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Waiting Times and DWI, Court-Mandated Treatment Completion

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Walden University

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Walden University
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Abstract

Waiting Times and DWI, Court-Mandated Treatment Completion

by

Cailyn Florence Green

MS, Sage Graduate College of Albany, 2011

BA, Western New England University, 2009

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Public Policy and Administration

Walden University

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Abstract

Drivers under the influence of alcohol cause nearly one third of all fatal motor vehicle accidents. Ambulatory outpatient alcohol abuse treatment has been clinically shown to increase abstinence, which could decrease the chance of subsequent DWI offences. A barrier to successful completion is extended waiting periods prior to treatment engagement. The theory of patient waiting supports the longer a patient waits to begin treatment the lower the likelihood of successful completion. By exploring the impact of waiting times on DWI court mandated clients, referral courts and treatment facilities can work together to create a successful completion strategy for offenders. The research question focused on if days waiting can predict successful outpatient treatment completion in court mandated adults. The TEDS-D archival data set was used, consisting of data collected between 2006—2011 from federally funded substance abuse treatment centers throughout the USA. The variables time awaiting treatment, treatment level, gender, race, employment status, and age were used as controls. A logistic regression using a random sample of 4,947 participants determined days waiting was significant but weak in nature. The variables of employment status and age are stronger predictors of treatment completion. An interaction effect analysis of days waiting and age results in clients over 45 years old being significantly impacted by days waiting while younger clients are not. Court and treatment agencies can use this information to give priority intake appointments to older clients to increase chances of treatment completion.

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Table of Contents

List of Tables	v
Chapter 1: Introduction to the Study.....	1
Introduction.....	1
Background.....	5
Statement of Problem.....	6
Purpose of the Study.....	7
Research Question and Hypotheses	8
Definition of Terms.....	9
Significance.....	10
Assumptions.....	11
Limitations	11
Summary	12
Chapter 2: Literature Review.....	15
Introduction.....	15
Alcohol Addiction.....	16
Disease Model of Addiction	17
Abstinence.....	18
Theory of Patient Waiting Based on Queuing Theory.....	27
Motivation.....	33
Reasons for Wait Times.....	36
Impact of Patient Wait Times on Treatment Outcomes.....	38

Counseling with Students	38
Relationship Counseling.....	40
Emergency Departments.....	41
Ambulatory Patient Settings	43
Counseling for Gambling.....	45
Counseling with Children	47
Substance Abuse Counseling.....	49
Pregnant Substance Abusing Clients	54
Interim Treatment While Waiting.....	56
Consequences of Not Completing Treatment.....	61
Implications of Past Research on Current Proposal.....	62
Literature Relating to Different Methodologies	63
Chapter 3: Research and Method.....	64
Purpose of Research.....	64
Research Rationale.....	64
Research Question	65
Instrumentation	65
Operationalization of Variables	66
Screening Criteria	69
Research Design.....	72
Simple Random Sample.....	72
Data Collection	75

Statistical Assumptions.....	75
Data Analysis.....	77
Threats to Validity and Reliability.....	77
Ethical Considerations.....	79
Conclusion.....	79
Chapter 4: Results.....	80
Introduction.....	80
Data Collection.....	80
Random Sample.....	80
Data Analysis.....	81
Assumption Tests.....	82
Box Tidwell.....	82
Multicollinearity.....	82
Outliers.....	83
Descriptive Statistics.....	84
Logistic Regression Analysis.....	87
Bootstrapping on Preliminary Analysis.....	89
Best Fit Model for Logistic Regression Analysis.....	92
Summary.....	92
Chapter 5: Discussion.....	94
Introduction.....	94
Interpretation of Findings.....	94

Independent Variable	94
Age Variable	97
Employment Variable	98
Gender Variable	99
Race Variable	99
Level of Outpatient Variable	100
Limitation and Recommendations for Future Research	101
Strengths	104
Implications for Social Change	105
Conclusion	107
References	109
Appendix A: TEDS-D Original Race SPSS Codes	124
Appendix B: TEDS-D Original Employment Status SPSS	125
Appendix C: TEDS-D Original Reason for Discharge SPSS Codes	126
Appendix D: TEDS-D Original Criminal Referral SPSS Codes	127
Appendix E: TEDS-D Original Service Setting SPSS Codes	128
Appendix F: TEDS-D Original Primary Substance of Use Codes	129
Appendix G: Independent Variable Cross Tabbed with Dependent Variable	130

List of Tables

Table 1. Research Variables and their Corresponding SPSS Coded	71
Table 2. Assumption Tests.....	83
Table 3. Descriptive Statistics.....	85
Table 4. Additional Descriptive Statistics	86
Table 5. Analysis Results.....	87
Table 6. Interaction Effects.....	90
Table 7. Age-Centered Interactions	91

Chapter 1: Introduction to the Study

The American Psychiatric Association (APA, 2013) classified addiction as a chronic and persistent mental health disease. This disease is unique because it negatively impacts its host and the lives of its victims, loved ones, and community. When a loved one is suffering from addiction, there is little someone can do to help the patient in recovering from his or her mental health disease. Only the client suffering from addiction can earn recovery, and only after they work for it on his or her own. Although no one can create a recovery path for a person suffering from addiction, his or her behaviors can warrant a stronger power to become involved. When an individual suffering from addiction becomes involved in the criminal justice system because of behaviors stemming from addiction, the law now holds power over treatment. Although court-mandated addiction treatment does not guarantee recovery, it does open a door for the patient to begin their recovery path.

Alcohol is a legal substance used recreationally and safely by many people. However, this line between the safe usage of alcohol and the risky behaviors associated with addiction is easy to cross. When the alcohol user crosses this line, he or she is not only in physical, mental and emotional danger, but he or she creates hazardous conditions for the surrounding individuals and the community.

Introduction

Although addiction is classified as a mental health disease, it is often recognized as a weak or irresponsible choice or behavior. Much of the public categorizes addiction as one of two models: disease model or a moral model (Henden, Melberg, & Rogeberg,

2013). Henden et al. (2013) defined the disease model of addiction as “compulsive and relapsing drug use over which the addict has little or no control” (p.1). The moral model is when addiction is seen as “a choice characterized by voluntary behavior under the control of the addict” (Henden et al., 2013, p. 1). A small collection of chronic offenders commit the majority of all driving while intoxicated (DWI) or driving while under the influence (DUI) offenses (DeMichele & Lowe, 2011). When this research is identified, the disease model takes center stage when examining DWI cases. Alcohol addiction being recognized as a disease allows for treatment to aid in the recovery process. Although there is no cure for alcohol addiction, prompt treatment can help lower relapses and improve the health of the individual.

Alcohol, which is a depressant substance, lowers inhibition and reaction time (APA, 2013). This lowered inhibition increases the likelihood of an individual engaging in risky behaviors. These behaviors can include various actions from unprotected sex and vandalism to operating a motor vehicle. The lowered reaction time associated with the depressant nature of alcohol is dangerous for someone who then drives a car. The compulsive behaviors associated with the disease of addiction includes loss of control and irresistibility (Henden et al., 2013). Often individuals will choose to drive to a location and plan on drinking alcohol responsibly. Yet, the compulsive nature behind the disease of addiction takes over and hinders this original plan from taking place. A DWI arrest is created by these actions. The combination of the compulsive nature of alcohol addiction and the risky behaviors associated with alcohol influence produce DWI recidivism rates. Recidivism is the cause of almost 1.5 million drunk driving arrests and

17,000 deaths related to drunk driving in the United State each year (DeMichele & Lowe, 2011).

The development and installation of vehicle alcohol interlock systems in cars of individuals who had DWI offenses in their lives is an effort to reduce recidivism. These devices prevent people who have a positive blood alcohol content from driving their vehicles (Voas, 2014). This device has shown to reduce recidivism in previously convicted DWI vehicle operators by two-thirds (Voas, 2014). The devices force the drivers to abstain from alcohol usage when they operate their vehicles. This pathway to abstinence lowers recidivism rates of DWI crimes. The vehicle interlock system proves that abstinence can reduce recidivism rates of these potentially fatal crimes.

The majority of the research about addiction in the criminal justice systems consists of best practices for treatment approaches and medication-assisted therapies. Although this information is crucial to courts when mandating alcohol abuse treatment for DWI offenses, it does not cover all effective treatment options. Treatment aids in lengthening abstinence periods of alcohol use by people suffering from addiction. Timko, Moos, Finnelly, and Lesar (2000) identified alcohol users who engaged in some form of treatment had a significantly higher likelihood of abstinence compared to those who engaged in no form of treatment. If the previous DWI offenders are now abstinent from alcohol, they are not able to commit a new DWI. Investigating patient wait times (WT) becomes relevant on the potential impact on alcohol treatment completion.

DWI offenders often must wait for an assessment appointment and must wait again to begin their court-mandated alcohol abuse treatment. The process of a court

mandating a DWI offender to alcohol abuse treatment commonly begins with a court date or drug court initiation. After the offender is part of the court process, the judge will mandate treatment and assign a case manager to monitor the offender. This often takes the form of a drug court case manager or a probation officer. The case manager or probation officer monitors the offender to an alcohol abuse outpatient facility. The client will engage in a formal assessment or evaluation at the facility. The case manager or probation officer is in charge of monitoring the offender to ensure he or she is making his or her alcohol abuse treatment assessment appointment and following all recommendations made by the alcohol treatment facility. It is common for clients to wait up to 14 days for their initial assessment appointment (Redko, Rapp, & Carlson, 2016). This initial assessment appointment is important to identify the most appropriate level of care and treatment approach for each individual client. Different states have different rules on waiting periods. After the initial assessment, the offender is given a treatment start date. This could be the next day, it could be a week later, or could be as long as a month's time. Many factors influence the WT from the moment the offender contacts the treatment facility to the time he or she attends his or her assessment appointment. These factors can include weather, available appointments, priority for certain primary substances of choice, and basic staffing issues. Inquiry on how waiting to begin treatment can impact the offender's successful completion needs to occur.

The idea of how WT can impact the success rate of treatment completion began in the medical hospitals. The theory of patient WTs is explained as "shorter WTs usually result in higher degrees of patient and citizen satisfaction" (Kozlowski & Worthington,

2015, p. 331). When patients have to wait to begin treatment or wait for formal assessment, he or she often walk out without receiving treatment (Kozlowski & Worthington, 2015). Humans who are unhappy with a service are less likely to complete the activity or engage in it again. DWI offenders are already unhappy with court-mandated alcohol abuse treatment. The likelihood of offenders positively and actively engaging in these treatment episodes is lowered when dissatisfaction due to long WTs is included.

The queuing theory is based on a mathematical approach to lessen the WTs and improve satisfaction with the patients (Ameh, Sabo, & Oyefabi, 2013). Satisfying the patients in regards to WTs would result in fewer patients walking out before receiving treatment, thus increasing the rate of successful completion of the program.

Background

DWI recidivism exists due to the chronic relapsing nature of alcohol addiction (Heyman, 2013). Rauch et al. (2010) identified when a person commits a DWI violation, his or her “rate of subsequent violation increased 615% by that first violation” (p. 921). Rauch et al. found a significant connection between a first DWI offense and a high rate of recidivism for a subsequent offense. When researchers interviewed a sample of 1,100 drivers over the phone, 60% reported understanding that driving while under the influence of alcohol was associated with a high risk of traffic accidents (Alonso, Pastor, Montoro, & Esteban, 2015). Of this same sample, 25.3% of interviewees reported that he or she, at some point, drove under the influence of alcohol (Alonso et al., 2015). These

reasons included, “I had to go home and couldn’t do anything else” “Done it unintentionally,” or “Something associated with meals” (Alonso et al., 2015, p. 4).

The theorist who created the disease model of addiction used it to explain why people continuously engage in the risky behavior of driving while under the influence of alcohol. Jellinek first introduced the disease model of addiction in the mid-1950s (Gunzerath, Hewitt, Li, & Warren, 2010). This model identified alcohol addiction as a medical disease by the APA that includes such symptoms of social, legal, and economic consequences as well as countless medical outcomes (Gunzerath et al., 2010). Jellinek described alcohol addiction as a loss of control over the ability to consume alcohol. It often creates the previously named behaviors (Gunzerath et al., 2010).

For those who do not agree on the compulsive nature of alcohol addiction, the idea of choice comes into play. These individuals see alcohol consumption and addiction as voluntary actions made by offenders (Henden et al., 2013). Viewing addiction as compulsive and relapsing in nature due to its neurological impact is not believed by all (Henden et al., 2013). Those who disagree with the disease model of addiction cannot dispute the high recidivism rates of DWI offenses.

Statement of Problem

A societal problem exists with the high number of deaths which occur each year because of alcohol-related traffic accidents. The Center for Disease Control (2016) stated, “In 2014, 9,967 people were killed in alcohol impaired related driving crashes, accounting for one third of all traffic related deaths in the United States” (para 1). An estimated annual recidivism rate of 24.3 out of every 1,000 DWI first-time offenders was

identified by Rauch et al. (2010). Rempel, Green, and Kralstein (2012) identified that after an 18-month follow up of DWI offenders, 27% were rearrested for another DWI charge while those who engaged in drug court had a much lower recidivism rate of 17%. Successful completion of drug court requires successful graduation from a mandated alcohol abuse treatment program (Lutze & Wormer, 2007). Andrews, Shin, Marsh, and Cao (2013) identified, on average, criminal justice clients were on treatment waiting lists over a month. This was for court-mandated alcohol abuse treatment. Lowering the recidivism rate of DWI offenders can start by identifying if the number of days the DWI clients have to wait to begin their legally mandated alcohol abuse treatment impacts their ability to successfully complete treatment.

Unlike opioid dependent clients who are offered interim counseling while they wait for their formal treatment to begin, DWI alcohol dependent clients are not offered treatment or counseling (Sigmon, 2015). Not only do DWI clients have health issues because of addiction, these clients have a high risk of recidivism that can potentially harm other innocent drivers. There was a gap in literature that could benefit the criminal justice and alcohol abuse treatment fields. This gap would be filled by answering to what extent WTs for the alcohol dependent DWI client's impact their ability to successfully complete treatment.

Purpose of the Study

The purpose of this study was to determine if the time awaiting outpatient treatment can predict successful completion for U.S. court-mandated DWI offenders based on records for 2006—2011. Regression analysis was used to identify the extent of

this relationship. The results of this study could be used to aid in lowering the recidivism rates of DWI offenders with alcohol addiction issues. The focus of this study was on identifying if a predictive relationship existed between the lengths of time a DWI court-mandated offender waits to begin treatment and likelihood of successful completion. To address this gap in literature a quantitative research inquiry was used.

Research Question and Hypotheses

After an exhaustive literature review, I identified a gap in the available research which lead to the development of the research question. It was derived from topics such as recidivism rates amongst DWI offenders, alcoholism as a mental health disease, and medical patient WTs.

Research Question #1. Do the variables time awaiting treatment, treatment level, gender, race, employment status, and age predict successful completion of U.S. court-mandated adult outpatient alcohol abuse treatment?

H_0 1: The variables time awaiting treatment, treatment level, gender, race, employment status, and age will not predict successful completion of U.S. court-mandated adult outpatient alcohol abuse treatment.

H_1 1: The variables time awaiting treatment, treatment level, gender, race, employment status, and age will predict successful completion of U.S. court-mandated adult outpatient alcohol abuse treatment.

Definition of Terms

Waiting time (WT): The time period from the day the client initially contacted the mandated alcohol treatment outpatient facility to the day he or she physically begins treatment.

Drive under the influence (DWI): When a formal arrest for a DWI traffic violation occurs. The client was found to be under the influence of alcohol over the legal limit. Different states classify this arrest as a DWI or a DUI. Both are being used for this research based on the state's designation.

Balking: When a client attempts to engage in treatment but never commits due to the anticipated long waits (Ameh et al., 2013).

Reneging: When a client leaves the services due to the line being too long (Ameh et al., 2013). A client may make an appointment and plan on keeping it but, because of other circumstances which have taken place during that WT period, not keep it.

Court-mandated: When a court judge, case manager, or probation officer offers the client to complete an alcohol abuse treatment program in lieu of jail time.

Successful treatment completion: When a client follows all treatment recommendations and maintains sobriety to the facilities satisfaction.

Outpatient treatment and ambulatory treatment facility: The type of alcohol abuse treatment facility this research was focused on. This treatment facility level is when the clients come and go on a daily basis for appointments and consists of intensive or nonintensive treatment services (Albrecht, Lindsay, & Terplan, 2011). They do not sleep

or live at the facility in any way. All the clients' information used in this research came from clients who were mandated to outpatient ambulatory treatment by their court entity.

Addiction: The use of alcohol which has caused problems in the clients' lives regarding their personal safety and illegal activity.

Significance

Research with the DWI treatment-mandated population holds significance as it fills a current gap in the literature. Current findings on this topic are limited to substance users of large broad populations and small populations of pregnant women. This research is an original contribution to the field of criminal justice and public policy by offering evidence regarding the impact of patient WT's on treatment completion. This research supports the professional practice of probation officers, parole officers, drug court case managers, outpatient treatment facilities, clinical case managers, and judges. Its findings offer criminal justice referral entities research-based evidence to lower recidivism rates by shortening the length of time their DWI clients wait to begin treatment.

The results can promote positive social change in the criminal justice populations and community. By telling the criminal justice referral services and outpatient treatment personnel the potential relationship patient WT's have on successful completion, this research is a knowledge-based tool to potentially increase successful completion. These findings of increasing successful outpatient treatment completion for DWI court-mandated clients can be a catalyst in reducing the participant's recidivism rates. A drop in recidivism not only benefits the DWI offenders by assisting them to live sober and healthy lives, but can also promote positive social change in the community. This can

occur by lowering the DWI offenses that have potential to cause deadly harm. Drug court, case managers, and treatment facilities can share these data to assist them in better serving their clients and offenders.

Assumptions

It was assumed the patient information (which was collected by the United States Department of Health and Human Services [USDHHS] in conjunction with Substance Abuse and Mental Health Services and Administration [SAMHSA], was collected in an unbiased manner and was accurate to the collecting agencies' knowledge. Other assumptions in this research included that the previously collected data set of the time period 2006 and 2011 is still relevant today. This data set was assumed to continue to hold relevance for this study as Rajczi (2014) spoke to the plethora of health experts collecting data in the field of patient waiting. Rajczi explained that for the health policy field to use the data, they must be analyzed by health policy researchers in a philosophical manner.

Limitations

A limitation of this data was the collection of information from the time period 2006 to 2011. Although these data are dated, multiple studies on patient waiting and substance abuse treatment used data that are collected from previous time periods. Hoffman, Ford, Tillotson, Choi, and McCarty (2011) used a sample of data collected previously from December 2003—2004. Guerrero and Andrews (2011) used data collected in 1995.

