12i11_5=0;
if sf12i12=1 then sf12i12_1=1;
else if sf12i12= then sf12i12_1=.;
else sf12i12_1=0;
if sf12i12=2 then sf12i12_2=1;
else if sf12i12= then sf12i12_2=.;
else sf12i12_2=0;
if sf12i12=3 then sf12i12_3=1;
else if sf12i12= then sf12i12_3=.;
else sf12i12_3=0;
if sf12i12=4 then sf12i12_4=1;
else if sf12i12= then sf12i12_4=.;
else sf12i12_4=0;
run;

/*weighting and aggregation of indicator variables using Physical and Mental regression weights*/
data bmsf.sf12monotoneraw;
set bmsf.sf12recode;
rawpcs= (-7.23216*sf121i2_1) + (-3.45555*sf121i2_2) + (-6.24397*sf121i3_1) + (-2.73557*sf121i3_2) + (-4.61617*sf121i4_1) + (-5.51747*sf121i5_1) + (-11.25544*sf121i8_1) + (-8.38063*sf121i8_2) + (-6.50522*sf121i8_3) + (-3.80130*sf121i8_4) + (-8.37399*sf121i1_1) + (-5.56461*sf121i1_2) + (-3.02396*sf121i1_3) + (-1.31872*sf121i1_4) + (-2.44706*sf121i10_1) + (-2.02168*sf121i10_2) + (-1.6185*sf121i10_3) + (-1.14387*sf121i10_4) + (-0.42251*sf121i10_5) + (-0.33682*sf121i12_1) + (-0.33682*sf121i12_2) + (-0.18043*sf121i12_3) + (0.11038*sf121i12_4) + (3.04365*sf121i6_1) + (2.32091*sf121i7_1) + (3.46638*sf121i9_1) + (2.90426*sf121i9_2) + (2.37241*sf121i9_3) + (1.36689*sf121i9_4) + (0.66514*sf121i9_5) + (4.61446*sf121i1_1) + (3.41593*sf121i1_2) + (2.34247*sf121i6_1) + (1.28044*sf121i1_4) + (0.41188*sf121i11_5);
rawmcs= (3.93115*sf121i2_1) + (1.8684*sf121i2_2) + (2.68282*sf121i3_1) + (1.43103*sf121i3_2) + (1.4406*sf121i4_1) + (1.6968*sf121i5_1) + (1.48619*sf121i8_1) + (1.76691*sf121i8_2) + (1.49384*sf121i8_3) + (0.90384*sf121i8_4) + (1.71175*sf121i1_1) + (-0.16891*sf121i1_2) + (0.03482*sf121i1_3) + (-0.06064*sf121i1_4) + (-6.02409*sf121i10_1) + (-4.88962*sf121i10_2) + (-3.29805*sf121i10_3) + (-1.65718*sf121i10_4) + (-9.20578*sf121i10_5) + (-6.29724*sf121i12_1) + (-8.26066*sf121i12_2) + (-5.63286*sf121i12_3) + (-3.13896*sf121i12_4) + (-6.82672*sf121i6_1) + (-5.69921*sf121i7_1) + (-10.19085*sf121i9_1) + (-7.92717*sf121i9_2) + (-6.3121*sf121i9_3) + (-4.09842*sf121i9_4)
+ (-1.94949*sf12i9_5) + (-16.15395*sf12i11_1) + (-10.77911*sf12i11_2) + (-8.09914*sf12i11_3) + (-4.59055*sf12i11_4) + (-1.95934*sf12i11_5);

run;
/*norm-based standardization of scale scores above*/
data bmsf.sf12monotonefinal;
set bmsf.sf12monotoneraw;
PCS= (rawpcs + 56.57706);
MCS= (rawmcs + 60.75781);
run;

/*calculate total scores for the multiple imputation data*/
data bmsf.sf12recode2;
set bmsf.sf12mimultiple;
if sf12i2=1 then sf12i2_1=1;
else if sf12i2=. then sf12i2_1=.;
else sf12i2_1=0;

if sf12i2=2 then sf12i2_2=1;
else if sf12i2=. then sf12i2_2=.1;
else sf12i2_2=0;

if sf12i3=1 then sf12i3_1=1;
else if sf12i3=. then sf12i3_1=.;
else sf12i3_1=0;

if sf12i3=2 then sf12i3_2=1;
else if sf12i3=. then sf12i3_2=.;
else sf12i3_2=0;

if sf12i4=0 then sf12i4_1=1;
else if sf12i4=. then sf12i4_1=.;
else sf12i4_1=0;

if sf12i5=0 then sf12i5_1=1;
else if sf12i5=. then sf12i5_1=.;
else sf12i5_1=0;

if sf12i6=0 then sf12i6_1=1;
else if sf12i6=. then sf12i6_1=.;
else sf12i6_1=0;

if sf12i7=0 then sf12i7_1=1;
else if sf12i7=. then sf12i7_1=.;
else sf12i7_1=0;

if sf12i8=1 then sf12i8_1=1;
else if sf12i8=. then sf12i8_1=.;
else sf12i8_1=0;
if sf12i8=2 then sf12i8_2=1;
else if sf12i8=. then sf12i8_2=.;
else sf12i8_2=0;
if sf12i8=3 then sf12i8_3=1;
else if sf12i8=. then sf12i8_3=.;
else sf12i8_3=0;
if sf12i8=4 then sf12i8_4=1; else if sf12i8=3 then sf12i8_4=0; 
if sf12i8=1 then sf12i8_1=1; else if sf12i8=2 then sf12i8_2=1; else sf12i8_2=0; 
if sf12i8=3 then sf12i8_3=1; else sf12i8_3=0; 
if sf12i8=4 then sf12i8_4=1; else sf12i8_4=0; 

if sf12i9=1 then sf12i9_1=1; else if sf12i9=2 then sf12i9_2=1; else sf12i9_2=0; 
if sf12i9=3 then sf12i9_3=1; else sf12i9_3=0; 
if sf12i9=4 then sf12i9_4=1; else sf12i9_4=0; 
if sf12i9=5 then sf12i9_5=1; else sf12i9_5=0; 

if sf12i10=1 then sf12i10_1=1; else if sf12i10=2 then sf12i10_2=1; else sf12i10_2=0; 
if sf12i10=3 then sf12i10_3=1; else sf12i10_3=0; 
if sf12i10=4 then sf12i10_4=1; else sf12i10_4=0; 
if sf12i10=5 then sf12i10_5=1; else sf12i10_5=0; 

if sf12i11=1 then sf12i11_1=1; else if sf12i11=2 then sf12i11_2=1; else sf12i11_2=0; 
if sf12i11=3 then sf12i11_3=1;
else if sf12i11= then sf12i11_3=;
else sf12i11_3=0;
if sf12i11=4 then sf12i11_4=1;
else if sf12i11= then sf12i11_4=;
else sf12i11_4=0;
if sf12i11=5 then sf12i11_5=1;
else if sf12i11= then sf12i11_5=;
else sf12i11_5=0;
if sf12i12=1 then sf12i12_1=1;
else if sf12i12= then sf12i12_1=;
else sf12i12_1=0;
if sf12i12=2 then sf12i12_2=1;
else if sf12i12= then sf12i12_2=;
else sf12i12_2=0;
if sf12i12=3 then sf12i12_3=1;
else if sf12i12= then sf12i12_3=;
else sf12i12_3=0;
if sf12i12=4 then sf12i12_4=1;
else if sf12i12= then sf12i12_4=;
else sf12i12_4=0;
run;
/*weighting and aggregation of indicator variables using Physical and Mental regression weights*/
data bmsf.sf12monotoneraw2;
set bmsf.sf12recode2;
rawpcs=((-7.23216*sf12i1_1) + (-3.45555*sf12i1_2) + (-6.24397*sf12i3_1) + (-2.73557*sf12i3_2) + (-4.61617*sf12i4_1) + (-5.51747*sf12i5_1) + (-11.25544*sf12i8_1) + (-8.38063*sf12i8_2) + (-6.50522*sf12i8_3) + (-3.80130*sf12i8_4) + (-8.37399*sf12i1_1) + (-5.56461*sf12i1_2) + (-3.02396*sf12i1_3) + (-1.31872*sf12i1_4) + (-2.44706*sf12i10_1) + (-2.02168*sf12i10_2) + (-1.6185*sf12i10_3) + (-1.14387*sf12i10_4) + (-0.42521*sf12i10_5) + (-0.33682*sf12i12_1) + (-0.49434*sf12i12_2) + (0.18043*sf12i12_3) + (0.11038*sf12i12_4) + (3.04365*sf12i6_1) + (2.32091*sf12i7_1) + (3.46638*sf12i9_1) + (2.32457*sf12i9_2) + (2.3741*sf12i9_3) + (1.36689*sf12i9_4) + (0.66514*sf12i9_5) + (4.61446*sf12i11_1) + (3.41593*sf12i11_2) + (2.34247*sf12i11_3) + (1.28044*sf12i11_4) + (0.41188*sf12i11_5);
rawmcs=(3.93115*sf12i1_1) + (1.8684*sf12i1_2) + (2.68282*sf12i3_1) + (1.43103*sf12i3_2) + (1.4406*sf12i4_1) + (1.66968*sf12i5_1) + (1.48619*sf12i7_1) + (1.76691*sf12i8_2) + (1.49384*sf12i8_3) + (0.90384*sf12i8_4) + (1.71175*sf12i10_1) + (0.16891*sf12i10_2) + (0.03482*sf12i10_3) + (0.06064*sf12i10_4) + (-0.60249*sf12i12_1) + (-4.88962*sf12i12_2) + (-3.29805*sf12i12_3) + (-1.65178*sf12i12_4) + (0.92057*sf12i12_5) + (-6.29724*sf12i12_1) + (-8.26066*sf12i12_2) + (-5.63286*sf12i12_3) + (-3.13896*sf12i12_4) + (-6.82672*sf12i12_5) + (-5.69921*sf12i12_1) + (-10.19085*sf12i12_2) + (-7.92717*sf12i12_3) + (-6.31121*sf12i12_4) + (-4.09842*sf12i12_5) + (-1.94949*sf12i9_1) + (-16.15395*sf12i11_1) + (-10.77911*sf12i11_2) + (-8.09914*sf12i11_3) + (-4.59055*sf12i11_4) + (-1.95934*sf12i11_5);
run;
/*norm-based standardization of scale scores above*/
data bmsf.sf12finalmultiple;
set bmsf.sf12monotoneraw2;
run;
/*means over time before imputation*/
title' means over time before imputation';
proc means data=bmsf.wideformat;
var mcs1-mcs4 pcs1-pcs4;
run;
proc sort data=bmsf.transposed;
bym timepoint;
run;
proc means data=bmsf.transposed;
var mcs pcs;
bym timepoint;
run;

/*means over time after multiple imputations*/
title' means over time after multiple imputation';
proc sort data=bmsf.sf12finalmultiple;
bym timepoint;
run;
proc means data=bmsf.sf12finalmultiple;
var pcs mcs;
bym timepoint;
run;

/*means over time after single/monotone item imputations*/
title' means over time after single/monotone imputation';
proc sort data=bmsf.sf12monotonefinal;
bym timepoint;
run;
proc means data=bmsf.sf12monotonefinal;
var pcs mcs;
bym timepoint;
run;

/*******************************************************************************
 ***
 * Mean comparisons were conducted to compare the scores of those who had missing item data
 * versus those who did not have missing item data. Also, mean comparisons were conducted for
 * those participants who dropped out compared to those who did not drop out to see if they were
 * significantly different. These analysis were stratified by the study group (group). The drop*
 * variables were named for the time period where the person did not have data. So drop3mo means*
 * they participated at baseline but not at 3 month. We then compared the baseline data to see
 * if those with subsequent drop-out differed at baseline than those who continued in the study.
 ********************************************************************************
 */

/*means of sf-12 dropout vs no dropout after baseline*/
title' means of dropped versus did not drop after baseline';
data bmsf.dropcomp6;
set bmsf.dropmeansmi;
if timepoint=1 and itemmiss1=1 then delete;
run;

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PROC SORT DATA=BMSF.DROPCOMP3;
   BY GROUP TIMEPOINT DROP3MO ITEMMISS1;
RUN;
PROC TTEST DATA=BMSF.DROPCOMP3;
   CLASS DROP3MO;
   VAR MCS PCS;
   WHERE TIMEPOINT=1;
   BY GROUP;
RUN;
/*means of no dropout vs missing item at baseline*/
TITLE 'means of missing items versus non-missing 3 month (no 6 month data)';
DATA BMSF.DROPITEMBASE;
   SET BMSF.DROPMEANSMI;
   IF TIMEPOINT=1 AND DROP3MO=1 THEN DELETE;
RUN;
PROC SORT DATA=BMSF.DROPITEMBASE;
   BY GROUP ITEMMISS1;
RUN;
PROC TTEST DATA=BMSF.DROPITEMBASE;
   CLASS ITEMMISS1;
   VAR MCS PCS;
   WHERE TIMEPOINT=1;
   BY GROUP;
RUN;
/*means of sf-12 dropout vs no dropout at 6 month*/
TITLE 'means of dropped versus no drop 3 month data';
DATA BMSF.DROPCOMP6;
   SET BMSF.DROPMEANSMI;
   IF TIMEPOINT=2 AND ITEMMISS2=1 THEN DELETE;
RUN;
PROC SORT DATA=BMSF.DROPCOMP6;
   BY GROUP RECODE2 TIMEPOINT DROP6MO ITEMMISS2;
RUN;
PROC TTEST DATA=BMSF.DROPCOMP6;
   CLASS DROP6MO;
   VAR MCS PCS;
   WHERE TIMEPOINT=2;
   BY GROUP RECODE2;
RUN;
/*means of no dropout vs missing items at 3 months*/
TITLE 'means of missing items versus non-missing 3 month';
DATA BMSF.DROPITEM6;
   SET BMSF.DROPMEANSMI;
   IF TIMEPOINT=2 AND DROP6MO=1 THEN DELETE;
RUN;
PROC SORT DATA=BMSF.DROPITEM6;
   BY GROUP RECODE2 ITEMMISS2;
RUN;
PROC TTEST DATA=BMSF.DROPITEM6;
   CLASS ITEMMISS2;
   VAR MCS PCS;
   WHERE TIMEPOINT=2;
   BY GROUP RECODE2;
RUN;
/*means of sf-12 dropout vs no dropout at 9 month*/
title 'means of dropped versus no drop 6 month';
data bmsf.dropcomp9; 
set bmsf.dropmeansmi; 
if clientid=2 then delete; 
run; 
proc sort data=bmsf.dropcomp9; 
by group_recode2 timepoint drop9mo itemmiss3; 
run; 
proc ttest data=bmsf.dropcomp9; 
class drop9mo; 
var mcs pcs; 
where timepoint=3 ; 
by group_recode2; 
run; 
/*means of no dropout vs missing items at 6 months*/
title 'means of missing items versus non-missing 6 month';
data bmsf.dropitem9; 
set bmsf.dropmeansmi; 
if clientid=53 then delete; if clientid=47 then delete; if clientid=32 then delete;if clientid=30 then delete; 
if clientid=14 then delete; if clientid=12 then delete;if clientid=1 then delete; 
run; 
proc sort data=bmsf.dropitem9; 
by group_recode2 itemmiss3; 
run; 
proc ttest data=bmsf.dropitem9; 
class itemmiss3; 
var mcs pcs; 
where timepoint=3 ; 
by group_recode2; 
run; 
/*means of sf-12 dropout vs no dropout at all*/
data bmsf.nodropcomp; 
set bmsf.dropmeansmi; 
if timepoint=4 and itemmiss4=1 then delete; 
run; 
proc sort data=bmsf.nodropcomp; 
by group_recode2 timepoint nodrop itemmiss4; 
run; 
proc means data=bmsf.nodropcomp; 
var mcs pcs; 
by group_recode2 nodrop itemmiss4; 
where timepoint=4; 
run; 

