THE DEVELOPMENT OF VIOLENCE SUBSCALES FROM THE LSI-OR

A Thesis Submitted to the College of

Graduate Studies and Research

In Partial Fulfillment of the Requirements

For the Degree of Master of Arts

In the Department of Psychology

University of Saskatchewan

Saskatoon

By

AMBER JEAN FRANKLIN

Permission to Use

In presenting this thesis in partial fulfillment of the requirements for a Postgraduate degree from the University of Saskatchewan, I agree that the Libraries of this University may make it freely available for inspection. I further agree that permission for copying of this thesis in any manner, in whole or in part, for scholarly purposes may be granted by the professor or professors who supervised my thesis work, or in their absence, by the Head of the Department or the Dean of the College in which my thesis work was done. It is understood that any copying or publication or use of this thesis or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to the University of Saskatchewan in any scholarly use which may be made of any material in my thesis.

Requests for permission to copy or make other use of material in this thesis in whole or part should be addressed to:

Head of the Department of Psychology
University of Saskatchewan
Saskatoon, Saskatchewan S7N 5A5

ABSTRACT

Current literature suggests that the Level of Service Inventory (LSI) and its derivatives (LSI-R, LS/CMI, LSI-OR) are capable of predicting violent recidivism, even though they were not initially designed for this function (Girard & Wormith, 2004; Mills & Kroner, 2006). The purpose of this study was to generate violence prediction scales, based on items or subscales from the LSI-OR, using five different statistical techniques. These analyses were completed on the full construction sample, then the males and the females separately to determine how the scales differ from each other and what, if any, benefits would accrue from utilizing a gender-specific scale.

A cohort of 27,027 offenders who were released from custody or entered into community supervision over a one year period was included in the study. There was an average followup time of 4.4 years. In this sample there was a general recidivism rate of 36.0% and a violent recidivism rate of 11.3%. Fifteen violence prediction scales were generated that ranged in predictive validity from $r = .139$ to $r = .214$. The scale with the highest predictive validity was the 11 item scale created from the full sample using the item linear regression technique. The scale contained items indicating that history of assault, lack of education and anger management issues were related to violent recidivism. Risk levels were developed for this new scale to classify offenders from very low to very high risk.

Although there was little difference in the predictive validity of the generated scales, the stepwise multiple linear regression technique was identified as the most successful method of creating a tool for predicting violent recidivism. There was no increase in predictive validity when using the scale that was developed for just the females in the sample, although fewer items were consistently generated for females than males. Therefore the full sample item linear regression scale is recommended for the prediction of violent recidivism of both male and female offenders in the jurisdiction from which the data were collected. Future research directions may replicate this study in other populations and further analyze the gender differences in violent recidivism.

ACKNOWLEDGMENTS

I was very fortunate to have the support of many people throughout my work as a graduate student. My supervisor, Dr. Steve Wormith provided unwavering enthusiasm about this project from the beginning and I was very fortunate to work with such a knowledgeable and dedicated researcher. I also need to thank the members of my committee, Dr. Gerry Farthing, Dr. Mark Olver and Dr. Philip Woods. The hours that they spent reviewing, revising and providing me with thoughtful questions for my defense were invaluable.

This thesis could not have been completed without the constant encouragement I received from my amazing friends. I am truly in awe of the amount of love and bright thoughts I had come my way from you all, as I was writing and defending this project. My grad school colleagues that turned into some of my greatest friends, Jody, Sarah and Karen made all the bad days so much better. Thank you to my other best friends Marina, Jordan, Tina and Lesley who listened to me talk about this thesis for hours, and never complained. Primarily, thank you to my family; Dan, Den and Jo. Nothing is more important than the security and support that you have provided me with.

Dedication:

To my brother Dan, my best friend; my dad Dennis, my rock; and my mom Jo, my everything.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

History of Risk Assessment

Assessing the risk that an offender poses to the public has been a goal of the criminal justice system for a long time. At least four generations of risk assessment approaches have been proposed to determine whether offenders will recidivate when released. As described by Bonta (1996), the first generation of risk assessment included a clinical judgment of whether or not an offender was likely to reoffend. Advancing from this, researchers developed actuarial measures of static factors that may predispose offenders to reoffend upon release. More recently, the inclusion of dynamic risk factors (third generation) and then the application of service plans and delivery throughout the offender's contact with the justice system (fourth generation; Andrews, Bonta & Wormith, 2006) has moved the current risk assessment tools into a more functional category, with recent research supporting the utility of these new measures.

A notoriously difficult charge, the classification of a heterogeneous group of people such as offenders involves many aspects of their lives and must take into consideration multiple factors. Risk assessment has traditionally been focused on the release decisions of a parole board (Clements, 1996) and became increasingly significant due to the public's growing fascination with the dangerous consequences and safety concerns surrounding the issue. Most current risk assessment tools take into account both clinical and actuarial approaches yet political forces have sparked a search for an adequate procedure to be able to apply to the general offender population in order to determine whether they will continue to commit crimes. Clements (1996) reviewed the history of risk assessment measures. He examined the use of a federal 'point' system where risk indicators were ascribed to offenders based on such factors as their crime severity, criminal history as well as other prison adjustment measures. Although this was considered an improvement over previous subjective measures, there was very little empirical evidence to bolster the validity of such a measure. Now, as more literature and systematic reviews have been published, it is believed by some that risk assessment tools that incorporate both actuarial information and clinical judgment may be the best hope for accurately determining the risk that an offender poses when released from prison (Clements, 1996). Furthermore, the development

of fourth generation tools that emphasize the offender's service and supervision needs as part of the client's follow-up may provide even better predictions of recidivism (Andrews, Bonta & Wormith, 2006).

In general, as the generations of assessment have progressed, different tools have cycled in and out of favour, relying on empirical literature to determine the predictive validity of each measure. Currently in Canada, popular risk assessment tools include the Psychopathy Checklist – Revised (PCL-R; Hare, 1990) and the Violence Risk Appraisal Guide (VRAG; Quinsey, Harris, Rice & Cormier, 1998). Although the PCL-R was designed to assess psychopathy and not as a risk assessment tool per se, it is widely used in the context of offender risk assessment. Since it is argued that many of its items are either static historical items or very stable personality characteristics, it most likely resembles a second generation risk assessment tool. The VRAG is also classified in the second generation of risk assessment measures. These tools have been used in offender populations to not only assign offenders to treatment groups but also to classify the offenders on the basis of the risk that they pose to the public when released.

As an advancement from this, third generation tools including the Level of Service Inventory – Revised (LSI-R; Andrews & Bonta, 1995) are also becoming a more accepted measure in order to take into account the changing factors that may influence whether an offender will recidivate or not. Fourth generation risk assessment measures in Canada include the Offender Intake Assessment (OIA) of Correctional Service Canada (Motiuk, 1997) as well as the Level of Service/Case Management Inventory (LS/CMI; Andrews, Bonta & Wormith, 2004), and the Violence Risk Scale (VRS; Wong & Gordon, 2006). In their meta-analysis comparing risk assessment tools on the prediction of violence, Campbell, French and Gendreau (2009) identify the Correctional Offender Management Profile for Alternative Sanctions (COMPAS; Brennan & Oliver, 2000) and Correctional Assessment and Intervention System (CAIS; National Council on Crime and Delinquency, 2004) as additional 4th generation tools. The promise of this new generation stems from the connections between assessment and programming, asserting the important principles of risk, need and responsivity (RNR).

With the continued development of assessment measures, there has been research interest in adapting previous scales and developing new tools that serve to target special groups of offenders. In response to this, versions of scales that are tailored to the specific offender

population are becoming more popular (e.g. LS/CMI). By being better able to target the salient criminogenic factors of certain populations, the ability of the assessment tool to predict recidivism will increase. New risk assessment instruments are now being developed to target the specific needs of females, young offenders, and offenders that commit specific crimes, such as sexual and/or violent offenses. This new direction in risk assessment measures is promising, as more specific tools will lead to better predictive accuracy.