Summary

The medical field is full of research about patient WTs and their effects on patients obtaining treatment (Carr et al., 2008; Hicks & Hickman, 1994; Kozlowski, & Worthington, 2015). The longer patients wait to begin their medical treatment impacts their rate of completing treatment or even engaging in treatment at all. A court-mandated patient is already unhappy with having to engage in alcohol dependence treatment. When time is added to the wait, the patients begin to lose the little amount of motivation they had. Patient WTs can cause dissatisfaction and allow outside factors to take precedent over treatment engagement. The patient waiting theory provides a background as to what happens when patients end up waiting longer than expected to receive their sought medical services. When this occurs, patients have higher chances of becoming unsatisfied with the services (Michael, Schaffer, Egan, Little, & Pritchard, 2013). These WTs create unhappy and frustrated clients which impacts the patients' rate of engaging and completing treatment.

In Chapter 2 of this dissertation, I explain the existing research in the field of WT on different populations in regards to their impact on successful treatment completion. Most existing research follows the theory of patient WTs. This theory was also used for this research. I begin this chapter with outlining topics that provide the history and support for this research. I will discuss the disease theory of addiction and explain why treatment is necessary in order to maintain abstinence. I introduce the patient WT theory and its relation to the queuing theory, which supports this research hypotheses. The focus will shift to the field of criminal justice and alcohol dependence and their connection

between abstinence and lowered recidivism rates of DWI offenders. I also present literature which does not support this dissertation's hypothesis. The conclusion of Chapter 2 includes past research in the field and how it is expected to impact the current research. I will explain how this dissertation will satisfy a gap in the existing literature.

In Chapter 3, I will explain the quantitative nature of this dissertation's methodology. It includes the reasoning behind the choice of using a logistic regression analysis in this ex post facto or causal comparative study research approach. I used a quantitative research approach to identify if a predictive relationship exists between patient WTs and treatment completion in outpatient treatment facilities in the United States [U.S.], of the time period 2006—2011. Variables included gender, race, employment status, age, and type of outpatient treatment to further the study's reliability. The chapter includes a detailed description of the population, random sampling process, research procedures, all ethical considerations, measures, and analysis of the data.

Chapter 4 consists of all quantitative statistically analysis results from the logistic regressions. I support the findings in a subjective manor by incorporating previous findings from the literature reviewed.

In Chapter 5, I will explain how the results from Chapter 4 impact society to promote positive social change. It includes in depth and objective thoughts, ideas, and limitations of the findings.

Chapter 2: Literature Review

Introduction

There is a need for continued research about DWI offenders' recidivism rates causing traffic accidents. The relationship between the time court-mandated DWI offenders wait to begin alcohol abuse treatment is relatively new in the field of addiction and criminal justice. Multiple studies exist about medical treatment WTs and the impact these WTs have on patients receiving and completing treatment. Just like patients in medical hospitals and outpatient settings wait for their appointment, DWI offenders who are court-mandated to attend treatment must do the same. I designed this research to fill the gap in literature which currently exists concerning the potential impact waiting has on DWI offenders' treatment completion.

The theoretical framework supporting this dissertation is the theory of patient WTs and its connection to the queueing theory. A literature search was conducted electronically through psychology, criminal justice, and medical databases such as PsyINFO, PsycARTICLES, MedLINE, ProQuest Criminal Justice, and SAGE Premier. A list of sample terms used to conduct the research included *alcohol dependence*, *DWI*, *driving while intoxicated*, *patient WTs*, *queueing theory*, *alcohol abstinence*, and *alcohol treatment*. The articles obtained and reviewed for this dissertation research were peer-reviewed and acquired digitally as well as through print versions in professional journals.

In this chapter I provide an in-depth review of the societal need for research to be conducted to lower the recidivism rates of DWI offenders. Patient WT theory, as it connects to the queueing theory, is the existing framework that supported the research.

The connection between abstinence and lowered recidivism rates are explored in this chapter. This will connect the importance of completed alcohol dependence treatment to lower the DWI recidivism rates. To maintain objectivity in the literature review, this chapter also contains research that contests some of the more common outcomes. It concludes with a description of how past research inspired this dissertation.

Alcohol Addiction

Alcohol is a psychoactive substance which, when drunk, can lead to cognitive dysfunction, disturbed emotional response, and behavioral deviations (Ma & Zhu, 2014). Alcoholism is categorized as a disease because the negative physical, emotional, mental, and social consequences outweigh its benefits of use (Heyman, 2013). Ma and Zhu (2014) state ethanol is a chemical component of alcohol “which penetrates the blood-brain barrier and inhibits central nervous system (CNS) functions; it is directly toxic to the brain” (p. 61). These CNS neurotransmitters are the player in alcohol addiction as they are the biological pieces in the human body that create pathways in brains. Heyman (2013) reported as the addictive drug, alcohol “changes the brain, genetic studies show that alcoholism has a substantial heritability, and addiction is persistent, destructive pattern of drug use” (p. 1).

There is controversy around alcohol addiction being a disease versus a weakness of the client’s willpower. Neuroscience researchers support the medical model of addiction and identified that the release of neurochemicals during the consumption of alcohol produces dependence, tolerance, and the onset of withdrawal symptoms (Hall &

Carter, 2013). The chronic nature of alcohol addiction is what originally sparked the hypothesis that alcohol addiction was a disease of the brain (Courtwright, 2010).

Disease Model of Addiction

The introduction of addiction to the medical world as a disease was by Jellinek in the mid 1950s (Gunzerath et al., 2010). The APA (2013) continued to identify addiction as a mental health disease that is chronic and persistent in nature. Diseases, both medical- and mental health-related, need treatment to relieve the symptoms that are causing the sufferer issues. Medical and counselling methods are proven to assist patients in working towards recovery, but there are no cures. George, Gilmore and Stappenbeck (2012) stated the research behind medical and counseling treatment for alcohol addiction that is supported by the “classic disease model, is that abstinence is the only acceptable treatment goal for alcoholism” (p. 190). When a person who suffers from alcohol addiction consumes one drink of alcohol, he or she loses his or her ability to control, or is impulsive in his or her consequential consumption (George et al., 2012). This abstinence recovery path aids the patient in living a longer and healthier life. The persistent and relapsing nature of the disease cause fatalities, legal infractions, and social problems. In this study, I focused on when an individual, suffering from addiction, operates a motor vehicle while under the influence of alcohol.

DeMichele and Lowe (2011) found that a small number of chronic, alcohol reoffenders commit a large amount of the DWI infractions. It would be impossible to identify every potential DWI offender. Scholars are working to lower the recidivism rates in populations who have been arrested and are likely to reoffend. This is an example of

how alcohol addiction is persistent and chronic in nature. To confirm the importance of research in the field of lowering these DWI recidivism rates, potential risk factors for recidivism must be studied. The main risk factor that influenced this research was relapse due to lack of outpatient treatment completion because of extended WTs.

Abstinence

Abstinence is the key to lowering recidivism rates. If past offenders of DWI crimes are no longer using alcohol, they cannot be arrested for driving while under the influence of alcohol in the future. Voas (2014) identified that installing vehicle alcohol interlock systems into cars of previously convicted DWI offenders can cut future DWI offenses by 2/3. These breathalyzers detect alcohol before the driver is able to start the car. The only option to drive the car is abstinence; yet, not all states mandate these devices in DWI offender's vehicle at the time of conviction (Voas & Fell, 2011). Kopak, Hoffmann, and Proctor (2016) predicted that a risk factor for recidivism and relapse are offenders who do not complete their court-mandated substance abuse treatment. Kopak et al. showed that "relapse was a key indicator of post-treatment arrest across all arrest outcome groups" (p. 26). Henden et al. (2013) agreed that abstinence is the best method of limiting future arrests because of the compulsive nature of addiction including nonvoluntary behaviors controlled by the disease. Although Kopak et al. (2016) did not examine clients who successfully completed treatment versus clients who did not, these findings still had an implication on my research. Kopak et al. provided information on understanding how recidivism rates are largely related to abstinence from alcohol and other substances. The key to lowering recidivism rates in the DWI offender population is

abstinence. This abstinence eliminates the compulsive and irresistible desires that are connected to the patient's actions while under the influence of alcohol (Henden et al., 2013).

I assumed that addiction treatment is useful in increasing abstinence rates and therefore lowering recidivism rates. The theory is that an inverse relationship exists between patient WTs and successful completion in outpatient substance abuse treatment facilities in The U.S. during the time period 2006—2011. Haug and Schaub (2016) wanted to identify if treatment outcomes in outpatient alcohol abuse treatment had impact on drinking behaviors 12-months after treatment ended. Haug and Schaub showed “treatment retention was a significant predictor of a positive treatment outcome...with 64.5% of clients with regular discharge and 48.2% of clients with irregular discharge showing nonproblem drinking at the 12 month follow-up” (p. 6). Haug and Schaub identified one predictor of treatment retention was clients in the older age groups had higher rates of retention. Both Kopak et al. (2016) and Haug and Schaub (2016) identified that an indicator of arrest after completing treatment is not maintaining abstinence. Both of these studies support that when clients complete treatment, they have a better chance of maintaining abstinence for longer periods of time over clients who do not complete treatment.

When looking at options for sustained lowered recidivism rates of DWI offenders, formal treatment continues to be a most effective. Timko et al. (2000) compared longterm outcomes of clients suffering from alcohol use disorders. Clients were grouped by types of treatment engagement. The groups included those who received some type of formal

treatment, those who attended Alcoholics Anonymous (AA), those who attended both as well as those who did not engage in either treatment or self-help. Data was collected by Timko et al. (2000) over an 8 year time period and consisted of a sample of 466 participants. “These four groups were comparable in terms of demographic characteristics” (Timko et al., 2000, p. 531). The researchers used a quantitative research design of logistic regression analysis for dichotomous outcomes and analysis of covariance for continuous outcomes. The first noted result was the difference between participants who received some form of help, either formal treatment or informal self-help. Timko et al. stated, “Although untreated and helped individuals were equivalent on abstinence at baseline, helped individuals were more likely to be abstinent at 1 year... and 8 years” (p. 533). This data collection time period differed from Haug and Schaub (2016) who did not collect data post 12 months after treatment was over. Timko et al. identified that after a time period of 8 years, participants who received formal treatment (i.e., outpatient, inpatient or detox) were significantly more likely to be abstinent from alcohol use compared to participants who did not. Kopak et al. (2016) found not maintaining abstinence was a strong marker for DWI recidivism. By completing treatment, clients had a better chance of abstaining from alcohol for longer periods of time and, therefore, reduce their chances of recidivism.

A limit of this naturalistic, self-selection design study is it did not use a randomized clinical trial (Timko et al., 2000). While these findings hold strong internal validity, they cannot be generalized to individuals who drink alcohol and do not recognize their alcohol consumption as an issue. This limitation is similar in Haug and

Schaub's (2016) research as both of these findings are difficult to generalize to larger populations. Another limit that is similar among Timko et al., (2000) and Haug and Schaub (2016) is the data they collected was reported to them by the patients themselves. While this is a trusted way to collect data, one must be wary about the possible alternative motives behind the patients reporting their addiction relapse rates. Clients who have current legal concerns do not want to share their relapse information as it may violate legal conditions. When working with offenders of DWI crime, there is no way to ensure they will characterize themselves with an alcohol problem. While these results make the connection between formal treatment and abstinence stronger, they also further the need to focus on DWI offenders to better identify methods of increasing abstinence with this specific population. This dissertation's research uses data collected through the treatment agencies and therefore eliminating self-reporting issues.

To further the connection between formal treatment and abstinence, Moos and Moos (2005) investigated if attending AA self-help meetings and/or participating in formal treatment within the first year after first seeking treatment would be a predictor of stable remission.. Participants who were engaged in both self-help and formal treatment reported stable remission of 42.4% (Moos & Moos, 2005). Clients who did not receive formal treatment and or AA were less likely to be stable from their alcohol dependency issues over clients who did (Moos & Moos, 2005, p. 344). These findings further supported Timko et al.'s (2000) findings that clients who received some type of treatment had greater rates of abstinence in future time periods. Moos and Moos found that stable remission was predicted by factors of less frequent consumption of alcohol and fewer

problems associated with their drinking patterns. Timko et al. identified abstinence as no intoxication or drinking of alcohol, where Moos and Moos asked their clients how their frequency of drinking had changed. Moos and Moos (2005) also identified that stable remission was associated with higher education, stronger and larger social networks, and a higher number of social resources. Haug and Schaub (2016) identified that predictors of treatment retention included clients who had scored higher in overall life satisfaction. A person who has a higher education, strong social circle, and a higher number of social resources may score higher in his or her overall life satisfaction.

Moos and Moos' (2005) research included limitations to their approach which included the use of a naturalistic study. The participants voluntarily chose to engage in treatment and/or AA. Moos and Moos identified future researchers to investigate why clients, who understand that they have a diagnosable alcohol dependence issue and begin the process of accessing treatment, do not receive treatment in a timely fashion. This need for further research directly opens the door to the gap in literature and created a need for the research in my dissertation.

These same researchers, Moos and Moos (2006) conducted similar research the following year using previously collected data by Finney and Moos in 1995. Moos and Moos (2006) compared untreated individuals clients who were in treatment to identify if "the duration of participation in professional treatment" had impact on treatment (p. 735). This differed from Moos and Moos's (2005) research by focusing on how long the participants remained engaged in treatment rather than on their periods of abstinence. Moos and Moos (2006) filled a gap in the existing literature. Moos and Moos (2006)

classified clients having an alcohol use disorder by exhibiting dependency symptoms, drinking to the extent of intoxication within the past month, or having the perception that their alcohol use was a significant problem. By controlling for covariates such as gender and marital status, Moos and Moos (2006) identified a “duration of participation in AA in year 1 and years 2 and was independently related to a higher likelihood of 16-year abstinence...and a lower likelihood of 16-year drinking problems” (p. 743). Moos and Moos’s (2006) research had stronger validity than the research conducted by Moos and Moos (2005) because of these controls. Moos and Moos (2006) identified a “significant independent association between 1-year duration of treatment...groups and 16-year outcomes” (p. 742). Participants who received 27 weeks or more of formal alcohol dependency treatment during the first year of the study were significantly more likely to be abstinent and report less problems associated with drinking patterns at the follow up survey at year 16. The patients who engaged in longer extended time periods in treatment of 2 and 3 additional years had a higher chance of 16-year abstinence (Moos & Moos, 2006). Timko et al. (2000) outlined the importance that formal treatment plays in increasing abstinence and identified “individuals who obtain help for a drinking problem, especially relatively quick, do somewhat better on drinking outcomes over 8 years than those who do not receive help” (p. 529). This increase in abstinence lowers recidivism rates of individuals with alcohol dependence.

Blonigen, Timko, Moos, and Moos (2009) investigated the relationship between alcohol use disorders and impulsive personality traits. Due to the high prevalence of “risk taking, poor self-control and lack of planning and forethought” it was thought that

impulsivity and legal problems caused by alcohol abuse were connected (Blonigen et al., 2009, p. 714). These symptoms and behaviors encourage DWI offences to occur. The study consisted of 628 alcohol dependent participants who lacked previous alcohol abuse treatment. Having an alcohol dependency issue was determined by symptoms of drinking to the point of intoxication within the past month or who had the insight that they had a significant alcohol drinking problem. The participant pool consisted of 52.9% males and 47.1% females. More than half of all participants (59.6%) identified as unemployed (Blonigen et al., 2009). The research requirements followed suit with Timko et al.'s (2000) original work because the participant pool had no prior treatment episodes. By continuing with this approach in 2009, Blonigen et al. (2009) created a stronger study that continued to support Timko et al. (2000) findings. The assessment of the participants occurred at 1 year and 16 year follow up time increments. The assessments were telephone inventory surveys. The survey included questions about how many times they experienced legal issues in the past 6 months, as associated with their drinking patterns (Blonigen et al., 2009). The survey also included questions asking if they participated in any type of AA or professional treatment for their drinking related problems within the past 6 months. Blonigen et al. (2009) examined impulsivity but Timko et al. (2000), Moos and Moos (2005), and Moos and Moos (2006) did not. Blonigen et al. (2009) incorporated impulsivity into the research because George et al. (2012) explained impulsivity, and the inability to control a person's alcohol consumption, is a part of the disease of addiction. No significant impact on participants who sought professional addiction treatment from baseline to year 1 follow up was identified. The 16-year follow-

up discovered neither the duration of AA nor professional treatment was found significantly related to legal issues. Among clients who reported high impulsivity at baseline, Blonigen et al. identified those who had more time of active involvement in AA were associated with less legal problems. Using Blonigen et al., Moos and Moos (2005), and Moos and Moos' (2006) findings, scholars summarized that AA or formal alcohol abuse treatment helps clients have higher rates of lowered drinking patterns as well as lowered impulsivity.

The limitations of Blonigen et al.'s (2009) study included the use of self-reports over the 16-year period and the method by measuring impulsivity. Rather than using a longer and more in depth scale, the effect size for AA in its relation to impulsivity and legal issues is small. The study does not support the findings that formal outpatient treatment had a significant impact in lowering legal involvement issues in our alcohol dependent population. However it does connect lower legal involvement when engaged in longer durations of AA self-help meetings. This can only be identified for research purposes if the client connects to formal treatment and then reports attending self-help. If clients quit before they begin they will never be able to identify which method of treatment is best suited to their individual addiction issues, formal treatment or self-help communities.

Timko, Desai, Blonigen Moos, and Moos (2011) examined the impact abstinence and treatment have on DWI recidivism rates. Timko et al. examined the connection between the frequencies of driving while intoxicated at two different time periods. First at baseline and then after the clients obtained one of two types of alcohol related treatment.

The participants included a total of 628 who had alcohol use issues but had not received treatment. At 1, 3 and 16-years post entering the study, each participant was asked to complete a phone survey which was identical to the survey they completed as baseline (Timko et al., 2011). Timko et al. asked how often the clients drank alcohol in the past 6 months, if he or she had any driving issues related to drinking alcohol, if he or she obtained any type of alcohol abuse treatment and if so, what type was obtained and for how long. The researchers used a logistic regression analysis to identify if a relationship between alcohol dependency treatment and alcohol related driving issues existed. Timko et al. found 22% of the participants reported having DWI occurrences once or twice in the past 6 months, 38% reported engaging in DWI behavior often in the past 6 months, and 40% reported they had no DWI occurrences at all in the past 6 months. After the surveys were collected at the 1-year mark, Timko et al. stated “a longer duration of outpatient treatment during year 1 was associated with a lower likelihood of DWI at the 1-year follow-up” (p. 178). This coincides with the Moos and Moos (2006) who stated the benefits of 1, 2, and 3-year’s duration of engagement in AA are “independently related to a higher likelihood of 16-year abstinence...and a lower likelihood of 16-year drinking problems” (p. 743). The likelihood of a DWI at the 16 years mark was lowered when a longer duration of AA engagement was combined with outpatient treatment (Timko et al., 2011).

