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A Measure Predicting Treatment Outcome For Sexual Offenders

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A MEASURE PREDICTING TREATMENT OUTCOME FOR SEXUAL OFFENDERS

by

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Kaitlin Alyssa Guston

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Abstract

Researchers generally agree that treatment reduces the likelihood of sexual offender recidivism. However, studies show attrition rates of up to 85% in some treatment programs for sex offenders. Because many risk factors for recidivism and treatment attrition are the same, the present study used gold-standard risk assessments to predict which sex offenders would not complete a community treatment program. The Static-99r, Stable-2007, and URICA assessed static risk factors, dynamic needs, and responsivity to treatment for 289 sex offenders. Pre-treatment scores from the sex offenders in the sample indicated that these assessment instruments could predict treatment attrition for sex offenders in community treatment (AUC = .928). The Stable-2007 was the best predictor of treatment attrition. Implications of the results and directions for future research are also discussed.

Introduction

The criminal justice system continues to struggle with sex offender recidivism. Studies suggest treatment is somewhat effective at reducing recidivism (Hanson et al., 2009a). However, the extent to which sex offender treatment reduces recidivism remains a highly contentious issue (Cohen, 2018; Grady et al., 2015; Lösel & Schmucker, 2017; Rettenberger et al., 2015). Disagreement among researchers stems from many sources, including fluctuations in post-treatment recidivism rates and consistently high rates of treatment attrition among high-risk offenders (Day et al., 2019; Hatcher et al., 2012; Jones & Neal, 2019). Many studies have examined risk factors to predict recidivism, but few researchers have looked at factors that predict failure to complete treatment.

Regardless of disagreements surrounding the degree to which treatment reduces recidivism, most researchers acknowledge it has ameliorating effects (Hanson et al., 2009a). Therefore, studies finding attrition rates of up to 85% for some sex offender treatment programs (Nunes, & Cortoni, 2008; Olver, & Wong, 2013; 2009) are deeply troubling. Recidivism causes harm to both victims (Mason, & Lodrick, 2013) as well as society. For example, lost wages and taxes; psychological, medical, and other assistance for victims (Adams & Farrandino, 2008); the expense of legal proceedings and reincarceration; and its psychological and emotional toll on survivors (Sawyer & Wagner, 2020). These expenses and costs are substantial. Offenders who do not complete treatment are typically in group treatment. Because of their antisocial behavior, they reduce treatment efficacy and increase the risk of recidivism for the other sex offenders in group treatment (Bonta et al., 2010; Doren & Yates, 2008).

Some states have taken precautions against these offenders by creating sexually violent predator laws. These laws allow sex offenders who are unable to control their behavior to be involuntarily committed to hospitals or private institutions until they are deemed safe for release (ATSA, 2013). Since deinstitutionalization in the 1970s, most hospitals can only accommodate the most dangerous sex offenders (Lamb & Weinberger, 1998; Rydberg, 2017). Accordingly, there may be many sex offenders are in community treatment even though they are better suited for civil commitment.

Considering civil commitment is not an option in most cases, clinicians must frequently make difficult decisions about sexual offenders' treatment and the likelihood of recidivism. Clinicians typically rely on the Risk Needs Responsivity (RNR) model of correctional treatment to assess and meet the needs of high-risk or unmotivated offenders (Bonta; 2010; Hanson et al., 2009a). Failure to identify high-risk offenders is potentially detrimental to other sex offenders in treatment and to society. One way to mitigate such harmful effects may be to determine whether the risk factors that predict recidivism can also predict treatment outcomes. Prior knowledge of an offender's potential difficulty in treatment would enable clinicians to adjust the treatment plan before treatment begins, thus preventing disruption in-group cohesion, attrition, and recidivism.

Due to the relationship between treatment attrition and recidivism, gold-standard risk assessments may be able to identify predictors of treatment outcome. (Brouillette-Alarie et al., 2018; Hanson et al., 2009b; Kim, Benekos, & Merlo, 2016). Since most clinicians already use these instruments to assess risk and needs, this method has the added benefit of clinicians not investing time or money into acquiring or learning a new assessment instrument. Clinicians can use these instruments to assess whether a sex offender is at risk of not successfully completing treatment. The current study will examine archival data to assess if the Static-99r, Stable-2007, and University of Rhode Island Change Assessment (URICA) can predict treatment attrition.

Each of these assessment tools is considered a gold-standard instrument in their area of assessment.

Literature Review

Risk for Recidivism

Risk factors targeted in sex offender (SO) treatment are similar in many ways to those of general offenders. Therefore, examining risk factors for SOs must be two-fold to account for both the risk of general and sexual recidivism. Risk factors typically fall into static and dynamic categories (Bonta, 2002). Static risk factors cannot be changed, such as age at first offense or criminal history. Dynamic risk factors are changeable, such as substance use and antisocial peer groups. Dynamic factors can be further divided into stable factors, which are more resistant to change (e.g., substance use, antisocial attitudes), and acute factors, which are more susceptible to change (e.g., mood, cooperation with authority; Hanson & Harris, 2001).