Gender and Risk Assessment

The applicability of current risk assessment tools to female offender populations is a current topic of great debate in the criminal justice literature. Traditionally, assessment tools were developed for and statistically tested on male offender populations, and then applied to female offenders without altering the instrument. Some researchers argue that this is not an appropriate way to classify female offenders, as they differ significantly from male offender populations (Hannah-Moffat, 2004; Blanchette & Brown, 2006). An argument is made in the literature that new, gender-specific measures need to be developed in order to provide an accurate categorization of female offender risk.

Blanchette and Brown (2006) reviewed the applicability of several existing risk assessment measures that have previously been used on males. The Statistical Information on Recidivism – Revised (SIR – R), the PCL-R, the LS/CMI and the Historical Clinical Risk Scheme (HCR-S) were all presented and discussed in terms of their validity in predicting recidivism in female offender populations. It was reported that these actuarial tools are more accurate at predicting recidivism in females than a simple clinical method but lacked substantial proof that points to comparable recidivism outcomes to male prediction. Blanchette and Brown (2006) acknowledged the usefulness of these tools, but cautioned administrators that reliability and validity of these tools are still in question for adult female offender populations until further research can be completed.

The criminogenic needs for female offender populations identified by Blanchette and Brown (2006) parallel some of those that are also identified for males. Education/employment, family and associates, as well as procriminal attitudes and substance abuse are all areas that are known program targets and will help reduce rates of recidivism. Areas that are unique to female

offenders may prove to center around areas such as self esteem, personal victimization, self-harm and parasuicide. Further research in this area may prove that identifying these needs possibly will need to be part of assessments for female offenders.

Hannah-Moffat (2004) supported the idea that current assessment and classification in the Canadian justice system does not take into account the gendered experiences and social life aspects that are specific to this population. This author draws on her previous research experience to provide evidence that female offenders differ from males on factors such as their motivations for offending and reoffending, types of offenses they commit, community support offenders receive, and their experiences of incarceration. This author calls for a new instrument that takes into account these differences and will be able to provide a more accurate assessment of female offenders' specialized needs.

Female offenders in the Canadian justice system are currently not being assessed with different tools than their male counterparts. Usually a position of gender neutrality is adopted, where female specific needs are not taken into account. Hannah-Moffat (2004) warned about utilizing this approach as the measures used may misrepresent the female offenders' actual risk of reoffense. A more in depth search into a female offenders' background may be a more appropriate way to determine recidivism risk. She reported that one-third of practitioners are more careful when assessing a female's risk of reoffending because of the uncertainty that exists with non-gender specific instruments. It is recommended that gender sensitivity training be mandatory for those assessing the risk of female offenders, so they are aware of additional factors which may influence this population differently than male offenders.

LSI-R and female offenders

A meta-analysis examining the use of the LSI-R as a tool for risk assessment for female offenders was carried out as a response to Gendreau, Little and Goggin's (1996) assertion that this assessment instrument was gender neutral. Holtfreter and Cupp (2007) examined whether the LSI-R was successful in accounting for the specific gender factors that make up the female offender population. The majority of the literature that they uncovered between the years 1986 – 2006 involved males, and only 5 studies focused solely on female samples. When taking into

account subsamples of female offenders that were included in some of the studies, the authors were able to include 11 studies in their meta-analysis.

Sample sizes for the 11 studies ranged from 38 to 4822, with 3 of the investigations taking place in Canada and 8 within the United States. The mean scores on the LSI-R ranged from mid teens to the high twenties, with the most commonly used outcome being recidivism. Studies used different follow up times (6 months to 3 years) and definitions of recidivism (any new offense to reincarceration), the LSI-R was found to have strength of prediction ranging from $r = .05$ for violation of supervision, rearrest, reconviction or revocation of supervision to $r = .37$ for reincarceration. These statistics represented the correlation in the individual studies, examined in the meta analysis. The statistics reported in this article were comparable to those that have been presented in studies focusing on males (Gendreau, et al., 1996).

Holtfreter and Cupp (2007) acknowledged the usefulness of the LSI-R in predicting some of the more severe recidivism outcomes for female offenders, but highlighted the fact that the assessment tool may be limited in predicting less severe offenses. By not using a gender specific theory, these authors argued that the LSI-R might not be adequately addressing the gender specific needs of women in the criminal justice system. They suggest that further research be done on this instrument to determine if this tool is identifying the needs of female offenders and if modifications are required.

Principles of Risk, Need and Responsivity and the Level of Service Inventory (LSI)

In their 1990 article, Andrews, Bonta and Hoge outline three principles that have proven to be instrumental in the risk assessment and treatment of offenders. These three principles relate to the classification for rehabilitation within the context of basic research and theory in the psychology of criminal conduct. The first of these principles is the concept of risk of recidivism that the offender poses. This principle states that higher levels of service should be reserved for higher risk cases. Those offenders who have a higher risk of recidivating should be allocated the most intensive interventions when compared to the lower risk offenders. Risk factors refer to the personal characteristics and circumstances that are accessible prior to service and are indicative of future criminal behaviour. An example of a risk factor in the context of recidivism is age of

first offense as this is an unchanging fact that is accessible before treatment with the offender starts.

The need principle purports that the targets of service are matched with the criminogenic needs of the offender. A criminogenic need refers to a subset of dynamic risk factors, that when changed, are associated with a change in the chance that the offender will recidivate (Andrews, Bonta & Hoge, 1990). Some examples of criminogenic needs include substance abuse, procriminal attitudes, and employment/education history. All of these factors are changeable, so recommending treatment programs to address these needs could significantly change the risk of recidivism.

The third principle is the concept of responsivity, which refers to the matching of offenders to different styles and modes of service to optimize learning (Andrews, Bonta & Hoge, 1990). It is known that the characteristics of offenders interact with style and mode of service and is an important consideration when assigning offenders to treatment groups. Factors such as gender, ethnicity and age may be examples of responsivity factors as they have an impact on learning styles and are important when designing and implementing treatment programs. Evidence suggests that the more these principles are adhered to, the greater the impact of the intervention on the offender. Therefore, it is important to use a measure that is capable of utilizing these principles to the maximum effect.

Following its inception in the 1980s by Andrews and colleagues, the LSI has become a well-researched risk/needs assessment instrument that has been used in Canada for over 20 years, and whose popularity has spread in other countries throughout the world (Girard & Wormith, 2004). Based on theoretical and empirical underpinnings, the LSI rose to the forefront as an instrument that could be administered to offenders regardless of their literacy levels and did not need a psychologist to interpret the results (Bonta & Motiuk, 1985). The LSI is derived from a social learning perspective and it has been proven to have high reliability and internal validity as well as providing a complete classification tool with clear operational definitions (Bonta & Motiuk, 1985, 1987; Gendreau, Goggin & Smith, 2002).

The LSI has produced several subsequent versions that have been adapted for specific populations. These include a revised version (LSI-R; Andrews & Bonta, 1995), the Level of

Service Inventory – Saskatchewan Youth Edition (LSI-SK; Andrews, Bonta &Wormith, 2001), Youth Level of Service/Case Management Inventory (YLS/CMI; Andrews, Hoge & Lescheid, 2002) and the Level of Service Inventory-Ontario Revision (LSI-OR; Andrews, Bonta & Wormith, 1995). The features that are common to all the derivations of the LSI are the multiple risk and criminogenic need items that have been grouped into 8 to 10 domains of risk (Girard & Wormith, 2004). The information that is necessary for the completion of the LSI is gathered through the review of official records and case files of the offenders, as well as a semi-structured interview, designed to assess all areas of criminogenic needs. Each edition does have characteristic features designed to enhance the prediction of a subset of offenders.