The findings continue to support the importance abstinence plays in lowering recidivism rates with DWI offenders. Although not all research supports that formal addiction treatment is necessary to increase abstinence, there is a connection between

alcohol addiction help and increased abstinence from alcohol. In this study, I further explored how waiting to receive treatment impacts successful completion rates.

Theory of Patient Waiting Based on Queuing Theory

The theory of patient WTs as associated with the queuing theory, served as the support for the research hypotheses. The theory of patient WT, as associated with queuing theory, is rooted in the original Markovian queuing model (Bhattacharjee & Ray, 2014). Bhattacharjee and Ray (2014) stated the original Markovian queuing model was a structured mathematical model that includes “time-related measures, congestion measures, measures of idle time, and utilization of the servers” (p. 302). The queuing theory, in terms of patient satisfaction, is less controlled but focuses on the same basic principles.

The development of the queuing theory was in response to the amount of time dissatisfied consumers waited for goods. Clients who waited longer than he or she deemed appropriate to engage in their desired product or activity generated the dissatisfaction. Suitable WTs can be different when speaking to different clients obtaining the same service. It is the service provider’s responsibility to identify a reasonable and appropriate WT and then make the clients aware of this waiting period. When medical facilities use the patient waiting theory they can develop a maximum waiting guarantee to educate their clients on the amount of time they should expect to wait to receive treatment (Kozlowski & Worthington, 2015).

Different fields use the queuing theory because it can be put into effect anywhere people wait in lines. I focused on the use of queuing theory in the medical realm of

receiving counseling services. Healthcare fields have used queuing theory models since the 1950s to analyze best practices in patient organization and scheduling (Bhattacharjee & Ray, 2014). Brahma (2013) stated, “queuing theory is the formal study of waiting in line” in an organized and designed way which maximizes consumer satisfaction (p. 83). The queuing theory, in the patient flow network, is broken down into four phases. The phases include the first arrival or contact, the physical WT period, the treatment or service that is given to the client, and the exit. Patient flow is the term which describes the physical movement of a client through the entire process (Bhattacharjee & Ray, 2014). Parts of this system include allocating resources, scheduling of staff, appointment scheduling, and making necessary changes to ensure proper queuing (Bhattacharjee & Ray, 2014).

The queuing theories four phases of patient flow are important to the framework of my research. It supports the overall research hypothesis and guides the literature review. The first phase is the arrival or initial contact. The arrival or initial contact is when he or she first steps into the hospital or first calls the medical facility to schedule an appointment. This occurred when the DWI offenders initially reached out to their court-mandated outpatient treatment facility. By reaching out and placing that phone call he or she have stepped into the queuing system for outpatient substance abuse treatment. The second phase is the physical wait which was after the DWI court-mandated offender set up their first appointment and waited to attend. The first two phases created the independent variable (IV). The third and fourth phase of how the offenders left treatment, i.e. success treatment completion or not, was the dependent variable (DV).

The queuing theory requires the satisfaction of three major assumptions. Assumption one is client flow is unidirectional and all patients move from one service to the next in the same direction (Wiler, Bolandifar, Griffey, Piorier, & Olsen, 2013). It includes the assumptions that there are no delays between the times the client enters the queuing system to the time they are seen. The second assumption is patients arriving for services are unpredictable and still manageable. Wiler et al. (2013) stated the third and final assumption necessary for a working queuing theory is that “the arrival rate of the system is stationary and constant over time” (p. 944). The assumptions are necessary to ensure all queuing systems in practice hold the same values and are able to obtain similar results.

Wiler et al. (2013) commented that while their research presented a queuing theory which helped to create shorter patient WTs, additional research is needed to validate this queuing model in other facilities. In a time where ambulatory outpatient medical facilities are the largest and fastest growing method to deliver medical services, Michel et al. (2013) stated “a strong inverse relationship between patient satisfaction and WTs in ambulatory care settings has been demonstrated” (p. 50). Treatment facilities and courts may gain insight on the role patient WT’s play by assessing their on DWI court-mandated alcohol abusing clients who are prone to high recidivism rates, (DeMichele & Lowe, 2011).

WTs are crucial in the medical field and hold importance in substance abuse treatment. Hoffman, Quanbeck et al. (2011) state by collecting data on WTs, facilities are able to “think critically about their recruitment and engagement strategies for improving

WT and no-show rates” (p. 263). By using the collected data to identify issues that arise because of WTs, facilities can be informed and work proactively to create change propelled by statistics and hard evidence. (Hoffman, Quanbeck et al. (2011) stated “measuring the point in time at which a client first makes contact with a treatment agency is important for monitoring WT to treatment” (p. 264). This is important to make an effort to lowering WTs.

Worthington (2009) identified customers who wait longer than expected are prone to balking or reneging. Baulking is when a client does not join a queue but wanders around looking for a possible way to enter the queue with a shorter WT (Ameh et al., 2013). Clients do this in outpatient treatment when he or she calls to make an appointment and receives a longer than expected time frame before their first scheduled session. He or she may call multiple other outpatient facilities and never actually commit to an appointment. He or she may never commit because they feel all of the WTs are too long. The waiting situation creates an unhappy client. Reneging is when a client makes multiple appointments and ends up leaving and not engaging in the service altogether because he or she are dissatisfied with the WT they are experiencing. If a client balks but completes the wait and starts their requested court-mandated treatment, they now have a negative outlook on the treatment process because of the dissatisfaction from the WT. The importance of a functional queue in a medical field is to lower the rates of clients balking or reneging and to maximize the engagement in treatment. This can help to maintain a high level of satisfaction from the start. Another behavior clients demonstrate when he or she wait longer than expected is jockeying. Jockeying is when a

client moves from one queue to the next in an attempt to find a shorter wait (Ameh et al., 2013). This would present itself when a client makes multiple appointments with different facilities and cancels them thinking the wait at another facility will be shorter.

Longer than expected WTs can be a result of the medical facility or fault of the consumer. Kozlowski and Worthington (2015) report situations created by the facility that make longer than expected WT include matching clients with incorrect staff, previous appointments running late, overbooking, and not having enough time slots for patients (Kozlowski & Worthington, 2015). WTs are extended by fault of the consumer because they reschedule due to personal time conflict or the client is late to the initial appointment and the facility needs to reschedule because of time constraints (Ameh et al., 2013).

Kozlowski and Worthington (2015) stated because “shorter WT usually result in higher degrees of patient and citizen satisfaction, considerable funds have been invested in their reduction over the years” (p. 331). Time a patient waits to be seen by a doctor is critical to the patient’s health and it is important to the image of the medical facility (Ameh et al., 2013). Ameh et al. surveyed the level of satisfaction medical patients expressed after waiting for various time periods for services. A cross sectional descriptive survey was taken by 210 patients who attended the Ahmadu Bello University Teaching Hospital outpatient medical clinic. WTs started at the time he or she entered the facility and went until the time their doctor saw them. This follows the waiting period researchers Hoffman, Quanbeck et al. (2011) identified as when the patient first makes contact and extends to when the patient begins treatment or is physically seen by the service provider.

Ameh et al. (2013) revealed majority of clients identified themselves as satisfied with the practice at the facility. The study also identified the amount of time spent in the queue prior to seeing the doctor significantly affects the patient's satisfaction (Ameh et al., 2013). Patients who spent one hour or less in the queue before being seen by a doctor identified higher satisfaction with the hospital's services over patients who were in the queue one hour or more. The longer amount of time a patient waits to receive services, the greater chance of dissatisfaction continues to support the patient waiting theory.

The queuing theory corresponds with the patient satisfaction model by suggesting a linear path with a specific WT should exist for clients as they move through a mental health treatment program (Schraeder & Reid, 2015). Westin, Barksdale, and Stephan (2013) discovered that longer WT can cause clients' medical issues to worsen and may reduce a client's motivation for receiving services. Schraeder and Reid's (2015) study consisted of follow up interviews at 6 and 12 months after 273 families initially made contact to set up mental health care services for his or her children. The researchers first collected an initial baseline data set. When the final data was gathered at month 12, almost half of the families (46%) had contacted a second treatment facility because of the longer than anticipated WTs. This is the jockeying and renegeing that Kozlowski and Worthington (2009) identified. I focused on clients encountering longer than expected WTs and not completing treatment because of renegeing and leaving.

The reasons for contacting additional treatment providers, as reported by the parents, included lengthy WTs which could have negative consequences for the children's mental health (Schraeder & Reid, 2015). Positive implications for this research

include supporting treatment facilities in developing a queueing system to prevent baulking or renegeing (Schraeder & Reid, 2015). The emotional distress connected to having to wait longer than anticipated for mental health treatment to begin may have further impact on treatment completion in terms of motivation.

Motivation

Motivation focuses on a predetermined goal and can be influenced by internal and external factors. Internal factors include a desire for a certain outcome, the value they personally place in that goal, and the influence the expected outcome may have on their lives. External factors that influence a person's motivation include pressure from other people, time constraints, and physical issues which can decelerate a person's momentum towards a goal.

Wolfe, Kay-Lambkin, Bowman and Childs (2013) stated counselors identify motivation as a crucial piece of treatment because "it is well established that motivated clients have significantly better treatment outcomes than those individuals who are not motivated to engage in therapy" (p. 2188). When clients try to engage in substance abuse treatment voluntarily their motivation is considered high. Treatment initiation shows dedication to the goal of abstinence. Clients who have a stronger motivated connection to his or her treatment are more apt to report higher degrees of satisfaction with their treatment as well as end with better therapeutic results (Melnick, De Leon, Kressel, & Wexler, 2001). Clients who are court-mandated to complete substance abuse treatment because of DWI arrests might be internally motivated to achieve abstinence, but at the least, are externally motivated by their legal obligations.

Wolfe et al. (2013) used 166 new and continuing substance abuse clients who were attending Central Coast Drug and Alcohol Clinical Service in New South Wales, Australia for their study. Wolfe et al. identified clients who scored higher on the Treatment Motivation Questionnaire for internal motivation were more responsive and sustained a more positive relationship with their therapist and treatment. Melnick et al. (2001) identified when clients have motivation for treatment they are going to build a stronger connection and engage better. Clients who are internally motivated for substance abuse treatment are more responsive to group sharing and creating a therapeutic relationship with his or her counselor (Wolfe et al., 2013). If WT's create dissatisfaction with a client, the client may be more dissatisfied with their treatment in general which could result in lower motivation for treatment completion. If a patient experiences dissatisfaction with any aspect of his or her initial processing procedure they are at risk of balking or reneging (Kozlowski & Worthington, 2009).

The limitations included the use of a of real-world community based drug and alcohol treatment facility sample, which resulted in a small number of participants. Clinicians who submitted clinical information may have been biased in which participants they selected for inclusion, which is another limitation. Wolfe et al. (2013) stated “given the proportion of the clients in the sample referred by DoCS and probation and parole, it may be that clients intentionally under-reported their AOD (alcohol or drug) use for fear of negative consequences from these organizations” (p. 2194). A similar limitation was identified with Timko et al. (2000) and Haug and Schaub's (2016) research about the possibility of untrustworthy data. Clients might not want to report

continued alcohol usage because of possible legal issues. This is a commonly identified limitation because legal issues are strongly connected to alcohol dependency. The current research did not use voluntarily collected responses, rather, it used data previously collected by the alcohol abuse treatment agencies themselves. The approach bypassed any possibly incorrectly reported data due to false information given by clients who may be facing further legal consequences.

While motivation is an important factor in the predictive aspect of treatment entry and shortened treatment waiting periods, some studies found no significant correlation between high levels of motivation and successful treatment completion. Gryczynski, Schwartz, O'Grady, and Jaffe (2009) used a logistic regression analysis on 120 participants from a larger parent study to examine this connection. The hypothesis of motivation was neither a significant predictor of readiness for treatment nor a predictor of treatment entry.

Limitations included use of a relatively small sample of participants who had racial and socioeconomic homogeneity and should not be generalized to other treatment systems. This is a common limitation when using participants from a community-based population for alcohol and drug treatment (Wolfe et al., 2013). By collecting data in one facility, or multiple facilities in the same geographic area, the population sample has strong potential for homogenous qualities. Wolfe et al.'s limitations supports using a random sampling for the entire U.S. population. The research can be generalized to smaller geographical populations.

Zhang, Friedmann, and Gerstein (2003) did not recognize a significant impact when researching client's motivation levels and engagement in treatment episodes. The sample consisted of 4,005 clients who participated in 62 different substance abuse treatment programs. Data collection about motivation levels was in the form of questions asked on a scale of 1, being not at all important and 3 being very important. The items were used to measure the levels of motivation each client had towards completing treatment. No significant correlation was found between these motivation variables and drug abstinence improvement. While this study does contradict the findings of Wolfe et al. (2013), Zhang et al. identified a positive relationship between treatment duration and drug use outcomes in outpatient nonmethadone clients. The positive relationship continued to support the hypothesis that the amount of time a DWI patient waits to begin alcohol abuse treatment negatively impacts completion.

Reasons for Wait Times

Recognizing why WTs exist is important in understanding how WTs impact treatment completion. Scheduling barriers and client issues can create or exacerbate patient WTs. Scheduling barriers are issues resulting from the treatment agency. These scheduling barriers include having to call clients back to schedule their appointment because of high call volume or accepting too many clients for initial assessments at once (Quanbeck et al., 2013). When Quanbeck et al. (2013) called the treatment clinics to inquire about the clinics' first available appointment for an assessment "nearly half the time (47%), a patient's first phone call is met by voicemail leaving the patient waiting for a return call" (p. 344). Quanbeck et al. called 192 treatment facilities. Having to call the

client back to schedule an appointment only adds time to the clients wait. Facilities overbook their staff because of the limited resource of counselors in the field of substance abuse (Hoffman, Ford et al., 2011). Although this overbooking happens, counselors often wait for clients who never arrive (Hoffman, Ford et al., 2011). This creates longer WTs because now the client, who did not show up to their initially given appointment, has to reschedule. Gallagher (2011) conducted a survey of ways to improve patient WTs in college counseling facilities and identified multiple issues that create WTs. Issues included low staffing during busy times of day, having to see individual clients too often, not moving clients into group counseling soon enough, and automatically generating clients weekly appointments (as cited in Blau et al., 2015). These are issues all types of counseling facilities encounter that create WTs for patients.

Clients are at fault for WTs because of missing appointments, not showing up at all, or calling to reschedule for personal reasons. These reasons all create longer WTs to treatment entry. The treatment agency has no control over clients calling to reschedule or not showing up. Perhaps if the WTs were initially shorter the clients would not reschedule or ‘forget’ their appointment and miss it. Albrecht et al. (2011) identified motivation can play a part in increasing patient WTs and stated “Pregnant women who wait for treatment may lose their original motivation for change and consequently be less likely to remain in treatment” (p. 72). Clients WTs can impact their motivation and vice versa. While the facilities have no control over the patient creating their own longer WTs, they can work towards focusing on lowering the times based on scheduling.

Impact of Patient Wait Times on Treatment Outcomes

Counseling with Students

Patient WT has been researched in other counseling and medical fields. DiMino and Blau (2012) used a sample of 411 undergraduate students to identify if patient WTs impact student populations involved in counseling. These participants registered to receive counseling resources at a large urban based campus located in the northeastern part of the U.S. These students were labeled as in need of nonurgent counseling after their participation in an assessment interview. The number of days waiting ranged from 1—35 for these nonurgent counseling requested students. DiMino and Blau (2012) found a positive significant correlation between patient WTs and the no show rate for scheduled intake appointments.

Three years later Blau and DiMino worked with a larger team to continue their work on the impact WTs have on counseling in an undergraduate population. Blau et al. (2015) completed an exploration of the impact patient WTs have on the undergraduate students' stigma and attitude towards the colleges counseling department. Blau et al. separated a sample of 99 undergraduate students into two groups based on if they waited up to two weeks or more than two weeks. The results suggest longer WTs for student clients may have implications beyond whether a student shows up to begin counseling treatment (Blau et al., 2015).

DiMino and Blau's (2012) results suggested a weaker connection to counseling treatment the longer the wait. This can impact the student from attending their initial scheduled intake appointment. Alternative reasons include that the participants were

grouped as having nonurgent symptoms and he or she began to recover from their initial issues on their own (DiMino & Blau, 2012). The implications of Blau et al. (2015) findings agreed with DiMino and Blau (2012) with students who waited longer were less likely to recommend the counseling department to other students. This directly impacts other student's likelihood of connecting to counseling. Blau et al. (2015) stated "students who receive a faster response...may perceive stronger customer service which has a positive impact on their perceptions of the university" (p. 287). Blau et al.'s findings can be connected to a student's motivation for counseling engagement.

Using a simple design of one independent and one dependent variable is a limitation of the DiMino and Blau's (2012) study. The positive correlation may have been influenced by the larger sample size. Blau et al. (2015) had an opposite limitation in the research design had a smaller number of students in the two comparison groups and used a restricted number of variables. Another limitation of the DiMino and Blau (2012) findings is they did not further investigate the reasons why students did not attend their intake sessions (DiMino & Blau, 2012). Implications for further research on this topic included separating genders because it is thought female have a more confident view of counseling (DiMino & Blau, 2012). The findings of DiMino and Blau support my hypothesis and motivated the dissertation to specifically identify differences in genders regarding their WTs. The outcome of the Blau et al.'s (2015) research influenced the dissertation by maintaining stronger retention rates with the students. The retention rates may gain strength with shorter patient WTs. The research identified this by distinguishing if patient WTs impact the DWI client's successful completion from treatment.

Relationship Counseling

Hicks and Hickman (1994) investigated relationship counseling by identifying the “impact of short v. long time-delays between initial referral and first appointment for relationship counseling” (p. 2). Hicks and Hickmans small population study focused on how the amount of time between initial referral to the counseling facility and the first appointment impacted attendance rate. The research used a retrospective study of 60 participants referred for marital counseling. Half of the couples were given their first appointment time slot within two weeks of the time they contacted the facility and the other half obtained an appointment between four and twelve weeks out (Hicks & Hickman, 1994). The results stated clients who offered an earlier intake appointment were significantly more likely to attend (Hicks & Hickman, 1994). Schraeder and Reid’s (2015) findings agree because offering longer WTs provide patients reasons to leave. If earlier appointments are offered to patients they will have less time for their symptoms to worsen. Schraeder and Reid identified when patients wait their symptoms can get worse and they begin to renege and find a new facility that will see them sooner. This only causes longer WTs as the patients are jumping queues. Jockeying creates longer patient WTs as he or she are now starting from the beginning again with another initial contact with a new facility.