The most empirically validated risk factors for recidivism come from the Risk-Needs-Responsivity (RNR) model (Andrews, Bonta, & Hoge, 1990). The RNR model is comprised of three principles (i.e., risk, need, and responsivity) and is the only model within correctional treatment proven to reduce recidivism (Andrews & Bonta, 2010; Blanchette & Brown, 2006; Bonta; 2010; Hanson et al., 2009a). The risk principle states that an offender's level of risk for recidivism should be the basis of the level of treatment. Thus, treatment levels range from minimal treatment intensity (low risk) to moderate intensity (medium risk) and to intensive treatment (high risk); Andrews & Bonta, 2010). The needs principle refers to criminogenic needs, which determine the level of treatment required. The responsivity principle describes the response an offender has to treatment and the factors impacting their response (e.g., motivation, learning style; Andrews & Bonta, 2010).

Stemming from the RNR model, Andrews & Bonta (1990; 2010) identified eight primary risk factors that carry the most risk for criminal behavior. The primary factors consist of family structure, years of education, leisure/recreation activities, substance use, history of antisocial behavior, antisocial personality patterns, antisocial cognition, and antisocial associates. These eight factors are the criminogenic needs targeted by the Risk principle in the RNR model. Consequently, they are the most validated general risk factors and are the basis for several risk assessments instruments (e.g., Level of Service Inventory-Revised, Historical Clinical and Risk Management 20; van der Knaap et al., 2012).

For sexual offenders, Mann, Hanson, and Thornton (2010) proposed that the highest standard of assessment and treatment should focus on factors empirically correlated to offending and that provide insight into the source of the risk factor. The authors refer to such factors as psychological meaningful risk factors. Psychologically meaningful risk factors are individual propensities (i.e., enduring individual characteristics) that can predict future thoughts, feelings, and behaviors. In addition to constituting individual characteristics, Mann et al. (2010) suggest these factors also describe an individual's interpersonal tendencies and his or her interactions with the environment.

An example of psychologically meaningful risk factors is when an individual frequents neighborhoods with high crime rates, which would increase his or her risk for recidivism. Psychologically meaningful risk factors can be static or dynamic (Hanson, Helmus, & Harris, 2015; Mann, Hanson & Thornton, 2010).

Mann and her colleagues conducted a meta-analysis in 2010 to identify empirically supported psychologically meaningful risk factors. Their meta-analysis identified the following factors: sexual preoccupation, sexual preference for pre/pubescent children, sexualized violence, multiple paraphilias, offense supportive attitudes, emotional congruence with children, lack of emotionally intimate relationships with adults, lifestyle impulsiveness, poor problem solving, resistance to rules and supervision, grievance (e.g., feelings of persecution) and hostility, and negative social influences (i.e., antisocial peer group). Some of these factors, along with two “promising” factors (i.e., hostility towards women and maladaptive coping), have been integrated into several of the most empirically supported risk assessments for SOs currently in use (e.g., STATIC – 99r, STABLE-2007; Brouillette-Alarie et al., 2018; Harris et al., 2003; Phenix, 2017).

In addition to risk factors targeted in treatment, risk management factors also influence treatment outcomes. Risk management factors focus on potentially destabilizing environmental aspects of an offender’s life in the community (Webster et al., 1997). Some of the most significant risk management factors include a prosocial post-release living environment, employment, and access to adequate treatment (Booth & Kingston, 2016). Risk management factors correspond closely with the responsivity principle in the RNR model and are important in predicting treatment success. Understanding factors most often targeted in treatment programs is crucial to predicting treatment outcomes.

Risk Factors for Treatment Attrition

Like recidivism risk factors, treatment attrition factors are also likely to follow the RNR model. In addition to factors included in risk assessment instruments, studies examining treatment outcomes show that motivation is a significant predictor of treatment outcomes. (e.g., Brunner et al., 2019; Hollin et al., 2008; Larochelle et al., 2011; Nunes, 2010). Motivation is a responsivity factor in the RNR model and can help in planning risk management strategies. Risk management strategies include external control measures, psychotherapeutic approaches, and pharmacologic approaches (Booth, & Kingston, 2016). These strategies reduce the likelihood of recidivism. Identifying salient static, dynamic, and motivational factors from validated risk instruments is essential to predicting treatment outcomes.

Many studies in this area have attempted to identify individual factors that predict treatment attrition. Some of the most commonly identified factors include age, marital status, criminal history, antisocial personality, recidivism risk, and motivation to change (Beyko & Wong, 2005; Daly, & Pelowski, 2000; Nunes, 2006; Olver, Stockdale, & Wormith, 2011; Pelissier, 2007; Wormith, & Olver, 2002). Nearly all these attrition risk factors overlap with recidivism risk factors, and some research supports combining them into screeners for treatment outcomes (Browne, Foreman, & Middleton, 1998; Edwards, 2005; Nunes, 2006; 2008; 2010). The most successful screeners use previously validated risk assessments factors (Nunes, 2006; 2010). Despite issues with some of the early screeners, their use of recidivism risk assessment lends credence to the current study.