Specifically, the LSI-OR was developed for use in Ontario due to managerial and staff beliefs that the LSI may be incomplete as a case management tool for correctional workers. In addition, the need for the province to have a common risk/need instrument that was employed within all offender institutions within the area was identified. To provide a high level of continuity of care, a measure was needed that involved widespread acceptance and use across the province. In addition to these reasons, the need for a periodically revised version of the original was acknowledged, due to the evolution of laws and legal terms, as well as the demographic changes in offender populations over time.

Described in Wormith (1997), the LSI-OR is a required assessment for all adult inmates undergoing an institutional classification or release decision as well as all adult probationers and parolees within the province of Ontario. Acknowledging the ability for an offender's score on this measure to change, the instrument is readministered every six months and at client-related decision points. With an extensive review of literature and input from key stakeholders, several important changes were made to this new version of the LSI.

Specifically, the scale was shortened by 10 items and some new concepts were introduced, such as taking into account the offenders' protective factors and specific risk/needs items. As well, the subscores for the eight categories that the 43 items are classified were given more consideration in this version, with a graphical representation of the client's profile making it easier to link adequate supervision and programming to the offender's needs. In addition, the number of risk levels was increased to five, as the qualifiers of low, medium and high were not found to be sufficiently descriptive. Clinical override is also given more attention in this version,

in concert with an additional section outlining other clinical issues that highlight the client's non-criminogenic needs that also may require attention. Finally, a section on responsivity considerations was also added in order to fully take into account proven moderating factors that may impact recidivism. This more comprehensive and client-focused version of the LSI was developed with the Ontario offender population in mind, meeting the diverse needs of this group with a dynamic risk assessment instrument. A commercial version of the LSI-OR, the LS/CMI, is now used by numerous agencies and departments of corrections in Canada, the United States and abroad.

Importance of the Prediction of Violence

Through both anthropological (Low, 2001) and psychological studies (Rountree & Land, 1996), the fear of crime, and specifically violent crime, has been documented as one of the most salient concerns of the public. There has been much research done on violent recidivism with the current assessment tools, but there is room to believe that the development of a new measure may be able to predict future violent offenses at a higher rate (Girard & Wormith, 2004; Mills & Kroner, 2006). It is now widely accepted that it is important to predict, not only general recidivism, but violent recidivism in relation to this public fear of violent crime in particular.

The prediction of violence has been an ethical and accuracy debate over the last 30 years (Shah, 1978; Quinsey & Ambtman, 1979; Grisso & Appelbaum, 1993; Litwack, 1993). Due to the importance and potential severe consequences of an offender being considered likely to violently reoffend, it is often debated whether or not it is appropriate for a professional to offer any opinion as to whether or not a person will be violent in the future. Thirty years ago, prominent researchers believed that the ability of a trained professional to accurately predict violent behaviour was little better than chance and their predictions showed very low inter rater reliability (Quinsey & Ambtmann, 1979; Steadman, 1983). With the advancement of risk assessment tools to a third generation model, the potentiality of accurate violence prediction has increased. Often times added into general recidivism literature as a footnote, the importance of violent recidivism in our society is a compelling reason for developing a specific measure to assess this subtype of recidivism in a definite manner.

History of Violence Risk Assessment

In his influential article, Shah (1978) discussed the legal and social responses to the term "dangerousness". He outlined how the practice of law had become interested in the behavioural predictions that psychology was offering, and the use that the prediction of dangerousness and violence could have for society. Although recognizing the social implications that such a prediction would likely have on offenders, Shah observed a tendency among the experts who were making violent recidivism judgments based on clinical intuition, to predict the dangerousness of offenders at a very high rate. He showed that adherence to the "better safe than sorry" principle was detaining a large number of offenders behind bars, when their true risk of offending violently was not as high as was believed.

Not blaming the errors of clinical practice for the over estimation of violent behaviour, Shah contended that it is the nature and social context of the judgmental task that is so influenced by social and political contingencies. This influence led to the conclusion that false positive errors (errors in which offenders are remanded even though they would not have committed a violent crime) are much more acceptable than false negative (errors in which offenders are released and violently recidivate) errors. Consequently, as far back as 30 years ago, psychologists and other forensic clinicians were encouraged to cease making clinical judgment decisions, which were proven to be mostly inaccurate, and focus on the development of empirical data that could serve to inform legal decisions.

A few years later, Monahan (1981) presented material emphasizing the difficulty that clinicians have in predicting the violent behaviours of their clients. Within the introduction of this monogram, many criticisms to predicting violence are outlined. Primarily, finding a working definition of dangerous and violent behaviour was regarded as an important but complex task. Beyond obvious examples of violence (e.g., murder, assault) the definition of violence was blurry. Due to this unfocussed definition of violent behaviour, multiple legal criticisms were discussed, including the attacks on the actual prediction rates and the changing of a clinician's role as a helper to an assessor. As well, the argument that violence prediction violates civil liberties was presented, purporting that people cannot be punished or detained for crimes that they may commit in the future, but only for the acts that they have actually done in the past.

Monahan (1981) went on to outline some of the moral, as well as political barriers that are encountered with the prediction of violent behaviour. He outlined that is it essential that the criterion that is used (how to define violence), the predictors (what indicates future violence), the accuracy (what is a good enough rate of accuracy) and the consequences of the prediction are all taken into consideration when making a judgment of this sort. In his personal views, he made it clear that the accurate clinical prediction of violence is impossible, and only best estimates can be made.

More encouraging literature began to emerge based on empirical data from new predictive instruments that were being developed. Quinsey (1980) highlights that, although the prediction of future violence may be impossible unless patients in mental hospital are to be all detained indefinitely, such predictions must be made. He made explicit reference to the unlikelihood that serious violent offenses occur on a regular basis, and makes a case that baserates should be examined when making these decisions. It is his position that accurate decisions are possible as long as a proportion of the offenders are assessed and released periodically with a conservative release strategy that is even modestly accurate. This would increase the baserate of violent persons who remain detained, and therefore makes it more likely that the correct decision is made as to whether to release patients.

A new focus on developing tools that assisted in this prediction was adopted. Risk assessment tools for different offender populations began to enter into the literature and provide encouraging data. Now, 25 years later, further data and revisions have been made to these instruments to increase the prediction rates. Empirical research reinforcing the success of such instruments in not only predicting recidivism but also outlining offender treatment targets ushered in a new view in the field of corrections focusing on ‘what works’.

Violent Recidivism

Correlates of Violent Behaviour

As far back as the early 1980s, there has been research investigating the factors which may be related to violent crime. Monahan (1981) indicated multiple major actuarial correlates of violent behaviour by assessing which factors have been most consistently related to violence. By reviewing the literature available at the time, the author was able to identify variables, which

have later been incorporated into risk assessment tools, such as the LSI and its derivations. Monahan (1981) highlighted past crime as the most important correlate of future violence prediction. Especially when the criminal history of an offender shows repeated violent crime, this is indicative of a risk factor for committing violent offenses in the future. He highlighted that it is usually a small number of offenders who are committing a large amount of crime. Being able to target and detain these habitual offenders is an important goal when assessing violence prediction.

Other characteristics that have proven to be related to the prediction of violence are age and sex. Using statistics from the United States in the 1970s, Monahan made the case for the majority of offenders being younger males. With a significant number of males aged from 15 to 20 committing a large amount of violent crime, this factor is vital to obtaining a profile to predict violence.

Monahan (1981) went on to highlight the relationship that violent behaviour has with race, socioeconomic status and employment stability. Although not a comprehensive discussion and not applicable to a Canadian population, Monahan outlined the issue of race as a variable that needs to be considered in a violence assessment. The stability of money and income from employment were also found to be protective factors when assessing violent crime. Those offenders who held stable jobs were more likely to be successful in their parole and less likely to recidivate than offenders who did not.