/*After the imputation of the missing item data the data must be transposed back into a wide data set for the subsequent analysis. That set is called "wideitemMI"*/
/*missing data pattern*/
ods select missPattern;
**proc mi data = bmsf.wideitemmi nimpute=0 simple;**
   var pcs_1-pcs_4 mcs_1-mcs_4 bprs1-bprs4 age race sex;
run;

**proc means data=bmsf.wideitemmi N mean std nmiss min max var skewness kurtosis maxdec=2;**
title 'simple descriptives by time point';
var pcs_1-pcs_4 mcs_1-mcs_4 bprs1-bprs4 age race sex;
run;

/*By Treatment group*/
**proc sort data=bmsf.wideitemmi;**
by group;
run;
title 'Missing data pattern by Tx group';
ods select missPattern;
**proc mi data = bmsf.wideitemmi nimpute=0 simple;**
   var pcs_1-pcs_4 mcs_1-mcs_4 bprs1-bprs4 age race sex;
   by group;
run;
title '';

/*******************************************************************************
*** Survival analysis was used to explore the relationship of the covariates on drop-out and the
*** time to drop-out. The censor variable is “Censind”
***
*******************************************************************************

Survival Analysis code*/;
ods graphics on;

**proc lifetest data=bmsf.wideitemMI plots=(survival atrisk) logsurv;**
time dropouttime*censind(1);
run;
**proc lifetest data=bmsf.wideitemMI ;**
time dropouttime*censind(1);
strata group;
run;

**proc lifetest data=bmsf.wideitemMI plots=(s);**
time dropouttime*censind(1);
strata group/trend test=(logrank wilcoxon tarone peto);
symbol1 c=blue l=12 h=.5;
symbol2 c=red l=1 h=.5;
symbol3 c=green l=8 h=.5;
run;

**proc lifetest data=bmsf.wideitemMI plots=(lls) ;**
time dropouttime*censind(1);
strata group;
run;
ods graphics off;

/*time invariant predictors (baseline)*/
title 'time invariant predictors';
proc phreg data=bmsf.wideitemMI;
model dropouttime*censind(1)= pcs_1 mcs_1 bprs1 age race sex
/selection=stepwise slentry=0.25 slstay=0.15 details ties=discrete;
run;
proc phreg data=bmsf.wideitemMI;
model dropouttime*censind(1)= pcs_1 mcs_1 bprs1 age race sex
/risklimits ties=discrete;
run;

/*time invariant predictors by group*/
title 'time invariant predictors by group';
proc phreg data=bmsf.wideitemMI;
model dropouttime*censind(1)= pcs_1 mcs_1 bprs1 age race sex
/selection=stepwise slentry=0.25 slstay=0.15 details ties=discrete;
strata group;
run;
proc phreg data=bmsf.wideitemMI;
model dropouttime*censind(1)= pcs_1 mcs_1 bprs1 age race sex
/risklimits ties=discrete;
strata group;
run;

/*time invariant predictors with treatment group as a predictor*/
title 'time invariant predictors with tx group predictor';
proc phreg data=bmsf.wideitemMI;
model dropouttime*censind(1)= pcs_1 mcs_1 bprs1 age race sex group
/selection=stepwise slentry=0.25 slstay=0.15 details ties=discrete;
run;
proc phreg data=bmsf.wideitemMI;
model dropouttime*censind(1)= pcs_1 mcs_1 bprs1 age race sex group
/risklimits ties=discrete;
run;

/*******************************************************************************
***
* After survival analysis the mean PCS and MCS scores over time were graphed
*
*******************************************************************************/
proc sort data=bmsf.sf12monotonefinal;
by group time;
run;

proc means data=bmsf.sf12monotonefinal noprint;
by group time;
var mcs;
output out=meansout (drop=_type_ _freq_) mean=mean stderr=stderr;
run;
/* each X for use with the HILOC interpolation. */
data reshape(keep=group_recode2 time mcs mean);
  set meansout;
  by group time;

/* Offset the X values to display two groups */
if group='1' then time=time - 0.08;
else if group='2' then time=time + 0.08;

mcs=mean;
output;

mcs=mean - stderr;
output;

mcs=mean + stderr;
output;
run;

axis1 offset=(0,0) minor=none value=(t=1 ' ' t=4 ' ');
axis2 label=(angle=90) order=(20 to 60 by 5) minor=(n=1);

/* Define the symbol characteristics */
symbol1 interpol=hiloctj color=vibg line=1;
symbol2 interpol=hiloctj color=depk line=2;

symbol3 interpol=none color=vibg value=dot height=1.5;
symbol4 interpol=none color=depk value=dot height=1.5;

/* Define the legend characteristics */
legend1 label=('Group:') frame;

/* Plot the error bars using the HILOC interpolation and overlay symbols at the means. */
proc gplot data=reshape;
  plot mcs*time=group / haxis=axis1 vaxis=axis2 legend=legend1;
  plot2 mean*time=group / vaxis=axis2 noaxis nolegend;
run;
quit;

/*PCS*/
proc means data=bmsf.sf12monotonefinal noprint;
by group time;
var pcs;
output out=meansout2 (drop=_type_ _freq_) mean=mean stderr=stderr;
run;

/* each X for use with the HILOC interpolation. */
data reshape(keep=group_recode2 time pcs mean);
  set meansout2;
  by group time;

/* Offset the X values to display two groups */
if group='1' then time=time - 0.08;
else if group='2' then time=time + 0.08;

pcs=mean;
output;
pcs=mean - stderr;
output;

pcs=mean + stderr;
output;
run;

axis1 offset=(0,0) minor=none value=(=1 ' ' t=4');
axis2 label=(angle=90) order=(20 to 60 by 5) minor=(n=1);

/* Define the symbol characteristics * /
symbol1 interpol=hiloctj color=vibg line=1;
symbol2 interpol=hiloctj color=depk line=2;

symbol3 interpol=none color=vibg value=dot height=1.5;
symbol4 interpol=none color=depk value=dot height=1.5;

/* Define the legend characteristics * /
legend1 label=('Group:') frame;

/* Plot the error bars using the HILOCTJ interpolation * /
/* and overlay symbols at the means. */
proc gplot data=reshape;
  plot pcs*time=group / haxis=axis1 vaxis=axis2 legend=legend1;
  plot2 mean*time=group / vaxis=axis2 noaxis nolegend;
run;
quit;

******************************************************************************************
*** The next step was to conduct multiple imputation for the intermittent and drop-out data. The
*** more variables included the more information SAS has to use to impute the missing values.
******************************************************************************************

/*multiple imputation*/
proc sort data=bmsf.wideitemmi;
by group;
run;
ods graphics on;
title 'multiple imputation';
proc mi data = bmsf.wideitemmi seed=501213 nimpute=114 out=bmsf.outallmi2
minimum=;... 
maximum=;...
mcmc chain=multiple displayinit initial=em(itprint)plots=trace plots=acf;
  var race sex mcs_1-mcs_4 pcs_1-pcs_4 bprs1_total bprs2_total bprs3_total bprs4_total age lifetimearrests;
run;
ods graphics off;
/* we cannot have values outside of 0 or 1 for race or sex, therefore we have to reassign the imputed values*/

data bmsf.outallmi3;
set bmsf.outallmi2;
if c1b9 ~= 0 and c1b9~= 1 then do;
  temp = ranuni(0);
  if temp < .5 then c1b9 = 0;
else clb9 = 1;
end;
run;

proc means data=bmsf.outallmi2;
title 'Descriptives by imputation';
class _imputation_;
var mcs_1-mcs_4 pcs_1-pcs_4 bprs1_total bprs2_total bprs3_total bprs4_total age race sex lifetimearrests;
run;

proc means data=bmsf.widetemmi;
title 'Descriptives with missing values';
var mcs_1-mcs_4 pcs_1-pcs_4 bprs1_total bprs2_total bprs3_total bprs4_total age race sex lifetimearrests;
run;

/*The data again has to be transformed into long format for Proc Mixed, the new data is "longmigroup2"*/

data bmsf.mixed2;
set bmsf.sf12monoton efinal;
if timepoint=1 then studytime=0;
else if timepoint=2 then studytime=1;
else if timepoint=3 then studytime=2;
else studytime=3;
run;

/* In order to run the Maximum likelihood models, and to use the imputed data for Proc MIanalyze we need to first build the regression model*/

title2 'mixed regression models';
/*building the model for comparison*/
proc mixed data=bmsf.mixed2 method=reml covtest;
title 'unconditional model';
class clientid;
model mcs=studytime/solution ddfm=kr;
random intercept/subject=clientid g v;
run;

proc mixed data=bmsf.mixed2 method=reml covtest;
title 'unconditional model random slope';
class clientid;
model mcs=studytime/solution ddfm=kr;
random intercept studytime/subject=clientid g v;
run;

proc mixed data=bmsf.mixed2 method=reml covtest;
title 'group predictor';
class clientid;
model mcs=studytime group/solution ddfm=kr;
random intercept studytime/subject=clientid g v;
run;

proc mixed data=bmsf.mixed2 method=reml covtest;
title 'MCS all predictors';
class clientid;
model mcs=studytime group pcs_bprs age race sex/solution ddfm=kr;
random intercept studytime/subject=clientid g v;
run;

proc mixed data=bmsf.mixed2 method=reml covtest;
title 'PCS all predictors';
class clientid;
```sas
/*The data again has to be transformed into long format for Proc Mixed, the new data is "longmigroup2"*/

/*Proc MIanalyze Imputed data*/
proc sql;
cREATE TABLE bmsf.longallmigroup2_a AS
SELECT *
, a.bprs-mean(a.bprs) AS cbprs,
  a.clage-mean(a.clage) AS cage,
  a.aljailife-mean(a.aljailife) AS cjaillife,
  a.pcs-mean(a.pcs) AS cpcs,
  a.mcs-mean(a.mcs) AS cmcs
FROM bmsf.longallmigroup2 AS a, bmsf.mixed2 AS b
WHERE a.clientid=b.clientid AND a.studytime=b.studytime;
QUIT;
proc sort data=bmsf.longallmigroup2_a;
by _imputation_;
RUN;

PROC MIXED data=bmsf.longallMIGroup2_a method=ml covtest;
title 'mcs repeated measures with imputed data by imputation';
class clientid;
model mcs= studytime group pcs cl age age race sex lifetimearrests/ solution covb;
by _imputation_; 
ods output solutionf=mixparms4 covb=mixcovb4;
run;
PROC MIANALYZE parms=mixparms4 edf=43
  covb(effectvar=rowcol)=mixcovb4;
title 'mcs repeated measures combined imputation regression coefficients';
  modeleffects intercept studytime group pcs bprs age race sex lifetimearrests;
run;

PROC MIXED data=bmsf.longallMIGroup2_a method=ml covtest;
title 'pcs repeated measures with imputed data by imputation';
class clientid;
model pcs= studytime group mcs bprs age race sex lifetimearrests/ solution covb;
by _imputation_; 
ods output solutionf=mixparms4 covb=mixcovb4;
run;
PROC MIANALYZE parms=mixparms4 edf=43
  covb(effectvar=rowcol)=mixcovb4;
title 'pcs repeated measures combined imputation regression coefficients';
  modeleffects intercept studytime group mcs bprs age race sex lifetimearrests;
```
run;

/*proc mixed without imputed data- this is the maximum likelihood estimation analysis*/
proc mixed data=bmsf.mixed2 method=ml covtest;
title' mcs repeated measures without imputed data';
class clientid ;
model mcs= studytime group pcs bprs age race sex lifetimearrests/ solution ddfm=kr;
random intercept studytime/subject=clientid type=un gcorr g v ;
run;

proc mixed data=bmsf.mixed2 method=ml covtest;
title' pcs repeated measures without imputed data';
class clientid ;
model pcs= studytime group mcs bprs age race sex lifetimearrests/ solution ddfm=kr;
random intercept studytime/subject=clientid type=un gcorr g v solution;
run;

title '';
Appendix C: Literature Review

Definitions

In order to understand the role of behavioral health in public health and public health within behavioral health, it is necessary to first define what public health and behavioral health are. The American Public Health Association (American Public Health Association, 2013) defines public health as “…the practice of preventing disease and promoting good health within groups of people, from small communities to entire countries.” (para. 1) This definition has been elaborated on by the What is Public Health campaign (2013) as:

Public Health is the science of protecting and improving the health of communities through education, promotion of healthy lifestyles, and research for disease and injury prevention. Public health professionals analyze the effect on health of genetics, personal choice and the environment in order to develop programs that protect the health of your family and community. (para. 1)

These definitions represent the varied nature and the wide berth of health issues that are addressed by the field of public health. In general, the field of public health is interested in improving a multitude of health problems through a population-based approach (Levin, Hanson, Hennessy, & Petrila, 2010). More simply put, public health encompasses all types of health and revolves around improving health for the population through education, promotion, and research. Public health is made up of different subdivisions, which allows for greater in depth study of different health concerns or illnesses (American Public Health Association, 2013).

One of the subdivisions within public health is behavioral health. There is not a sole definition of behavioral health, but it has been defined as “…the delivery of mental health/substance use services…” (Mauer & Druss, 2010, p. 530) and more generally as mental
health and substance use services (Collins, Hewson, Munger, & Wade, 2010). Mental health is considered to be one of the cornerstones of good health. According to the World Health Organization, the definition of health is "A state of complete physical, mental and social well-being, and not merely the absence of disease" (World Health Organization, 2013). Mental well-being refers to “the promotion of well-being, the prevention of mental disorders, and the treatment and rehabilitation of people affected by mental disorders” (World Health Organization, 2013). In order to achieve good population health, you must also have good population mental health.

Additionally, the achievement of good mental health has been specified as one of the Healthy People 2020 objectives (U.S. Department of Health and Human Services & Office of Disease Prevention and Health Promotion, 2012). The objective is to “Improve mental health through prevention and by ensuring access to appropriate, quality mental health services” (U.S. Department of Health and Human Services & Office of Disease Prevention and Health Promotion, 2012). Mental disorders are one of the most common causes of disability and they have one of the highest disease burdens (U.S. Department of Health and Human Services & Office of Disease Prevention and Health Promotion, 2012). Substance abuse also continues to be a focus of the Healthy People objectives (U.S. Department of Health and Human Services & Office of Disease Prevention and Health Promotion, 2012). Both mental health and substance abuse need to be addressed in order to achieve good overall health.

**Role of Behavioral Health within Public Health**

It is important to understand the role of behavioral health within the field of public health. The role of behavioral health within public health can be viewed as the provision of services to improve the mental health and substance use and abuse issues of the population (Mauer & Druss, 2010). Without behavioral health, the population would never be able to achieve their full health
potential (World Health Organization, 2013). Behavioral health provides services to improve mental health and drug and alcohol abuse to help individuals achieve overall better health. Mental health is intertwined with physical health; to achieve good health, all aspects of health must be improved (Druss et al., 2009).

It is the role of the behavioral health field to protect and improve the health of the population through the delivery of mental health and substance abuse programs and interventions (Collins et al., 2010; Mauer & Druss, 2010). The behavioral health field is responsible for ensuring that research is conducted to develop, evaluate, and improve mental health and substance abuse services (U.S. Department of Health and Human Services & Office of Disease Prevention and Health Promotion, 2012). In addition, the behavioral health field is responsible for promoting knowledge and education on how to achieve good mental health (Mauer & Druss, 2010). Without the field of behavioral health, public health would neglect a substantial portion of population health issues, which would result in poorer health. Behavioral health provides one of the cornerstones of health that the field of public health is focused on achieving (World Health Organization, 2013).

**Role of Public Health within Behavioral Health**

Similarly, the behavioral health field would not function appropriately without the influence of public health. Public health provides the perspective from which behavioral health is viewed, and drives how mental health services are provided (Levin et al., 2010). Public health takes a population approach to services, which is the approach also taken by behavioral health (Levin et al., 2010). Other fields, such as psychology, are focused on providing care on an individual basis to those who have mental health needs, whereas behavioral health is focused on improving mental health services for all individuals with mental health needs (Collins et al., 2010; Mauer & Druss, 2010). By taking a public health perspective, behavioral health is able to target a
much larger portion of individuals with mental health needs to provide appropriate and effective services. Beyond providing behavioral health services and behavioral health interventions, a public health perspective encourages the evaluation of behavioral health services to ensure that effective, cost-effective services are provided (Collins et al., 2010).