One of the earliest attrition risk instruments was a 9-item screening tool created by Browne et al. (1998). Using factors from recidivism literature and the Structured Anchor Clinical Judgement Scale (SAC-J; Grubin, 1998), Browne and his colleagues amassed 30 potential treatment risk factors (1998). Using retrospective analysis of treatment records from 96 child sex offenders, they identified nine factors that predicted treatment outcomes. They consisted of the following primarily static risk factors: a violent index offense, previous violent offending, non-contact offenses, previously known to police, history of incarceration, unemployment, substance use, uncooperative with treatment, deterioration in treatment (Browne, Foreman, & Middleton, 1998). Despite poor specificity (<75%) and lack of generalizability due to sample size (n=96), this screener suggested that sexually risk predictors do not generally predict treatment outcome.

A 2005 study on adolescent sexual abusers produced similar results. The Risk Of Drop-Out (RODO) scale is based on the recidivism literature and items from a previously validated risk assessment: the Estimate of Risk of Adolescent Sexual Offender Recidivism (ERASOR; Whorling, & Curwen, 2001). Like the 9-item screener, the RODO's items consist primarily of static factors. In contrast, Edwards et al. (2005) used only dynamic factors from the ERASOR in creating their screener. They analyzed the retrospective data of 53 male adolescents and identified 23 items, which had adequate internal consistency (i.e., a Cronbach alpha of .84) (Edwards et al., 2005). Although some of these factors are irrelevant to an adult population, many are adult factors that were previously identified in the literature (e.g., criminal background, antisocial attitudes; Olver, Stockdale, & Wormith, 2011) and in Browne et al.'s 9-item screener (e.g., previous non-sexual offenses; Browne et al., 1998). However, the most notable difference between Browne's screener is that several of the RODO's items are sexually related predictors of treatment attrition (i.e., male victim, unrelated victim, anal penetration).

The most recent screener is also the most empirically supported measure of treatment attrition. The Drop-out Risk Scale (DRS) created by Nunes (2006) is the only screener to follow the RNR model of risk assessment, focusing on the responsivity principle illustrated by the three-pronged attrition prediction model. The model consists of static and dynamic recidivism risk factors representing the risk and needs principles and a component assessing motivation for treatment, encompassing the responsivity principle (2006; 2008; 2010). Following the RNR model, Nunes utilizes an empirically supported static risk assessment, the Statistical Information on Recidivism Scale (SIR), along with age, marital/family needs, prosocial attitudes, and motivation for treatment to create the DRS (Nunes, 2006). Nunes and colleagues (2010) demonstrated the DRS has excellent predictive validity for termination among sex offenders (n=994) who participated in at least one correctional treatment program (AUC=.77). Some analyses even suggest the DRS can predict drop-out among SOs better than that of general offenders (AUC=.70; Nunes, 2010).

In his research validating the DRS with SO populations, Nunes acknowledged some ambiguity regarding the effect of sexual deviance on treatment attrition. Nunes and Cortoni (2008) sought to provide some clarity by testing the ability of general criminality and sexually deviant items on the Static-99 (i.e., the gold standard static risk assessment for SOs; Hanson, 2009) to predict attrition. With a sample of offenders from a prison-based treatment program (52 dropouts, 48 completed), results suggest general criminality factors predict treatment attrition and sexually deviant factors do not. These findings indicate that risk for sexual recidivism and treatment attrition may be two distinct constructs (2008).

Similar results from a recent study bolster Nunes and Cortoni's (2008) claims. Stinson (2016) used the Static-99r and mental health diagnoses as predictors of treatment attrition for a sample of SOs with serious mental illness residing at an in-patient psychiatric hospital (n=156). The results of their study showed that the Static-99r predicted treatment attrition, but sexually deviant risk factors did not predict attrition. Nonetheless, both their studies have limitations in their generalizability to community samples because their samples consisted of offenders in highly controlled environments.

The measures to predict treatment attrition align with several aims of the current study, including the use of previously validated risk assessments and static, dynamic, and motivation factors to predict treatment attrition in sex offenders. As Browne et al. (1998) demonstrated, static factors alone fail to separate high-risk and low-risk offenders. This left clinicians in the same position as before using the measure, unable to focus scarce treatment resources on offenders who need them most (Fortunately, modern risk assessments such as that Static 99 have reportedly remedied this issue, that is, scores distinguish between low and high-risk offenders). The RODO demonstrated higher predictive ability and specificity with the addition of several dynamic risk factors (Edwards et al., 2005). Although more reliable than Browne's screener, its focus on adolescent populations disqualifies its use with adult SOs. The DRS followed suit, also adding dynamic factors to its model. However, the DRS improves upon predictive ability, specificity, and generalizability by adhering to the RNR model of corrections research by combining static, dynamic, and motivational factors into a single measure (Nunes, 2006; 2010).

Although the DRS appears to be a reliable tool to predict treatment attrition among SOs, there remain several factors supporting the utility of gold standard SO risk assessments for this purpose. Most importantly, the validation of the DRS has been limited to offenders in prison. Accordingly, it may not generalize to community-based treatment programs (Nunes, 2006; 2010). The differences in attrition-related risk treatment factors between prison and the community are vast. The most obvious is the increased risk for reoffending in such an uncontrolled environment. Although opportunities to engage in sexual offending exist in prison, access to vulnerable persons (e.g., children) is typically limited.