Monahan (1981) also discussed the use of substances such as opiates and/or alcohol. The variables outlined by Monahan in this paper have been incorporated in multiple risk assessment tools in the last decades and are the starting points to where a risk assessment tool targeting the prediction of violent behaviour should begin.

Violence Assessment Tools

In their article on discordance between measures on predictive accuracy Mills and Kroner (2006) explained how clinical evaluators, when charged with the job of assessing the risk of recidivism may employ more than one instrument to assist with the estimate of risk. One of the reasons for this technique was to use specific instruments to measure different types of recidivism (i.e., the VRAG is designed to measure violent recidivism vs. the LSI-R is designed

to measure general recidivism). This study looked at the effect of discordance between risk assessment instruments in a sample of 209 adult males sentenced to over 2 years in prison. Specifically, four separate risk assessment instruments were used that were developed from different theoretical underpinnings. The scales were also developed for different purposes, but all have some level of proven accuracy with predicting general or violent recidivism for different populations of offenders. It was anticipated that convergence of risk estimates between multiple risk assessment tools would support the overall accuracy of the estimate. The purpose of the study was to examine the performance of the instruments under conditions of low and high agreement between the estimates of risk of recidivism.

The participants in this study were 209 adult males who were incarcerated with a sentence of two years or more. Four risk assessment tools were used in this sample including the PCL-R, the LSI-R, the VRAG and the General Statistical Information on Recidivism (GSIR). The outcome variable of recidivism was recorded from official police records, with violent offenses being considered as uttering threats, assault, sexual assault, armed robbery, and robbery with violence. All other offenses were considered general recidivism, with the baserates of the sample being 49% for general recidivism and 29% for violent recidivism. Discordance between instruments was measured by calculating the mean difference between standardized instrument scores. Taking the top third of average difference scores and considering them 'high discordance' and classifying the others as 'low discordance' the authors were able to analyze the measure of discordance.

It was found in this study that inter-correlations between the instruments were significantly high. Correlations between each instrument and recidivism were calculated for both the high and low discordance groups. A weak relationship was found in the high discordance group between the PCL-R and both violent and general recidivism. Similar weak relationships were found in the low discordance group between the LSI-R and general recidivism and the VRAG with violent recidivism. It was found that high discordance rates between risk assessment instruments threaten predictive accuracy of recidivism, and had a greater effect on some instruments than others.

It was found that discordance had a moderating effect on the PCL-R and LSI-R but not the VRAG and GSIR, due to the nature of the latter instruments relying more on static, historical

variables, rather than clinical judgment. The tools that incorporated clinical judgment were more susceptible to the effects of discordance, but it was also highlighted in this article that higher inter-rater agreement in the clinical judgment of recidivism resulted in better predictive accuracy.

LSI-OR and Violent Recidivism

In their article on the predictive validity of the LSI-OR, Girard and Wormith (2004) conducted a longitudinal validation of the measure in regards to both general and specific offender groups, including sex offenders, domestic violence and offenders with mental health problems. This study also served to examine the contribution of the LSI-OR's additional components and their relationship to improved prediction of recidivism. Various statistical analyses were completed to examine how scores on these sections affected recidivism rates for multiple kinds of offenses after 2.5 years.

A sample of 630 adult male offenders who had completed an LSI-OR were included in this study. This population included inmates as well as probationers that ranged in offenses from assault to drug charges. All offenders were in the provincial system therefore no participants had committed offenses that incurred sentences longer than two years less a day. Recidivism data was generated from computer databases that tracked criminal offenses both in Ontario and nationwide. Three general measures of recidivism outcome variable were coded including a dichotomous variable informing any new conviction. A violent conviction was defined as any conviction during the follow up period for robbery or an offense against the person, which included homicide, serious violent, sexual, weapons, assault and/or arson/property damage offenses. In addition, offense severity was measured.

Results showed that by the end of the follow up period, 54.4% of the adult male offenders had recidivated with at least one conviction, and 24.1% recidivated with at least one violent conviction. Expected results showed that recidivists scored higher on all levels of risk assessment, except for the strengths section, in which they scored significantly lower than non-recidivists. It was shown in this study that the best subscale predictor of violent recidivism was the History subscale of the Specific Risk/Need section, and outperformed the General Risk/Need scale on an aggregate basis. Girard and Wormith (2004) also reported the hierarchical regression analysis results, indicating that a multiple *R* of .39 was obtained with the History subscale of the

Specific Risk/Need section and Antisocial Pattern sequentially entered into the regression equation.

This article provides support for the creation of a specific violent subscale to be developed out of the LSI-OR. It is apparent that there are factors in the current assessment tool that are more predictive of violence recidivism, including the History subscale of the Specific Risk/Need section. The authors present this result and call for further investigation, as the predictive ability of this tool is substantial when compared to other weighted mean correlations of other assessment tools that are presented in the discussion.

Table 1.1 represents effect sizes garnered from the literature for some popular risk assessment tools. Varying sample characteristics and scales are reflected in the ranging effect sizes but give a general view of the predictive accuracy of these measures for violent recidivism.

Table 1.1. Reported Effect Sizes for the Prediction of Violent Recidivism using Popular Risk Assessment Tools

Author (Date)	Scales	Sample	Followup	Effect Size (r)
Mills & Kroner (2006)	PCL-R LSI-R VRAG GSIR	209 incarcerated adult males	Average = 424 days	0.180 0.26** 0.26** 0.30**
Snowden, Gray, Taylor & MacCulloch (2007) ‡‡	VRAG OGRS	998 mentally disordered male offenders	Minimum of 2 years Range – 2.02 – 11.96 years	AUC = .785; approx. r conversion = .488 AUC = .762; approx. r conversion = .449
Gendreau, Goggin & Smith (2002)	PCL-R LSI-R	Meta analysis: N = 4823, k = 26 N= 3297, k = 16	64% of studies had followup time of greater than 2 years	.21 .26
Mills, Kroner & Hemmati (2007)	HCR-20 VRAG	83 offenders sentenced for 2 years or more	Average = 1675 days	.37** .28*
Campbell, French & Gendreau (2009)	HCR-20 LSI/LSI-R	Meta analysis: N = 1395, k = 11 N = 4361, k = 19	39.4% : less than 1 year 41.7 %: 2 – 5	.25 .25

	PCL/PCL-R	N = 4757, k = 24	years	.24
	SIR Scale	N = 5618, k = 17		.24
	VRAG	N = 2082, k = 14		.27
				(Sig. not reported)
Wormith, Olver, Stevenson & Girard (2007)	LS/CMI	N = 60	6.4 – 12.7 years	.33**
	PCL-R			.30*
	DSM-III APD			.39**
Girard & Wormith (2004)	LSI – OR	N= 630 adult male offenders in Ontario provincial prisons	Average 932.73 days	.26**

Note: ‡‡ Conversions to r used the table in Rice & Harris, 2005, *p < .05, **p < .01

Objectives

Although designed to predict general recidivism, research has shown that the LSI-R also predicts violent recidivism at about the same rate as tools designed to predict violence (e.g., VRAG; Mills & Kroner, 2006). Also, the success of the LSI-R in predicting more severe recidivism offenses for women, suggests that this measure may contain items that are useful in creating a violence prediction scale for women (Holtfreter & Cupp, 2007; Gendreau, Little, & Goggin, 1996). This raises questions as to whether a violence subscale might be derived from the existing LSI items, and if so, whether it is better to have a common scale or individual scales for males and females. Therefore, the objectives of this study are twofold. The first was to determine whether a violence prediction scale may be derived from the existing items in the LSI-OR that exceeds the predictive validity of the existing scales. The second objective of this study was to determine if gender specific violence risk assessment scales are superior to a single generic scale for both genders. Although some evidence suggests that males and females do not differ on criminogenic factors that predict violent recidivism (Rettinger & Andrews, 2010; Salisbury, Van Voorhis & Spiropoulos, 2009), other research suggests different factors will be more salient for females than males (Hannah-Moffat, 2004). This investigation was also designed to examine the differences in the male and female derived scales and identify the factors that provided the best predictive validity for each group. The study was archival in nature, as existing offender databases were examined to determine if some, as yet unknown set of items may be used to create a subscale from the regular LSI-OR to specifically predict violent recidivism.