In addition, because of the interplay between behavioral health and physical health, public health provides a platform for people in the behavioral health field to collaborate with people in other fields of public health (Mauer & Druss, 2010). This collaborative approach allows for a better understanding of how multiple diseases can be managed, or prevented. Public health provides a setting for the subdivisions of public health to collaborate to improve health. Unlike other disciplines, which sometimes may work in parallel silos, like sociology and psychology, public health provides an understanding that illnesses and diseases are complex, and must be addressed through the knowledge of many sub-disciplines (Collins et al., 2010; Druss & Mauer, 2010; Mauer & Druss, 2010). Public health provides a population-focused, collaborative framework for people in behavioral health to use as a guide to improve mental health and substance use (Collins et al., 2010; Druss & Mauer, 2010).

The main subdivisions, or core competencies, of public health are typically defined as environmental health, epidemiology, biostatistics, global health, health-policy and management, and social and behavioral science (Calhoun, Ramiah, Weist, & Shortell, 2008). Behavioral health plays a role within all these subdivisions and all of these subdivisions play a role within behavioral health. For example, different behavioral health problems can be measured using epidemiology and biostatistics-like victimization rates among individuals with mental illnesses (Chapple et al., 2004). The improvement of behavioral health has been called for by the World Health Organization and researchers from different countries focus on improving behavioral health.
outcomes, which intertwines with the global health field (Funk & Ibijaro, 2008; World Health Organization, 2013). Policy plays a major role in all fields of public health and dictates how mental health and substance abuse issues are viewed and how new research and appropriate treatments are specified and implemented (Glied & Frank, 2009). Finally, the area of social and behavioral sciences is thoroughly intertwined with the behavioral health field, and sometimes they are considered synonymous (Association of Schools of Public Health, 2013). The relationship between all of the competencies and behavioral health show how public health and behavioral health are interrelated, and the role they play within each other.

Conclusion

It is difficult to conceptualize behavioral health as a distinct entity from public health, as it is a necessary subdivision of public health. In addition, the field of public health provides the population approach to improving health that is the cornerstone behind behavioral health (Levin et al., 2010). Without behavioral health population health can never be fully achieved (World Health Organization, 2013). It is much more conducive to view behavioral health as a subdivision within the broader field of public health that interacts and collaborates with the other subdivisions within public health to achieve population health. Conceptually these two entities cannot be thought of as distinct, but in practice this is often not the case.

Integration of Physical and Mental Health

A greater understanding of the interplay between mental and physical illness has been at the forefront of the idea of greater integration of behavioral health and physical health services (Druss & Mauer, 2010; Druss, 2002; Druss et al., 2010, 2001; Giles & Collins, 2010; Manderscheid, 2010; Mauer & Druss, 2010; Parks, 2007; Satcher & Druss, 2010; Vreeland, 2007; Wakefield, 2011). Individuals with serious mental illness face a disproportionate amount of
physical health problems compared with the general public (Bushe et al., 2005; Chwastiak et al., 2006; Colton & Manderscheid, 2006; Kilbourne et al., 2009; Leung et al., 2010; Lord et al., 2010; Mitchell & Lord, 2010; Oud & Meyboom-de Jong, 2009; Viron & Stern, 2010; Weber et al., 2009). Individuals with a serious mental illness die as many as 25 years younger than the general population, typically due to physical illnesses (Colton & Manderscheid, 2006; Sherman et al., 2013; Viron & Stern, 2010). In addition, a greater percentage of individuals with mental illnesses receive services for their mental illness from their primary care physician, or through a community health center, not from a specialized mental health center (Druss et al., 2006; Manderscheid, 2010; Mauer & Druss, 2010; Regier et al., 1993). Not only can we bridge the gap between behavioral health and physical health services, but it is necessary in order to address the large amount of individuals who seek mental health care outside of the traditional or specialty behavioral health system (Mauer & Druss, 2010; Sherman et al., 2013).

Public health services have traditionally been thought of as services geared towards physical health diseases and illnesses. This way of thinking has led to behavioral health services that are typically provided as a distinct entity from physical health services (Manderscheid, 2010; Satcher & Druss, 2010). The divide between physical and mental health services can be attributed to the separate federal, state, and local mental health agencies and funding structures in place for public health and behavioral health services (Manderscheid, 2010). Agencies such as the Centers for Disease Control and Prevention (CDC), the Substance Abuse and Mental Health Services Administration (SAMHSA), the National Institute of Mental Health (NIMH), the U.S. Department of Health and Human Services, the President’s New Freedom Commission on Mental Health, and the Surgeon General have all called for integration of behavioral health and physical health services, which have been working parallel as opposed to a united entity (Institute of Medicine
Committe on Crossing the Quality Chasm: Adaptation to Mental Health and Addictive Disorders, 2006; Manderscheid, 2010; Satcher & Druss, 2010; Sherman et al., 2013; U.S. Department of Health and Human Services, 1999; Unutzer, Schoenbuam, Druss, & Katon, 2006). Currently, mental health services are disjointed and fragmented, resulting in the need for partnerships between multiple agencies and at multiple levels in order to increase the coordination between behavioral health and physical health (Power, 2010; Satcher & Druss, 2010).

At the policy and at the research levels, there has been a realization that services need to address both physical health and behavioral health needs. In the past two decades, there has been a realization that physical and mental health care can and should be provided using an integrative or collaborative approach (Druss & Mauer, 2010; Druss, 2002; Druss et al., 2010, 2001; Giles & Collins, 2010; Manderscheid, 2010; Mauer & Druss, 2010; Parks, 2007; Satcher & Druss, 2010; Vreeland, 2007; Wakefield, 2011). The calls for unity from multiple agencies at the policy level have led to increased research focusing on how to implement integrative care and the benefits (. Druss & Mauer, 2010; Druss, 2002; Druss et al., 2010, 2001; Giles & Collins, 2010; Manderscheid, 2010; Mauer & Druss, 2010; Parks, 2007; Satcher & Druss, 2010; Vreeland, 2007; Wakefield, 2011 Institute of Medicine Committe on Crossing the Quality Chasm: Adaptation to Mental Health and Addictive Disorders, 2006; Manderscheid, 2010; Satcher & Druss, 2010; U.S. Department of Health and Human Services, 1999; Unutzer, Schoenbuam, Druss, & Katon, 2006).

These multiple calls for greater integration have led to the exploration of ways to make physical health care and behavioral health care work more closely together. Typically, the combination of behavioral health and physical health services are either referred to as integrated care or collaborative care (Collins et al., 2010). The terms integrated care and collaborative care have been used interchangeably, but are not necessarily the same (Collins et al., 2010). Typically
collaborative care refers to behavioral health and physical health services working with each other, whereas integrated care refers to behavioral health and physical health services working within the respective field (Collins et al., 2010). In a collaborative care model the patient receives services from the respective physicians or care providers as distinct services, but there is a notion that these physicians or care providers are working with each other and collaborating to optimize the patient’s care (Collins et al., 2010). Unlike the collaborative care model, integrated care involves the patient receiving their behavioral health care services by their primary care physician, or having their physical health needs addressed by their behavioral health care service team (Collins et al., 2010).

**How to Integrate Care**

Proponents of integrated services have proposed different methods of how behavioral health and physical health care, mainly primary care, can be integrated. There are three main categories for integrated care models: coordinated care, co-location, and integrated care (Collins et al., 2010). These basic distinctions can be viewed as a continuum of collaboration, with integrated care representing the most collaborative approach for behavioral and physical health care (Collins et al., 2010). In practice, these models are not always distinct and may contain a blend of attributes from multiple models (Collins et al., 2010). All of these models have been shown to improve both the physical and mental health of the patients utilizing the services (Vreeland, 2007).

First, programs can be based on a coordinated care model, where the location of services is separate, but mental health and primary care services are coordinated through referrals (Druss & Mauer, 2010; Manderscheid, 2010; Vreeland, 2007). In this approach, the primary care provider may provide the behavioral health services to the patient following evidence-based practices, or
they can refer the patient to other providers as needed (Collins et al., 2010). This model is a step above the current field standard of providing a patient with a referral, as the services are coordinated between the multiple providers (Druss & Mauer, 2010; Manderscheid, 2010; Vreeland, 2007).

Second, mental health service providers can be integrated into primary care programs, otherwise known as colocation (Collins et al., 2010; Druss & Mauer, 2010; Manderscheid, 2010; Vreeland, 2007). Colocation typically occurs when both the behavioral health and primary care services are in the same facility and the medical providers can refer patients to behavioral health services as needed (Collins et al., 2010; Vreeland, 2007). Reverse colocation is when the primary care services are integrated into the behavioral health services, or provided at a behavioral health center (Collins et al., 2010).

Third is the integration of behavioral health and physical health services (Collins et al., 2010). The services may not actually be in one location, but all of the service providers share the same treatment plan that addresses both the physical and behavioral health needs of the patient. This approach usually involves a team of providers to ensure that all aspects of the patient’s health are being addressed (Collins et al., 2010).

Within models of integrated care, there are four concepts that are typically present that provide the basis for most models focused on improving care. First, is the medical home, which includes self-management, referral and patient tracking, and the use of non-physician staff for case management (Collins et al., 2010). This model allows for the patient to have a designated health home, where they receive the majority of their care unless they need something out of the purview of that provider (Druss & Mauer, 2010).
The second concept of integrated care is a health-care team, which is made up of multiple providers who are responsible for addressing the patient’s healthcare needs (Collins et al., 2010). These providers typically have a varied background to give the patient the most comprehensive care and include providers from both the physical health field and the behavioral health field. The team takes a holistic approach to the patient’s care and can fill in for a missing member if necessary (Collins et al., 2010).

Third, is stepped care, which is based on the tenet that the intensity of care should be responsive to the needs of the patient, and stepped up, or increased, if the patient’s functioning is not improving at the desired pace. Stepped-care represents the least-restrictive approach to improving health, with hospitalization as the last option (Collins et al., 2010). In addition, stepped care encourages the use of the least expensive and invasive procedures to treat the patient (Collins et al., 2010).

Fourth is the four quadrant clinical integration, which can be used to plan local health care systems, and address the quadrant where the patient has the greatest need (Collins et al., 2010; Mauer & Druss, 2010; Mauer, 2006). Specifically, the four quadrant model is based on both physical health and behavioral health needs of the patient, to determine the healthcare needs of the patient. The four quadrants are: low behavioral health and physical health needs, high behavioral health and low physical health needs, low behavioral health and high physical health needs, and high behavioral health and high physical health needs (Mauer & Druss, 2010; Mauer, 2006). Depending on the level of need, the appropriate staff and location of health services are determined to address the needs of the patient (Mauer & Druss, 2010; Mauer, 2006).

An important consideration of integrating care is that not all behavioral health conditions require the same intensity of treatment. The majority of depression cases can be treated using
standardized care, which can be delivered by a primary care physician if they have the time and are trained in the treatment protocols (Butler et al., 2008). Other mental illness, such as bipolar disorder and schizophrenia, are better treated at a specialty behavioral health center, with the integration of primary care physicians into this system to treat their physical and mental health conditions (Butler et al., 2008). The four quadrant approach to understand healthcare needs is appropriate for deciding the best way to provide services based on patient needs (Mauer & Druss, 2010; Mauer, 2006). Despite having very clear models of how to integrate care, there are barriers that must first be overcome.

**Barriers to Integrated Care**

Although there is a lot support for the effectiveness of integrated care, there are many barriers that must be addressed in order to implement integrated care. The most notable barrier to implementing integrated care is financial limitations (Butler et al., 2008). Despite evidence of improvement in primary care, there continue to be concerns over the financial sustainability of these programs (Druss, von Esenwein, et al., 2011). The cost of providing behavioral health services in a medical setting can be modest (Druss & von Esenwein, 2006), but issues remain with insurance reimbursements for services provided (Mauer & Druss, 2010). Billing practices for Medicaid and Medicare reimbursement remain elusive to providers, although there have been new codes emerging for integrated care billing (Mauer & Druss, 2010). Additionally, a difference in co-payment between mental health and physical health conditions in primary care remain, with mental health copays remaining more than double physical health copays (Mauer & Druss, 2010). Additional barriers are in place for uninsured individuals, as agencies typically end up spending money to serve them because they do not receive adequate reimbursement (Mauer & Druss, 2010). Beyond financial issues with community health agencies and primary care physicians, there are
also issues with complex financial structures in community mental health centers that need to be addressed (Institute of Medicine Committee on Crossing the Quality Chasm: Adaptation to Mental Health and Addictive Disorders, 2006; Unutzer et al., 2006). Community mental health centers receive funding from multiple sources, which makes it difficult to link patients to appropriate funding sources to receive services (Doub, Morrison, & Goodson, 2010).

Another barrier to the integration of behavioral health and public health services are workforce issues with both physicians and mental health providers. Physicians need to receive further training about how to provide care for mental health and substance use disorders using evidenced-based practices (Mauer & Druss, 2010). Mental health providers and clinicians also lack appropriate training on how to identify and address physical health issues that their patients may be experiencing (Druss et al., 2008; Vreeland, 2007). Having providers who have the appropriate skills to encourage and perpetuate the integration of services is necessary in order to achieve the desired outcomes (Mauer & Druss, 2010). Both the public health and behavioral health fields agree that the practitioners working in the respective fields have a responsibility to their patients to understand and provide holistic care (Giles & Collins, 2010; Mauer & Druss, 2010; Parks, 2007; Vreeland, 2007; Wakefield, 2011).

In addition, behavioral health and physical health practitioners historically have practiced as separate entities, which has led to a lack of information sharing between these two sectors (Collins et al., 2010). Information sharing ensures that all providers are up-to-date with current treatment, allowing the providers to make more informed decisions, especially when it comes to new medications (Druss, 2007; Mauer & Druss, 2010). Concerns with confidentiality have also been expressed as a potential barrier to information sharing, but HIPPA does not preclude providers from sharing information with each other, making this an unfounded barrier (Collins et
al., 2010; Mauer & Druss, 2010). In order to integrate care, there needs to be increased information sharing between providers, to ensure that all of the patient’s needs are being addressed.

The most compelling reason for integrated care is the shorter life spans faced by individuals with mental illness who are involved in the public mental health system (Colton & Manderscheid, 2006; Sherman et al., 2013; Viron & Stern, 2010). There are a variety of factors that mitigate the shorter life span for individuals with mental illness, including difficulties with the separate health care systems, trouble understanding or negotiating the health care system, lifestyle factors, side-effects of antipsychotic medications, and substance use (Druss, Zhao, et al., 2011; Druss et al., 2009; Kane, 2009; Manderscheid, 2010). Other reasons that individuals may receive poorer physical health care is mental health clinicians may not know how to manage the physical health conditions, or they may not even ask about physical health conditions (Carney, Jones, & Woolson, 2006; Levinson Miller, Druss, Dombrowski, & Rosenheck, 2003; Manderscheid, 2010). Primary care physicians have limited time that they spend meeting with each patient, which typically does not allow for the provision of evidence-based mental health services (Druss, Rosenheck, Desai, & Perlin, 2002; Lord et al., 2010; Manderscheid, 2010). Integrated care can overcome these barriers because the patient receives services from multiple providers who are either collaborating, collocated, or integrated and working as a team providing services (Collins et al., 2010).

**Reasons we Should Integrate Care**

Although there are barriers to implementing integrated care, there are many reasons to integrate care that overcome or exceed the barriers presented above. Collaborative and integrated care improve physical and mental health outcomes, although the specific mechanisms behind the health improvements are not clear (Butler et al., 2008). The amount of integration and the implementation of integration are not necessarily related to treatment response and remission
(Butler et al., 2008). Instead, improvements in health may reflect the providers’ systematic effort to follow the recommended treatment, compared to treatment as usual (Butler et al., 2008). Primary care physicians can provide appropriate mental health treatment for certain conditions, like depression, when they follow evidence based practices. Sometimes time constraints make the provision of evidence-based practices infeasible, so the addition of a care manager may be necessary (Butler et al., 2008). Just by introducing the notion of integrated care, individuals with mental illness may receive more evidence-based treatment, and therefore experience improved health (Butler et al., 2008). There is less evidence about the success of integrating primary care services into behavioral health services, although studies conducted at the Veterans Administration show promising outcomes (Butler et al., 2008; Druss et al., 2001; Druss & von Esenwein, 2006).