Furthermore, the literature examining differences in risk for dropping out of treatment indicates that loss of motivation for treatment is highest upon reentry to the community (Doren, & Yates, 2008). Such variations in risk could indicate a need for more thorough measures of treatment responsivity (i.e., motivation for change). Another issue is that the validation sample of the DRS varied in the type of treatment their sample received (Nunes, 2006; 2010). Variance in type of treatment within the sample introduces possible confounding factors. Additional relevant research is necessary before risk factors included in the DRS can be generalized to community programs.

In the meantime, it would be beneficial to follow Nunes's example of predicting attrition using the RNR method by using validated static, dynamic, and motivational risk assessments. Such a study could provide further support for the three-pronged prediction model. It could also help determine whether sexually related risk factors predict attrition from community-based treatment programs.

Gold Standard Sex Offender Risk Assessment

There are four generations of risk assessment instruments (Bonta, 1996). First generation instruments consist of actuarial assessments. Actuarial assessments are highly structured and use only empirically validated risk factors to predict recidivism (i.e., they are nomothetic and quantitative risk assessments). The items derived from these risk factors are quantified to provide a total score reflecting risk level (Bonta, 1996). Second-generation instruments expanded actuarial models by recognizing the complexity involved in predicting and managing risk for homogeneous groups, not just a specific individual. These instruments use risk formulation which includes professional judgement that considers both environmental and individual factors to assess potential future offending based on present factors (Whittington R., et al., 2002-8). The appraisal of present factors allows clinicians to formulate a reason for current criminal behavior and predict the circumstances with which the behavior could happen again. Third-generation instruments also follow the actuarial and SPJ models. Their items are empirically derived predictors of recidivism and are quantifiable like the first and second-generation instruments; however, third-generation instruments emphasize dynamic risk factors. The newest wave of risk assessments is the fourth generation, which emphasizes the responsivity principle in the RNR model (Wilcox, 2018).

This evolution of risk assessment has dramatically improved the prediction of recidivism. Particularly important to improving recidivism prediction has been the development of actuarial predictors that replaced subjective clinical judgment. (Harris, & Hanson, 2010; Hanson & Morton-Bourgon, 2009; Menzies et al., 1994). The second-generation instruments reliably predict recidivism but still have weaknesses. For instance, they rely heavily on static factors, making it impossible to gauge changes in the level of risk over time.

Researchers created the third generation of risk assessments to remedy this difficulty, consisting of static and dynamic risk factors. The addition of dynamic factors allows clinicians to measure changes in treatment over time. Although some argue that third-generation assessments allow for too much clinical judgment, most researchers find the benefits of these measures outweigh the risks (Hanson, 2010). Lastly, fourth-generation instruments focus on responsivity by helping clinicians determine the appropriate type and amount of treatment an offender needs to receive to improve (PSRAC, 2018). This most recent generation is the first to introduce the regular use of motivation for treatment as a predictor of recidivism.

Static

A wealth of risk assessment research supports the Static-99r as the standard against which other static instruments are measured (Helmus, & Thornton, 2015; Jackson & Hess, 2007; Kelley et al., 2020; McGrath et al., 2009; Olver, & Wong, 2013). The Static-99r is a 10-item actuarial instrument that estimates the probability of sexual and violent recidivism among adult men charged or convicted of at least one sexual offense against a child or non-consenting adult.

Developed by Hanson & Thornton (1999), the Static-99 was the product of two risk assessments, the Rapid Risk Assessment of Sex Offender Recidivism (RRASOR) and the Structured Anchored Clinical Judgement – Minimum (SACJ-Min). Shifts in the base rate of SO recidivism caused the Static-99 to be revised a decade after its initial release (Helmus, 2009). The Static-99r has moderate to high predictive validity for reoffending (AUC = .70 - .86) and demonstrates excellent inter-rater reliability correlations (ICC = .86-.92; Hanson et al., 2014; Boer & Hart, 2012; Helmus, 2009; Levenson, 2004; Murrie et al., 2009).

Static risk assessments have a notable weakness regarding their ability to predict recidivism. They do not consider post-treatment changes. Olver and Wong 2014 confirmed this hypothesis with the Static-99, during which predictive efficacy decreased as the amount of treatment increased. Similar studies using other static risk assessments support Olver and Wong's findings (Nunes, 2008; Phenix et al., 2016). The shortcomings of static factors demonstrate a need for dynamic factors in predicting recidivism and, likely, treatment attrition.

Dynamic

As previously mentioned, dynamic risk factors represent the needs principle in the RNR model and are therefore the primary focus in SO treatment. As such, these factors are particularly important to predicting treatment attrition. Numerous studies suggest the Stable-2007 is the most reliable measure of dynamic risk for sexual recidivism in Canada and the United States (Bourgon, et al., 2018; McGrath et al., 2010). A recent survey of preferred assessments further bolsters this suggestion. Among forensic evaluators (Kelley et al., 2020) the Stable-2007 is the second most widely used instrument (57%) after the Static-99r (82.4%), making it the most widely used dynamic risk assessment.

The Stable-2007 assesses stable dynamic risk factors associated with sexual, violent, and general recidivism. This measure aligns itself with the RNR model meaning the total scores reflect the level of criminogenic needs. Studies measuring the predictive ability of the Stable-2007 report good AUC values ranging between 0.67-0.71 (Brankley, Babchishin, & Hanson, 2021; Rettenberger & Craig, 2015). The inter-rater reliability of the Stable's total score is adequate, with average ICC values between .86 and .92 (Fernandez & Helmus, 2017; Hanson, 2009b).