Based on the literature on the LSI-OR and particularly the results of Girard and Wormith (2004), it is expected that the LSI-OR items that would correlate the highest with violent recidivism will come from the History subscale of the Specific Risk/Need section. The Specific Risk/Need scale outperformed the General Risk/Need scale on violent recidivism; therefore it is that specific portion of the LSI-OR that is predicted to be most informative to the development of a new scale. It is predicted that these items will prove significant in predicting future violence in both males and females. In summary, this study was an analysis of offender records to obtain theoretically derived and clinically valuable tools to improve the prediction of violent recidivism for both genders.

CHAPTER 2

METHOD

Participants/Sample

The database used in this study was a cohort of all offenders with sentences of more than 30 days, excluding those with intermittent sentences, who were released from custody or entered into community supervision in the province of Ontario between January and December, 2004. January 9, 2009 was used for all offenders as the end of their followup and any evidence of reoffending up to that date was identified as recidivism. Followup time for the sample was determined for the custodial offenders by taking the time from the custody release date to the recidivism check date. For the community offenders, followup time was determined by taking the time from the offender's assessment date to the recidivism check date. These data were entered into a followup time variable which had a mean of approximately 4.4 years (1610 days).

The general recidivism rate was 36.0% and, utilizing our definition of violent recidivism, the violent recidivism rate was 11.3% over the 4.4 year followup period. The sample was predominantly young (under 25), male and white, with the majority of offenders coming from the most populated area of Ontario (the Central region). The sample proved to have a relatively low LSI-OR average score of 12.5, and the most common risk level identified was medium (i.e., 38.8%). This was to be expected since the majority of the sample (81.7%) consisted of community offenders.

In order to perform both the construction and validation of the violent recidivism prediction scales from one database, the cohort was randomly split into two approximately equal sections. The construction and validation samples did not differ significantly on any of the descriptive statistics that were collected. The scale construction techniques were only applied to the construction sample and the generated scales were validated with values from both the construction and validation samples, yielding information about the predictive validity for all of the constructed scales.

Measures

LSI-OR

The LSI-OR is a mandatory assessment tool used for all adult inmates that are undergoing any institutional classification or release decision within the province of Ontario (Wormith, 1997). Theoretically grounded in social learning theory and empirically developed, the LSI-OR is a risk/need assessment instrument that is designed to determine an offenders' risk to recidivate and identify criminogenic needs that may be targeted in treatment. The General Risk/Need Factors section contains 43 dichotomously scored (0 = not present, 1 = present) items that address eight areas of offender needs: Criminal History (8 items), Education/Employment (9 items), Family/Marital (4 items), Leisure/Recreation (2 items), Companions (4 items), Substance Abuse (8 items), Pro-criminal Attitudes (4 items), and Antisocial Pattern (4 items). The Specific Risk/Need Factors section has two subscales containing 23 dichotomous items: Personal Problems with Criminogenic Potential (14 items) and History of Perpetration (9 items). In addition to these further risk factors, the LSI-OR has three additional sections that assist the development of a treatment plan for the offender: Institutional Factors (10 items), Other Client Issues (18 items) and Special Responsivity Considerations (8 items) (Girard & Wormith, 2004).

Recidivism

OTIS provides information on all offender movement, including admissions to Ontario correctional facilities and probation offices. The follow up time for all offenders was the period of time that offenders were eligible to reoffend in the community. This was determined by subtracting the date of the data extraction, which was common for all offenders, from the date of their release from prison (for custody offenders) or the date of admission into community supervision (for probationers and other community offenders).

Recidivism was defined as any criminal offense for which an offender is returned into the Ministry of Community Safety and Correctional Services (MCSCS) system, either to sentenced incarceration or community supervision. This description of recidivism however, does not include offenses committed in other provinces or receiving sentences besides incarceration or community supervision (e.g., fines, alternative measures). In order to differentiate between violent and other re-offenses, two measures of recidivism are coded. A simple, dichotomous conviction variable will identify in a yes/no fashion whether any convictions were made during

the follow up period. A violent conviction variable will determine whether or not the offense was considered violent or not. A violent conviction will be defined as any conviction during the follow up period for robbery or an offense against a person. Offenses against a person include homicide and related offenses, serious violent offenses, sexual offenses, weapons offenses, miscellaneous offenses against the person, as well as assault and related offenses. Time from release to reconviction was calculated in order to determine the amount of time that each offender had to recidivate, this allowed for the plotting and analysis of survival curves. General recidivism included these and all other offenses.

An ordinal rating system, used by MCSCS, measured offense severity in which offenses that are similar in nature and sentence length are grouped together. No recidivism was coded 0, unknown offense was assigned a missing data code (99) while offense groupings 1 (homicide and related offenses) though 25 (municipal bylaw offenses) were reverse coded such that homicide and related offenses were coded as 25 and municipal bylaw offenses were coded as 1 (Stasiuk, Winter & Nixon, 1996)

Research Design

Extraction Procedure

Information from OTIS was used to identify a combination of static and dynamic variables on the LSI-OR that most closely predict the commission of violent crimes after release from prison. As our sample included both males and females, this study derived scales for the female sample, the male sample, as well as the mixed sample. More than one subscale was generated for each of these samples from the statistical procedures, and these variations were systematically compared to each other in order to identify the scales with the highest predictive validity. The statistical analyses for this study was completed using the Statistical Package for the Social Sciences (SPSS).

To derive our sample, a database search was conducted within OTIS to identify offenders that were admitted to probation or a conditional sentence, or released from a custodial sentence between January and December 2004. A computer search was then completed on the LSI database to determine which of these offenders had been administered an LSI-OR after their period of supervision began but prior to release from supervision for the community offenders

and before their release from custody for the custodial offenders. The data from the two offender files was merged by offender identification number and saved in a single file for data analyses. Any evidence of recidivism, as indicated by a reconviction during the designated follow-up period, was recorded for each offender and saved in the derived database. In cases where offenders were admitted more than once during the test year (2004), only their first release from custody or their first admission to community supervision was considered. Offenders who had not had an LSI-OR completed prior to their release from correctional supervision were excluded.

From this database, offenders who recidivated with a violent offense (as described above) were identified. The sample was randomly divided into two samples (construction and validation) for the development and validation of various violence risk scales. Five different statistical approaches were used to develop violence risk scales on the construction sample. The approaches reflect five commonly used statistical techniques in the creation of offender risk tools. Moreover, each approach was applied on three occasions, once on the entire construction sample, a second time on the male participants and a third time on the female offenders. With the five techniques in use (described below), there were five scales for females, five scales for males and five scales for the combined group of males and females. This permited both a comparison of scale construction techniques and a comparison of predictive accuracy of offenders by gender. The construction sample and validation sample allowed for violence prediction scales to both be generated and then validated on a second independent sample, therefore predictive validity coefficients will not capitalize upon chance associations.

Statistical Analyses

Descriptive Statistics and Correlation Matrix

Descriptive statistics used to depict the characteristics of the sample are presented using frequencies, means and standard deviations. This included comparisons between the construction and validation sample to ensure their equivalence on legal and demographic descriptive variables, as well as risk measures. It also included comparisons by gender and by location type (community or prison).