Hicks and Hickman’s (1994) findings coincided with DiMino and Blau’s (2012). According to Hick and Hickman (1994) if patients wait longer than expected he or she are less likely to attend the first appointment. DiMino and Blau (2012) identified a similar result that when a patients waits, the connection he or she have with the counselor

is weakened. This can hinder his or her motivation for treatment and chances of returning to attend future sessions.

The limitations included Hicks and Hickman (1994) using a small scale population and because of this the findings must be reflected upon with caution. The dated research is important to the current dissertation because of its discovered impact of WTs. While Hicks and Hickman give a strong background on the impact of WTs on clients attending their first appointment, the further implications on the client's rate of completion should also be identified. These findings opened the door for my dissertations study.

Emergency Departments

Any situation where clients are waiting to obtain a service can use the patient flow theory. Wiler et al. (2013) researched if the queuing theory predicts patients leaving without being seen (LWBS) in an emergency department setting. The identification is important to the urgent care situations which take place in an emergency department. Pascoe, Rush and Rotondi (2013) stated "wait lists are associated with negative health and social consequences for clients" and if these consequences are occurring in an emergency department, the hospital could be seeing higher negative outcomes (p. 485). It is common for clients who wait longer for his or her desired treatment to have higher rates of LWBS (Wiler et al., 2013). Emergency department patients who leave without being seen by a physician have greater health consequences. The study applied retrospectively collected data from all patients who were present at a triage in an urban, adult only emergency department in 2008 (Wiler et al., 2013). Wiler et al. used all 87,705

visits to create the data set. Patients were time stamped for the following periods; “1) patient arrival time; 2) Emergency Severity Index triage acuity score; 3) ED placement time; 4) patient time to LWBS...5) total treatment time....6) ED boarding time” (p. 940). A patient was marked LWBS when they were called three times for bed placement but did not respond. After the third attempt it was assumed the client LWBS. Wiler et al. used a Weibull probability distribution to illustrate the patient WT tolerance and discovered a 10% increase of patient checking in for treatment per hour, while 10.74% patients LWBS . Wiler et al. (2013) commented that as more patients arrive per hour, it is not surprising the queue grows larger which results in longer WTs for patients.

Improving treatment service time is expected to have a significant impact on patients that LWBS (Wiler et al., 2013). This was the reason behind the queuing theory as framework for Wiler et al.’s research and created a model based on their findings. Wiler et al. stated this “model predicts a decrease of current LWBS rates from over 3.9% to 1.4% with a reduction of 30 minutes in average service time” (p. 944). These findings connect to Melnick et al.’s (2001) research that reported clients with higher levels of satisfaction with their treatment have better results. Working to improve these patient WTs may have drastic effects on patients who would have otherwise LWBS (Wiler et al., 2013). Gryczynski et al. (2009) supported this by stating motivation plays a role in predicting improved retention for drug abuse treatment. These findings have strong implications on the current research proposal. Clients who LWBS are going to have a low or nonexistent successful completion rate.

Wiler et al. (2013) identified multiple limitations in the study. The first was the emergency department only used the observatory unit for bed placement. This is a limitation because emergency departments commonly hallway beds to place patients. In a queueing theory model there are an infinite number of space to queue patients. Wiler et al. used a research model which operated a fixed queue with its capacity being its waiting room. The study provides support of the patient WT theory and how it may manifest itself in the court-mandated DWI population in spite of its limitations.

Ambulatory Patient Settings

Patients not only wait for their treatment in emergency department settings but they also wait in ambulatory outpatient care settings. Health care provided in an ambulatory outpatient facility is the most often used process in the American health care system (Schappert & Rechsteiner, 2008). The ambulatory outpatient care setting in Schappert and Rechsteiner's (2008) study is similar in nature to the dissertations research treatment level of care. Research conducted by Michael, Schaffer, Egan, Little, and Pritchard (2013) identified a "strong inverse relationship between patient satisfaction and WTs in ambulatory care settings has been demonstrated" (p. 50). Timeliness in patient care settings had not previously been studied in depth. The researchers evaluated time between when a client entered the waiting room to the time they were escorted into an exam room. This differs from Hoffman, Quanbeck et al. (2011) definition of patient WTs. Hoffman, Quanbeck et al. (2011) describe the waiting period to be when a client initially makes contact with a treatment facility to the time they begin treatment. Researcher Rajczi (2016) explained how the US health system has no national claim to

patient WTs and that “there are several ways to measure WTs” and these must be identified when comparing research in this field (p. 632).

Michael et al. (2013) used a patient satisfaction instrument which was a 29 item survey consisting of open ended questions, a summary question, and Likert scale questions. The items focused on three aspects of patient satisfaction: if the time spent in the waiting room satisfied the patient, the level of likelihood that this patient would refer their friends to the facility based on their level of satisfaction, and the patient satisfaction of the WT spent in the exam room prior to the doctor entering (Michael et al., 2013). The study included a final sample population of 349 patients who were seen in a specific adult patient care unit. Michael et al. identified reasons for dissatisfied patients included “waiting room WTs, exam room WTs, turnaround time for return of phone calls, and time spent waiting for laboratory testing and results” (p. 55). These responses accounted for half of all fair to poor ratings of the ambulatory outpatient facility. Michael et al. found a decrease in inpatient WTs in the waiting room of the ambulatory outpatient facility has potential to increase patient satisfaction (Michael et al., 2013). This further supports the current hypothesis.

Limitations included a convenience sample of patients as well as the use of a pre experimental pretest posttest design. Michael et al. (2013) noted replication of these findings will help strengthen the evidence for facilities to use them in their practice to strive for higher patient satisfaction and higher treatment completion success rates.

Counseling for Gambling

Gambling has its own place in the DSM-V with diagnosable criteria similar to those required for alcohol addiction (APA, 2013). Gambling is included in this literature review as an additional treatment situation where patient WTs impact completion and is similar to emergency department and ambulatory patient care. Identifying how WTs impact the gambling addiction population can support the impact that WT have on clients suffering from alcohol addiction. When clients call to schedule their first assessment appointment for gambling addiction they are given a future day and time which is where the WTs begin. Pascoe et al. (2013) conducted a study describing the definitions of WTs and the different processes for intake that are used by drug and gambling treatment facilities in Ontario, Canada. The study consisted of surveys completed by 139 different publicly funded substance use and gambling treatment agencies from June to August 2011 (Pascoe et al., 2013). This is similar to my dissertation as the data will be coming from federally funded treatment facilities, not private agencies.

Pascoe et al. (2013) based the research in the theoretical framework of longer WTs correlating with lower rates of treatment result and retention. The framework of patient WTs was used and verified when DiMino and Blau (2012) found the longer a patient waits the less of a connection they feel with the treatment program. This directly influences the client's rate of attending their first or next scheduled treatment appointment. The same theoretical framework, theory of patient WTs based on the queuing theory, is being used as background for my dissertation. Pascoe et al. (2013) identified long WTs are connected to negative social and health consequences for clients.

The findings concluded that 65% of the facilities maintained an active wait list for their clients and 59% of these facilities reported in the last five years their number of clients on their wait list had increased 25% (Pascoe et al., 2013). The survey also recognized that certain populations of clients were recognized as priority. Pascoe et al. (2013) stated these groups “included those at risk of harming themselves...pregnant women...people with personal safety issues...or serious mental health problems...homeless individuals...and those with concurrent disorders” (p. 490). Clients referred by probation and a legal entities were also identified as a priority group, which connects to the current research’s population.

Pascoe et al. (2013) identified the average WT for a priority client, from the time they contacted the facility to the time they completed the assessment, was two to four weeks in length. These WTs varied based on the type of treatment facility. In an emergency department setting the average WT varied by time of day and number of hours (Wiler et al., 2013). Hicks and Hickman’s (1994) study which involved relationship counseling found average WTs to be anywhere from four to twelve weeks for their first scheduled appointment. The treatment type and facility must be taken into consideration when contrasting studies in patient WTs field.

When focusing on gambling treatment facilities, Pascoe et al. (2013) reported “across all agencies, respondents indicated that 19% of clients left intake before receiving assessment” (p. 492). When the responding facilities asked the clients why he or she left without completing their assessment, the reasons included relapse, life circumstances changed, lack of motivation for change, and long WTs.

The agencies had no way to identify if a client was wait listed at a different facility and was a limitation. This could influence the client to drop off from the first facility but receive treatment at a different facility (Pascoe et al., 2013). Another limitation was the inclusion of publically funded facilities which ranged in offered programs. The survey did not instruct the facilities to include all programs or types of counseling they offer. The study only consisted of agencies who chose to complete the survey which meant they had time and the resources to do so (Pascoe et al., 2013). Agencies who did not complete the survey may have had limited time because of a lack of resources which could create longer WTs for these facilities. The facilities with longer WTs might not be represented due to the voluntary survey nature of the study. The restriction mirrors a major limitation in the findings identified by Quanbeck et al. (2013). While 197 completed the survey out of the 201 who were asked, these missing four clinics might have not had the time to respond due to long WTs. Facilities who are overburdened with high client numbers, which could result in higher WTs, would not have found completing the questionnaire to be a priority. The findings identified by Pascoe et al. (2013) further support the patient wait theory. Pascoe et al.'s study only included a very small number of court referred clients which opened the door to the gap in literature about DWI populations.

Counseling with Children

Inspecting WT with children in counseling exhausts the literature of how WTs impact different population's medical and mental health treatment completion in different

treatment settings. It creates a well-rounded exploration of WT as they are associated with many forms of emergency department medical and counseling treatment facilities.

Different approaches are taken when counseling children and adolescents because their brains and emotions have not yet fully developed. Previous research discussed and analyzed on adults differs greatly from research on the adolescents.

When working with adolescents, the amount of time the child and their family waits to begin treatment can impact their rate of success. McLennan (2015) addressed the lack of interventions that exist for mental health patients and stated “unlike the structure of some medical and surgical WT goals in which specific interventions are designated...targets for mental illness tend to refer to WTs until contact with the service system, with no specification to accessing specific evidence-based interventions” (p. 55). McLennan (2015) identified reducing WTs for adolescents starting treatment may have positive effects on their long term success rates. A situation that could do more harm than good to the adolescent is if the intervention or treatment was more harmful than beneficial to the client. But this could hold true for any counseling approach (McLennan, 2015). If the treatment plan is going to negatively impact the client, the quicker it is implemented, the quicker the negative consequences will occur. Of course, no treatment plan is put in place with the intention of causing harm but not all counseling techniques work for every individual client.

Substance Abuse Counseling

The research existing on the impact of patient WTs in the substance abuse treatment field is small. Many studies are broad and include treatment for a variety of substances on large diverse populations.

Andrews et al. (2013) spoke to the association of specific characteristics among clients with higher rates of waiting one month or more to begin their addiction treatment. The sample included 2,920 clients who were part of a previously collected data set called National Treatment Improvement Evaluation Study. The data set included information collected from 22 major cities across the country. While Andrews et al. study is a national scope collection, it is not a national representation of the U.S. Andrews et al. used a random sample of a national data set so it has the ability to represent the entire U.S. The study included the covariates age, education, employment status, and used races groups White, African American and Latino. It was found that characteristics associated with high WT included clients being male and having a lower education background. Andrews et al. found insignificant differences between races having to wait less than or more than one month period to begin treatment.

Leigh, Ogborne and Cleland's (1984) was one of the first to conduct research focused on the reasons associated with patients dropping out from outpatient substance abuse treatment. The longer a patient waited had a negative impact on their attendance to future clinical appointments, which support the current hypothesis (Leigh, et al., 1984). Leigh et al. identified a high degree of failing to attend treatment all together was associated with a 14 days or longer WT longer. The study set the initial precedent that

patient WT theory is applicable to substance abuse treatment as well as in hospitals and other medical settings. Wiler et al. (2013) and Pascoe et al., (2013) later identified these same results and continued to support Leigh et al.'s (1984) original findings.

Hoffman, Ford et al. (2011) used Leigh, Ogborne and Cleland's research to support their own review. Hoffman, Ford et al. (2011) conducted a mixed effects logistic regression to identify the affect patient WT had on retention in drug and alcohol treatment programs. The focus of the study was on the WT between the first assessment and the time that formal treatment was scheduled to begin. This differs from Wiler et al. (2013) who used the patient WT starting when the client first entered the hospital to when they were given bed placement. This is not necessarily the time the client was seen by a physician. Hoffman, Ford et al.'s (2011) "findings demonstrated a strong decrement in the probability of completing four sessions of treatment with increasing time between clinical assessment and first treatment session" (p. 643). While the research conducted by Hoffman, Ford et al. focused on a different WT period than I looked at, it supports the idea that the longer a patient waits can cause a decrease in the likelihood of engagement.

Since the evidence shows alcohol abuse treatment increases abstinence rates, researchers are seeking to find variables to increase the likelihood of successful completion from treatment episodes. Carr et al. (2008) investigated the possible relationship between times spent waiting for an assessment and a lowered desire to change. Lowered motivation is connected to lower chances of completing treatment episodes (Wolfe et al., 2013). Carr et al. (2008) was part of an effort to test interventions to try and improve engagement in substance abuse treatment by reducing barriers. The

participants of this study had to first contact a centralized intake unit (CIU) to schedule an intake assessment (Carr et al., 2008). After the clients attended their first assessment, Carr et al. (2008) notified him or her that they “must wait approximately 7 days before they call back to the CIU and receive notice of their actual treatment admissions date” (p. 194). The 604 participant’s statistics were formally documented in September of 2006. The study developed and used the 59-item Barriers to Treatment Inventory (BTI). This inventory was to help identify specific barriers that participants were facing before their treatment episode. The researchers were looking for barriers similar to those later on identified by Quanbeck et al. (2013). The barriers included overcrowding, patients canceling and not enough staff to handle the amount of appointments for new clients.

Carr et al. (2008) identified patient WTs amongst different populations. They identified that clients who were court referred waited longer than others. Carr et al. Identified many clients did not believe they had a problem with substance abuse and many also had a lowered desire for any type of change. Carr et al. discovered longer WT for pre assessments were significantly related to a lower readiness for the client to begin their treatment. This connects to Wolfe et al. (2013) by supporting the idea that there is a strong connection between patient motivation and rates of successful treatment completion. When clients have more time to sit with their own disease they have a higher chance of rationalizing their behaviors (Keane, 2012). This is part of the disease and is important to keep in mind when looking at the legally involved population (Keane, 2012). A common characteristic of the disease of addiction is the drinking leads to “social problems such as failure to fulfill major role obligations, interpersonal conflict,

and legal issues” (American Psychiatric Association, 2000 as cited in Keane, 2012, p. 357).

One limitation of Carr et al.’s (2008) study is if the participants were diagnosed with an alcohol abuse or dependence diagnoses alone, they were not eligible to partake in the data collection. It was required for them to have been diagnosed with addiction to multiple substances to be considered for the study. Another limitation is it only represented a convenience sample collected at one CIU. The CIU’s services were only available for clients who entered treatment through a publically funded entity (Carr et al., 2008). This is a common limitation which was also found in Michael et al.’s (2013) research using a convenience sample of clients from one specific adult treatment unit. Carr et al. (2008) did identify, in their limitations, future research should include a broader range of mix of participants with variables. I focused this dissertation to fill this new gap in literature.

While much of the existing research on patient WTs has been quantitative because of the availability of numeral data, a study completed by Redko et al. (2006) used a qualitative approach. Redko et al.’s qualitative approach used focus groups of participants 18 years of age or older who were diagnosed with a substance abuse disorder. The participants were not suffering from schizophrenia and were referred to some type of substance abuse treatment facility. The sample was 57 participants who previously engaged in a larger study. He or she completed either a personal interview or a focus group in order to obtain the data for the research. Of this participant pool, males made up 66.5% of the participants while females only accounted for 36.5%. Participants

identified as 55.8% White and 42.3% identified as African American. Through the use of qualitative interviews, Redko et al. identified 53.8% of clients reported WT was a significant barrier to them entering treatment. This barrier was identified by numerous negative comments regarding the waiting experience (Redko et al., 2006). The interviews uncovered that several participants reported continuing to use their drug or alcohol substance while he or she were waiting for the initial treatment to begin. With this information discovered, serious social consequences may exist with the population of DWI clients who already have high recidivism rates.

Limitations of Redko et al.'s (2006) study included not using any participants who suffered from only alcohol dependence issues. Another limitation is the data drew from a convenience sample of participants actively involved in another research study at the time. This is similar to the limitation in Carr et al.'s (2008) study because the Redko et al.'s participants also came through a CIU system. This CIU system gives the facilities a chance to triage and identify what the best level of treatment is for each individual client, before creating recommendations. Another limitation of the Redko et al. research is that all of the information was self-reported and not substantiated. This is a common limitation of a qualitative research approach.

As researchers in the field are gaining more knowledge about the impact patient WTs have on client's treatment results, some facilities are now conducting research on how WTs impact the length of a patient's treatment engagement. Stewart, Horgan, Garnick, Ritter, and McLellan (2013) evaluated a performance contract (PC) and its impact on a specific substance abuse treatment facility. The PC quality initiative (QI)

goals included reducing patient WT, reducing patient no show rates, and to increase continuation of care (Stewart et al., 2013). The researchers employed a multilevel linear regression quantitative study analysis using WTs and length of stay (LOS) as dependent variables. Client's demographics were used as IVs. The implementation of the performance contract was found to significantly reduce client WTs by 20 days (Stewart et al., 2013). Stewart et al. also identified the PC had increased the average client's length of stay from 102 days to 116 days, which was a 13% increase. Stewart et al (2013) stated "these findings suggest that the PC resulted in shorter WTs and longer LOS, and the combination of the PC and QI has even more significant effect on both measures" (p. 32).

The analysis was done on a facility in the state of Delaware, which is one of the smallest states in the U.S. (Stewart et al., 2013). It is likely that PC and QI's would work differently in larger populated areas. This limitation supports the random sampling plan that I use in this dissertation. A random sampling approach of the entire U.S. creates a sample that strongly represents the entire U.S. population (Boden, 2018).

Pregnant Substance Abusing Clients

The potential impact WTs have on a client's ability to successfully engage and complete treatment is new and gaining getting attention in the past few years. Pregnant women are viewed as a very unique and high risk population due to the nature or their physical state.