A particular strength of The Stable-2007 is that Hanson and Thornton (1998) created it to complement the Static-99r dynamically. As such, there is considerable research validating the incremental validity of the Stable-2007 when coupled with the Static-99r (Brankley et al., 2021; Hanson et al., 2009b; Helmus et al., 2021; Mann, Hanson, & Thornton, 2010). Another strength concerning the current study is the wealth of research supporting the Stable's use in controlled environments (e.g., prison) and the community (Bourgon et al., 2018; Fernandez & Helmus, 2017; Hogan & Sribney, 2019; Veith, 2018).

Motivation

Motivation for treatment is a recent addition to risk assessment variables due to its ability to inform on responsivity to different treatment types and dosage. The Transtheoretical Model of behavioral change (TTM) is how clinicians most often assess motivation for treatment (Brunner et al., 2019; Olver & Wong, 2013). The TTM is the gold standard for the Stages of Change (SOC) model assessing readiness to change by placing individuals into four stages: pre-contemplation, contemplation, action, and maintenance (Prochaska, DiClemente, & Norcross,1992). Movement through this continuum aligns closely with research on success in treatment (Tierney & McCabe, 2002).

Co-developer of the TTM, Carlo DiClemente, is the co-author of the University of Rhode Island Change Assessment (URICA) scale (DiClemente & Hughes, 1990). The URICA comprises 32 self-report items and places respondents into one of the four TTM levels of change (i.e., Precontemplation, Contemplation, Action, and Maintenance). Per DiClemente and Hughes (1990), The Precontemplation stage of change reflects no intention of changing behavior in the foreseeable future (i.e., within the next six months). Individuals at this stage are often unaware that their behavior is problematic and underestimate the benefits of changing it. The Contemplation stage marks the recognition that one's behavior may be problematic. Individuals at this stage begin considering the costs and benefits of behavioral change. The Action stage represents individuals who have decided to change and are working towards specific goals. Lastly, the maintenance stage reflects individuals who have reached their behavioral change goals but still have trouble maintaining new adaptive behavioral patterns (DiClemente & Hughes, 1990).

The URICA has successfully tracked treatment progress for common psychological disorders (e.g., anxiety and depression; DiClemente, 2005) and more severe disorders and diseases (e.g., addiction, terminal illness; Soderstrom et al., 2007). Furthermore, this instrument has found support in offender populations including offenders who have psychological disorders or who committed sexual offenses. A particular advantage of the URICA with offender populations is the scoring, which takes into consideration the tendency to over-endorse post-treatment (i.e., action/maintenance stages) characteristics (e.g., "I am finally doing some work on my problems.") and under-endorse pre-treatment (i.e., pre-contemplation/contemplation) characteristics (e.g., "I may be part of the problem, but I do not really think I am." DiClemente, 2005). The URICA appears capable of conceptualizing and expediting behavioral change among SO populations (Burrowes & Needs, 2009; Tierney & McCabe, 2002).

Aim Of Current Study

The current study aims to determine whether gold standard sex offender instruments can also predict attrition in community treatment programs as well as recidivism. The present study will determine if commonly used gold-standard sex offender assessments measuring static risk, dynamic risk, and motivation for change can identify offenders at risk for treatment dropout or termination.

Hypotheses

As was stated in the literature review, many of the same risk factors for recidivism overlap with risk factors for treatment attrition. Additionally, research frequently cites motivation as a significant stand-alone predictor of treatment outcomes. Hypothesis I: A model using the combined score of the Static-99r and the Stable-2007 along with the URICA will significantly predict treatment recidivism (i.e., offenders suspended from treatment, terminated from treatment, or had their probation revoked while in treatment).

As described in the literature review, the predictive efficacy of the Static-99r decreases as treatment increases (Olver & Wong, 2014). Additionally, screeners using a combination of factors to predict treatment outcome show a significant increase in predictive ability (i.e., increase in AUC values) with the addition of dynamic factors (Edwards et al., 2005; Nunes, 2010). The same increase was not seen with the addition of motivational factors to the model (Nunes, 2010), suggesting dynamic factors play a more prominent role in treatment outcomes. Hypothesis II: The best individual predictor of treatment recidivism will be the Stable - 2007.

Probation revocation has a dual role as a type of treatment attrition and a type of recidivism. Since the Static-99r and Stable-2007 are the gold standard instruments to predict recidivism, it would make sense that a model using them would predict a type of recidivism better than treatment attrition. However, there is insufficient data to determine whether the URICA predicts recidivism better than treatment attrition. Hypothesis III: The combined use of these instruments will predict probation revocation better than treatment termination or suspension.

Methodology

Sample

The sample consists of approximately 289 males who participated in a cognitive behavioral treatment program with the Sex offender Treatment and Assessment of North Dakota (STAND). The sample is primarily white (90%) and single, with an average age of 29 years. Native American subjects were excluded because the Stable-2007 lacks norming data for them. Offenders are assessed by clinicians using the Static-99r, the Stable-2007, and the URICA as part of a standard battery upon entering treatment with STAND.