From a policy perspective, there are multiple reasons that care should be integrated. Funk and Ivbijaro (2008) provided a list of seven reason that we should integrate care:

1. Mental disorders cause economic and social hardships and are a burden to society—especially for the individual and their family.

2. Integrated care treats the person in a holistic manner which addresses the high number of individuals that suffer from comorbid mental health and physical health issues.

3. Coordinating care helps to provide care to a greater number of individuals with a mental disorder who face a disproportionate treatment gap.

4. Integration of behavioral health services into primary care allows individuals with mental illness to access services closer to their home, and allows them to remain with their family. It also helps to promote mental health, and reaches more individuals in the community.

5. Providing behavioral health services in a primary care setting can help to reduce stigma.
6. It is cost-effective to treat common and not complex mental disorders in a primary care setting.

7. The outcomes for people treated in a primary care setting are generally good, and are even better when the person is linked to specialty behavioral health services in the community.

These seven reasons for integrated care represent a summation of the field of collaborative and integrated care and provide the reasons of why care should be integrated from a policy perspective. Not only does integrated care improve outcomes for the population, but it also can be cost-effective.

One of the biggest pushes for the integration of behavioral health and public health services is the provisions in the Affordable Care Act of 2010 (ACA). Under the ACA, Medicaid will be expanded, and will allow for the provision of behavioral health services with copays comparable to other public health services (Druss, von Esenwein, et al., 2011; Garfield et al., 2010). The expansion of Medicaid through the ACA will also allow for increased access to substance abuse treatment (Busch et al., 2013). The ACA provides a perfect financial platform for the integration of care to commence, as it overcomes many of the financial barriers that were faced in the past.

Conclusion

In order to overcome the health disparities faced by individuals with mental illnesses, it is necessary to address the multiple barriers that exacerbate their poor health. When individuals with mental illness access physical health services, they receive poor preventative care, which results in higher rates of medical illnesses (Kane, 2009). Integrated medical and mental health services lead to increased use of preventative services, more primary care visits, and improved health compared to individuals who do not receive integrated care (Druss et al., 2001; Kane, 2009). Integration of the behavioral health and physical health systems can lead to overall improvement
in the health of individuals with mental illnesses, while decreasing the health disparities faced by this population (Viron & Stern, 2010). From a policy perspective, it is important to understand that behavioral health and public health services can be integrated, and that there are models of collaboration, co-location, and integrated care that can be used as a guide. Additionally, it is necessary to integrate these services in order to provide the best care to the population, especially because individuals with mental illness face such devastating health disparities (Colton & Manderscheid, 2006; Manderscheid, 2010; Sherman et al., 2013; Viron & Stern, 2010).

**Jail Diversion Program Background**

There are an estimated 2.1 million individuals with serious mental illness (SMI) entering jails annually in the U.S. (Steadman et al., 2009). Individuals with a SMI are more likely to commit a violent crime than individuals without mental illness or substance use disorders (Van Dorn et al., 2011). Individuals with SMI who are not medication compliant and abuse drugs are also more likely to be violent (J. A. Swartz & Lurigio, 2007; M. S. Swartz et al., 1998). Individuals with mental illnesses who are male, homeless, have had an involuntary psychiatric evaluation, prior arrests, are not medication compliant, and not receiving outpatient mental health treatment are more likely to be arrested and to spend more days in jail (Constantine, Petrila, et al., 2010; Lamb et al., 2007; Wilper et al., 2009). Individuals who have had prior involvement with the criminal justice system are more likely to be arrested in the future (Case et al., 2009). The majority of individuals who are released from jail do not receive adequate discharge planning, making them less likely to seek outpatient treatment services (Morrissey, Steadman, et al., 2006). Inmates who receive services while incarcerated receive more benefits and services upon release, helping to break the cycle of recidivism (McLean et al., 2006).
Approximately 14.5% of male jail inmates and 31% of female inmates suffer from SMI (Steadman et al., 2009). Many of these individuals also qualify for a substance abuse diagnosis. Jail diversion programs have been cited as one way to decrease jail time for persons with mental illnesses (Broner et al., 2004; Case et al., 2009; Frailing, 2010; Hiday & Ray, 2010; Ryan et al., 2010; Sirotich, 2009).

Mental health diversion programs background. Mental health diversion programs are intended as an alternative to incarceration for individuals with mental illnesses (Draine & Solomon, 1999). Diversion programs can be defined as:

…specific programs that screen defined groups of detainees for the presence of a mental disorder; use mental health professionals to evaluate those detainees identified in screening; negotiate with prosecutors, defense attorneys, community-based mental health providers, and the courts to produce a mental health disposition as a condition of bond, in lieu of prosecution, or as a condition of a reduction in charges (whether or not a formal conviction occurs); and link the detainee directly to community-based services. (Steadman et al., 1994, 1995, pp. 1630–1631)

Jail diversion programs are typically provided within the criminal justice system, and at the broadest level are classified as either prebooking or postbooking programs (Draine & Solomon, 1999; Steadman et al., 1995). This delineation is based on the time the intervention is provided during the processing of an individual into jail custody (Draine & Solomon, 1999). Prebooking diversion consists of diversions that are conducted prior to the individual being booked into jail and are typically delivered by police (Steadman et al., 1995). Instead of being arrested or being incarcerated, the individual is diverted to psychiatric treatment (Draine & Solomon, 1999). Prebooking diversions are the first point of intercept to keep individuals with mental illness out of
the criminal justice system (Munetz & Griffin, 2006). Postbooking diversion programs can be broken down further into prearraignment, postarraignment, and mixed, all of which occur in court or jail (Steadman et al., 1995). Post-booking diversion can involve jails, pretrial service agencies, courts, special diversion programs, community mental health centers, and probation services (Steadman et al., 1995).

Jail diversion represents the first three intercepts of the Sequential Intercept Model: 1) law enforcement and emergency services; 2) post arrest—initial detention and initial hearings; and 3) post-initial hearings—jail, courts, forensic evaluations, and forensic commitments (Munetz & Griffin, 2006). The Sequential Intercept Model was designed for individuals with mental illness at these stages to prevent initial criminal justice involvement, decrease jail admissions, increase treatment, and lower time spent in the criminal justice system (Munetz & Griffin, 2006).

**Pre-booking diversion.** The most common type of pre-booking diversion program is the Crisis Intervention Team (CIT) model (Memphis Police Department, 2011; Vickers, 2000). The purpose of CIT is to keep individuals with SMI from being arrested because of their mental illness. CIT provides individuals with SMI services that are based on collaborations between law enforcement, community mental health services, and other stakeholders (Memphis Police Department, 2011; Munetz & Griffin, 2006; Vickers, 2000). In the CIT approach, law enforcement officers are specially trained to know how to react to an encounter with a person with SMI (Deane, Steadman, Borum, Veysey, & Morrisey, 1999; Watson et al., 2010). The trained police officers then decide the appropriate action to take, including diverting the person to mental health services or the emergency room or charging them with a crime when they judge it to be appropriate (Hails & Borum, 2003; Memphis Police Department, 2011; Vickers, 2000). CIT-trained officers are more prepared to handle individuals with SMI and are less likely to use physical force unless it is
warranted (Borum, Deane, Steadman, & Morrissey, 1998; Heilbrun et al., 2012; Skeem & Bibeau, 2008). CIT also results in cost shifting from the criminal justice system back into the mental health system, as officers are more likely to link individuals with mental health services so they spend less time in jail (Compton, Bahora, Watson, & Oliva, 2008; Heilbrun et al., 2012; Steadman & Naples, 2005).

As an alternative to training specialty police officers, police departments also hire mental health professionals or use police-based specialized mental health response to consult with police officers on-site and in the field (Deane et al., 1999; Hails & Borum, 2003). Collaborations between police departments and community mental health systems have resulted in mobile mental health crisis teams who are part of the mental health system—not the police department—and are able to assess individuals with SMI in the field prior to booking or arrest (Deane et al., 1999; Hails & Borum, 2003). In general, these police and mental health intervention programs are effective at reducing criminal justice involvement and improving treatment outcomes (DeMatteo, LaDuke, Locklair, & Heilbrun, 2012; Steadman, Deane, Borum, & Morrissey, 2000; Steadman & Naples, 2005).

**Post-booking diversion.** When pre-booking services either do not exist or individuals with SMI are not diverted at this point, a post-booking diversion may be warranted. The purpose of post-booking diversion is to reduce the number of days spent in jail and to link individuals with mental health services as an alternative to jail (Draine & Solomon, 1999; Steadman et al., 1995). The most popular form of post-booking diversion is mental health courts; currently, there are over 250 mental health courts in operation (Almquist & Dodd, 2009; Ryan et al., 2010). Mental health courts vary based on the program, but they do share some common features such as: 1) they are criminal courts that have separate dockets for individuals with SMI; 2) they divert individuals with
SMI into community mental health treatment; 3) treatment in the community is typically mandated; 4) the court continues to supervise the individuals during their treatment period; 5) there are punishments for noncompliance, but they also recognize successes; and 6) participation is voluntary (Redlich, Steadman, Monahan, Robbins, & Petrila, 2006; Steadman, Redlich, Callahan, Robbins, & Vesselinov, 2011). Other post-booking services include release from jail with conditions, deferred prosecution, probation, inpatient treatment, or community-based alternatives to jail (Steadman, Deane, et al., 1999).

**Rationale and Justification for Diversion Programs**

Jail diversion is unique in that it focuses on keeping individuals with SMI out of the criminal justice system by providing those individuals with mental health and substance abuse services (Draine & Solomon, 1999). Jail diversion services are a policy response to the increasing number of individuals with SMI involved in the criminal justice system (Draine et al., 2005; Draine & Solomon, 1999; Steadman et al., 1994; Thompson et al., 2003). Lack of available or sufficient mental health treatment has been hypothesized to be a contributing factor to the increase of individuals with SMI in the criminal justice system (Thompson et al., 2003). Most jails are unable to provide even basic mental health screenings and services to individuals with SMI (Anno, 2001; Ditton, 1998; Redlich et al., 2012). Frustration has been expressed by individuals in law enforcement, courts, and corrections at the inability to appropriately respond and assist individuals with SMI (Thompson et al., 2003).

The desire to improve outcomes for individuals with SMI and divert them from the criminal justice system has received bipartisan support (Thompson et al., 2003). The rationale for criminal justice diversion programs is to prevent individuals with SMI from continuing to cycle through the criminal justice system, to decrease costs, and to decrease the criminalization of individuals with
SMI (Steadman, Deane, et al., 1999). Diversion programs were designed to divert individuals with SMI into a less restrictive environment to receive mental health treatment (Draine et al., 2005; Draine & Solomon, 1999; Steadman et al., 1994). The general premise behind jail diversion programs is that mental health treatment is a more effective and appropriate alternative for individuals with SMI than spending time in the criminal justice system (DeMatteo et al., 2012; Draine et al., 2005). By providing treatment in the community, individuals with SMI can receive treatment tailored to their specific needs, including their criminogenic, substance use, and mental health needs (DeMatteo et al., 2012; Heilbrun et al., 2012). An additional principal behind the support for jail diversion programs is the increased contact that individuals with SMI may have with police and the criminal justice system contact because of their mental illness symptoms (Lamb et al., 2007; Munetz & Griffin, 2006).

Evaluating the effectiveness of jail-diversion programs has presented some issues, because programs are at different points of diversion and may target different sub-groups (Draine et al., 2005). Nevertheless, overall jail diversion programs have been shown to be effective (Lange et al., 2011). Post-booking jail diversion services have a multitude of beneficial outcomes to participants including: 1) reducing recidivism, 2) reducing the number of days in jail, 3) decreasing substance use, 4) increasing service use, 5) improving quality of life, and 6) some support for improving mental health, although this is not a consistent finding. Overall, individuals who take part in diversion programs at this level spend more time in the community, may be less likely to be rearrested, and are more actively engaged in treatment (Broner et al., 2004; Broner, Mayrl, & Landsberg, 2005; Case et al., 2009; Cowell et al., 2004; DeMatteo et al., 2012; Gordon & Barnes, 2006; Heilbrun et al., 2012; Hoff et al., 1999; Lamb, Weinberger, & Reston-Parham, 1996; Lamberti et al., 2001; Lange et al., 2011; National GAINS Center for People with Co-Occurring
Disorders in the Justice System, 2005; Rivas-Vazquez et al., 2009; Rowe et al., 2007; Shafer et al., 2004; Sirotich, 2009; Steadman & Naples, 2005; Steadman, Deane, et al., 1999).

Mental health courts specifically: 1) reduce recidivism, 2) increase services use, 3) decrease the number of days in jail, 4) reduce substance use, 5) improve mental health, and 6) there is limited support that they improve quality of life (Boothroyd, Poythress, McGaha, & Petrila, 2003; Case et al., 2009; Cosden et al., 2005; Ferguson et al., 2008; Frailing, 2010; Herinckx, Swart, Ama, Dolezal, & King, 2005; Hiday & Ray, 2010; McNiel & Binder, 2007; Moore & Hiday, 2006; Steadman et al., 2011; Trupin & Richards, 2003). One caveat of mental health courts is that they are not necessarily faster than a traditional jail route and actually may involve the individual in the criminal justice system longer than if they had not been diverted (Redlich et al., 2012), although the participants retain the above listed benefits of being in a mental health court. Overall, individuals who participate in mental health courts have lower recidivism and jail time (Heilbrun et al., 2012).

The final justification for diversion programs is the financial savings to the criminal justice system. Mental health services can be provided in the community at a much lower cost than in the criminal justice system (DeMatteo et al., 2012). Although not unique to diversion programs, providing appropriate services to individuals involved in the criminal justice system, whether diverted or incarcerated, can produce cost-savings in the long run. The initial cost-savings when appropriate services are provided in jail may be negligible, but can be seen in reduced recidivism, leading to lower number of future jail days, which does save money (Robst et al., 2011; Romani, Morgan, Gross, & McDonald, 2012). In general, the number of arrests influence the overall amount that an individual costs (Petrila, Andel, Constantine, & Robst, 2010). Cost-savings are associated with a lower number of days spent in jail, and may be more prominent for individuals
with more severe diagnosis and criminal charges at the post-booking diversion level (Hughes, Steadman, Case, Griffin, & Leff, 2012). Although the cost savings that are seen in the criminal justice system are shifted to the mental health system, federal funding programs, such as Medicaid, may help to make these costs negligible (Hughes et al., 2012).

Overall, jail diversion programs have been shown to be effective and provide individuals with SMI treatment in a less restrictive environment (Draine et al., 2005; Draine & Solomon, 1999; Lange et al., 2011; Steadman et al., 1995). Jail diversion programs are imperative in reducing the number of individuals with SMI in the criminal justice system (Broner et al., 2004; Case et al., 2009; Frailing, 2010; Hiday & Ray, 2010; Ryan et al., 2010; Sirotich, 2009). Jail diversion programs provide the most effective way to get treatment to individuals with SMI who are justice-involved.

**Mental Illness and Physical Illness**

Mental illness has been shown to be the most burdensome disease, and account for approximately one-third of all disabilities in the United States (Druss, Marcus, et al., 2002; Druss et al., 2000). Mental illnesses are more impairing than chronic medical conditions, and have the most adverse effects on social functioning and relationships (Druss et al., 2009). A person’s impairment is compounded if they experience mental and chronic physical illnesses, due to the synergistic relationship between mental and physical health (Druss et al., 2009).