To identify if patient WTs impact pregnant substance abusers, Albrecht et al., (2011) explored if a shorter WT would predict a higher number of successful treatment completions. Albrecht et al. used Redko et al. (2006) as the foundation for their

hypothesis and used the Treatment Episode Data Set- Discharges (TEDS-D) collected by SAMHSA's Office of Applied Studies (OAS) and the USDHHS for the data source. Albrecht et al. conducted a retrospective cohort study on the available data for 10,661 pregnant clients on the day of admission in the year 2006. The population consisted of 56% White and 20% African Americans or Latinas (Albrecht et al., 2011). Researchers separated admission into three categories, ambulatory, residential, and detoxification treatment settings. Albrecht et al. used control variables race, age, criminal justice referral, education, employment, and primary substance of choice. Albrecht et al. then conducted a logistic regression to identify if the IV of days waiting to enter treatment had impact on treatment completion. WT for the pregnant population was a predictor of treatment completion. The demographic factor of a criminal justice referral significantly increased the odds of treatment completion. The highest number of pregnant clients received treatment in an ambulatory care setting (Albrecht et al., 2011). This is also where their immediate entry to treatment showed the strongest correlation (Albrecht et al., 2011). An immediate start for treatment was a significant predictor of successful substance abuse treatment completion. Albrecht et al. discovered methamphetamine was the most commonly used primary substance in the study where Hoffman, Ford et al. (2011) identified alcohol as the most commonly used primary substance of choice. Albrecht et al. (2011) also identified a large portion of their participant pool, 87%, was unemployed or not in the labor force. The large number of unemployed participants is drastically different from Blonigen et al.'s (2009) participant pool which consisted of only half identifying as unemployed. Albrecht et al.'s (2011) findings relate to the current

research by using the same previously collected data to examine the impact of the ambulatory outpatient programs for the criminal justice DWI population.

Limitations included the TEDS-D only containing information from substance abuse facilities receiving public funding (Albrecht et al., 2011). This is the same limitation as expressed in Pascoe et al. (2013). Albrecht et al.'s research recognized data was unavailable from a large percentage (43%) of pregnant women regarding their patient WT's at discharge. This large piece of missing data could potentially have impacted the overall findings. Another limitation included that because SAMHSA is the facility collecting the data, it is possible a client entered and was discharged from treatment more than once. This would challenge the assumption of independence of all samples (Albrecht et al., 2011).

Strengths of Albrecht et al.'s research by using this data set include it was a large national population. This is opposite of the limitation as presented by Stewart et al., (2013) whose data only included agencies in the state of Delaware. The findings were the first to inquire about the impact of WT's on the population of pregnant substance abusers. Efforts are being made to continue to close the gaps of different populations in the literature within the patient WT field. I continue to close this gap in the literature through this dissertation focusing on DWI court referred clients.

Interim Treatment While Waiting

Interim treatment is when the facility offers treatment to the patient after he or she make initial contact but before beginning formally scheduled treatment. This impacted the dissertation because by offering interim treatment at substance abuse clinics, the

clinic is removing the WT period where the patient has no resources for recovery.

Sigmon (2015) examined the possibility that interim treatment would benefit opioid dependent patients while he or she wait for formal treatment to begin. Sigmon chose this topic because it is common for methadone clinics to have long wait lists due to their insufficient funding. Sigmon (2015) conducted a literature review on all randomized trials which previously evaluated the efficacy of offering some type of interim opioid dependence treatment while the patients were awaiting to begin their formal treatment. The literature included four randomized trials that evaluated the impact offering interim treatment has on the treatment outcomes (Sigmon, 2015).

The first study included in this research was conducted originally by Yancovitz, Jarlais, Peyser, Trigg, and Robinson in 1991 (as cited in Sigmon, 2015). The researchers conducting the study did not offer the control group any form of interim treatment. The clients were on a waitlist for one month with urinalysis conducted on a biweekly basis. Interim methadone pharmacological treatment was given to the experimental group (as cited in Sigmon, 2015). Yancovitz et al. identified participants who were part of the interim methadone pharmacological treatment were more likely to test negative for heroin at the one month mark (as cited in Sigmon, 2015). More of the clients who received interim treatment entered formal treatment.

The second study Sigmon (2015) used in the research was data originally analyzed by Krook, Brørs, Dahlberg, Grouff, Magnus, Røysamb and Waal in 2002. This study gave their double blind placebo experimental sample group interim buprenorphine pharmacological treatment for their opioid dependency over a three month waiting period

(as cited in Sigmon, 2015). Krook, Brørs, Dahlberg, Grouff, Magnus, Røysamb and Waal identified that patients testified greater decreases in heroin use when given the pharmacological interim treatment (as cited in Sigmon, 2015). The study also identified the experimental group ended up remaining in formal treatment for longer periods than the group who did not receive any interim treatment (as cited in Sigmon, 2015).

The third study Sigmon (2015) used in the review analysis was originally conducted by Schwartz, Highfield, Jaffe, Brady, Butler, Rouse, Callman, O'Grady, and Battles in 2006. Methadone was the interim pharmacological treatment offered to these opioid dependent patients over a four month wait list period (as cited in Sigmon, 2015). Patients in the control group received no treatment and had no other contact with the treatment facility until their formal treatment began. Schwartz et al., (2006) identified that more participants who engaged in the interim treatment entered formal treatment over the control group (as cited in Sigmon, 2015).

The fourth and final study Sigmon (2015) used in the research was originally conducted by Schwartz, Kelly, O'Grady, Gandhi, and Jaffe in 2011. The study used methadone at the interim treatment for seven visits a week over a four month period for the experimental group (as cited in Sigmon, 2015). Schwartz et al. conducted this study with heroin dependent participants at one of two methadone treatment programs in the Baltimore, Maryland area. Random assignment placed participants in a group which received interim methadone (IM), standard methadone treatment (SM), or restored methadone treatment (RM) (Schwartz et al., 2011). Restored methadone treatment was defined as clients who were referred to an experienced counselor with a smaller caseload.

While all three groups received methadone, the environment in which he or she received methadone differed (Schwartz et al., 2011). All three groups who received interim methadone treatment showed a decrease from their baseline self-reported heroin use. The retention rates after four months were similar for all three groups (as cited in Sigmon, 2015). Sigmon explained how offering interim treatment can be effective in patient retention and reducing opioid usage. When clients are treatment immediately he or she has a higher retention rate which can lead to higher rates of successful treatment completion, which provided evidence to the dissertations study.

Schwartz, Alexandre, Kelly, O'Grady, Gryczynski, and Jaffe (2014) conducted a study on the potential benefits of offering interim methadone treatment to opioid dependent patients. While Schwartz et al., (2014) focused on cost benefit analysis of offering interim treatment, the study also identified patient's beneficial treatment outcomes. Schwartz et al. collected the original data participant pool in 2011 and published different analyses. Schwartz et al. identified not only the treatment results but also follow up arrests and incarceration rates of these participants. No statistical difference in the retention rates of the interim methadone, standard methadone or restored methadone was discovered. The interim methadone group of participants had a substantial reduction in number of days incarcerated as well as in number of arrests during the study involvement (Schwartz et al., 2014). These findings impacted the current research and society in general because a decline in antisocial behaviors and drug related incidents can positively benefit the community (Schwartz et al., 2014). The offering of

interim treatment can eliminate the potential waiting period and lower criminal recidivism arrests rates.

The time spent waiting to begin treatment can be difficult for the clients because they continue to suffer from the symptoms of their illness with no guidance or medical treatment. Westin, Barksdale, and Stephan (2014) focused on identifying if prolonged patient WT to receive mental health treatment would have negative consequences. The study focused on youth referred to mental health evidence based treatment (EBT) services and used a sample of 2,045 participants between January 2009 and March 2011. Westin et al. used groups of EBT, functional family therapy, and multisystemic therapy. Westin et al.'s random effects logistic regression model recognized "WT was significantly associated with treatment refusal...such that youth and their families waiting for longer periods of time were less likely to start treatment" (p. 224). Westin et al.'s study also found no significant correlation existed between the length of waiting and client's premature termination from treatment because of lack of engagement in treatment. While these findings do not support the proposals hypothesis, Westin et al. (2014) did discover a possibility that the longer length of time a patient waits may lower the patient's interest in receiving treatment. Melnick et al.'s (2001) research connects to this because they identified when a client feels less connected to their treatment he or she are less motivated to commit. Westin et al.'s (2014) findings also continued to support Gryczynski et al., (2009) research as it stated "motivation has been found to be predictive of important drug abuse treatment variables, including treatment entry...and improved retention" (p. 290).

Westin et al.'s (2014) limitations included the correlational design because it's not possible to identify a causal relationship between prolonged WTs and treatment engagement. Westin et al. noted these findings should not be generalized to other populations or field of services because both multisystemic treatment and functional family therapy may be impacted, more than normal, by prolonged WTs.

Consequences of Not Completing Treatment

The goal of alcohol addiction treatment is to lower the client's rate of relapsing or to increase the time before their next relapse. Identifying the best predictor for lowering relapse rates was a question investigated by Lopez-Goni, Fernandez-Montalvo, Cacho, and Arteaga (2014). Lopez-Goni, Fernandez-Montalvo, Cacho, and Arteaga used a sample of 252 participants who had sought out outpatient substance abuse treatment. Of this sample, 65.9% of patients were readmitted. The demographic information collected on the participants included gender, employment status, and marital status. The patients readmitted to a second outpatient treatment episode identified this population had issues with complying with treatment (Lopez-Goni et al., 2014). The control variables of gender, employment status and marital status were not found to be statistically significant. An issue with treatment compliance included failure to adhere to individually created medical recommendations. Lopez-Goni et al. (2014) noted a dysfunctional social support system was vital for treatment loyalty (Lopez-Goni et al., 2014). The findings are contrary to Gryczynski et al. (2009) who identified no significant differences on the variables between clients who participated in a methadone treatment program (MTP) and clients who did not enter. Gryczynski et al. (2009) stated the exception was "among those

failing to enter an MTP, there was a significant decrease from baseline to follow-up in self-reported days of heroin use” (p. 292).

Lopez-Goni et al. (2014) reported “an adequate treatment course that is aimed at meeting the needs of a patient, favors the completion of therapy” is the best predictor of continued abstinence (p. 176). A limitation of Lopez-Goni et al.’s (2014) research is the the entire sample only contained 19.4% women. These findings support Kopak et al.’s (2016) theory that a strong risk factor for recidivism and relapse for clients are those who did not complete their substance abuse treatment. Abstinence is a strong method of reducing recidivism due to relapse.

Implications of Past Research on Current Proposal

Research on the relationship between WT and successful alcohol addiction treatment completion exists in a variety of population samples. The existing research about patient WTs’ impact on treatment completion opens the door to lowering the recidivism rates of alcohol addiction suffering individuals. A relationship exists between the amount of time a patient waits to begin treatment and his or her chances of successfully completing treatment (Worthington, 2009). When looking at court-mandated offenders, Kopak et al. (2016) identified a connection between recidivism caused by relapse and lack of treatment completion. By continuing this train of thought and delving deeper into reasons for lack of treatment completion, I fills this literature gap with my dissertation.

The existing research leads us to the current gap of examining the specific alcohol abusing population of DWI offenders in the U.S. who were court-mandate to outpatient

treatment. The existing literature supports that lowered DWI recidivism rates are related to abstinence from alcohol (Kopak et al., 2016). Clients who successfully complete treatment are more likely to remain abstinent (Timko et al., 2000). DeMichele and Lowes' (2011) discussed that 1.5 million arrests for DWI crimes occur each year and estimates a majority of DWI crimes committed are by a small number of chronic reoffenders. The high risk population involved with the criminal justice system has a strong association with relapse because of the severity of their substance abuse behaviors (Kopak et al., 2016). Filling this gap was key in focusing on lowering DWI recidivism rates in The US.

Literature Relating to Different Methodologies

Many studies identifying the relationship between patient WTs and successful completion have been executed by using a quantitative regression analysis approach. For the past 17 years researchers have been following Timko et al.'s (2000) logistic regression analysis method. A regression approach is strong because it allows researchers to identify the extent of the relationship rather than just if a relationship exists or not.

The only relevant research in the field using a qualitative interview approach was by the study by Redko et al. (2006). The interviews revealed extensive WTs were a boundary for substance abuse patients completing or even starting their treatment episode (Redko et al., 2006).

In Chapter 3 I provide, in detail, the quantitative research method analysis for this dissertation.

Chapter 3: Research and Method

Purpose of Research

The purpose of conducting this study was to determine if the WT to start outpatient treatment can predict the likelihood of completion for DWI court-mandated offenders in the United State for the period 2006—2011. I controlled for gender, race, employment status, age, and level of outpatient treatment.

This chapter will include reasons and explanations behind a quantitative analysis approach and explain details about the characteristics and size of the population, sampling, and instrumentation. I present a description of ethical considerations, validity threats, and processes in how the data were collected and analyzed.

Research Rationale

How WTs impact a patient's treatment completion is a new topic in the fields of patient care and substance abuse. The longer a patient waits can predict the rate of patients leaving the facility without seeing their doctor. Although subject matter about WTs in medical and hospital settings has gained attention, the criminal justice and substance abuse fields lack such exploration. The existing research consists of limited convenience samples based on one or a few substance treatment facilities data (Carr et al., 2008).

Wiler et al. (2013) commented that although they identified how queuing theory helps to predict shorter patient WTs, further research should be conducted to support the model in other institutions. Michael et al. (2013) identified a significant inverse relationship between patients' satisfaction and their time spent waiting in an ambulatory

care facility. These ambulatory outpatient medical facilities are the largest and fastest growing method to deliver medical services (Schappert & Rechtsteiner, 2008).

Research Question

Research Question #1. Do the variables time awaiting treatment, treatment level, gender, race, employment status, and age predict successful completion of U.S. court-mandated adult outpatient alcohol abuse treatment?

H₀1: The variables time awaiting treatment, treatment level, gender, race, employment status, and age will not predict successful completion of U.S. court-mandated adult outpatient alcohol abuse treatment.

H₁1: The variables time awaiting treatment, treatment level, gender, race, employment status, and age will predict successful completion of U.S. court-mandated adult outpatient alcohol abuse treatment.

Instrumentation

The trusted government entities of SAMHSA's OAS and the USDHHS funded and gathered the archival data set TEDS-D. The TEDS-D contains collected data on over 34 variables from licensed substance abuse treatment facilities who received federal public funding. Treatment facilities who fit the criteria in the U.S. were provided the TEDS-D instruction manual. They were asked to complete and submit the survey online through the State TEDS Submission System (STSS) Guide.

SAMHSA created the STSS which was the route for all data to be confidentially submitted online. The STSS instruction manual contained detailed directions to obtain a login ID and password. The manual also contained directions and explanations of each

question and answer option. The TEDS-D holds a total of 9,829,536 pieces of secondary client data. Applying the time period of 2006—2011 provided the research with a well-rounded and robust amount of archival data to analyze.

Operationalization of Variables

Table 1 represents all coding and recoding protocols. The IV was the number of days a client waited to begin treatment. This is an interval level of measurement. SAMHSA (2011) defined days waited as the time between a client's initial contact and admission to the program. The variables range was 1—996 days and was labeled as Days Waiting.

The DV was measured by whether treatment was successfully completed or not. The TEDS-D defined successful completion as when all parts of the treatment plan or program were successfully completed (SAMHSA, 2011). The label for this was Reasons for Discharge and is shown in Appendix C. It was recoded as Reason_recode into a categorical binary DV by transforming it into a new variable through the Statistical Package for the Social Sciences (SPSS).

The use of control variables created a more reliable result by identifying possible outside influences. I chose the variables selected based on the literature review. Gender was selected as a control variable based on DiMino and Blau (2012) who identified females have a more positive view of counseling in general over males. This disparity could account for females having stronger completion rates than males.

I chose employment status as a variable because Albrecht et al. (2011) noted that 87% of participants in their study were unemployed or not in the labor force.

Employment status in the TEDS-D was initially clustered into four sets and was recorded at the time of intake. It is shown in Appendix B. Clients' employment status was recorded at the time of intake. The variable set was recoded into a dummy variable. This was transformed into a binary categorical level in SPSS.

In the literature review I included articles which recognized race as a control variable. The race categories aligned with those of Albrecht et al. (2011) and are shown in Appendix A. Despite Andrews et al.'s (2013) finding that there was no statistical significance between the races of White, African American, and Latino in regards to WTs, the use of the race variable is common in research. This is to identify possible contrasts.

It is a common research practice to recognize age as a control variable. Michael et al. (2013) used large age spans of 18—44, 45—64, and greater than 65 as control variables. Mutter, Ali, Smith, and Strashny (2015) used small age clusters of 3—4 year spans. These spans included 18—20, 21—24, 25—29, 30—34, 35—39, 40—44, 45—49, 50—54, and greater than 55. Using age as a screening criteria and also as a control variable was supported by Haug and Schaub (2016). Haug and Schaub identified older clients had a better predictive quality of higher retention in substance abuse treatment. TEDS-D grouped ages, as outlined in Table 1, in clusters. The clusters were kept the same for the analysis. I used age as continuous interval appearing, although it is ordinal. Long and Freese (2006) spoke to the capacity and frequency of using ordinal data as continuous interval appearing if the assumption of linearity is justified. The assumption must be made that the consecutive groupings of the ordinal variables are spaced equally.

Pasta (2009) further supported this by explaining it is often a stronger approach when analyzing ordinal variables to treat them as continuous. If researchers do not treat ordinal variables as continuous, it is possible to overlook informative relationships (Pasta, 2009). When uniform spacing does not exist in the ordinal variable groupings, Pasta reported the results are usually unresponsive to the actual spacing, except for extreme cases.

Williams (2016) explained the researcher must decide if there is value, based on the data set, to treat the variable as continuous appearing. Lynne-Landsman, Komisky, Livingston, Wagennar, and Komro (2016) supported managing the control variable of age as continuous interval appearing. Lynne-Landsman et al. managed their control variable of age as a continuous interval appearing in a logistic regression by using six communities that had large population censuses that ranged from 1417—9507. Lyons and Hosking (2014) also viewed the ordinal control variable of yearly income as continuous interval appearing. The large sample size of 1,034 came from 1,777 possible participants who consisted of men from multiple major areas all over the country (Lyons & Hosking, 2014). Lyons and Hosking used logistic regression with income being a continuous interval even though the dollar amounts were not equally spaced. Researchers using the TEDS-D data collection have set a precedent using age as an interval appearing variable. Albrecht et al. (2011) and Mutter et al. (2015) used the demographic control variable of age as interval appearing for their logistic regressions. The previously conducted studies provide support managing the control variable of age as continuous interval appearing.