Measures

Static-99r

The Static-99r is a ten-item, actuarial assessment which assess for: prior sexual offenses, prior sentencing dates, any conviction for non-contact sex offenses, current convictions for non-sexual violence, prior convictions for non-sexual violence, unrelated victims, stranger victims, male victims, age, and marital status (Hanson, Phenix, & Helmus, 2009). A total score determines the risk level for an SO. The levels based on a SO’s total score are Level I - Very low

(-3 to -2), Level II – Below average (-1 to 0), Level III – Average (1 to 3), Level IVa – Above average (4 to 5), and Level IVb – Well above average (6+; Hanson et al., 2009b).

Stable-2007

The Stable-2007 evaluates 13 risk factors over the last six months to a year. They include offender's attitudes, ability for self-regulation (general and sexual), willingness to work with supervision, and intimacy deficits. The Stable-2007 assesses an SO’s current density of criminogenic needs (i.e., the quantity of criminogenic needs one has) and predicts risk and supervision needs over the next year (Fernandez & Helmus, 2017). Items are scored using information gathered during intakes, clinical interviews, and collateral reports (e.g., case files, correspondence with probation officers). Based on data collected, each item receives a score of 0 (i.e., not present), 1 (i.e., partially present), or 2 (i.e., fully present) with a total possible score of 26, or 24 if they do not have child victims (Fernandez et al., 2014). The interpretive ranges for total score are low dynamic needs (0 – 3), moderate dynamic needs (4 – 11), high dynamic needs (12+) (Fernandez et al., 2014).

URICA

The URICA consists of 32 self-report items, and responses are given on a 5-point Likert scale ranging from 1 (strong disagreement) to 5 (strong agreement). This instrument has four categorical subscales, which follow an adapted version of the stages of change found in the TTM (i.e., Precontemplation, Contemplation, Action, and Maintenance). Each subscale has eight items. Scores for each subscale are averaged, and their total is compared to the following cut-off scores: Precontemplation 8 or less, Contemplation 8-11, Action 11-14, and Maintenance 14+.

Procedure

Data consists of archival records of former clients of Sex offender Treatment and Assessment of North Dakota (STAND). Total scores were obtained from the Static-99r, Stable-2007, and URICA. Additionally, demographic factors including age, ethnicity, and marital status were also collected.

Analysis

A logistic regression was used to determine if the Static-99r, Stable-2007, and URICA predict suspension, termination, and probation revocation for the participants. Demographic factors were controlled for the Static-99r and Stable-2007 except for age and marital/relationship status, which are used as predictors in these instruments.

Results

A binomial logistic regression determined whether the total scores from the Static-99r, Stable-2007, and URICA predicted attrition (coded 1) versus non-attrition (coded 0) group membership. The assumption of linearity of the continuous variables (i.e., Static-99r, Stable-2007) was assessed using the Box-Tidwell (1962) procedure. All continuous independent variables were found to be linearly related to the logit of the dependent variable (i.e., related to the log of the probability that a SO will meet criteria for treatment attrition). Additionally, no problems with collinearity were apparent between any independent variables ($VIF \leq 1.36$). The levels of behavioral change from the URICA were coded as categorical dummy variables with Maintenance as the reference category and Action, Contemplation and Precontemplation coded as 1 or 0 in the analysis. Two outliers due to data entry error were removed from the analysis.

A base rate of 35% (i.e., the sample's dropout rate) was used in the logistic regression model, and the model was statistically significant, $\chi^2(5) = 156.571$, $p < .001$. Therefore, the first hypothesis was supported. The model explained 66.3% (Nagelkerke R^2) of the variance in attrition and correctly classified 85.2% of cases. Table 1 illustrates the regression. Sensitivity for the model (i.e., Static-99r, Stable-2007 and URICA predicting attrition vs. non-attrition group membership) was 86.2% and specificity was 84.6%. Indicating that the model predicted 86.2% of offenders who dropped out of treatment, and 84.6% of offenders who did not drop out of treatment. The positive predictive value (PPV) for the model was 76.5% and the negative predictive value (NPV) was 91.3%. Meaning the model was correct 76.5% of the time when it predicted offenders would drop out of treatment. The model was correct 91.35% of the time when it predicted offenders would not drop out of treatment.

Table 1

Logistic Regression Predicting Likelihood of Treatment Attrition Based on the Static-99r, Stable-2007, and URICA

	B	SE	Wald	*df*	*p*	Odds Ratios	95% CI for Odds Ratio Lower	Upper
Static-99r	0.39	0.12	11.37	1	<.001	1.49	1.18	1.86
Stable-2007	0.52	0.08	49.33	1	<.001	1.69	1.46	1.95
URICA			10.54	3	.01			
Action	-3.28	1.57	4.36	1	.04	0.4	0.09	6.85
Contemplation	-0.48	1.15	0.18	1	.67	0.62	0.00	0.28
Precontemplation	-0.26	0.55	0.55	1	.81	1.30	0.15	11.57
Constant	-6.56	1.34	22.95	1	<.001	0.001		

Note: For the URICA the Action, Contemplation, and Precontemplation stages were compared to the Maintenance stage.