Individuals with SMI are at increased risk for diabetes, metabolic syndrome, coronary heart disease, COPD, congestive heart failure, obesity, smoking, hepatitis, and decreased preventive screening (Bushe et al., 2005; Leung et al., 2010; Lord et al., 2010; Oud & Meyboom-de Jong, 2009; Weber et al., 2009). Adults with SMI have a shorter life span, with estimates as high as 25 years shorter than the average adult life span (Manderscheid et al., 2010; Viron & Stern, 2010).
Between 58-90% of individuals with SMI have at least one comorbid medical condition (Chwastiak et al., 2006; Leung et al., 2010). People with SMI have a two-fold increase in the risk of mortality across medical conditions compared to individuals without mental illnesses (Druss, Zhao, et al., 2011; Sherman et al., 2013), which is mainly due to medical causes. Individuals with comorbid mental and physical illnesses experience high health disparities compared to the general population.

**Illness and Incarceration**

Incarcerated people have high rates of mortality upon release from prison (Zlodre & Fazel, 2012). Rates of medical conditions are up to four times higher for individuals in prison compared with the non-incarcerated population (Binswanger et al., 2009). Individuals with SMI already experience increased mortality rates in the general population, which may be compounded for incarcerated individuals with SMI who do not receive psychiatric medication (Tiihonen et al., 2009; Wilper et al., 2009; Zlodre & Fazel, 2012). Individuals with SMI who have an incarceration history are 40% more likely to have any medical problem, and 30% more likely to have multiple medical problems compared with individuals with SMI who do not have an incarceration history (Cuddeback et al., 2010).

**Health and the Biopsychosocial Model**

In order to understand why individuals with SMI are more likely to have a co-morbid medical illness, it is necessary to approach the topic from a multi-faceted lens, such as the biopsychosocial model. The biopsychosocial model focuses on the biological, psychological, and social interactions of disease within an individual, as opposed to addressing each as a single entity (Engel, 1977). The biopsychosocial model posits that we cannot focus on one aspect of an illness or one aspect in the interplay of multiple illnesses (Engel, 1977). Instead, we must understand the
effect that the molecular level (biological), the mind and patient behavior (psychological), and society (social) can have on the presentation and outcome of the illness (Engel, 1977). The biopsychosocial model provides a conceptual model that can be used to further understand an individual’s illness and the impact that this illness has on their overall functioning.

**Biological factors.** Mental illnesses are biologically based, but can be influenced or triggered through psychological and social occurrences (Cross-Disorder Group of the Psychiatric Genomics Consortium, 2013). Mental illness may be directly related to physical illness through the physiological effects of the mental illness, or underlying genetic factors (Viron & Stern, 2010). Mental illness, mental health, and physical health are all inter-related, and can impact the course of chronic disease, occurrence, and treatment (Perry et al., 2010). The genetic basis of mental illness is only beginning to be understood, and therefore the connection to other physical illnesses at a biological level is still under investigation (Cross-Disorder Group of the Psychiatric Genomics Consortium, 2013).

Besides the genetic influence of SMI on physical illness are the additional effects on physical health from the treatment of the person’s SMI. Medication side-effects contribute to high rates of comorbidity in individuals with SMI (Weber et al., 2009). Atypical antipsychotic medications cause significant weight gain, inability to regulate glucose, and metabolic syndromes, which increase the risk for diabetes mellitus, coronary artery disease, hypertension, cancer, and cardiovascular disease (Attari, Amini, Mansoori, & Bagherian, 2009; De Hert et al., 2011; Elias & Hofflich, 2008; Henderson, 2008; Henderson et al., 2006; Kane, 2009; Newcomer, 2007; Scheen & De Hert, 2007; Weber et al., 2009). In addition, individuals diagnosed with schizophrenia have a much higher rate of hypothyroidism (Weber et al., 2009). Individuals with SMI are also predisposed to certain medical illnesses like metabolic disorders, diabetes, and cardiovascular
disease (Kane, 2009). These biological factors of mental illness are compounded by additional risk factors at the psychological and social levels.

**Psychological factors.** Individuals with SMI may be less likely to receive a diagnosis for a co-morbid physical condition, potentially due to their inability to communicate about the medical problem, or inability to monitor their health because of their mental illness symptoms (Kane, 2009). Individuals with SMI may be disorganized, have cognitive deficits, fear the medical system, have impaired insight into their illnesses, lack motivation, or be unable to describe or recognize physical symptoms (Goff, 2007; Kane, 2009; Viron & Stern, 2010). Even when individuals with SMI are diagnosed with a physical condition, their mental illness may make it difficult to adhere to the prescribed treatment (Goff, 2007). In addition, individuals with SMI and a comorbid physical illness are much less likely to seek treatment than a person without mental illnesses (Druss et al., 2009).

Health behaviors also play a role in the development of comorbid physical illnesses for individuals with SMI (Kane, 2009). Individuals with SMI have poorer exercise and eating habits, contributing to obesity, which can lead to diabetes and heart disease (Druss, Zhao, et al., 2011; Kane, 2009; Kilbourne et al., 2009; Paton et al., 2004). A high prevalence of co-occurring substance abuse in individuals with SMI leads to high rates of HIV and hepatitis C that are extremely elevated over the general population (Davidson et al., 2001; Rosenberg et al., 2001, 2005), a relationship that is compounded when the person has criminal justice involvement (Springer et al., 2011; Westergaard et al., 2013). Individuals with schizophrenia are more likely to smoke cigarettes and have a harder time quitting than individuals without SMI (Mobascher & Winterer, 2008). On the contrary, individuals who have good mental health are at lower risk for
coronary heart disease and other chronic diseases (Keyes, 2005; Kubzansky, Sparrow, Vokonas, & Kawachi, 2001; Perry et al., 2010).

**Social factors.** There are multiple social factors that impact increased mortality in people with SMI. Low socioeconomic status accounts for about 25% of increased mortality (Druss, Zhao, et al., 2011). Lack of access and low quality healthcare account for another 25% of increased mortality (Druss, Zhao, et al., 2011). The combination of socioeconomic deprivation, adverse health behaviors, and poor quality of medical care produce a cumulative effect that accounts for about 70% of the increased mortality risk of individuals with SMI (Druss, Zhao, et al., 2011).

At the social level, individuals with SMI live in resource-poor areas and are less likely to complete high school, both of which are contributing factors to poorer health (Kessler, Foster, Saunders, & Stang, 1995; Link & Phelan, 1995; Weber et al., 2009). It is estimated that 24.9% of homeless individuals in the U.S. have SMI (Housing and Urban Development, 2010; Long, Rio, & Rosen, 2007). Individuals with SMI have a high risk of being a victim of a violent crime, which again predisposes them to increased psychiatric and physical symptoms (Teplin et al., 2005; Viron & Stern, 2010). In addition, individuals with SMI have a five-fold greater risk of being a victim of homicide compared to the non-mentally ill population (Crump, Sundquist, Winkleby, & Sundquist, 2013).

Death after release from prison can be attributed to social factors such as drug-related causes (18%), suicide (8%), and homicide (9%) in the general population (Zlodre & Fazel, 2012). Reasons for increased physical illnesses among offenders with SMI are impacted by where they live, lifestyle choices, and behaviors that are all associated with arrests (Cuddeback et al., 2010), which also includes psychological factors.
Health care infrastructure also contributes to comorbidity in individuals with SMI. It is difficult to coordinate between the behavioral health and the primary care system, which presents as a barrier to receiving services (Kane, 2009), and care that is received through the medical system is typically suboptimal (Druss, Rosenheck, et al., 2002; Levinson Miller et al., 2003; Lord et al., 2010). Other factors that contribute to poor medical care are lack of health insurance and lack of access to health care (Goldman, 1999). In addition, the provider’s ability to deliver appropriate care that focuses on the physical illnesses, not the mental illness, is not always present. Lack of provider continuity also results in individuals with SMI receiving less care proportionate to their physical illnesses (Zolnierek, 2009).

Conclusion

Overall, there are many factors that contribute to poorer health for individuals with SMI at all levels of the biopsychosocial model. In addition, these health problems are compounded for individuals with SMI who are justice-involved, possibly due to increased psychological symptomology, lifestyle choices, and lack of resources (Cuddeback et al., 2010). There are a multitude of reasons for the increase in health problems in this population.

Integration of Mental Health and Physical Health

Individuals with SMI have an increased burden of comorbid physical illness and experience increased impairment (Chwastiak et al., 2006), requiring greater integration of physical illnesses into treatment (Druss et al., 2009). In order to improve mental health for individuals with SMI, we need to provide comprehensive care that focuses on multiple levels of the biopsychosocial model (Engel, 1977). Only treating an individual’s mental illness results in increased mortality and morbidity compared to the general population (Chwastiak et al., 2006; Perry et al., 2010; Viron & Stern, 2010; Weber et al., 2009). Without treating comorbid physical illness, the behavioral
health field will never be able to fully treat mental illnesses, because there is a synergistic effect between physical and mental illness (Druss et al., 2009). The behavioral health field in general has realized the need for integration with the primary care field to address both mental and physical health (Institute of Medicine Committee on Crossing the Quality Chasm: Adaptation to Mental Health and Addictive Disorders, 2006; Manderscheid, 2010; Satcher & Druss, 2010; U.S. Department of Health and Human Services, 1999; Unutzer et al., 2006).

**Reasons to Provide Integrated Care as Part of Mental Health Diversion Programs**

Diversion programs were designed to target mental health problems, and to keep individuals from spending time in the criminal justice system because of their SMI (Draine & Solomon, 1999; Steadman et al., 1994, 1995). In order to improve mental health and to decrease future contact with the criminal justice system, it is important to consider and treat all of the determinants of health. People with SMI who are justice-involved experience even worse medical outcomes than people with SMI who are not justice-involved (Cuddeback et al., 2010). It is a public health problem to continue to allow these individuals to not receive treatment for their illnesses, which are exacerbated upon release to the community (Cuddeback et al., 2010).

Although the primary focus of diversion programs should remain on treating the mental illness and criminogenic factors that have contributed to the person’s involvement with the criminal justice system, physical illnesses also need to be addressed. Without diversion, people with SMI will remain in the criminal justice system, which is not equipped to address their physical or mental illnesses (Cuddeback et al., 2010). Diversion provides an opportunity to provide care for both physical and mental illnesses that would not be received in jail.

Having jail diversion programs incorporate physical health into the goals of the program will help to improve the person’s overall well-being. Treating physical illnesses should not
become the primary goal of jail diversion programs, as the mental illness and criminogenic factors are the most pressing issues, but they should be recognized and treated when possible. Improving the physical health while also improving the mental illness of these individuals will allow for better progress in overall health. Because mental illness and physical illness are so intertwined, it is prudent to treat one illness only, as the physical illness will continue to exacerbate their mental illness (Druss et al., 2009).

Providing more integrated care has many positive benefits for individuals with SMI. Integrated care reduces costs, it provides more holistic care, it can provide care to more individuals with SMI, it reduces stigma, access to care is easier, and it improves outcomes for individuals with SMI (Funk & Ivbijaro, 2008). With the disproportionate health issues faced by individuals with SMI, especially justice-involved individuals, a holistic approach to care must be taken in order to reduce recidivism and improve their outcomes (Druss et al., 2009; Funk & Ivbijaro, 2008; Kane, 2009; Manderscheid, 2010).

**Reasons Not to Provide Integrated Care as Part of Mental Health Diversion Programs**

There are multiple reasons why improving physical health is not always a goal of diversion programs. In order for diversion programs to address both mental and physical health, there needs to be increased integration between the behavioral health and physical health agencies (Power, 2010; Satcher & Druss, 2010; Viron & Stern, 2010). Without integration, it is very difficult for diversion programs to bridge the gap between the disjointed systems currently in place. The integration of behavioral health and physical health agencies needs to be done in general for all individuals with SMI, but is even more imperative for individuals who are justice-involved, as they have increased treatment needs (Cuddeback et al., 2010). For the most part, because integration of behavioral health and physical health systems is in progress, it is difficult for
diversion programs to ensure that all physical illnesses are being treated. The current field standard is to make a referral for the individual with SMI to see a primary care physician, which is not always followed through due to transportation barriers, financial barriers, and overall difficulty navigating the system (Goldman, 1999; Kane, 2009).

Beyond health care system fragmentation, it is also difficult for diversion programs to include physical illnesses as a priority due to financial constraints. Diversion programs typically receive funding from either the federal government through grants, and through billing insurances, such as Medicaid (Fisher, Grudzinskas, Roy-Bujnowski, & Wolff, 2011; Frank, Goldman, & Hogan, 2003; Morrissey, Cuddeback, Cuellar, & Steadman, 2007). Because diversion programs were created with the intent to improve mental illness and relieve the criminal justice system of this burden, there is not funding in place to improve physical illnesses also. The majority of grant programs are focused on decreasing recidivism, and therefore have not allowed for much exploration into improving physical health (Rotter & Carr, 2011). Without appropriate funding, diversion programs cannot be expected to provide services to improve physical health. Changes need to be made at the funding structure prior to diversion programs incorporating physical health as an area of focus.

Finally, diversion programs are run with a focus on mental health, and are therefore often provided by mental health practitioners. These individuals were not trained in improving physical health, and therefore do not have the expertise to treat physical illnesses (Druss et al., 2008; Vreeland, 2007). In order for diversion programs to focus on physical health, there either needs to be improved communication at the behavioral health and physical health system level or more medically trained individuals need to be involved in these programs (Collins et al., 2010). Although medical professionals provide physical health services to incarcerated and released
inmates, they only make referrals for mental health services and do not directly work with mental health diversion programs (Collins et al., 2010). There needs to be a greater coordination between the medical professionals who are interested in improving the health of prisoners and diversion programs in order to improve both physical and mental health. Again, the problem lies in the funding structure and the debate that continues in the system-level integration is: who is going to pay for the services? By hiring a medical professional as part of diversion team, it would still be unclear who would pay for the services. The use of nurses as care coordinators on diversion teams is one way this gap can be filled. An example of a successful program that does incorporate nurses is Forensic Assertive Community Treatment (FACT) (Cusack, Morrissey, Cuddeback, Prins, & Williams, 2010). FACT utilizes a team of professionals to address the needs of their clients, which includes a nurse to address physical health issues (Cusack et al., 2010).

**Conclusion**

Although ideal, it may not be feasible at this time for diversion programs to incorporate physical health treatment. The infrastructure is not currently in place in the majority of places to support this incorporation (Satcher & Druss, 2010). Behavioral health and physical health services are still trying to integrate services for non-incarcerated individuals, and until this is in place, it will be difficult to deliver integrated services to individuals in jail diversion programs (Power, 2010; Satcher & Druss, 2010). Most jail diversion programs rely on services already in place in the community due to sparse resources; the design of these programs is to get individuals back into community mental health care (Draine & Solomon, 1999; Steadman et al., 1994, 1995). Until community mental health is provided along with physical health services, it will be difficult for jail diversion programs alone to implement these integrated services.
Notwithstanding, jail diversion services should strive to provide the most integrated services possible that are feasible based on the current infrastructure. Integration of behavioral health and physical health services leads to improved health for individuals (Vreeland, 2007), and may lead to improved criminal justice outcomes including reducing recidivism. Therefore, the goal of jail diversion programs should be to provide the most holistic care possible within the constraints of the program, local infrastructure, and available funding.

**Risk-Need-Responsivity Background**

Throughout history, offender rehabilitation efforts have been targeted at preventing inmates from reoffending once they are released back into society. Prior to the 1980s, a belief that “nothing works” was pervasive, as most of the risk factors for recidivism that had been studied were static risk factors such as: age, race, gender, prior arrests, type of crime, intelligence, and previous employment (Andrews et al., 1990; Taxman & Thanner, 2006). Advances in risk assessment tools in the 1980s led to greater consideration of dynamic, changeable risk factors such as lifestyle and psycho-social functioning (Taxman & Thanner, 2006). These dynamic factors contributed to the understanding that there were attributes about offenders that could be used to change their behavior. In order to prevent recidivism, there was a realization that the offender’s risk and needs must be addressed (Taxman & Thanner, 2006).