I used the levels of outpatient ambulatory treatment, intensive, and nonintensive, as a control variable because of the distinct time commitments they each require.

Andrews et al. (2013) identified discrepancies in WT between different levels of outpatient and methadone maintenance programs.

Screening Criteria

I applied screening criteria in SPSS by creating filters. By using filters I only allowed analysis to occur on data meeting those criteria.

The TEDS-D data set classified DUI and DWI court referrals as a subgrouping under the court and criminal justice referral section (depending on which state identifies this crime as a DWI or DUI). The original data set included six types of court and criminal justice referrals, as shown in Appendix D. The data were recoded as CrimeReferral_Recode by transforming it into a new variable in SPSS.

In the research I included the two levels of ambulatory outpatient treatment together as screening criteria. The data set identified the type of treatment facility as 'service_setting' in SPSS. The definition of intensive outpatient treatment are clients who received 2 or more hours of treatment per day, for 3, or more days a week (SAMHSA, 2011). Clients requiring less than 2 hours of treatment a day for any number of days a week are participants in nonintensive ambulatory outpatient treatment. Haug and Schaub (2016) supported using ambulatory outpatient treatment as a screening criteria. Half of the patients in the Haug and Schaub study were sober at the 2- and 5-year follow up after completing outpatient treatment. The screening criteria of ambulatory outpatient treatment will place focus on a treatment method that is proven to lower relapses in substance abuse clients. The original data set included eight groups of treatment types as

shown in Appendix E. The treatment setting was recoded as Setting_Recode by transforming it into a new variable in SPSS.

A limitation in my study is it focused only on clients who identified alcohol as their primary substance of use at intake. The original SPSS coding included 19 different categories of substances which could have been the client's primary choice, as shown in Appendix F.

In the screening criteria I only included adults over the age of 18. Research on adolescents should be conducted separately from adult findings due to their developing brains (Konrad, Firk, & Uhlhaas, 2013). The original age variable is listed above as a control variable. The ages were recoded into a dummy variable as Age_recode to represent 1 as all clients aged 18 and over and 0 to represent all clients aged under 18. The variable was recoded in SPSS by transforming it into a new variable.

Table 1

Research Variables and their Corresponding SPSS Codes

Variable	Coding/Recoding
Independent Variable	Interval Variable 9-missing data All days waiting are coded as the numeric number of days client waited (ex: 1-1 day, 2-2days)
Dependent Variable	Binary categorical 1-Successfully completed 0-did not successfully complete
Control Variables	
Gender	Binary Categorical 1-Male 2-Female
Race	Nominal Categorical 1-White 2-African American 3-All Other
Employment Status	Binary Categorical 1- Employed 0-Not Employed
Age	Interval (appearing) Categorical 4- 18—20 5- 21—24 6- 25—29 7- 30—34 8- 35—39 9- 40—44 10- 45—49 11- 50—54 12- 55 and over
Level of Outpatient Treatment	Binary Categorical 6- Intensive 7-NonIntensive
Screening Criteria	
Ambulatory Outpatient	Binary Categorical 1-Ambulatory outpatient, intensive and nonintensive 0-All other treatment facility types
DWI	Categorical 8-DWI Referral
Alcohol	Categorical 2-Alcohol
Age	Binary Categorical 0-Ages 0—17 1-Age 18 and over

Note. Substance Abuse and Mental Health Services Administration. (2011). Treatment episode dataset: Admissions (ICPSR No. 30122). No permission needed.

Research Design

I used a quantitative approach to identify the predictive value of the relationship between the independent and DVs. I chose a quantitative method over a qualitative or mixed -methods approach because of the large amount of existing secondary data. USDHHS and SAMHSA's OAS previously collected this data set. Logistic regression was the most appropriate design to examine the relationship between a dichotomous DV with one or more predictors (Ranganathan, Pramesh, & Aggarwal, 2017). Albrecht et al. (2011) used a similar logistic regression on WT to identify the impact on treatment completion in pregnant clients.

Simple Random Sample

I used a simple random sampling strategy of clients who met screening criteria in the TEDS-D data set. When using a large population, a random sample is representative of the whole as a mini version of the population (Grafstrom & Schelin, 2014). A simple random sample is when every data point has the same chance of being selected (Setia 2016). Simple random sample without replacement ensured no data were duplicated for analysis. I chose a simple random sample over a stratified sample because a stratified sample divides the data into subgroups and takes random samples from each subgroup to represent minority (Setia, 2016). Setia stated, "Community based studies" often use cluster sampling over a random sample (p. 508). The research I conducted was not a community-based study so a cluster sample was not the most appropriate to use. I took true simple random sample from the eligible data by using SPSS: data, select cases, random sample of cases, 5,000 cases.

When I conducted logistic regression research on the entire U.S. population previous research guided the decision to use a simple random sampling approach. Bellis et al. (2017) used a survey of data collected from the national population of the country Wales. Researchers conducted a logistic regression analysis on the sample of 7,500 out of 28,349 households in Wales. Another logistic regression study that used data collected from an entire country was Agushyana, Siramaneerat, Raksamat, and Siriphakhamongkhon (2018) who used a random sample of 1,508 women out of a possible 45,607 women who met screening criteria based on the Indonesian population census.

I used a large year range of 2006—2011 in the dissertation. Grant et al. (2017) supported a random sample approach when using data collected over multiple years which contained surveys collected from the National Epidemiological Survey on Alcohol and Related Conditions III from 2012—2013. It resulted in a total sample size of 36,309 participants (Grant et al. 2017).

There were 191,328 data in the TEDS-D that meet screening criteria. I excluded Data missing the IV from the analysis. Both Wiler et al. (2013) and Andrews et al. (2013) spoke to the practice of excluding incomplete data. After excluding incomplete data, there were 126,350 eligible data for analysis.

The G*Power 3 software, downloaded from <http://www.gpower.hhu.de/en.html>, calculated a minimum sample size. The software is a statistical analysis program commonly used in behavioral and social research fields for computing power analysis (Faul, Erdfelder, Buchner, & Lang, 2009). Logistic regression uses odds ratio as effect

size because it was “originally proposed to determine the probability of an event...and is increasingly utilized in epidemiological studies” (Chen, Cohen, & Chen, 2010, p. 861). Chen et al. (2010) considered an odds ratio of 1.68 to be a small effect size. Albrecht et al. (2011) used an effect size ranging from 1.14 to 1.41. In this research I was conservative and used an effect size of 1.14.

I chose a Poisson distribution over a normal distribution because the IV of days waiting had a skewness of 15.10 and a standard deviation error of skewness of .007. The z skewness is calculated by dividing the skewness by the standard deviation error of skewness. This gave a z skewness of 2157.29 (Field, 2013). Field (2013) reported that if the z skewness is greater than .05, the skew is significant. Fu, Chu, and Lu (2015) supported using a Poisson distribution when the data are not normally distributed. A 95% confidence interval is based on previous research with similar population sizes. Kebede, Keno, Ewunetu, and Mamo (2014) conducted a logistic regression on an expected population of 1,647,576 using a 95% confidence interval.

I selected the statistical test of logistic regression under the test family of Z from the G*Power calculator. The following information calculated the A Priori; Tails=Two, Odds Ratio=1.14, X distribution=Poisson. G*Power calculator provided the following based on the manual: Pr=.2, error probability=.05, Power=.95, R squared=0 (Buchner, Erdfelder, Faul, & Lang, 2017). I included six variables in the analysis to determine sample size. The G*Power calculator gave a minimum sample size of 4,237. Hoffman et al. (2011) completed their logistic regression using a sample size of 4,937 when identifying the relationship between days waiting to enter outpatient treatment with

substance abusing clients. I followed suit and increased the sample size by 10% to 5,000 to account for data cleaning.

Data Collection

The government agencies collected the TEDS-D from 2006—2011. These data are freely accessible to the public for the purpose of statistical research. The University of Michigan Inter-University Consortium for Social and Political Research (ICPSR) require no permission to download this data set from their website, <http://www.icpsr.umich.edu/icpsrweb/ICPSR/series/238>, into IBM SPSS Version 21.

Statistical Assumptions

A logistic regression analysis has seven assumptions to review before running statistical analysis. The first assumption is the DV is dichotomous (Field, 2013). This was true because the recoding is 1 for ‘yes’ or 0 for ‘no’. The second assumption is there are two or more independent and control variables of either a continuous or nominal nature (Field, 2013). The independent and control variables are either nominal or interval, as listed in Table 1. The third assumption is the dependent, independent, and control variables are all exclusive. This was true because the variables are categorized as either zero, one, two, etc. in SPSS. No piece of data may be coded or belong to more than one, above mentioned, category. The fourth assumption is there needs to be a minimum of 15 cases of data pieces (Field, 2013). This was true for this data set as it contains 126,350 pieces of data that fit the screening criteria. The fifth assumption is additivity and linearity, which means there was a linear relationship between the outcome variable and any predictor variable (Field, 2013). I will use a Box-Tidwell to test this assumption. The

sixth assumption is there is no multicollinearity. An inspection was done on the variance inflation factor (VIF) and the tolerance statistic to identify if any two or more independent or control variables were significantly related to each other. Field (2013) states if the average VIF is greater than 1, the presence of multicollinearity should be a cause for concern. Midi and Bagheri (2010) argue that the VIF cutoff point is more subjective (as cited in Thompson, Kim, Aloe, & Becker, 2017). Midi and Bagheri (2010) provide support for this research to use a VIF cutoff of 2.5. This research followed Midi and Bagheri (2010) cutoff of 2.5. If highly collinear variables exist and are logically related, I would have combined them. If combining related variables did not solve the multicollinearity issue, I would have eliminated one from the research (Field, 2013). The collinear variable that produced the best fit of the model was kept.

The seventh assumption is there are no outliers (Field, 2013). The independent variables were converted into standard deviation units. If their absolute values were greater than 3, they would have been identified as a cause for concern and removed from the data set (Field, 2015). Yang, Xie & Goh (2011) state “there is no rigid mathematical definition for outliers, and determining an observation is whether or not an outlier is ultimately a subjective exercise” (p. 422). Orr, Sackett & Dubois’ (1991) study explained how 29% of published authors in the psychology field included all data in their research and 67% only excluded extreme outliers. Extreme outliers are determined as data which are far removed from the main cluster of the set (Yang et al., 2011). Specifically when speaking about a skewed data set, like mine, Payne, Gebregiazbher, Hardin, Ramakrishnan & Egedde (2018) identified there is no current set threshold for

determining the need to exclude outliers. If outliers existed in the data set, they were filtered out and the regression rerun. I was not going to replace the outliers with the highest valid nonoutlier value as this can create bias.

Data Analysis

I used logistic regression to reject the null hypothesis and I removed control variables that were not predictive of the DV. The Variables in the Equation table provided the output information on the overall results of the degree of prediction on the outcome variable and the actual contribution of each control variable (Field, 2015). I used the b-value to identify that the number of days a client waits to begin treatment significantly predicts successful completion. The b-value was less than .05, so the test showed the IV significantly predicts the DV (Field, 2015). If the analysis was not statistically significant I would have employed a standard forced entry logistic regression method by taking out any control variables that were not statistically significant. Then I would run the analysis again. I did not use of a stepwise method as the results are rarely able to be replicated (Field, 2015). By using the standard forced entry method I had control over which variables were removed for further analysis.

Threats to Validity and Reliability

The possibility of threats to validity and reliability exist. SAMHSA made no requirements of an employee's level or position to qualify for reporting the data. Employees who reported the data may have had different trainings and certifications. This could account for differences in interpreting the TEDS-D questions and answers.

By using the TEDS-D data set I only included data collected from alcohol abuse treatment facilities who received public funding in this research (Albrecht et al., 2011). This is a threat to the external validity and the capacity to generalize the findings to privately funded treatment facilities.

Construct validity limitations are related to the assessment tool each treatment facility used to initially collect their data. Information was transferred from their initial assessment tool, through the STSS, and filtered into the TEDS-D. Data collectors assume all data was initially collected by a comprehensive biopsychosocial assessment. While this was assumed, there was no formal assessment every facility was instructed to use. Questions may have been asked differently at different facilities due to a lack of a uniform assessment strategy. When mental health professionals ask questions differently, clients may give different answers.

Content validity should be safe as SAMHSA developed The Crosswalk Plan (SAMHSA, 2014). The Crosswalk Plan is a computer program which organized entered data into categories previously created for the TEDS-D (SAMHSA, 2014). As not all treatment facilities organize data uniformly, the Crosswalk Plan was to distinguish possible differences and classify accordingly.

I used random sampling because in a large data set a random sample works to create unbiased and valid results (Grafstron & Schelin, 2014). Albrecht et al. (2011) identified the possibility of one client's information to be entered more than once. This could challenge the assumption of independence of the samples. Part of the

Crosswalk Plan included a fatal error duplicate record rejection system and was designed to reject any data reported twice (SAMHSA, 2014).

The control variables work as delimitations in an effort for control and provide a framework of boundaries to limit the study's scope.

Ethical Considerations

By filtering data through a routine top to bottom coding, SAMHSA created safeguards in the TEDS-D to protect confidentiality. This prevents the highest and lowest codes from connecting to any individual records. For example; age is a continuous variable and can identify the youngest and the oldest clients in the data set. The age variable was recorded into categories rather than raw numbers. Previous coding which prevents identification ensures there are no ethical considerations with the secondary data. No informed consent was necessary as all identifying information was removed by the reporting facilities. Contact was not made with any client.

Conclusion

I began this chapter by introducing the study's purpose and rationale behind its quantitative approach. I then introduced the research question, the null hypothesis, the research hypothesis, and the instrumentation. A discussion of the operationalization of variables lead to specific screening criteria and random sampling. I outlined the research design, data analysis strategy, assumptions, limitations, and lack of ethical issues in this chapter. In Chapter 4 I will present the logistic regression outcome with all descriptive statistics that were conducted based on this chapters outline.

Chapter 4: Results

Introduction

In this study I examined if days waiting to begin treatment could predict the likelihood of treatment completion. I explored the relationships' extent while considering age, gender, race, employment status, and treatment level. The population consisted of adults arrested for DWI/DUI and mandated by court to attend alcohol abuse outpatient treatment. Screening criteria included adults who reported alcohol as their primary substance of choice at intake.

Chapter 4 includes six sections with the first providing an explanation of the data collection and the second outlining the random sample and its creation. I focus on the data analysis in detail and provide results on the assumption tests. The final two sections will include descriptive statistics, the null hypothesis, and the best fit model.

Data Collection

I uploaded the data set into SPSS from ICPSR's database which was available for public research use. SAMHSA's OAS and USDHHS originally collected the TEDS-D data set between 2006—2011 from federally funded substance abuse treatment centers throughout the U.S.

Random Sample

The TEDS-D was the source of 126,350 eligible data that fit the screening standards. Chapter 3 included information on the G*Power calculator computing a necessary sample size of 4,237 which I increased to 5,000 for cleaning purposes.

Hoffman et al. (2011) used 4,937 as their sample size when conducting research to answer a similar question about WTs with alcohol abuse clients. The SPSS tools' select cases, random sample, and then create new casefile created a new data set containing only the random sample.

Data Analysis

A logistic regression was the best approach because the research question examined the correlation between a dichotomous DV and multiple predictors (Ranganathan, Pramesh, & Aggarwal, 2017). The DV was binary: did the client successfully complete treatment or not, and it included six predictors. The results will support accepting or rejecting the null hypothesis.

Chapter 3 included reasoning to use a standard forced entry method to direct the analysis through SPSS. A forced entry method includes variables based on previous research and enters them in the analysis simultaneously (Field, 2015). The forced entry method also continually provides replicable results, which was important so future researchers to replicate the findings (Field, 2015).

Stepwise and hierarchical methods are not the strongest theory testing approaches so I did not use them. A stepwise approach allows SPSS to choose which variables to include in the analysis (Petrocelli, 2003). When SPSS has the power to make these choices the calculation estimations can have bias. Biases can create a lack of reliance in a single best fit model (Whittingham, Stephens, Bradbury, & Freckleton, 2006). The significance of previously entered variables steer SPSS's choices which can create random variations. Variations influence the ability to reproduce results (Petrocelli, 2003).

A hierarchical method is proper when researchers want to include certain variables at different times (Petrocelli, 2003). Researchers do this during the analysis to test how new variables impact the result. I examined the relationship with all variables simultaneously so a hierarchical method was not suitable.

Assumption Tests

Certain assumptions must be true when running a regression analysis. Linearity and multicollinearity need testing to prove if these assumptions are true or not. All other assumptions are true based on support I provided in Chapter 3. I used a box Tidwell test to check the data for linearity. VIF scores were calculated for multicollinearity and I identified if outliers existed.

Box Tidwell

The box Tidwell test calculated for linearity between the dependent and IVs. The first step was to create a natural log with the DV. A new variable, days waiting plus 1, was created. A natural log cannot contain any 0s and adding 1 for statistical analysis is a common approach (Field, 2015). The interaction was nonsignificant with a $p=.053$. The assumption of linearity was true.

Multicollinearity

Multicollinearity shows if any variables share a significant relationship. In Chapter 3 I provided support to use 2.5 as a VIF score cutoff. A VIF score above 2.5 identified if any two variables were significantly collinear.

Table 2 lists the variables and their respective VIF scores and showed there were no VIF scores above the cutoff point. No significant relationships between any variables exist and the assumption of nonmulticollinearity was true.

Table 2

Assumption Tests

Variable	VIF Score
Days waiting to enter treatment	1.007
Age	1.015
Gender	1.013
Race	1.012
Employment status	1.021
Outpatient treatment level	1.014

Outliers

The IV ranged between 0—996 days. The mean was 12.5 with a standard deviation of 41.613. I excluded any outliers greater than three standard deviations, as

outlined in Chapter 3. A calculated three standard deviation was 137.7 days waiting. Data were only excluded from the high end as this set did not contain negative numbers. The final analysis did not include any IV data greater than 138 days, reducing the sample to 4,947. The final sample exceeded the G*Power minimum sample size required for adequate statistical power.

Descriptive Statistics

The SPSS random sample tool generated the sample from the eligible 126,350. After completing the assumption tests and removing outliers, 4,947 was the final sample size. Table 3 presents the predictor variables compared to treatment completion status and the percentages and total numbers (*N*) of each variable.