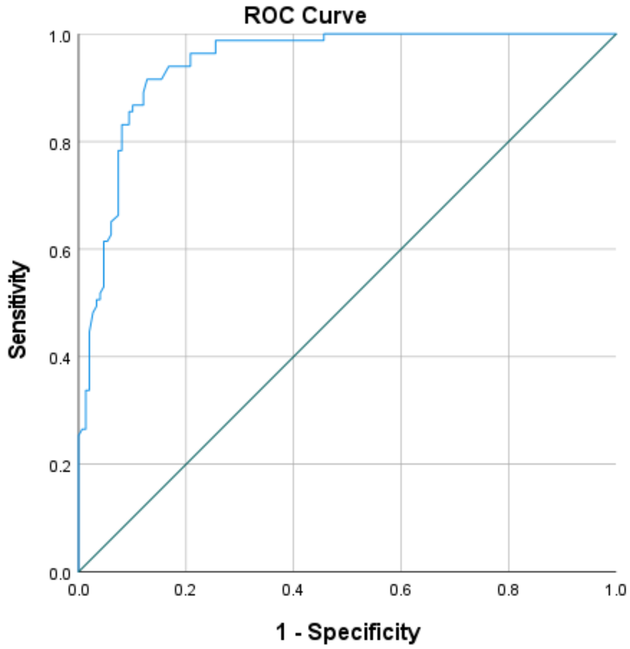
The Static-99r and Stable-2007 were significant predictors of treatment attrition. Only the Action (p <.05) stage of change was a significant predictor for the URICA. Higher scores on the Static-99r and Stable-2007 were associated with an increased risk of treatment attrition. Only participants in the Action stage of change for the URICA had a lower risk of treatment attrition compared to the reference group (i.e., the Maintenance stage) . The Stable-2007 was the best predictor of treatment attrition supporting the second hypothesis. The odds ratio for the Stable-

2007 was 1.69. This result indicates that for every unit increase in the Stable-2007 a participant is 1.69 times more likely to drop out of treatment. The odds ratio for the Static-99r was 1.49. This means that for every unit increase in the Static-99r a participant is 1.49 times more likely to drop out of treatment.

A Receiver Operating Characteristic (ROC) analysis was also conducted to measure the overall discriminative ability of the model (i.e., ability of the model to delineate treatment attrition versus non-attrition). The ROC curve indicates how well the model discriminates between offenders who drop out of treatment versus those who do not drop out. The area under the curve (AUC) provides a determination of how well the model can discriminate between treatment attrition and non-attrition SOs, the closer the AUC is to 1.0, the better the model discriminates. The area under the ROC curve was .945, [95% CI .917, .972], (see Figure 1a) which demonstrates an excellent level of discrimination (Hosmer et al., 2013). The optimal cut-off scores for the individual predictors (see Figure 2) are approximately 9 for the Stable-2007 and 3.50 for the Static-99r. Because the data from the URICA is categorical, the analysis could only provide the optimal cut-off value for the URICA, which fell between Action and Contemplation Prochaska & DiClemente, 1998).

Figure 1

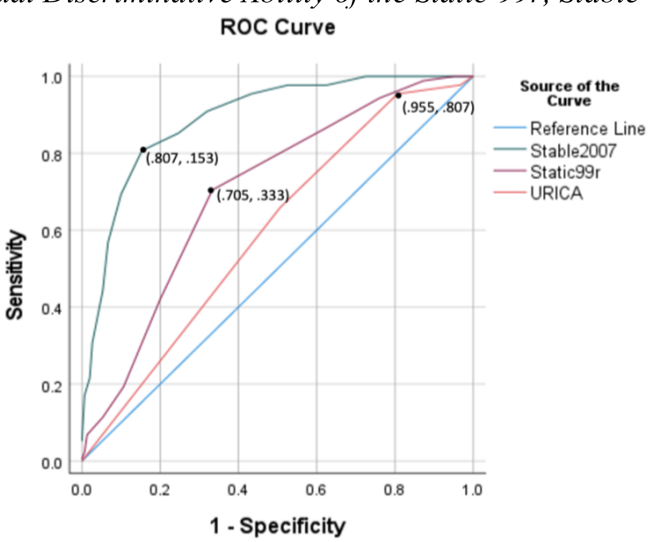
ROC Curve for the Model



Note. ROC analysis assessing ability of the Static-99r, Stable-2007, and the URICA to discriminate between treatment attrition and non-attrition. Area Under the Curve = .929.

Figure 2

Individual Discriminative Ability of the Static-99r, Stable-2007, and the URICA



Note. ROC analysis assessing individual discriminative ability of the Static-99r, Stable-2007, and the URICA, which provided optimal cut-off scores for each instrument based on sensitivity and specificity.

Binomial logistic regressions were conducted for each level of attrition (i.e., suspended, terminated, revoked) to examine the ability of the Static-99r and Stable-2007 to predict probation revocation over and above suspension and termination. Regarding suspension, the regression model was statistically significant, $\chi2(2) = 9.504$, $p = .009$. The model explained 98% (Nagelkerke R^2) of the variance in attrition and correctly classified 94.6% of cases. However, this was due to so few cases of suspension in the sample (n=15). Thus, the model was able to correctly classify all participants that were not suspended (specificity = 100%) and none of those that were suspended (sensitivity = 0%). It is worth noting that the Static-99r was not a significant predictor in this model ($p = .621$; Stable-2007: $p = .004$).