The Risk-Need-Responsivity (RNR) model was developed as a contribution to the “what works in corrections” literature, as opposed to the previous notion that “nothing works” (Andrews et al., 1990; Bonta & Andrews, 2007; Bonta, Canada, Pacific, Psychiatry, & Columbia, 2011; Taxman & Thanner, 2006). RNR was developed for use with high-risk offenders to provide them with appropriate services based on their psychological and social needs by targeting multiple
dimensions of their behavior with the ultimate goal of reducing recidivism (Taxman & Thanner, 2006). The principles of RNR are based on the history of offender risk and are focused on identifying factors that make an inmate successful when they are released on parole (Taxman & Thanner, 2006). There are three constructs of RNR: risk of recidivism, criminogenic need, and responsivity of offenders to specific treatments and programs (Andrews et al., 1990).

**RNR constructs.** The first construct is the risk of recidivism. This is when the level of service required for the offender is determined. The determination of risk is based on the individual’s propensity or risk to re-offend; the level of treatment is then matched to the individual’s risk to re-offend (Bonta & Andrews, 2007). Typically, higher risk offenders require more intensive services compared to lower risk offenders who do not require intensive services in order to prevent recidivism (Andrews et al., 1990).

The criminogenic need construct identifies the offender’s specific criminogenic needs, which are used to match the offender with services that can work to change characteristics to reduce their risk of recidivism (Andrews et al., 1990). This construct is focused on targeting dynamic risk factors that are linked to criminal behavior (Bonta & Andrews, 2007). The most important dynamic risk factors to focus on, as identified by the authors of RNR, are: antisocial personality pattern, procriminal attitudes, social supports for crime, substance abuse, family and marital relationships, school and work, and prosocial recreational activities (Bonta & Andrews, 2007). Other secondary need factors that are not as important to focus on are: self-esteem, vague feelings of distress, major mental disorder, and physical health (Bonta & Andrews, 2007).

The responsivity construct matches the offender to services that work with their specific learning styles and abilities (Andrews et al., 1990). These services are focused on the offender’s criminogenic needs and other factors, such as mental illness or substance abuse (Andrews et al.,
The purpose of the responsivity construct is to provide services to the offender that are respectful, encourage a collaborative relationship, and are structured with a goal towards change (Bonta & Andrews, 2007). It is necessary for the treatment to be tailored to the specific learning style of the offender in order to facilitate learning (Bonta & Andrews, 2007).

**RNR and the intervention.** The 11th Judicial Criminal Mental Health Project (CMHP) is a jail-diversion program for individuals with mental illness who are involved with the justice system. Currently the services provided by CMHP work well for the majority of their clients, but there is a pervasive high-risk population who continues to be involved with the criminal justice system despite receiving jail-diversion services. In order to improve the outcomes and reduce the costs associated with these high-risk users, CMHP is implementing a new intervention focused on improving mental illness and reducing recidivism. In order to address their specific needs, CMHP is using RNR as the guiding model for their intervention. The new intervention is a care coordinator position. The care coordinator is responsible for individualizing and tailoring services for high-risk users based on their needs, strengths, and criminal risk factors. The reason the intervention is based on RNR is to utilize a more holistic treatment approach to improve the outcomes of the high-risk participants (Andrews et al., 1990).

The risk of the participants is identified through criteria that were formulated by CMHP. The high-risk users being targeted by this intervention are required to have had three or more jail bookings in the past year or seven or more lifetime jail bookings. Additionally, these participants must be identified as being a moderate or high risk for violence, self-harm, suicide, self-neglect, or general offending/recidivism as rated by their CMHP case manager on the Short-Term Assessment of Risk and Treatability (START), a risk assessment tool (Webster et al., 2009).
Lastly, they must suffer from a diagnosed serious mental illness that is either bipolar disorder, psychotic disorder, or a schizophrenia spectrum disorder.

Once an individual is identified as eligible for the intervention, they are randomized to receive CMHP’s usual treatment, the usual treatment plus the care coordinator intervention and a peer specialist (CC group), or usual treatment, the care coordinator intervention, a peer specialist, and cognitive-behavioral therapy (TX group). If they are randomized to the CC or TX group, the care coordinator is responsible for assessing the criminogenic needs of the participant. Once the care coordinator assesses the specific risk of the participant and their criminogenic needs, they are then responsible for making sure the participant receives services that are tailored to their learning style by referring them to appropriate services. Additionally, in the TX group, the participants will receive a cognitive-behavioral therapy focused on addressing their mental health, social, and criminogenic needs.

RNR is meant to be used as a guiding model to match offenders with the appropriate services in order to address criminal needs, by incorporating the offender’s learning style, with the ultimate goal of reducing recidivism (Andrews et al., 1990; Taxman & Thanner, 2006). CMHP is utilizing this strategy to target their high-risk users, to help lower their criminal justice involvement and improve their mental illness. Using RNR as the guiding model for the care coordinator position is meant to provide more tailored and effective services to these high-risk users. Although this model is appropriate for guiding the intervention, it is not comprehensive enough on its own to be used as the sole theory in my proposed study.

**Impact Evaluation Background**

Public health programs and interventions are typically designed with a goal of improving health (American Public Health Association, 2013). In my proposed research, the intervention is
aimed at improving mental health and criminal justice outcomes for individuals with serious mental illness (SMI) involved with the criminal justice system. In order to understand if the intervention is achieving the intended goal, it is necessary to incorporate a theory or framework that allows for a determination of the intervention’s impact.

Impact evaluations allow for an understanding of whether an intervention has had the intended effects (Khandker, Koolwal, & Hussain, 2010; Leeuw & Vaessen, 2009). The purpose of an impact evaluation is to use the knowledge gained from the current functioning of a program to determine the overall value of the program, which then informs the next stages of life of the program (Patton, 2008). Impact evaluation provides information about the results of the intervention, whether the intervention works, whether the intervention makes a difference, if the intervention is cost-effective, and how to replicate the results (Leeuw & Vaessen, 2009; Patton, 2008). The results from an impact evaluation can be used to inform policy makers, to promote accountability of resources, and to further understand what works and how the effects can be attributed to the intervention (Khandker et al., 2010).

Impact evaluation is especially useful as the guiding framework for the research design and methods. In order to assess the impact of the intervention, it is necessary to understand the specific mechanisms that influence the outcomes (Khandker et al., 2010). The most distinguishing feature of impact evaluation is the ability to determine whether changes in the participants are actually due to the intervention, instead of other factors (Khandker et al., 2010). The ability to isolate the effects of the intervention from confounding factors allows for the inference of causation (Khandker et al., 2010; Mohr, 1995). In my proposed study, impact analysis will focus on an Ex post evaluation of the intervention, which means the intervention is already in place and the
evaluation is designed to measure the impacts of the intervention on the participants that are attributable to the intervention (Khandker et al., 2010).

One of the main tenets behind impact evaluations is to determine what would have happened to the participants if the intervention did not exist (Khandker et al., 2010). Stated differently, impact evaluation is focused on comparing what appears after implementing the intervention that would not have appeared if the intervention was not implemented (Mohr, 1995). We can never be sure what would have occurred if the intervention had not been implemented (Mohr, 1995). Because it is impossible to actually know what the outcome of a participant would be without the intervention, it is necessary to create a comparison group (Khandker et al., 2010). In order to deal with the issue of a comparison group, a discussion of causality, and the appropriate research design and analysis are needed (see question 3) (Khandker et al., 2010; Mohr, 1995).

An additional benefit of doing an impact evaluation is the ability to determine the direct and indirect program impacts on participants, which is important to my proposed research (Patton, 2008). Impact evaluation also allows for the identification of priority or key program components, and the evaluation of the program components by subsets, which is important for my proposed research, as it is not an all-encompassing study (Leeuw & Vaessen, 2009). Because the intervention being put into place by CMHP involves multiple agencies, the evaluation will take place at multiple levels, so it is important to be able to identify a subset of the overall evaluation to be analyzed as part of this dissertation proposal. It is not feasible to utilize all of the information from the overall evaluation, as it will detract from the main hypothesis and research questions posed in my proposed study.

Impact evaluations also allow determination of whether a program’s theory is true (Mohr, 1995). In this case, the program theory is focused around the principles of RNR to reduce
recidivism and improve mental health. Although the goal of impact evaluation is to determine whether this theory holds true, this proposed research study will not focus on testing the program theory, as that is part of the larger evaluation. The larger evaluation is already focusing on the direct impacts of improved recidivism and mental health, whereas this proposed study will focus on the indirect impact of the intervention on HRQOL.

Because this is a criminal justice intervention, it is important that the proposed research and theories are congruent with the field. The U.S. Bureau of Justice Assistance states “The purpose of the impact evaluation is to provide management information needed by Federal, State and local officials and community leaders involved in policy and programming decisions which clearly confirms that specific programs and/or activities do work, or do not work” (Kirchner, Przybylski, & Cardella, 1994, p. 2). This idea of impact evaluation is in line with the evaluation that has been designed for CMHP’s intervention. The overall purpose of the intervention is to improve mental health outcomes, criminogenic thinking, and reduce recidivism, whereas this proposed dissertation will be looking at the intended and unintended effects of the intervention on the participants’ HRQOL. By understanding the impact that this intervention has on the participants, this proposed research will be able to help inform individuals at the Federal, State, and local levels about whether this intervention works.

**Impact evaluation and the proposed study.** This proposed study is interested in assessing an intervention to see whether the invention is worthwhile and significant (Patton, 2008). The purpose of evaluations are to “…describe and assess what was intended (goals and objectives), what happened that was unintended, what was actually implemented, and what outcomes and results were achieved” (Patton, 2008, p. 5). My proposed research is not interested in implementing a new intervention; instead, the focus is on assessing the intervention
being put into place by CMHP, to understand the effects on the participants in the intervention. In order to answer these questions, it is necessary to use an evaluation framework to guide the study.

Impact evaluation very basically is focused on whether an intervention works (Khandker et al., 2010; Leeuw & Vaessen, 2009; Mohr, 1995; Patton, 2008). Because impact evaluation is interested in both the direct and indirect effects of an intervention, it allows for the exploration of multiple impacts (Patton, 2008). Although not specifically stated as one of the goals of the intervention, improvement in HRQOL is a potential indirect effect of this intervention. In order to address the impact that the intervention has on this indirect goal, it is necessary to utilize an evaluation framework that allows for the exploration of all the possible effects, which is why impact evaluation fits this proposed research. In addition, impact evaluation provides a framework to design and analyze the data from the evaluation in order to make direct associations between the intervention and the desired outcome (Khandker et al., 2010; Mohr, 1995). This approach will allow for direct connections between the intervention and the impact on HRQOL, even though it is an indirect effect of the intervention (Khandker et al., 2010; Mohr, 1995).

Impact evaluation will be utilized in my proposed research to guide the research design, and more importantly as a way to analyze the data. Using an evaluation framework allows for a more rigorous design and analysis of the research data (Khandker et al., 2010; Mohr, 1995). In addition, by using an impact evaluation framework, it will allow the conclusions drawn from the proposed study to be useful in determining the effectiveness of the intervention to the stakeholders and the participants (Patton, 2008).
Integration of Theories

It is necessary to conceptualize issues by using theories or frameworks at multiple levels (Goodson, 2010). It is important to have a strong evaluation framework in order to determine causality and effectiveness, but it is also necessary to incorporate other theories and models to understand and interpret the outcome of interest (Goodson, 2010). My proposed research is focused on the relationship between the intervention and the impact on HRQOL. Impact evaluation provides a framework to evaluate this relationship; it is necessary to incorporate a theory to explain why a relationship may exist, and why improvement in mental health and criminal justice outcomes can impact HRQOL.

The biopsychosocial model provides the basis for the hypothesis in my proposed research. Specifically, providing an intervention targeted at recidivism and improving mental illness and substance abuse may also have the indirect effect of improving the participant’s HRQOL. HRQOL is based on the notion that an individual’s quality of life is related to their physical and mental health (Wilson & Cleary, 1995). It is well known that an individual’s quality of life can be directly mediated by their illness (Meijer, Schene, & Koeter, 2002). Furthermore, it is well understood that mental illness and physical illness are interrelated and improvement in one area impacts the other (Druss et al., 2009). HRQOL can be defined as the way illness impacts a person’s physical, social, and emotional abilities (Nicassio, Kay, & Custodio, 2011). To fully understand an individual’s HRQOL, it is necessary to measure biological and physiological factors, symptoms, functioning, general health perceptions, and overall quality of life (Wilson & Cleary, 1995). Understanding an individual’s HRQOL allows for improvement in their outcomes through
interventions or clinical care (Wilson & Cleary, 1995). Because HRQOL is a concept based on the biopsychosocial model of health, it is necessary to use the biopsychosocial model to understand how the intervention will affect the participants.

The biopsychosocial model states that instead of focusing on a single entity of the individual, their biological, psychological, and social interactions must be considered (Engel, 1977). The biopsychosocial model posits that we cannot focus on one aspect of an illness, but instead we must understand the molecular biology, the effect that the mind and patient behavior (psychological), and society (social) can have on the presentation and outcome of the illness (Engel, 1977). This model is aimed at straying from the reductionist principle of looking at diseases through reducing these complex entities into their component parts for study and analysis. The biopsychosocial model is based on systems theory, which states that by changing or focusing on one aspect of health, we can impact the other levels of health (Engel, 1978).

The biopsychosocial model will provide the base theory for the research questions, why certain outcomes may be plausible, and will allow for further integration of theory at the different levels. Impact theory fits well with the biopsychosocial model, because it also addresses the impact that the intervention has on multiple (Engel, 1978; Leeuw & Vaessen, 2009). Using a multi-level framework will allow this proposed research to include the impact on the individual from both the interpersonal and intrapersonal level, by examining the presentation of their mental illness, and physical illness, and the impact this has on their HRQOL and service usage. This proposed study will look at the signs and symptoms of the mental illness (psychological level), the impact of a care coordinator (social level), on the participant’s HRQOL of life (psychological level) (Engel, 1978). It is known that mental illness has a biological basis, although this proposed
research will not be able to measure this outcome due to the complexity of the issue (Cross-Disorder Group of the Psychiatric Genomics Consortium, 2013).

The intervention that is being put into place is focusing on the psychosocial aspects of the participants in order to improve their mental illness and reduce recidivism. It is therefore reasonable to assume for the hypothesis in the proposed study that an intervention that is targeting two levels of the biopsychosocial model may impact another dimension of health (Engel, 1978). The study design is not focused on the biological aspects of disease, but will rather focus on the psychosocial levels of the individual using HRQOL. The reason for this is the difficulty of obtaining biological samples from these individuals to look at their physical health; in addition to cost concerns, it is not feasible to ask the participants to undergo additional medical testing beyond the requirements of the intervention, as it may cause a higher drop-out rate (Moon et al., 2012).

The interrelationship of mental health and physical health based on the biopsychosocial model guides the main outcome variable of the impact evaluation. Additionally, as in all evaluations, it is necessary to understand the theory behind the intervention, which is RNR in this situation. The principles of RNR as discussed above fit into the biopsychosocial model. The risk of an individual can be assessed within the different levels of the biopsychosocial model, although for this intervention, they mainly will be identified at the psychosocial levels. The criminogenic needs of the individuals again most likely will lie in the psychosocial level of the model, and the responsiveness of matching the participant to the appropriate treatment by the agency addresses the psychosocial level. These models address what the intervention is targeted to do and how it will affect the individual. Impact evaluation is then used as the lens to measure the impact of the intervention on the areas specified through the biopsychosocial model and RNR. Impact evaluation provides guidance for the research design and methods, based on what is theorized to occur from
the use of RNR, and through the understanding of how an individual’s health aspects are all interrelated (the biopsychosocial model) (Khandker et al., 2010). There is already evidence to support the fact that mental illness and physical health are related and have an impact on each other (Druss et al., 2009), which is how the outcome variable, HRQOL, for the impact evaluation is being specified.