The IV ranged from 0—138 days with a 40.5% right skew of clients' days waiting to be 0 days. Pallant (2007) stated the predictors' distribution and skew are irrelevant to the result in a logistic regression. Pallant advised against transforming or adjusting the predictor. Pallant also stated that logistic regression variables are sensitive to multicollinearity and outliers. The final sample contained no outliers and the nonmulticollinearity assumption was true. Based on Pallant's reasoning, the IV remained as is. Appendix G includes the IVs descriptive statistic cross tabbed with the DV.

Table 3

Descriptive Statistics

Variable		<i>N</i>	%	Did not complete	Completed
Gender	Male	3827	77.4	1090	2737
	Female	1120	22.6	321	799
Age	18-20	279	5.6	104	175
	21-24	736	14.9	210	526
	25-29	867	17.5	270	597
	30-34	595	12.0	184	411
	35-39	535	10.8	149	386
	40-44	577	11.7	158	419
	45-49	566	11.4	157	409
	50-54	381	7.7	93	288
	55 and over	411	8.3	86	325
Race	White	3779	76.4	1026	2753
	African American	495	10.0	169	326
	All other races	673	13.6	216	457
Employment status	Employed	3207	64.8	816	2391
	Not employed	1740	35.2	595	1145
Outpatient treatment level	Intensive Outpatient	669	13.5	326	343
	Nonintensive Outpatient	4278	86.5	1085	3193

Completion status	Nonsuccessful completion	1411	28.5
	Successful completion	3536	71.5

Table 4 represents all other descriptive statistics for all variables including mean, median, mode, range, standard deviation and variance.

Table 4

Additional Descriptive Statistics

Variable	Mean	Median	Mode	Range	Variance	SD
Age	7.77	7.00	6	8	5.606	2.368
Race	2.6279	3.00	3	2.00	.506	.71122
Employment status	1.3517	1.0000	1.00	1.00	.228	.47756
Outpatient treatment level	1.0000	1.0000	1.00	.00	.000	.00000
Gender	1.23	1.00	1	1	.175	.419
Days waiting	9.46	2.00	0	137	317.899	17.830

Logistic Regression Analysis

I used SPSS to analyze all data. In this study I included both continuous and categorical variables. Days waiting and age were continuous while gender, race, employment status, and treatment level were categorical. SPSS sets the degree of freedom for all noncategorical, including continuous predictors, to 1 (Field, 2015). Categorical and continuous predictors are 1 minus the number of existing categories in the variable (Field, 2015). A negative number could never be the result because categorical variables must have minimally two categories. The degrees of freedom are 1 or greater and a forced enter method guided the regression.

Table 4 lists the analysis results. The variables in the equation table provided the predictors statistical significance on days waiting.

Table 5

Analysis Results

Variable	B	S.E	Wald	<i>df</i>	Sig.	Exp (B)
Days waiting	.005	.002	7.711	1	.005	1.005
Age	.080	.014	33.092	1	.000	1.084
Gender	-.006	.077	.006	1	.940	.994
Race			9.592	2	.008	

Race_(1)	.110	.094	1.386	1	.239	1.117
Race_(2)	-.314	.105	9.011	1	.003	.730
Treatment level	-1.013	.086	137.219	1	.000	.363
Employment status	.409	.067	37.097	1	.000	1.506
Constant	.095	.155	.378	1	.538	1.100

The IV, number of days waiting, significantly predicted the DVs likelihood to complete treatment. Wald X^2 ($df=1$) = 7.711, $p = .005$. The odds ratio (OR) was 1.005. A client was 1.005 times more likely to not complete treatment for each additional day he or she waited.

Gender did not predict treatment completion likelihood. Wald X^2 ($df=1$) = .006, $p < .940$. However, the output showed increased age did predict an increased likelihood of not completing treatment. Wald X^2 ($df=1$) = 33.092, $p < .001$. Each older age cohort had 1.084 greater odds of not completing treatment than the previous age cohort.

The race variable is statistically significant in predicting treatment completion. Wald X^2 ($df=2$) = 9.592, $p = .008$. The race variable had 3 categories, SPSS compared these categories against each other. It is less likely for African American clients to complete treatment than White clients with an odds ratio of .730 (Wald X^2 ($df=1$) = 9.011, $p < .003$). SPSS recoded this to Race_(2). The other race comparative groups are not statistically significant. Relative to non-White and non-African American clients,

White clients do not have greater odds of completing treatment. Wald X^2 ($df=1$) = 1.386, $p = .239$. SPSS recoded this to Race_(1).

Employed clients were significantly more likely to complete treatment. Wald X^2 ($df=1$) = 37.097, $p < .001$. Employed clients had 1.506 greater odds for completing treatment relative to unemployed clients.

Outpatient treatment level was statistically significant to treatment completion. Wald X^2 ($df=1$) = .137.219, $p < .001$. Clients who were in intensive outpatient treatment were .363 less likely to complete treatment over client who were in nonintensive outpatient treatment.

Bootstrapping on Preliminary Analysis

I ran the SPSS bootstrap analysis with a 95% confidence interval. Banjanovic and Osborne (2016) supported using a 95% confidence interval. Banjanovic and Osborne reported that it is the most desired confidence interval in regression. Field (2015) supported using 1,000 samples as a reasonable number. Bootstrapping removes bias that may occur in a random sample (i.e., the existing skew and lack of normality for the IV; Field, 2015). Using 1,000 samples for a bootstrap analysis and a 95% confidence interval on the preliminary analysis provided statistical conclusions identical with the original findings.

Table 6

Interaction Effects

Variable	B	S.E	Wald	df	Sig.	Exp (B)
Days waiting * Gender	.005	.005	1.327	1	.249	1.005
Days waiting * Age	.002	.001	4.171	1	.041	1.002
Days waiting * Employment status	-.007	.004	2.583	1	.108	.993
Days waiting* Race			3.047	2	.218	
Days waiting* Race (1)	-.004	.006	.416	1	.519	.996
Days waiting* Race (2)	-.014	.009	2.742	1	.098	.986
Days waiting * Treatment level	-.006	.005	1.684	1	.194	.994

Belzak and Bauer (2018) reported that although it is useful to conduct interaction effects in addiction research, it is not commonly discussed. Table 5 reports the effects for variables when multiplied with days waiting. Age was the only variable with a statistically significant interaction effect. As age of clients increases, the effect of days waiting on treatment completion became greater, Wald X^2 ($df=1$) = 4.171, $p < .041$. This interaction required further examination because these age findings were stronger predictors than days waiting.

Table 7

Age-Centered Interactions

Age	B	S.E	Wald	<i>df</i>	Sig.	Exp(b)
centered						
cohorts						
18-20	.005	.008	.367	1	.545	1.005
21-24	.007	.008	.764	1	.382	1.007
25-29	.009	.008	1.321	1	.250	1.009
30-34	.001	.007	2.015	1	.156	1.011
35-39	.013	.007	2.793	1	.095	1.013
40-44	.014	.008	3.586	1	.058	1.015
45-49	.016	.008	4.325	1	.038	1.016
50-54	.018	.008	4.961	1	.026	1.018
55 and	.020	.009	5.472	1	.019	1.020
above						

Table 6 reflects how the model was rerun with all age cohorts centered. The age centered cohorts were not statistically significant until ages 45—49, indicating days waiting was unrelated to treatment completion among younger age cohorts.

The age centered cohort 45—49 was when the effect of days waiting begins to reflect statistical significance ($p=.038$). Wald X^2 ($df=1$) = 4.325, $p = .038$. Among the clients aged 45—49, the OR was 1.016, which indicated for each additional day waited they were 1.016 times more likely to not complete treatment. As the age cohorts increased, the effect became stronger with small p values and stronger ORs.

Best Fit Model for Logistic Regression Analysis

I used an R squared value to determine best fit because a logistic regression cannot produce this statistic (Geissert et al., 2018). The Nagelkerke R squared is a pseudo measurement to identify the best fit in a logistic regression. It is a way to identify the IVs success on predicting the DV (Nagelkerke, 1991).

Haug and Schaub (2016) identified the best fit using the Nagelkerke R Square in predicting regular discharge from substance abuse treatment. Moos and Moos (2005) also explored their findings by using a Nagelkerke R square. Moos and Moos only included statistically significant variables in their best fit model for one year predictors of alcohol remission. Moos and Moos (2005) excluded nonsignificant variables in the best fit model, I followed this pattern in my research

The Nagelkerke R squared was .063 for the independent, dependent, and significant predictors in this study. Hair, Hult, Ringle, and Sarstedt (2013) assert any Nagelkerke R Square value below .25 as being weak. Geissert et al. (2018) state a Nagelkerke R Square value below .11 has a low predictive nature.

The Nagelkerke R squared value for just days waiting and treatment completion was .001. The model which included the significant variables was stronger than the best fit outcome.

Summary

All assumptions were true and eligible for statistical analysis. Removing outliers created the final random sample. Days waiting significantly predicts the treatment completion outcome based on its *p* value, and rejects the null hypothesis. Predictor

variables provided control by examining their effect on treatment completion. Age, employment status, race, and outpatient treatment level can predict treatment completion while gender had no predictive value. Further interaction effect analysis on the age variable indicated age cohorts 45 and up are significantly impacted by days waiting, while clients in the age cohorts 45 and below are not. The bootstrapping analysis was identical to the original findings. I identified the the best fit model by following previous research and only including significant variables in the Nagelkerke R squared. While the analysis presented a statistically significant value, the predictive value of this model was weak.

In the final chapter I offer a discussion of key findings and explanations to the statistical outcomes. Chapter 5 is crucial in communicating the findings and how they impact positive social change in communities.

Chapter 5: Discussion

Introduction

In chapter 5 I present an interpretation of data and statistical analysis. I also discuss limitations and recommendations for future research while explaining how the findings can promote positive social change in the fields of criminal justice and alcohol abuse treatment. Offering courts and treatment agencies this new scientific research can promote positive social change in lowering recidivism rates.

Interpretation of Findings

Independent Variable

The analysis showed a DWI client was .6% less likely to complete treatment with each added day he or she waited. Although the IV predicted the DV, the analysis can only support a correlational role (Westin et al., 2014).

I used a Nagelkerke R Square to include significant covariates when identifying a best fit model, which resulted in .063. According to Geissert et al. (2018), .063 was a weak predictive model as it is under .11. Haug and Schaub (2016) included the demographics of age, means of financial income, and life satisfaction. Haug and Schaub identified a Nagelkerke R Square of .12 to predict their DV, which was regular treatment discharge. Bauernfeind and Babbitt (2017) identified a similar weak Nagelkerke R Square value of .07 in their research about proteins in the brain corresponding with facial expressions. Bauernfeind and Babbitt recognized the predictive value was weak and explained it may be because variations exist in protein genes. They did not include these

possible variations in the study. Maybe WTs are influenced by variations like transportation, overbooking, or clients lacking general motivation. A qualitative piece asking these questions could further the research in the WT field.

The articles which support the current research did not commonly report a best fit model for the impact days waiting have on treatment completion. Possibly, the predictive values were also weak in nature and the previous authors chose to stick to the statistically significant piece rather than speaking to the predictive values. The best fit model is important because without it the calculation can be misleading. A Cox and Snell R Square showed the outcome explaining only 4% of the predictive analysis. Baurenfiend and Babbitt (2017) reported their variables only had a 3% predictive play in the overall result. Baurenfiend and Babbitt continued to report these findings as significant and important to the field for future research in brain proteins and expressions. I expressed the findings as significant but will speak to other variables that had stronger predictive values.

Albrecht et al. (2011) agreed with the statistically significant findings, but reported stronger odds of 1.27 in their population of pregnant clients. I acknowledged the differences in effect sizes between these studies. Albrecht et al. used a small to medium effect size ranging from 1.14—1.4, where in this dissertation I was conservative with a small effect size of 1.14. By using a small effect size with a large sample, Chen et al. (2010) stated it is possible to have a “statistically significant finding from a weak, but true, association” (p. 862).

Albrecht et al. (2011) explained that their strong statistical results could come from the internal motivation pregnant clients have because of their unborn child's health. DWI court-mandated clients may not share this same internal source of motivation. Pascoe et al. (2013) identified pregnant clients are often priority and get appointments earlier and faster due to physical condition. This might include counselors reminding them of their appointments, giving special treatment, leniency, and favorable time slots. Special treatment could influence a pregnant client's commitment to completion, which might account for these statistical differences.

Carr et al. (2008) supported my study's predictive connection by findings as court-referred clients' WTs increased, their belief in having a substance issue decreased. Quanbeck et al. (2013) explained how patients with addiction issues may lose motivation for treatment while he or she waits for the appointment. When a client's desire to attend treatment dropped, so did his or her motivation to make changes in alcohol consumption. Timko et al. (2000) supported increasing abstinence through treatment completion to lower recidivism.

Albrecht et al. (2011) identified pregnant women who entered treatment immediately, with 0 days waiting, had the highest successful completion rates. Westin et al. (2014) agreed a longer WT was predictive to treatment refusal because a client cannot complete if he or she does begin.

Wiler et al. (2013) focused on half hour increments of waiting time in emergency room hospital settings. Wiler et al. identified that every extra 30 minutes of waiting predicted a 3.9%—1.4% increase rate for clients leaving without receiving treatment.

Clients go to emergency rooms for urgent medical attention. Discrepancies could emerge if he or she feel they need to go to another hospital quickly to receive immediate care (Wiler et al., 2013). An added 30-minute waiting period supports a client's decision to jockey to another hospital. Multiple hospitals are often within the same city so clients can bounce between emergency rooms or urgent care facilities easily.

Age Variable

According to the results, age was a stronger predictor than days waiting. As the age of court-mandated client's increased, the rate of treatment completion decreased. Heyman (2013) supported a positive correlation between the years since alcohol dependence onset and remission rates. The longer a client suffers from addiction predicts lower relapse chances.

One third of all addiction research included interaction effects (Belzak & Bauer, 2018). As the age cohorts increased, odds ratios also increased. Days waiting had a significant impact on clients in the age cohorts 45 years and older, and no significant impact on clients in age cohorts 44 years and younger. The second most common amount of days waited, after the first being 0, was 7 days with 312 clients waiting this long. Clients aged 55 and older would have 14% less chance of completing treatment if he or she wait 7 days. Wolfe et al. (2013) discovered as clients' age increased, external motivations lacked strength to keep them engaged in treatment, which directly connects with days waiting impacting older clients more significantly. Similar to Wolfe et al. (2013), I focused on the external motivation of possible jail time, fines, and probation. Perhaps the older clients who engaged in risky behaviors lacked internal motivation and

the external motivators were not effective. Older clients have been suffering from his or her addiction issues for longer periods of time, which is associated with higher relapse rates (Heyman, 2013). These new findings support including interaction effects in future studies.

Although I found older clients had lower rates of successful completion, previously conducted studies identified opposite findings. Mutter et al. (2015) identified a positive correlation between the client's age and successful graduation. As client's ages rose, so did their odds of treatment completion. Lapham et al. (2012) concentrated on lifetime alcohol drinking patterns of female DWI offenders and identified abstinence rates increased with age. Haug and Schaub (2016) identified a weaker OR of 1.02 in older clients having a higher treatment retention likelihood. With this new research identifying a different result compared with previous findings, a new gap exists to further explore this inconsistency.

Employment Variable

Employment had a strong predictive value with employed clients having a significantly greater likelihood of completing treatment successfully over nonemployed clients. Albrecht et al. (2011) also identified employment significantly increasing the client's odds of completing outpatient treatment, but with a weaker odds ratio of 1.28. Employed clients may have access to child care, transportation, and a strong support network (Albrecht et al., 2011). All of which could strengthen treatment engagement.

Lopez-Goni et al. (2014) discovered patients receiving substance abuse treatment for the first time were younger and more likely to be employed compared to patients who

had multiple previous treatments. Lopez-Goni et al.'s findings identify younger clients have higher rates of treatment completion. An employed client may have more motivation to complete treatment successfully based on his or her professional responsibilities (Lopez-Goni et al., 2014). By clients not completing court-mandated outpatient treatment, he or she may stand to lose much more than an unemployed client would.

Gender Variable

Gender not being statistically significant in predicting treatment graduation contradicts previous findings. DiMino and Blau (2012) explain females often have a more confident view of counseling. Melnick, De Leon, Kressel, and Wexler (2001) identified patients with a positive view about counseling had reported more trust in their counselor (as cited in Wolfe et al. 2013). Having confidence in treatment showed results of better therapeutic outcomes (Wolfe et al. 2013). Andrews et al. (2013) report women have a tendency to wait longer to start treatment than men but no findings about gender were statistically significant. While previous studies support females having a stronger inclination to complete treatment, in this research I do not identify a statistical connection.

Race Variable

The results suggest race does have a predictive nature on treatment completion. When I compared the race groups against each other, the White race group had 72.8% clients successfully complete while the other groups, African Americans, and all other races, had 48.4% and 67.9% respectively.

Relative to clients who identified as White, those who identified as African American have .730 less likely odds to complete. Andrews et al.'s (2013) research on African American clients having a strong association with higher wait times could explain this. Specifically, Andrews et al. discovered African Americans referred by a criminal justice entity were 1.40 times more likely to wait 30 days or more to begin substance abuse treatment.

Andrews et al.'s (2013) findings identified African American clients are more likely to drop out of treatment than any other racial group. African American women had significantly decreased odds of completing outpatient treatment (Albrecht et al., 2011). Westin et al. (2014) continued to support these findings by detecting African American, Hispanic, and all other groups were more likely to leave treatment relative to the White race group.

Guerrero and Andrews (2011) recognized racial disparities about cultural competence in substance abuse outpatient treatment. Guerrero and Andrews identified difficulty in hiring ethnic minority staff in outpatient treatment which could hinder the minority clients feeling connected to their counselors. Wolfe et al. (2013) determined clients who develop strong rapport with their therapists have higher motivation for treatment.

Level of Outpatient Variable

Clients admitted into intensive treatment had lesser odds of successfully completing over those admitted into nonintensive. Wise (2010) identified reasons clinicians recommend intensive level of care include clients having a record of

cooccurring mental health disorders, suicidal tendencies or impulsive, and dangerous drinking patterns. Clients who drink alcohol often and in high amounts receive a recommendation to intensive treatment because of his or her need for concentrated therapy (Wise, 2010). Clients may refuse or leave recommended treatment because he or she do not see themselves as having an issue that needs such a high treatment level.

The IV, days waiting, was statistically significant but weak in overall predictive value. I included demographic variables to control the results. Age and employment status have statistically stronger p values than days waiting. The interaction effect of age centered cohorts provided information about older clients being impacted more by days waiting. Race was significant when the groups were compared to each other. Gender was not significant which contradicts previous research. Results from the research offer new quantitative findings to the substance abuse treatment field.