The model assessing the predictive ability of these instruments for termination (n = 37) was also statistically significant, $\chi2(2) = 35.247$, $p < .001$. The model explained 98% (Nagelkerke R^2) of the variance in attrition and correctly classified 86.4% of cases. However, the model's sensitivity was only marginally improved for cases of termination, correctly classifying only 8% of the sample. Specificity remained high with the model correctly identifying cases of non-termination 98.3% of the time. Again, the Stable-2007 was the only significant predictor in the model ($p < .001$; Static 99r: $p = .30$).

The model assessing probation revocation (n = 45) was statistically significant, $\chi2(2) = 57.389$, $p < .001$. The model explained 31.7% (Nagelkerke R^2) of the variance in attrition and correctly classified 81.7% of cases. Like the previous cases, sensitivity was low with the model only correctly identifying 13.3% of the sample as participants who had their probation revoked while in treatment. The model more successfully identified individuals whose probation was not revoked during treatment (94.9%). In this model, the Static-99r reached nominal significance ($p = .051$) while the Stable-2007 remained a statistically significant predictor ($p < .001$).

Discussion

The present study significantly predicted treatment attrition using the Static-99r, Stable-2007, URICA, and a sample of 289 sexual offenders. However, the categorical nature of the URICA data likely limited its predictive ability due to range restriction. Despite this limitation, the results suggest that only offenders who entered treatment in the Action stage of change were less likely to drop out of treatment than those in the reference group (i.e., those in the Maintenance stage). These results align with previous research that suggests that static, dynamic, and motivational factors can predict dropout from treatment for sexual and general offenders (Nunes, 2006; 2010; Olver et al., 2016). This result is also consistent with the measurement of the Action stage by the URICA. An individual who has decided to change is an individual who is likely prepared to complete the tasks necessary to make said change (DiClemente, 2005). In contrast, those in the Maintenance stage of change have typically graduated from treatment and thus cannot drop out.

Despite its popularity among clinicians, the current study is the first to use the Stable-2007 to predict treatment attrition. In the present study, the Stable-2007 accounted for most of the variance in the full model predicting treatment attrition. The Stable 2007 also accounted for additional variance in treatment outcomes for SOs beyond the variance accounted for by the Static-99r and URICA. The static, dynamic, and motivational predictors all appear to predict the outcome of community treatment for offenders. However, the dynamic predictors were the best predictors in the present study. Therefore, future research should place particular emphasis on using dynamic factors in predicting treatment attrition.

Despite difficulty in discriminating between types of attrition in mind (i.e., suspension, termination, and revocation), risk assessments may be better at predicting attrition consistent with recidivism (i.e., probation revocation). However, per the results, dynamic risk factors may be the only factors that can adequately predict this type of attrition. The failure of the Static-99r to reach statistical significance in any analysis predicting the type of attrition aligns with previous literature regarding the limitations of static factors. Due to the inability of static factors to consider treatment changes when predicting risk, the more treatment an offender completes, the less likely static factors are to predict risk accurately (Olver et al., 2014). However, the variance accounted for by the Static-99r in the full model predicting attrition supports its continued use alongside the Stable-2007 (Hanson & Thornton, 2009).

One major limitation of the current study is that only categorical URICA data was available for the SOs in our sample, not their numerical scores. Furthermore, most SOs were in the Precontemplation stage of change before starting treatment. The range restriction of the URICA data in the present study may have affected the results. It could explain why only one of the stages of change (Action) reaches statistical significance in predicting treatment attrition. Additionally, the unequal distribution and small sample sizes among the types of attrition (i.e., suspension, termination, revocation) is another major limitation of the current study. As a result, the Static-99r and Stable-2007 could not effectively discriminate between individuals in each group. Therefore, the findings of hypothesis 3 cannot be considered reliable.

Future research using the Static-99r, Stable-2007, and URICA should examine treatment attrition using item-level data from these instruments. Based on the current study, it is evident that there are items in each of these instruments that predict treatment attrition. However, as was true in previous screeners of treatment outcomes (Brown et al., 1998; Edwards, 2005; Nunes, 2006; 2010), some items in these instruments may reduce the predictive ability of these instruments. Consequently, item-level data from these instruments may improve predictions of treatment attrition compared to the present model. Item-level data would also help researchers and clinicians identify items from these instruments that predict risk for recidivism, risk for treatment attrition, or both. Such information may help researchers design future assessments and screeners that can further improve clinicians' ability to tailor treatment to an offender's needs, and that can help improve the effectiveness of SO treatment.

Conclusion

The current study demonstrates that the Static-99r and Stable-2007 can be used to predict treatment attrition as well as SO recidivism. These findings are important because they mean that clinicians can use readily available, gold-standard instruments to not only predict sex offender recidivism, but also their treatment outcomes. This will save clinicians time and money in predicting treatment outcomes. Furthermore, effectively targeting those individuals most at risk to have a treatment failure (drop out, be revoked, quit) will help clinicians tailor treatment accordingly, and provide additional supports and oversight to those most at risk of non-completion. This in turn, will hopefully lead to more SO's successfully completing treatment, and as such, decrease recidivism, and increase community safety.

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