Despite this portion of the evaluation not focusing on recidivism and criminogenic needs, it is important to understand the theory behind the intervention and how this will impact all of the direct and indirect outcomes (Khandker et al., 2010; Mohr, 1995). The direct, intended outcomes of the intervention are to reduce recidivism and improve mental health by targeting high-risk individuals and providing them with tailored treatment. A potential indirect outcome is that when these participants receive the treatment they need, along with improving their mental health, their HRQOL may also improve. It is not known if this will be an indirect consequence of receiving more appropriate behavioral health treatment, or if the participants may have increased access to primary care services as part of their identified needs. The biopsychosocial model will be used to determine how the different services interact to improve participants’ functioning at the psychosocial level. Impact evaluation will allow this proposed research study to delineate the actual contributing factors to the individuals HRQOL through the use of impact analysis, which will allow for exploration into how the indirect effects of the intervention are being achieved (Khandker et al., 2010; Mohr, 1995).

**Conclusion**

It is necessary to evaluate a multi-leveled intervention using theories at multiple levels (Goodson, 2010). The combination of RNR, the biopsychosocial model, and impact evaluation specify the intervention theory, the theory behind the outcome of interest, and the research design
to measure the outcome (Bonta & Andrews, 2007; Engel, 1977; Khandker et al., 2010; Mohr, 1995). The use of multiple theories and models will allow for direct assessment of the intervention in order to make recommendations to stakeholders about the effectiveness. In my proposed research, it will be necessary to use multiple models or theories in order to get at the complex relationship being postulated through my research questions.

**Defining Causality**

The notion of causality has a long history among researchers and philosophers. Recently, public health researchers have found a need to further define causality in order to understand how certain illnesses or diseases begin (Susser, 1973). At the most basic level, causality requires the knowledge of the direction of the relationship between two variables, and the time-order of this relationship, to understand whether one variable causes the other (Susser, 1973).

Statistical associations alone do not denote causation; instead, it is important to understand the relationship between the variables and the order in which they occur (Susser, 1973). In order to infer causation, there needs to be an asymmetrical relationship between the two variables, so that only one variable can cause or impact the other variable (Susser, 1973). If the variables had a symmetrical relationship, they would equally be able to impact the other variable, therefore eliminating the ability to infer causation (Susser, 1973). The asymmetrical relationship between the direction of the variables is what allows researchers to determine causality (Susser, 1973). In order for this relationship to hold, the time sequence dictates that the causal variable must precede its effects (Susser, 1973). Time alone does not demonstrate causality and the relationship can only be considered a causal relationship when the causal variable precedes the effect, and the relationship between the variables is asymmetrical, with the causal variable impacting the other
variable (Susser, 1973). In addition, the cause needs to be related to the effect, with no other plausible explanations to be found for the effect (Shadish et al., 2002).

**Additional causality criteria.** In order to further understand the relationship between variables, it is important to consider the necessary and sufficient prerequisites in the context of an experiment. The purpose of an experiment is to uncover effects that occur from manipulating a variable and how that impacts a different variable at a later time, which fulfills the time-order and asymmetry relationship between the variables (Shadish et al., 2002; Susser, 1973). When there are more than two variables involved in an experiment, the cause may not be clear-cut, as there may be multiple conditions impacting the outcome variable of interest. When this situation occurs, it is important to consider the necessary and sufficient relationship, as not all of the potentially causal variables may be impacting the outcome variable of interest (Shadish et al., 2002).

The necessary and sufficient relationships help to further understand the multiple ways that variables can interact and the bearing of these interpretations on causation. There are four combinations of necessary and sufficient prerequisites for any independent variable that is associated with a dependent variable (Susser, 1973). If an independent variable, X, is necessary and sufficient to cause a dependent variable, Y, then they always occur together and only X is needed to cause Y (Susser, 1973). This situation allows for an easy inference of causality. If X is necessary but not sufficient to cause Y, then X is always present when Y is present, but Y is not always present when X is present, and requires an additional factor (Susser, 1973). This means that in combination with another factor, X has a causal impact on Y. If X is not necessary but sufficient to cause Y, then Y can be caused without X being present, but X may be present and can cause Y (Susser, 1973). This situations means that X can cause Y, but is not the sole cause of Y, and Y can occur even if X is not present. If X is neither necessary nor sufficient to cause Y, then...
X may or may not be present when Y occurs, but if X is present there is always some additional factor also present to cause Y (Susser, 1973). Many times in public health research we are faced with the case where X is not necessary, but is sufficient to cause Y, which has also be referred to as an inus condition (Shadish et al., 2002). Many of the conditions of interest in public health, or the Ys, have multiple causes, which are not always present, but when they are they cause the Ys (Shadish et al., 2002). Therefore, we must be careful in our interpretation of causality between two variables, as X may cause Y, but may not be the sole cause of Y. If we interpret this relationship as X is the sole cause of Y, we would be making an incorrect inference about what causes Y.

Causation and research designs. There are multiple frameworks within which to view causation and what it entails. One of the more common ways to view causation is through the use of the counterfactual or potential outcomes (Angrist, Imbens, & Rubin, 1996; Rubin, 2005; Shadish et al., 2002). In an experiment, the counterfactual is what would have happened to the participants if the intervention or program was not put into place (Mohr, 1995; Shadish et al., 2002). Because counterfactuals can never be observed, experimental design has proposed approximations, such as random controlled trials, pre- and post- assessments of participants, and case-control designs (Khandker et al., 2010; Mohr, 1995; Shadish et al., 2002). These designs allow for a proxy to be used as the counterfactual, because we can never measure the true counterfactual (Khandker et al., 2010; Mohr, 1995; Shadish et al., 2002). There is an assumption when using a counterfactual approach to causation, that a change in treatment status for one participant does not impact the potential outcome for any other participants, which is called the stable unit treatment value assumption (SUTVA) (Rubin, 1986; Winship & Morgan, 1999).
In order to infer a causal relationship, certain steps in the experimental design need to be taken to allow for the proper interpretation of causation (Susser, 1973). First, the situations or treatment conditions that are being compared need to be alike except for one variable, which is the basis for experimental designs (Susser, 1973). Second, the situations or treatment conditions that are compared have only one outcome or disease in common, and this needs to occur across multiple studies (Susser, 1973); this means that despite different studies with different designs, the outcome remains the same or SUTVA (Rubin, 2005; Susser, 1973). Third, whenever the independent variable varies, the dependent variable also varies accordingly, which is akin to dosage responses (Susser, 1973). Finally, the causal variable should be removed from the design and the leftover effect of the other factors needs to be determined (Susser, 1973). This expansion on the basic principles of causation discussed above allows for a more thorough understanding of cause and effect (Susser, 1973). Although ideal, it is difficult in the social sciences to determine the exact causes in complex systems, which has led to greater use of research designs and statistics to help reduce some of the complexity (Susser, 1973).

Experimental designs provide a much clearer understanding of how a manipulated variable effects the outcome variable of interest through the control of potentially confounding conditions (Shadish et al., 2002). In order to infer causality from a randomized control trial, certain assumptions must be fulfilled (Holland, 1986; West et al., 2008). The assumptions require that the participants must be independent, the treatment must be received as intended by the participants, there cannot be attrition from the posttest measurement, and the existence of other treatment conditions cannot impact the participant’s outcome (Holland, 1986; West et al., 2008). One of the biggest benefits of the experimental design is the ability to control for heterogeneity between groups by assigning participants to groups randomly, which in effect allows for equality
between the level of heterogeneity in each group (D’Agostino, 2007; Rosenbaum & Rubin, 1983). This allows for similarity in the groups for all of the covariates, except for the independent variable of interest that can then be intentionally manipulated (Shadish et al., 2002; Susser, 1973).

The purpose of randomization is to make the relationship between the independent and dependent variables clearer, by reducing the plausibility of an alternative explanation (Shadish et al., 2002). Randomization is important in research designs because it gives unbiased estimates of the average treatment effect (Shadish et al., 2002). The basic tenet behind randomization is that participants are assigned to a treatment condition based on chance, and therefore all participants have a nonzero probability of being assigned to a condition (Shadish et al., 2002). Random assignment allows for the researcher to know the selection process; equates the groups on variables prior to implementation of the intervention; distributes threats to validity across conditions, thereby reducing the plausibility; it reduces confounding of alternative causes with the treatment condition; and allows for valid estimates of error variance (Shadish et al., 2002). The different treatment conditions remain equal on the distribution of covariates, which means that they only differ on the treatment variable resulting in an easier interpretation of causality (Susser, 1973). Randomization also offsets bias that may occur when individuals are assigned to be a treatment group based on certain characteristics, as attributes of those individuals may impact the treatment effectiveness (Susser, 1973). Additionally, by randomly assigning participants to treatment groups it reduces the bias of the researcher because the random assignment precedes the outcome of the study (Susser, 1973).

Experimental designs that employ random assignment have the benefit of increased confidence of inferring a causal pattern (D. C. Miller & Salkin, 2002). Also, experimental designs allow for maximum variation in the independent and dependent variables, while holding other
variables constant that might impact the outcome (D. C. Miller & Salkin, 2002). Experimental designs allow for a clearer inference of causality, due to the nature of controlling for other potentially confounding variables, and through randomly equating the groups on covariates (D. C. Miller & Salkin, 2002; Shadish et al., 2002; Susser, 1973)

The use of a randomized-control trial, or an experimental design, is considered the gold-standard of all fields, but it is not always a feasible approach to assessing a hypothesis (D’Agostino, 2007; Shadish et al., 2002; West et al., 2008; Winship & Morgan, 1999). In place of experimental design, many studies employ a quasi-experimental design, which does not use true randomization of participants to the treatment groups (Shadish et al., 2002). Because individuals who are not explicitly randomized into groups are not independent of their potential outcomes, we can no longer use the standard estimator, as it would not give accurate results of the true average treatment effect in the population (Winship & Morgan, 1999). In order to overcome the selection bias inherent in quasi-experimental designs, statisticians have developed statistical methods that mimic the group equality achieved through randomization (D’Agostino, 2007; Rosenbaum & Rubin, 1983, 1984; Winship & Morgan, 1999).

**Propensity Score Matching**

One of the more common statistical methods that has been used in non-experimental designs is propensity score matching (D’Agostino, 2007). Because observational studies do not have random assignment of subjects, there are inherent differences between participants in the treatment and those not receiving the treatment (Khandker et al., 2010). Propensity score matching uses a statistical approach to construct a comparison group using observed characteristics based on the participants propensity of participating in the treatment compared to nonparticipants (Khandker et al., 2010). The goal is to construct a statistical counterfactual group as similar to the
treatment group as possible based on observed characteristics (Khandker et al., 2010). Treatment participants are matched with an observationally similar control participant, based on characteristics not affected by the intervention (Khandker et al., 2010). Propensity score matching uses a single propensity score to match treatment participants to controls (Khandker et al., 2010). Treatment effect is then analyzed by looking at the average differences between the matched pairs across the study (Khandker et al., 2010).

Propensity score matching utilizes the information on participants’ pre-treatment characteristics to determine the probability that the specific participant would be in the treatment group based on their background, or observed covariates (D’Agostino, 2007; Rosenbaum & Rubin, 1984). In experimental studies that use randomization, the true propensity score is known because the participant has a 50% chance of being assigned to either group (assuming two-group randomization) (Rosenbaum & Rubin, 1983). In non-randomized studies, the propensity to be in either the treatment versus control is not known, and must be estimated (Joffe & Rosenbaum, 1999; Luellen, Shadish, & Clark, 2005; Rosenbaum & Rubin, 1983). Calculating propensity scores helps to balance all of the covariates and can account for much of the bias (90% when sub classifications, or stratification, are used) due to the observed covariates (Rosenbaum & Rubin, 1983, 1984). There remains a small proportion of bias due to unobserved covariates, but the level of bias is based on the correlation of the unobserved covariates to the observed covariates (Rosenbaum & Rubin, 1984). Again, balancing covariates between the treatment groups fulfills the assumption that the groups will only vary on the treatment variable, so when an effect is found it can be attributed to the treatment variable, which is the asymmetrical relationship necessary in causal inference (Susser, 1973).
Propensity scores—In general. The propensity score is a balancing score that allows for direct comparison between treatment groups in non-randomized studies (Rosenbaum & Rubin, 1983). The propensity score can be used to match pairs, create sub classifications, and for covariance adjustment to create unbiased estimates of the treatment effects (Rosenbaum & Rubin, 1983). Through estimating the participant’s propensity score using logistic regression, the propensity score can either be used as a weight or factor in regression adjustment, or it can be used to construct comparisons through stratification or matching (D’Agostino, 2007). Using the propensity score to match or stratify participants can actually result in better balance of the observed covariates than would be expected from randomization. Despite this benefit, randomization addresses unobserved covariates but propensity scores do not (Joffe & Rosenbaum, 1999).

Propensity scores are most commonly used for stratification because it is not as sensitive to nonlinear relationships between the propensity score and the outcome compared to covariance or weighting, and it is almost as efficient and easier than matching (Luellen et al., 2005; Rosenbaum & Rubin, 1983). The biggest benefit of using propensity score adjustments is that they may approximate the results that would have been found if the participants had been randomized (Shadish, Clark, & Steiner, 2008). Unlike other strategies of matching, stratification, or covariance adjustment, propensity score methods use all of the covariate information to reduce bias and increase precision, which again allows for an inference of causality (D’Agostino, 1998; Rosenbaum, 1984; Susser, 1973).

Propensity scores and causation. Propensity scores can account for the bias introduced by using data from an observational study and produce accurate and robust treatment effects (Rosenbaum & Rubin, 1983, 1984; Rosenbaum, 1984). Using propensity scores allows for the
satisfaction of the basic criteria of causation—an asymmetrical relationship between the variables and temporal ordering (Rosenbaum & Rubin, 1983, 1984; Rosenbaum, 1984). Using propensity scores fulfills the requirement of a proxy for the counterfactual, so that the researcher can approximate what would have happened to the participant in the treatment group if they had not received the treatment (Angrist et al., 1996; Rubin, 2005). Propensity scores allow for statistical adjustments to be made to account for heterogeneity between the groups, which is the biggest benefit of using an experimental design, therefore increasing the ability to infer causation (D’Agostino, 2007; Rosenbaum & Rubin, 1983). Again, the heterogeneity between treatment groups means that they only vary on the treatment variable, which fulfills the first assumption of causal inference in experimental designs (Rosenbaum & Rubin, 1983; Susser, 1973). The ability to statistically model the relationship between the variables and account for heterogeneity has allowed researchers to use non-randomized studies to infer causation, which is a huge advance in the field due to difficulties in conducting randomized studies (D’Agostino, 2007; Rosenbaum & Rubin, 1983; Winship & Morgan, 1999).

**Randomization and Intervention Implementation Failure**

Many randomized experiments fail when applied to the real world outside a laboratory because of unanticipated interventions that disrupt randomization or treatment effects (Barnard, Du, Hill, & Rubin, 1998; King, Nielsen, Coberley, Pope, & Wells, 2011). When a study employs randomization that fails, the study must be treated as an observational study for statistical purposes or use statistical methods that were designed for randomization failure (King et al., 2011). Viewing the study as observational instead of randomized allows for the reintroduction of potential confounding by variables that were not controlled for in the randomization (King et al., 2011).
This is only necessary when the failure occurs at the point of randomization and does not apply after participants have been randomized (King et al., 2011; Shadish et al., 2002).

An issue that is frequently encountered when conducting research in the community is difficulty with implementation of the intervention (Shadish et al., 2002). In this proposed research study, the cognitive behavioral therapy, designed as the treatment arm, is not being implemented in a timely manner for the participants who are randomized to this group. This is a common occurrence with experimental designs in the community (Shadish et al., 2002).

Most interventions do not provide the treatment, as planned, with every participant randomized to that arm of the study receives the full intervention, the participants fully compliant with the treatment, and no diffusion of treatment across treatment arms (Shadish et al., 2002). Implementation of treatment includes the delivery of the treatment, the receipt of the treatment by the participants, and the adherence of participants to the treatment (Shadish et al., 2002). Treatments can be delivered less successfully by practitioners when they are complex, time-consuming, expensive, a burden, not within the comfort zone of the practitioner, or inconvenient (Shadish et al., 2002). Proper implementation of the treatment helps to improve the construct validity of the treatment (Shadish et al., 2002). In the case of my proposed research, issues with delivery of the treatment have led to randomization failure.