Limitation and Recommendations for Future Research

Limitations exist in all statistical studies and the research I completed is no exception. Although the result was statistically significant, the IV had a weaker odds ratio compared to age and employment status. After further analysis of age centered interaction effects, I identified days waiting significantly predicting clients over the age of 45 completing treatment. I opened the door for age and employment status as a focus for future research. The younger age cohorts are not impacted by days waiting so a qualitative approach would investigate what hinders younger clients from completing court-mandated treatment. This is important because a majority of DWI offenders are under the age of 37 (Carey, Allen, Einspruch, Mackin, & Marlowe, 2015).

The findings support asking a similar research question using other demographics as the IV. Demographics which I did not use may have a stronger predictive nature on treatment completion when paired with days waiting. The current research did not use ethnicity, marital status, education, veteran status, living arrangement, primary source of income, and number of arrests before treatment. Stewart et al. (2013) speaks to the demographic of marriage status possibly impacting patient motivation. Moos and Moos (2005) identified how alcohol treatment remission is predictive of clients with higher levels of education. Haug and Schaub (2016) found clients reporting higher life satisfaction to have higher rates of completion. Studies using levels of education, life satisfaction, and the age centered interaction effect results recently discovered could create a very interesting outcome. Such demographics could have a stronger affiliation with the population and future researchers can fill these new gaps.

Clients may report addiction to multiple substances at intake. Carr et al. (2008) only included clients who had multiple primary substances at intake and I only included clients who reported alcohol as his or her primary choice. Research on clients coming from other referral sources, primary substances of choice, and other treatment types would benefit the field.

The screening criteria I used consisted of adults court-mandated to outpatient treatment for alcohol abuse. Due to the specific population the findings can be generalized to all DWI court-mandated clients but cannot be generalized to other populations. Gryczynski et al.'s (2009) research contains a similar limitation because of the socioeconomic homogeneity sample. Other precise populations, such as clients

arrested for possession, probation violations, and drug sales, can expand the information on with the same research question. Other researchers can ask the same question but focus on single states rather than a sample of the entire US population.

SAMHSA only sent the TEDS-D survey to agencies receiving public funding, which causes a limitation within the data set. Research with agencies receiving private funding may find different results (Albrecht et al., 2011). Often clients with private insurance have higher paying jobs which may act as a source of motivation for treatment completion. As the previous research shows, higher motivation yields higher treatment completion rates (Wolfe et al., 2013).

Another possible weakness could be the TEDS-D data set itself. SAMHSA used a self-made cleaning program called the Crosswalk to adjust and organize the incoming data from the surveyed agencies. The Crosswalk was responsible for cleaning and keeping accurate records, but it is possible it lost some data (Albrecht et al., 2011). If the system lost any data it would not be available for the random sample, which would threaten the studies external validity.

Another limitation was the data's age which contained statistics collected from 2006—2011. While a trusted government agency gathered the data, it is aged as the mental health field is ever changing and updating its practices. Changes may have taken place in the past 7 years which would heavily influence the results if I analyzed the same research question with newer data.

The TEDS-D did not include information about the number of visits needed for successful treatment completion. The centers themselves decided how many sessions a

client needs to attend to qualify for completion (Wise, 2010). It is possible a difference in the number of required sessions could impact completion (Mutter et al., 2015).

Identifying if the number of sessions needed predicts successful completion may offer insight in creating successful graduation conditions.

I explained in Chapter 3 that while SAMHSA collected the TEDS-D data set, they did not mandate agencies to complete and send in the survey. It is possible the current study only represented agencies with the time to complete the yearly surveys (Pascoe et al., 2013). Agencies with less time and money might spend it building stronger therapeutic relationships with clients, which could lower dropout rates. It is also possible agencies with limited resources did not want to record the information because of low retention rates. Future studies could focus on mandating survey completion in a random sample of existing treatment agencies.

Another limitation was the lack of qualitative analysis. I could have added depth by asking why clients were not successful in completing treatment. Perhaps their nonsuccessful completion had nothing to do with the days the clients waited, but had to do with personal issues or external legal reasons. By delving deeper with a qualitative piece a future researcher could pinpoint exact reasons for DWI clients not successfully graduating.

Strengths

The strengths included using a simple random sample taken from a large national population which adds depth to the existing literature. Albrecht et al. (2011) have a similar strength because they used the same data set. The large random sample offers

statistical power to examine multiple covariates. It is the only quantitative research focusing on days waiting and DWI client's treatment completion rates. Majority of the background research conducted on this topic did not include separating intensive versus nonintensive, as I did in this study. Another strength was the additional analyses of Nagelkerke R Square and interaction effects. The findings offer explanations and insight behind the original logistic regression results.

Implications for Social Change

I gave new information to the alcohol abuse and DWI treatment fields through this dissertation. Courts who mandate DWI clients to formal counseling can use this information as well as the treatment agencies themselves. The research supports giving older client's priority for program entry, this is a major policy implication. Not only was age a stronger predictor than days waiting, but older clients are impacted more significantly than younger clients by the number of days waiting. Courts can work with treatment agencies to give earlier appointments to older clients to raise completion rates. This can come in the form of courts mandating older clients to obtain an appointment by a certain date and the court case managers can contact treatment agencies to explain the client's legal obligations.

Drug courts send clients to treatment agencies which use best practices in their methods (Lutze & Wormer, 2007). Referring clients to agencies which use best practices are to ensure he or she has accessibility to relevant and high quality treatment. Studies show a client's first appointment is important in setting a positive counseling relationship (Redko et al., 2016). Counselors can connect the new research by supporting lowering

days waiting and putting emphasis on a positive first sessions to create a new best practice. If courts cannot or choose to not mandate older clients to obtain earlier appointments, counselors can give the earlier appointments to the older age population to increase completion rates. Both the courts and the treatment facilities can use age as a predictor when assigning intake appointments.

Nordfjaern (2011) identifies majority of recorded relapses in substance abusing clients occur within the first few months after treatment. When a client completes treatment the facility works with him or her to create an aftercare plan in place to help against relapse. If a client did not successfully complete treatment he or she will not have the chance to create a strong aftercare plan. The aftercare plans give the DWI clients support to continue abstinence from alcohol.

Locally, the courts' case managers can work with treatment agencies to move mandated clients into treatment with less days waiting. While the predictive nature was weak, they are still statistically significant findings. A treatment center should use all possible means when helping a client (Lutze & Wormer, 2007). Case managers knowing a client's age and employment status are statistically stronger than days waiting provides them leverage. While a court cannot change the client's age they can place emphasis on a client gaining employment sooner than later, which may increase the client's odds for successful completion. Counselors can work with older clients as days waiting impacts this age demographic more than younger clients. DeMichele (2011) reports offenders arrested for DWIs are more likely to be under the age of 29 and have little education. Treatment agencies might lower the WTs for unemployed clients as employed clients

have stronger odds of successfully completing treatment on their own. Nordfjaern (2011) supports counselors connecting clients to employment as part of aftercare plan to lengthen periods of abstinence, which lowers recidivism rates.

Raising completion rates is the ultimate goal because Timko et al. (2010) connected treatment completion to lowered DWI recidivism rates. Courts could ask treatment centers to offer shorter WTs for mandated clients over the age of 45 and are unemployed. Lowering DWI recidivism creates safer roads by lessening the injuries and deaths these incidents cause. Less injuries caused by DWI accidents is a positive social change because of the new research.

Conclusion

The research I completed gives courts and counselor's new information about WTs. The longer a DWI court-mandated client waits to begin treatment predicts a lesser chance of successful completion. While the predictive nature was weak, it still exists. Age is a strong predictor of treatment completion with clients over the age of 45 being impacted significantly by days waiting. Employment status had the strongest statistical significance on completion and should be part of treatment planning, even more than days waiting. Addiction is a mental health disease in which formal counseling is valuable in guiding a client to control their drinking habits (George et al., 2012). The information discovered here could be useful in treatment agencies changing patterns and policies as well as lowering WTs. These findings open the door to future analysis on DWI clients. Raising treatment completion rates helps to lower DWI recidivism rates. Using the

TEDS-D data set provides a wide scope of trusted information to guide these social changes in treatment and criminal justice areas.

Abstinence is the only successful treatment goal for alcohol addiction (Klingemann, 2011). DWI clients cannot commit more offenses if he or she are abstinent from alcohol, which means lowered recidivism rates (George et al., 2012). Older DWI court-mandated clients should be given priority to alcohol abuse outpatient treatment intake appointments.

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Appendix A: TEDS-D Original Race SPSS Codes

Value	Race
1	Alaskan Native: (Aleut, Eskimo, Indian): Origins in any of the original people of Alaska.
2	American Indian (other than Alaska Native): Origins in any of the original people of North America and South America (including Central America) and who maintain cultural identification through tribal affiliation or community attachment
3	Asian or Pacific Islander: Origins in any of the original people of the Far East, the Indian subcontinent, Southeast Asia, or the Pacific Islands
4	Black or African American: Origins in any of the black racial groups of Africa
5	White: Origins in any of the original people of Europe, North Africa, or the Middle East
13	Asian: Origins in any of the original people of the Far East, the Indian subcontinent, or Southeast Asia, including for example, Cambodia, China, India, Japan, Korea, Malaysia, Philippine Islands, Thailand, and Vietnam
20	Other singular race: Use this category for instances in which the client is not classified in any category above or whose origin group, because of area custom, is regarded as a racial class distinct from the above categories. (Do not use this category for clients indicating multiple races.)
21	Two or more races: Use this code when the State data system allows multiple race selection and more than one race is indicated
23	Native Hawaiian or other Pacific Islander: Origins in any of the original peoples of Hawaii, Guam, Samoa, or other Pacific Islands

Note. Substance Abuse and Mental Health Services Administration. (2011). Treatment episode dataset: Admissions (ICPSR No. 30122). No permission needed.

Appendix B: TEDS-D Original Employment Status SPSS

Value	Employment Status
1	Full time: Working 35 hours or more each week; including active duty members of the uniformed services.
2	Part time: Working fewer than 35 hours each week.
3	Unemployed: Looking for work during the past 30 days or on layoff from a job.
4	Not in labor force: Not looking for work during the past 30 days or a student, homemaker, disabled, retired, or an inmate of an institution.

Note. Substance Abuse and Mental Health Services Administration. (2011). Treatment episode dataset: Admissions (ICPSR No. 30122). No permission needed.

Appendix C: TEDS-D Original Reason for Discharge SPSS Codes

Value	Reason for Discharge
1	Treatment completed: All parts of the treatment plan or program were completed.
2	Left against professional advice: Client chose not to complete program, with or without specific advice to continue treatment. Includes clients who "drop out" of treatment for unknown reason and clients who have not received treatment for some time and are discharged for "administrative" reasons.
3	Terminated by facility: Treatment terminated by action of facility, generally because of client non-compliance or violation of rules, laws, or procedures (not because client dropped out of treatment, client incarcerated, or other client motivated reason).
4	Transferred to another substance abuse treatment program or facility: Client was transferred to another substance
5	Incarcerated: This code is to be used for all clients whose course of treatment is terminated because the client has been incarcerated. Includes jail, prison, and house confinement.
6	Death
7	Other: Moved, illness, hospitalization, or other reason somewhat out of client's control
8	Unknown: Client status at discharge is not known because for example, discharge record is lost or incomplete.

Note. Substance Abuse and Mental Health Services Administration. (2011). Treatment episode dataset: Admissions (ICPSR No. 30122). No permission needed.

Appendix D: TEDS-D Original Criminal Referral SPSS Codes

Value	Criminal Referral
1	State/Federal court
3	Probation/Parole
5	Diversionary program
6	Prison
7	DUI/DWI
8	Other recognized legal entity: Other recognized legal entities include local law enforcement agency, corrections agency, youth services, review board/agency)

Note. Substance Abuse and Mental Health Services Administration. (2011). Treatment episode dataset: Admissions (ICPSR No. 30122). No permission needed.

Appendix E: TEDS-D Original Service Setting SPSS Codes

Value	Service Setting
1	Detoxification, 24 hour service, hospital inpatient: 24 hours per day medical acute care services in hospital setting for detoxification for persons with severe medical complications associated with withdrawal
2	Detoxification, 24 hour service, free standing residential: 24 hour per day services in non-hospital setting providing for safe withdrawal and transition to ongoing treatment
3	Rehabilitation/Residential- Hospital other than detox: 24 hour per day medical care in a hospital facility in conjunction with treatment services for alcohol and other drug abuse and dependency
4	Rehabilitation/Residential- Short term (30 days or fewer): Typically, 30 days or less of non-acute care in a setting with treatment services for alcohol and other drug abuse and dependency
5	Rehabilitation/Residential- Long term (More than 30 days): Typically, more than 30 days of non-acute care in a setting with treatment services for alcohol and other drug abuse and dependency; this may include transitional living arrangements such as halfway houses
6	Ambulatory intensive outpatient: As a minimum, the client must receive treatment lasting two or more hours per day for three or more days per week. (Includes partial hospitalization)
7	Ambulatory nonintensive outpatient: Ambulatory treatment services including individual, family, and/or group services; these may include pharmacological therapies
8	Ambulatory-detoxification: Outpatient treatment services providing for safe withdrawal in an ambulatory setting (pharmacological or non-pharmacological)

Note. Substance Abuse and Mental Health Services Administration. (2011). Treatment episode dataset: Admissions (ICPSR No. 30122). No permission needed.

Appendix F: TEDS-D Original Primary Substance of Use Codes

Value	Primary Substance of Use
1	None
2	Alcohol
3	Cocaine/Crack
4	Marijuana/Hashish: Includes THC and any other cannabis sativa preparations
5	Heroin
6	Nonprescription methadone
7	Other opiates and synthetics: Includes buprenorphine, codeine, Hydrocodone, hydromorphone, meperidine, morphine, opium, oxycodone, pentazocine, propoxyphene, tramadol, and any other drug with morphine-like effects
8	PCP: Phencyclidine
9	Other hallucinogens: Includes LSD, DMT, STP, hallucinogens, mescaline, peyote, psilocybin, etc
10	Methamphetamine
11	Other Amphetamines: Includes amphetamines, MDMA, phenmetrazine, and other unspecified amines and related drugs.
12	Other stimulants: Includes methylphenidate and any other stimulants.
13	Benzodiazepines: Includes alprazolam, chlordiazepoxide, clonazepam, clorazepate, diazepam, flunitrazepam, flurazepam, halazepam, lorazepam, oxazepam, prazepam, temazepam, triazolam, and other unspecified benzodiazepines
14	Other non-benzodiazepine tranquilizers: Includes meprobamate, tranquilizers, etc
15	Barbiturates: Includes amobarbital, pentobarbital, phenobarbital, secobarbital, etc
16	Other non-barbiturate sedatives or hypnotics: Includes chloral hydrate, ethchlorvynol, glutethimide, methaqualone, sedatives/hypnotics, etc
17	INHALANTS: Includes chloroform, ether, gasoline, glue, nitrous oxide, paint thinner, etc
18	Over the counter medications: Includes aspirin, cough syrup, diphenhydramine and other anti-histamines, sleep aids, and any other legally obtained non-prescription medication
20	Other: Includes diphenylhydantoin/phenytoin, GHB/GBL, ketamine, etc

Note. Substance Abuse and Mental Health Services Administration. (2011). Treatment episode dataset: Admissions (ICPSR No. 30122). No permission needed.

Appendix G: Independent Variable Cross Tabbed with Dependent Variable

Variable Days Waiting	N	%	Did Not Complete	Completed
0	2005	40.5	670	1335
1	292	5.9	59	233
2	185	3.7	43	142
3	159	3.2	35	124
4	120	2.4	25	95
5	218	4.4	61	157
6	152	3.1	44	108
7	312	6.3	73	239
8	83	1.7	34	49
9	70	1.4	20	50
10	129	2.6	32	97
11	43	.9	12	31
12	64	1.3	16	48
13	63	1.3	18	45
14	129	2.6	33	96
15	87	1.8	20	67
16	35	.7	7	28
17	26	.5	7	19
18	24	.5	5	19
19	26	.5	7	19

20	55	1.1	15	40
21	53	1.1	14	39
22	22	.4	3	19
23	17	.3	3	14
24	20	.4	4	16
25	24	.5	5	19
26	20	.4	5	15
27	24	.5	5	19
28	31	.6	9	22
29	16	.3	8	8
30	58	1.2	12	46
31	14	.3	4	10
32	16	.3	4	12
33	16	.3	4	12
34	14	.3	5	9
35	14	.3	5	9
36	12	.2	4	8
37	7	.1	2	5
38	11	.2	5	6
39	11	.2	5	6
40	12	.2	5	7
41	5	.1	2	3
42	13	.3	4	9
43	6	.1	1	5
44	2	.0	2	0
45	14	.3	5	9

47	6	.1	3	3
48	4	.1	1	3
49	4	.1	0	4
50	6	.1	0	6
51	2	.0	1	1
52	1	.0	1	0
53	7	.1	2	5
54	4	.1	0	4
55	5	.1	1	4
56	8	.2	1	7
57	3	.1	1	2
58	3	.1	0	3
59	2	.0	1	1
60	38	.8	6	32
61	2	.2	0	2
62	1	.1	0	1
63	3	.1	0	3
64	2	.0	2	0
65	2	.0	1	1
66	1	.0	1	0
67	2	.0	0	2
68	1	.0	0	1
69	2	.0	1	1
70	14	.3	1	13
71	3	.1	0	3
72	1	.0	1	0

74	1	.0	1	0
75	3	.1	0	3
77	3	.1	1	2
78	1	.0	0	1
79	1	.0	0	1
80	4	.1	2	2
81	1	.0	0	1
82	3	.1	1	2
83	2	.0	1	1
85	1	.0	0	1
87	1	.0	0	1
88	2	.0	1	1
89	1	.0	0	1
90	7	.1	4	3
91	2	.0	1	1
92	2	.0	0	2
93	2	.0	1	1
94	2	.0	0	2
96	1	.0	0	1
97	4	.1	1	3
98	1	.0	0	1
99	7	.1	1	6
100	1	.0	0	1
101	1	.0	0	1
102	3	.1	1	2
103	1	.0	0	1

104	1	.0	1	0
110	1	.0	0	1
111	3	.1	1	2
113	2	.0	2	0
115	1	.0	1	0
116	1	.0	1	0
117	1	.0	0	1
118	2	.0	0	2
120	5	.1	1	4
121	1	.0	1	0
123	1	.0	0	1
124	1	.0	0	1
125	1	.0	0	1
126	2	.0	0	2
128	2	.0	0	2
131	2	.0	0	2
135	1	.0	0	1
136	2	.0	1	1
137	3	.1	0	3