Subscale Correlations

There are two ways to utilize the correlation matrix to generate scales. The first is to identify the significant subscales on the instrument that correlates with recidivism. Subscales on the LSI-OR are the defined sets of questions that encompass a section of the instrument (i.e., Criminal History, Education/Employment, etc.). Taking the subscale scores and identifying which components of the LSI-OR predict violent recidivism more than others allowed me to create a more succinct tool by only focusing on those sets of items that are significantly correlated with violent recidivism.

Item Correlations

The second method of using the correlation matrix to create a scale is by breaking the LSI-OR into its individual items, and correlating them with the recidivism variable. A simple correlation matrix was generated from the construction sample correlating scores for each item on the LSI-OR and whether the participant had recidivated violently in their follow up period.

Burgess Method (Equal Weight Linear Model)

The third method that was used to generate both a gender neutral and two gender specific violence prediction scales was the Burgess-type model of simple summation. This method outperformed two other statistical techniques (regression and predictive attribute analysis) in developing the SIR scale (Nuffield, 1982) which is a standard risk assessment tool used in the Correctional Service of Canada (CSC). This model follows a traditional method where the number of points assigned to each predictor variable depends on the difference in recidivism rates between those who qualify or do not for the predictor variable (e.g., each point difference in recidivism would result in assigning the predictor variable a weighting of 1; Farrington & Tarling, 1985). This simple weighting tool is lauded for its parsimonious approach to identifying dichotomous variables that add to the predictive validity of the instrument. Any interdependence between predictors is ignored in this technique, and a scoring system is developed based on the sum of values that predictors are assigned from their ability to predict recidivism. Offenders are then assessed on an individual basis and receive a statistical score representing their chance of recidivating (Nuffield, 1982).

Nuffield (1982) described five basic steps to use this technique. First, the average recidivism rate is calculated for the construction sample and predictors (LSI-OR items) were

selected for their theoretical or historical ability to predict violent recidivism. For each item's ability to predict recidivism that showed a difference of plus or minus five percent from the average rate, a score of plus or minus one was assigned. As an item's predictive ability differed from the average by a factor of five, a score was attributed to each item (i.e., if an item differed from the average by 10% it was assigned a value of 2, if it differed from the average by -15% it will be assigned a value of -3). The score for an item was 0 if it did not differ from the average recidivism rate by more than 5%. Each item had a scoring system like this developed for it and then a cumulative recidivism score for each offender was calculated with the higher the positive score, the greater that offender's risk of violent recidivism was.

Subscale Stepwise Multiple Linear Regression

Another method that was employed in scale construction is stepwise multiple linear regression on the subscales of the LSI-OR. In order to determine which subscales add significantly to the prediction of violent recidivism, stepwise regression allowed each significant subscale to be entered into the linear regression equation. To be included in the model, the scales had to have a *p*-value of less than .001, and then to be excluded from the model, the *p*-value had to increase to more than .10.

Item Stepwise Multiple Linear Regression

The last technique used to generate the violence prediction scales was the item multiple linear regression method. Having the same inclusion and exclusion criteria as the subscale linear regression, this was an analysis involving the individual items that were on each of the subscales. This stepwise regression analysis allowed for the inclusion of individual, significant items that were applicable to each of the samples tested.

Analyses Used for Validation of Scales

Correlations

Correlations between the new scales generated from the above techniques and the violent recidivism variable were analyzed for both the construction and validation samples. Simple correlations allowed us to determine how well the new scales predicted violent recidivism in the

sample by identifying the magnitude of the relationship between the new scales and violent recidivism.

Receiver Operating Characteristic (ROC) analysis

ROCs, which are usually presented in the form of a graph, and produce Area Under the Curve (AUC) statistics is another important measure of predictive accuracy for the developed scales. The graphs present the proportion of actual recidivists on the vertical axis and the proportion of false positives along the horizontal axis, to create a curve that represents where the successful predictions meet the false prediction (Andrews & Bonta, 2003). A curve that produces a greater AUC value indicates higher predictive accuracy. There is some evidence to suggest that this method is robust to changes in the base rates of violent recidivism between samples and produces more stable predictive validity statistics (Rice & Harris, 1995).

Risk Level Derivation Techniques

In following with LSI tradition, risk levels were created on the scale that was identified as most useful to predict violence. These risk levels classify offenders in five categories (very low, low, medium, high, and very high) based on a set of cut-offs used to create the five risk groups. There were two techniques used to determine the cutoffs for these risk levels.

The first technique that was used to generate the risk levels involves taking the range of possible scores on the risk assessment measure and dividing it into five equal sections (equal range). This creates risk levels that may not have equal numbers of offenders in each group, but provides classifications that are reflective of the offenders' actual risk to reoffend violently.

The second technique employs the use of percentiles to categorize an individual with respect to the other offenders in the sample (equal percentiles). With this method, approximately one fifth of the sample was classified in each risk level demonstrating close to equal numbers of offenders. These cutoffs were the closest number to the 20^{th}, 40^{th}, 60^{th} and 80^{th} percentiles when analyzing the scale values that offenders obtain.

Survival analysis

Survival analyses were conducted to determine if the risk levels were effective at separating the offenders into risk categories that truly differ in violent recidivism rates over time. This technique generates a graph illustrating the length of time it takes the members in each risk level to recidivate. Ideally, as risk level increases the graph shows that the amount of time that the offender group takes to recidivate will decrease. These figures present a graphical representation of how the created risk level groups differ in survival time in the community. Survival time for custodial offenders was calculated by taking the difference between the date of release and the date of reoffense or the data check date if there was no reoffense. Survival time for community offenders was calculated by taking the difference between the assessment date and the date of reoffense or the data check date if there was no reoffense.

CHAPTER 3

RESULTS

Sample Characteristics and Comparison of Construction and Validation Samples

Demographic characteristics for the construction, validation and full samples are presented in Table 3.1. The majority of the sample was male (81.7%) and white (59.2%). Most of the sample was under 25 (33.9%) with similar amounts of the sample being between 26 and 35 (25.8%) and 36 and 45 (24.8%). The average community sentence length was 391.6 (*SD* = 267.0) days for community offenders and 35.9 (*SD* = 96.1) days for custodial offenders. The sentence length for custodial offenders had a large standard deviation as the sample was greatly skewed (skewness statistic = 3.38, standard error = .015). Not surprisingly, the Central Region, which is the most populous of MCSCS's five regions, comprised the largest proportion of the sample (33.9%). The sample proved to have a good followup period with a mean of 1610.45 days (*SD* = 129.8), which is equivalent to 4.4 years. There was an average LSI score of 12.53 (*SD* = 8.8), with the most common final risk level being 3 (38.8%). In the breakdown of initial and recidivism offence severity, the most common violent offence was assault and related offences (29.3%, 6.3%), whereas nonviolent offences were more common for both time periods. A total of 11.3% of the sample had a violent offence as their recidivism offence.

The sample was split using an SPSS function that generates random subsamples from within the dataset. A random selection of approximately 50% of the sample yielded a construction sample, on which the scales were generated and a validation sample, on which the scales were assessed for their predictive validity. Independent sample t tests were run on the continuous dependent variables in the sample to determine if the samples differed significantly. There were no significant differences found between the groups on violent recidivism ($t(27025) = .709$, $p = .478$, *ns*), community sentence length ($t(27025) = 2.067$, $p = .039$, *ns*), custodial sentence length ($t(27025) = .069$, $p = .945$, *ns*), followup time ($t(27025) = 1.769$, $p = .077$, *ns*) or total LSI-OR score ($t(27025) = .542$, $p = .588$, *ns*). As well, there were no significant differences between the construction and validation samples on gender, [$\chi^2(1) = .312$, $p = .577$, *ns*], ethnicity [$\chi^2(3) = 4.168$, $p = .244$, *ns*], age [$\chi^2(4) = 5.164$, $p = .271$, *ns*], region [$\chi^2(3) = 5.806$, $p = .121$, *ns*],

final risk level [χ^2 (4) = .261, p = .992, *ns*], original offence [χ^2 (7) = 8.651, p = .279, *ns*], recidivism offence [χ^2 (8) = 5.401, p = .714, *ns*], general recidivism [χ^2 (1) = 1.330, p = .249, *ns*] and violent recidivism [χ^2 (1) = .503, p = .478, *ns*].