Although improper treatment implementation can be an issue, it is not unusual in studies conducted in the community (Shadish et al., 2002). This is one of the big differences between efficacy and effectiveness; the latter allows for issues with implementation as it is the measurement of how effective the intervention is in real-world situations (Shadish et al., 2002). Additionally,
in order to maintain internal validity, and to infer that the random assignment to a specific treatment caused the outcome of interest, the treatment does not have to be fully implemented (Shadish et al., 2002).

Measuring SF-12 Outcomes

My proposed research study is designed to understand the health-related quality of life of participants in a jail diversion intervention. One of the most widely used measures of health-related quality of life is the Short Form Health Survey (SF-36) and the other shortened versions (SF-12, SF-8) of this measure (Ware & Gandek, 1998; Ware et al., 1996). Due to time constraints, the SF-12 is being utilized in my proposed research to assess the health-related quality of life, or health status, of the participants.

The SF-12 uses norm-based scoring for calculating the results of the administered surveys (Gandek et al., 1998). In order to assess baseline differences in health status scores across treatment arms, the scores need to be analyzed to determine whether they follow a normal distribution. Because there are only 12 questions, the SF-12 has less variability than some of the longer forms, and therefore the total scores may have floor or ceiling effects (Gandek et al., 1998). If the health status scores do follow a normal distribution, then an Analysis of Variance (ANOVA) can be used to calculate the difference in scores between treatment groups at baseline (Stevens, 2007). If the ANOVA is significant, a post-hoc Tukey test will be conducted to determine which treatment group or groups have statistically different baseline health status scores (Stevens, 2007). ANOVA is thought to be robust to violations of normality, so depending on the normality analysis, it may be an appropriate technique to determine differences in health status score (Shadish et al., 2002). If normality assumptions are not upheld, then a Kruskal-Wallis one-way analysis of variance will be used to determine baseline treatment group differences (Stevens, 2007).
The purpose of using random assignment to treatment groups is to make sure that the different treatment arms are equally distributed on different observed and unobserved variables (equal heterogeneity) at baseline (Shadish et al., 2002). Therefore, it is reasonable to assume that if randomization failure did not occur, the treatment arms would not differ on health status (D’Agostino, 2007; Rosenbaum & Rubin, 1983). Baseline analysis of group differences on the SF-12, and other observed covariates, will allow for a measurement of the treatment arm characteristics prior to any treatment implementation. Conducting baseline analysis will allow for a determination of the heterogeneity present between the groups at baseline to determine if there were issues with randomization (Shadish et al., 2002).

If there is no heterogeneity present at baseline, when differences arise between groups later in the data collection there is an ability to infer that the specific treatment has had an impact on health status by using the basic principles of causality (Khandker et al., 2010; Shadish et al., 2002; Susser, 1973). For instance, if the three treatment arms are equivalent at baseline, the principle of only varying on one aspect, the treatment, is fulfilled (Susser, 1973). Additionally, the health status is measured prior to the intervention implementation, which supports the temporal order requirement (Susser, 1973). Finally, the relationship between health status and the treatment arm is asymmetrical, because the treatment arm can impact health status, but health status cannot impact the treatment arm that the individual is assigned to (Susser, 1973).

If randomization failure occurs, the groups can no longer be considered equal in their heterogeneity, which violates the principle of the treatment groups only varying on the treatment variable (D’Agostino, 2007; Susser, 1973). In this specific situation, the treatment variable in the treatment arm is the receipt of cognitive behavioral therapy. The participants in this arm are not getting the treatment in a timely manner, and not all of the participants in this arm are attending
the treatment. Because this is not a true randomized control trial, but rather a randomized field experiment, there is an expectation that issues will arise in getting all participants in the treatment arm to fully participate and receive the full intervention (Brown et al., 2008). It is generally accepted that the issues that arise in the community in general when interventions are implemented, and therefore represent the effectiveness of the intervention instead of the efficacy (Brown et al., 2008).

**Statistical Techniques to Deal with Implementation Issues**

There are multiple statistical techniques that have been employed in instances when randomization is broken, or when treatment is not fully implemented. The most common statistical techniques are intention-to-treat analysis, as-treated analysis, per protocol, and instrumental variable analysis (Barnard et al., 1998; Shadish et al., 2002). These analysis techniques were developed to deal with the real-world situations that occur when trying to implement an intervention in the community that is not implemented as planned (Barnard et al., 1998; Shadish et al., 2002).

Intent-to-treat analysis groups participants for analysis based on the treatment group they were randomized into, or the intended treatment, and does not take into consideration the treatment they actually received (Barnard et al., 1998). One of the benefits of using an intent-to-treat analysis is that the benefits obtained through random assignment are maintained for causal inferences (Shadish et al., 2002). This means that analysis will produce unbiased estimates on the effects of being assigned to the specific treatment category (Shadish et al., 2002). The issue that arises is that the estimates of effects do not take into consideration the treatment that was actually received, which may be different than the assigned treatment (Shadish et al., 2002). Intent-to-treat analysis
should not be conducted as the sole analysis and should incorporate other analysis to mitigate these issues (Shadish et al., 2002).

As-treated analysis group participants are based on the treatment they actually received, regardless of the initial group they were randomized into (Barnard et al., 1998). As-treated analysis does not provide unbiased estimates (Shadish et al., 2002). Using this statistical analysis leads to issues with inferences of causality, as the participants may self-select into a different treatment group, therefore biasing the estimates (Shadish et al., 2002). This type of analysis does not estimate the effect of the received treatment or the intent to treat (Barnard et al., 1998).

Per protocol analysis does not use data from participants whose received treatment was different from their assigned treatment (Barnard et al., 1998). This method discards all of the cases where the participant did not receive the treatment that they were randomized, which ignores potentially informative data (Barnard et al., 1998). The problem with all of these methods is they do not correctly estimate the effect of the receipt of treatment, which is typically the outcome variable, because they ignore relevant data that impacts the effectiveness estimate (Barnard et al., 1998).

An additional way proposed by statisticians to deal with issues in implementation is instrumental variable analysis (Angrist et al., 1996; Shadish et al., 2002). Instrumental variable analysis uses random assignment as an instrumental variable in the analysis of the data to obtain unbiased estimate of the causal effects for individuals who received the intervention (Shadish et al., 2002). This type of analysis was designed for issues with participant treatment compliance, and therefore is not necessarily applicable to situations where treatment delivery is the issue (Shadish et al., 2002). There are five assumptions that must be fulfilled in instrumental variable analysis: 1) participants’ outcomes are independent of other participants’ treatment assignment, 2)
standard intent-to-treat analysis can be used to estimate the causal effect of assignment on receipt and outcome, 3) treatment assignment has a nonzero effect on receipt of treatment, 4) the outcome is only impacted by the random assignment through the receipt of treatment, 5) there are no participants who would refuse treatment if assigned to it, and take treatment if not assigned to it (Angrist et al., 1996; Shadish et al., 2002). Issues arise with proving that both assumptions 4 and 5 are fulfilled, as they require information that is beyond what is available in most studies (Shadish et al., 2002).

The issue in my proposed research is not one of participant compliance, which may arise later, but of getting the treatment delivered to the participants in a reasonable time-frame. Although other techniques have been proposed to deal with randomization issues, they are mainly focused on issues with participant treatment compliance (Barnard et al., 1998; Barnard, Frangakis, Hill, & Rubin, 2003; Frangakis & Rubin, 2002). Intent-to-treat analysis is the only statistical technique that takes into consideration issues with delivering the intervention, and therefore is an appropriate analysis for my proposed research to compare the outcomes of participants by randomization groups for treatment effects (Little & Rubin, 2000; Shadish et al., 2002).

**Intent-to-treat analysis.** Intent-to-treat analysis is widely used for analyzing data that has incurred problems with randomization (Brown et al., 2008). Intent-to-treat analysis maintains the benefits that randomization imposes on balancing heterogeneity and represents what the likely effectiveness of the intervention will be if it is implemented in other communities (Bang & Davis, 2007; Brown et al., 2008). Compliance issues can attenuate the estimate of the treatment effect, but intent-to-treat is considered the best way to deal with this data as it eliminates selection bias (Bang & Davis, 2007). Intent-to-treat analysis will always underestimate the effect of the treatment, unlike other methods, and therefore continues to be the best method to use in
randomized studies with treatment noncompliance (Bang & Davis, 2007). The instrumental variable approach may overestimate the treatment effect, making it a less desirable option (Bang & Davis, 2007). Intent-to-treat analysis can incorporate information on the actual treatment received by participants by taking the compliance information into the consideration of treatment effectiveness (Salim, Mackinnon, & Griffiths, 2008).

In order to conduct an intent-to-treat analysis, there cannot be drop-out; if there is drop-out, a statistical method, like multiple imputation, must be used to deal with the drop-out (Salim et al., 2008). The underlying principle behind intent-to-treat is the inclusion of all participants in the analysis (Lachin, 2000). It is also important to understand how drop-out may be related to treatment compliance, which can then be taken into consideration in the statistical model (Salim et al., 2008).

The biggest limitation with using the intent-to-treat analysis is that when there is nonrandom missing outcome data, the estimates of treatment effectiveness will be biased (Shadish et al., 2002). If the data is missing completely at random or missing at random, it is sometimes considered “ignorable,” as there are different data analysis mechanisms that will continue to result in asymptotically unbiased estimation (Raudenbush & Bryk, 2002). When data are not missing at random, the missing-ness needs to be taken into consideration, as future responses cannot be predicted based on the past responses (Little & Rubin, 2002). One of the biggest issues with the above classification system is the difficulty of determining whether or not data are missing at random (Little & Rubin, 2002). It may not be an apparent variable that is causing the participants to drop out, but may be a potential covariate that was not identified. If the mechanism of missing data is not properly modeled during analysis, the estimate of the treatment effects will be biased,
which will result in an inability to make a proper determination about causality (Shadish et al., 2002). This means that additional analysis beyond a basic intent-to-treat model must be used.

**Proposed study data analysis.** In order to analyze the eventual treatment effectiveness in this proposed study the data analysis techniques will be multi-faceted. At the very basic level, an intent-to-treat model will be used. One of the eventual issues of using an intent-to-treat model for a longitudinal study is attrition of participants (Mazumdar et al., 2007). In order to deal with attrition imputation will be used, but the specific imputation technique to be employed is not known at this time, although incorporating the propensity score of a participant’s probability of remaining in the study at time \( t \) may be incorporated (Mazumdar et al., 2007). The data will need to be collected prior to determining the mechanism of missing data, which will then be used to inform the appropriate statistical technique (Little & Rubin, 2002). To analyze the longitudinal data and properly model the repeated measures, a multi-level model will be used (Raudenbush & Bryk, 2002). All of these modeling issues will impact the eventual interpretation of treatment effectiveness. The issue of randomization failure will be one issue that will be taken into consideration in the interpretation of the data, and that can affect the ability to infer a causal relationship between the treatment and the outcome of health status.

**Inference of Causality in This Study**

Using an intent-to-treat analysis upholds the basic tenets of causality—the time order relationship and an asymmetrical relationship between variables (Susser, 1973). In this regard, intent-to-treat analysis will not impact the interpretation of causality; it is when we consider the way we interpret the relationship between the variables that we run into issues with determinations of causality. Experimental designs are frequently used in studies that want to infer causality, because they allow greater control over the delivery of the treatment, allowing the researchers to
infer that the treatment is impacting the outcome variable (Shadish et al., 2002). When the treatment is not delivered as intended, we can no longer assume that the treatment groups are alike except for one variable, because that one variable is not being implemented properly (Susser, 1973). This situation makes it difficult to attribute the outcome of the participants’ health status to the treatment, because it was not implemented as intended.

Statistically, the treatment effectiveness will most likely be underestimated, because it was not received or implemented as intended (Bang & Davis, 2007). Intent-to-treat analysis groups participants by their originally assigned treatment group, so the individuals who are supposed to receive cognitive behavioral therapy will remain in the treatment group regardless of whether the therapy is actually provided. When participants who have received the therapy and who have not received the therapy are in the same group for analysis, the treatment effect will be decreased due to the scores of the participants who did not receive the treatment (Bang & Davis, 2007). In the final analysis, there will be a high chance of a type II error occurring, although this is typically thought of as less of an issue than overestimating the treatment effect and committing a type I error (Bang & Davis, 2007; Stevens, 2007).

The biggest benefit of using intent-to-treat analysis is that it retains the equal dispersion of heterogeneity between groups achieved through randomization (Bang & Davis, 2007). Maintaining the benefits of randomization of participants allows for the benefits of using a randomized control trial, specifically, a clearer understanding of the impact of the treatment on the outcome variable of interest (Shadish et al., 2002). By understanding the relationship between the variables, we can infer causality and treatment effectiveness by understanding the asymmetrical relationship (Shadish et al., 2002; Susser, 1973).
Conclusion

The notion of causality can simply be thought of as two variables, with the causal variable preceding the outcome variable, and an asymmetrical relationship that dictates only the causal variable impacts the outcome variable and not vice versa (Susser, 1973). One of the most common and straightforward ways to examine this relationship is through the use of an experimental design that employs randomization of participants to treatment groups (Khandker et al., 2010; Mohr, 1995; Shadish et al., 2002). Experimental designs are not always plausible, or feasible, and many studies instead use an observational design (D’Agostino, 2007; Shadish et al., 2002), which has led to advances in statistical techniques to estimate causality in studies that employ randomization of participants (D’Agostino, 2007; Rosenbaum & Rubin, 1983; Rosenbaum, 1984; Winship & Morgan, 1999).

Issues occur in randomized studies when there is randomization failure. Traditional techniques alone cannot be used, as the sample estimates may be biased (Barnard et al., 1998; Shadish et al., 2002). One way to overcome randomization failure is by using intent-to-treat analysis, which maintains the benefits of randomization to help with eventual inferences of causality (Bang & Davis, 2007). Intent-to-treat does underestimate treatment effects, making it more difficult to infer a causal relationship and the effectiveness of the treatment (Bang & Davis, 2007). But, when used in conjunction with other statistical techniques, intent-to-treat analysis provides the best estimates of the treatment effectiveness compared to other methods (Bang & Davis, 2007; Shadish et al., 2002). Understanding the strengths and limitations of intent-to-treat analysis provides the information necessary to properly interpret the estimates of treatment effectiveness. Instead of being able to make a definite statement of causality, the randomization
failure will need to be discussed at length as a limitation and how the treatment effectiveness may be underestimated as a result (Bang & Davis, 2007).
Appendix D: IRB Letter of Determination

11/14/2013

Robin Telford, M.A.
Community and Family Health
The Harrell Center for the Study of Family Violence
15201 Bruce B. Downs Blvd., MDC 56
Tampa, FL 33612-3807

RE: NOT Human Research Activities Determination
IRB#: Pro00015154
Title: Physical and Mental Health Status of Adults with Serious Mental Illness Participating in a Jail Diversion Intervention

Dear Ms. Telford:

The Institutional Review Board (IRB) has reviewed the information you provided regarding the above referenced project and has determined the activities do not meet the definition of human subjects research. Therefore, IRB approval is not required. If, in the future, you change this activity such that it becomes human subjects research, IRB approval will be required. If you wish to obtain a determination about whether the activity, with the proposed changes, will be human subjects research, please contact the IRB for further guidance.

All research activities, regardless of the level of IRB oversight, must be conducted in a manner that is consistent with the ethical principles of your profession and the ethical guidelines for the protection of human subjects. As principal investigator, it is your responsibility to ensure subjects' rights and welfare are protected during the execution of this project.

We appreciate your dedication to the ethical conduct of human subject research at the University of South Florida and your continued commitment to human research protections. If you have any questions regarding this matter, please call 813-974-5638.

Sincerely,

Kristen Salomon, Ph.D., Vice Chairperson
USF Institutional Review Board