Table 3.1. Demographic Characteristics and Comparisons for Construction, Validation and Full Samples

	Frequency [*n (%)*]		
	Construction Sample	Validation Sample	Full Sample
Overall total	13594 (50.3%)	13433 (49.7%)	27027 (100%)
Gender			
Male	11121(81.8%)	10954 (81.5%)	22075 (81.7%)
Female	2473 (18.2%)	2479 (18.5%)	4952 (18.3%)
Ethnicity			
Aboriginal	825 (6.1%)	893 (6.6%)	1718 (6.4%)
Black	1021 (7.5%)	977 (7.3%)	1998 (7.4%)
White	8067 (59.3%)	7937 (59.1%)	16004 (59.2%)
Other	1391 (10.2%)	1368 (10.2%)	2759 (10.2%)
Missing	2290 (16.8)	2258 (16.8%)	4548 (16.7)
Age at admission			
25 & Under	4593 (33.8%)	4572 (34.0%)	9165 (33.9%)
26 – 35	3441 (25.3%)	3519 (26.2 %)	6960 (25.8%)
36 - 45	3442 (25.3%)	3268 (24.3%)	6710 (24.8%)
46 – 55	1535 (11.3%)	1489 (11.1%)	3024 (11.2%)
56 +	583 (4.3%)	584 (4.3%)	1167 (4.3%)
Average Sentence Length (days)			
Community	394.9 (*SD* = 270.2)	388.2(*SD* = 263.7)	391.6 (*SD* = 267.0)
Custodial	36.0 (*SD* = 96.4)	35.9 (*SD* = 95.8)	35.9 (*SD* = 96.1)
Region			
Central	4545 (33.4%)	4482 (33.4%)	9027 (33.4%)
Eastern	2956 (21.7%)	2872 (21.4%)	5828 (21.6%)
Northern	2756 (20.3%)	2864 (21.3%)	5620 (20.8%)
Western	3148 (23.2%)	3005 (22.4%)	6153 (22.8%)
Missing	189 (1.4 %)	210 (1.6 %)	399 (1.5%)
Followup Time (days)	1611.83 (*SD* = 129.5)	1609.04 (*SD* = 130.0)	1610.45 (*SD* = 129.8)
Average LSI Score	12.56 (*SD* = 8.8)	12.50 (*SD* = 8.8)	12.53 (*SD* = 8.8)
Final Risk Level			
1	2064 (15.2%)	2049 (15.3%)	4113 (15.2%)
2	3025 (22.3%)	3016 (22.5%)	6041 (22.4%)
3	5283 (38.9%)	5205 (38.7%)	10488 (38.8%)
4	2483 (18.3%)	2443 (18.2%)	4926 (18.2%)
5	739 (5.4%)	720 (5.4%)	1459 (5.4%)

Offence Severity for Initial Offence			
Homicide and related	30 (0.2%)	25 (0.2%)	55 (0.2%)
Serious violent	271 (2%)	267 (2%)	538 (2%)
Violent sexual	239 (1.8%)	202 (1.5%)	441 (1.6%)
Non-violent sexual	149 (1.1%)	172 (1.3%)	321 (1.2%)
Weapons	423 (3.1%)	406 (3.0%)	829 (3.1%)
Misc. against the person	1113 (8.2%)	1022 (7.6%)	2135 (7.9%)
Assault and related	3952 (29.1%)	3965 (29.5%)	7917 (29.3%)
Nonviolent	7417 (54.6%)	7374 (54.9%)	14791 (54.7%)
Offence Severity for Recidivism Offence			
Homicide and related	10 (0.1%)	12 (0.1%)	22 (0.1%)
Serious violent	109 (0.8%)	112 (0.8%)	221 (0.8%)
Violent sexual	44 (0.3%)	32 (0.2%)	76 (0.3%)
Non-violent sexual	24 (0.2%)	30 (0.2%)	54 (.02%)
Weapons	127 (0.9%)	107 (0.8%)	234 (0.9%)
Misc. against the person	379 (2.9%)	375 (2.8%)	754 (2.8%)
Assault and related	867 (6.4%)	842 (6.3%)	1709 (6.3%)
Nonviolent	3381 (24.9%)	3282 (24.4%)	6663 (24.7%)
No recidivism	8653 (63.7%)	8641 (64.3%)	17294 (63.4%)
General Recidivists	4941 (36.3%)	4792 (35.7%)	9733 (36.0%)
Violent Recidivists	1550 (11.4%)	1495 (11.1%)	3045 (11.3%)

Predictive Validity Comparisons of Existing Scales in the LSI -OR

In order to compare the predictive validity of the developed scales to the existing scales, the correlations and Area Under the Curve (AUC) values for the General Risk/Need total score (Section A) and the Specific Risk/Need total score (Section B) with violent recidivism are presented for both the construction and validation samples in Table 3.2.

Table 3.2. Correlations Between Violent Recidivism and the Total Scores for A and B Scales on the LSI – OR for Construction and Validation Samples

	Construction			Validation		
(N)	Full Sample (13594)	Males (11121)	Females (2473)	Full Sample (13433)	Males (10954)	Females (2479)
A Scales Total						
r	.202***	.199***	.193***	.181***	.182***	.139***
AUC	.677***	.669***	.705***	.663***	.656***	.680***
B Scales Total						

r	.207***	.199***	.212***	.197***	.188***	.171***
AUC	.671***	.660***	.698***	.663***	.649***	.694***

*** p < .001, ** p < .01, * p < .05

Prediction Models Based on Scale Correlations

Descriptives

Full sample

The correlations for the subscales of the LSI-OR with violent recidivism are presented in Table 3.3. The most highly correlated subscales include B1 (Personal Problems with Criminogenic Potential), $r = .186$, $p < .01$, A1 (Criminal History) $r = .178$, $p < .01$ and B2 (History of Perpetration) $r = .174$, $p < .01$. All of the subscales were significantly correlated with violent recidivism at the $p < .01$ level.

Table 3.3. Construction Sample Subscale Correlations with Violent Recidivism

Scale (N)	Full Sample Correlations (13594)	Male Correlations (11121)	Female Correlations (2473)
Criminal History (A1)	.178***	.175***	.133***
Education/Employment (A2)	.137***	.143***	.126***
Family/Marital (A3)	.111***	.121***	.112***
Leisure/Recreation (A4)	.097***	.094***	.091***
Companions (A5)	.131***	.132***	.102***
Procriminal Attitude/Orientation (A6)	.118***	.113***	.097***
Substance Abuse (A7)	.151***	.142***	.178***
Antisocial Pattern (A8)	.165***	.162***	.149***
Personal Problems with Criminogenic Potential (B1)	.186***	.182***	.167***
History of Perpetration (B2)	.174***	.161***	.203***

*** p < .001, ** p < .01, * p < .05

Males

The correlations of the subscales for males are presented in Table 3.3 as well. The highest correlations match the full sample B1 (Personal Problems with Criminogenic Potential), $r = .182$, $p < .01$, A1 (Criminal History) $r = .175$, $p < .01$ and B2 (History of Perpetration) $r = .161$, $p <$

.01. All of the subscales were significantly correlated with violent recidivism at the $p < .01$ level.

Females

Correlations for the females in the construction sample are presented in the third column of Table 3.3. The most highly correlated subscales for females was B2 (History of Perpetration), $r = .203$, $p < .01$, A7 (Substance Abuse), $r = .178$, $p < .01$ and B1 (Personal Problems with Criminogenic Potential), $r = .167$, $p < .01$. All subscales again were correlated with violent recidivism at the $p < .01$ level.

Scale Validation

Construction sample

Full sample. Since all eight subscales in scale A and the two subscales in scale B were significant at $p < .001$, the total of the A and B scales was calculated and correlated with the violent recidivism variable. For the full sample containing both males and females, there was a correlation of $r = .215$, $p < .001$.

Males. When only the males of the groups were considered in the validation, the correlation between the A and B scales and violent recidivism decreased to $r = .210$, $p < .001$.

Females. The female portion of the sample displayed the same correlation as the full sample, $r = .209$, $p < .001$, in its validation.

Validation sample

Full Sample. The validation sample was used to determine whether the scales developed on the construction sample displayed similar predictive validity. When the subscales from sections A and B were added together and correlated with the violent recidivism variable for the validation sample, $r = .195$, $p < .001$, which is very similar to what was obtained in the construction sample.

Males. When the males from the validation sample were used to create a correlation between the A and B subscales and violent recidivism, it turned out to be the same correlation as the full sample, $r = .193$, $p < .001$.

Females. The female validation group demonstrated a smaller correlation than the construction, males and full samples. When the subscales total from sections A and B were correlated with violent recidivism, $r = .154$, $p < .001$.

Prediction Models Based on Item Correlations

Descriptives

Full sample

The second analysis examined the correlations between individual items on the LSI-OR and violent recidivism. Table 3.4 presents all of the significant correlations for the participants in the construction sample. The items with the highest correlations include A18 (Charge laid, probation breached or parole suspended during prior community supervision), $r = .147$, $p < .001$, B16 (Anger management deficits), $r = .144$, $p < .01$, A12 (Two or more prior adult/youth dispositions), $r = .143$, $p < .001$ and B23 (Physical assault (extrafamilial)), $r = .141$, $p < .001$.

Table 3.4. Significant Item Correlations for the Construction Sample

Item (N)	Full Sample Correlations (13594)	Male Correlations (11121)	Female Correlations (2473)
A11: Any prior y.o. or adult dispositions	.133***	.130***	.106***
A12: Two or more prior adult/youth dispositions	.143***	.139***	.113***
A13: Three or more prior adult/youth dispositions	.138***	.136***	.093***
A14: Three or more present offences	.101***	.101***	.066**
A15: Arrested or charged under 16	.123***	.122***	.095***
A16: Ever incarcerated upon adjudication	.137***	.133***	.097***

A17: Ever punished for institutional misconduct/behaviour report	.100***	.100***	ns
A18: Charge laid, probation breached or parole suspended during prior community supervision	.147***	.146***	.106***
A29: Currently unemployed	.078***	.087***	.065***
A210: Frequently unemployed	.094***	.096***	.100***
A211:Never employed for a full year	.074***	.077***	.082***
A212: Less than regular grade 10 or equivalent	.068***	.067***	.079***
A213: Less than regular grade 12 or equivalent	.102***	.099***	.113***
A214: Suspended or expelled at least once	.102***	.100***	.073***
A215: Participation/Performance	.095***	.105***	.072***
A216: Peer interactions	.091***	.098***	.083***
A217: Authority interactions	.090***	.096***	.090***
A318: Dissatisfaction with marital or equivalent situation	.052***	.055***	.056**
A319: Nonrewarding, parental	.067***	.072***	.058**
A320: Nonrewarding, other relatives	.061***	.065***	.077***
A321: Criminal – Family/Spouse	.086***	.097***	.080***
A422: No recent participation in organized activity	.055***	.054***	.052**
A423: Could make better use of time	.099***	.096***	.093***
A524: Some criminal acquaintances	.110***	.109***	.096***
A525: Some criminal friends	.114***	.119***	.068**
A526: No anti-criminal acquaintances	.053***	.052***	.054**
A527: No anti-criminal friends	.071***	.068***	.075***
A628: Supportive of crime	.086***	.082***	.072***
A629: Unfavourable toward convention	.108***	.105***	.099***
A630: Poor, toward sentence/offence	.049***	.045***	ns
A631: Poor, toward supervision/treatment	.081***	.080***	.066**
A732: Alcohol problem, ever	.123***	.107***	.187***
A733: Drug problem, ever	.105***	.098***	.127***

A734: Alcohol problem, currently	.128***	.114***	.184***
A735: Drug problem, currently	.078***	.078***	.053**
A736: Law violations	.111***	.101***	.140***
A737: Marital/Family	.117***	.113***	.126***
A738: School/Work	.097***	.098***	.067**
A739: Medical or other clinical indicators	.058***	.057***	.073***
A840: Specialized assessment for Antisocial pattern	.059***	.056***	.067**
A841: Early and diverse antisocial behaviour	.127***	.124***	.112***
A841A: Official record of assault/violence	.116***	.101***	.166***
A841B: Escape history	.067***	.064***	.070***
A842: Criminal attitude	.115***	.112***	.098***
A843: A pattern of generalized trouble	.118***	.119***	.105***
A843A: Financial problems	.041***	.045***	ns
A843B: 3 or more address changes	.050***	.054***	ns
B11: Clear problems of compliance	.128***	.126***	.096***
B13: Diagnosis of other personality disorder	.019*	.021*	ns
B14: Threat from third party	.038***	.046***	ns
B15: Problem-solving/self-management skill deficits	.088***	.090***	.066**
B16: Anger management deficits	.144***	.132***	.174***
B17: Intimidating/Controlling	.090***	.083***	.087***
B18: Inappropriate sexual activity	.021**	ns	ns
B19: Poor social skills	.077***	.083***	ns
B110: Peers outside age range	.045***	.041***	.065**
B111: Racist/sexist behaviour	.027***	.023**	.045*
B112: Underachievement	.081***	.090***	ns
B113: Outstanding charges	.068***	.075***	ns
B114: Other	.035***	.032**	.057**
B21: Sexual assault (extrafamilial)	.027**	.023**	ns
B23: Physical assault (extrafamilial)	.141***	.138***	.128***
B24: Physical assault (intrafamilial)	.074***	.066***	.087***
B25: Assault on authority figure	.116***	.106***	.170***

B26: Weapon use	.109***	.104***	.114***
B27: Fire setting	.035***	.031**	.049*
B28: Escapes/U.A.L.	.076***	.075***	.042*
B29: Impaired driving	.039***	.030**	.059**

*** p < .001, ** p < .01, * p < .05

Males

Table 3.4 also presents all the significant items for males within the construction sample. The highest correlations that were exposed through this analysis include A18 (Charge laid, probation breached or parole suspended during prior community supervision), $r = .146$, $p < .01$, A12 (Two or more prior adult/youth dispositions), $r = .139$, $p < .01$, B23 (Physical assault (extrafamilial)), $r = .138$, $p < .01$ and A13 (Three or more prior adult/youth dispositions), $r = .136$, $p < .01$.

Females

The correlations of the female portion of the sample with violent recidivism are also presented in Table 3.4. The highest correlated items for the females in the construction sample include, A732 (Alcohol problem, ever), $r = .187$, $p < .01$, A734 (Alcohol problem, currently), $r = .184$, $p < .01$, B16 (Anger management deficits), $r = .174$, $p < .01$, B25 (Assault on authority figure), $r = .170$, $p < .01$.

Scale Validation

Construction sample

Full Sample. The items that were correlated significantly at $p < .001$ with violent recidivism in the full sample were then combined to create an item-based scale to predict violent recidivism. When the scores of these items were added together and correlated with the violent recidivism variable, the full sample generated a correlation of $r = .215$, $p < .001$. The males of the construction sample generated very similar items as the full sample to be included in their violent recidivism scale and had a correlation of $r = .210$, $p < .001$. When the scale that was generated for the males and full sample was applied to just the females in the construction sample, a correlation of $r = .210$, $p < .001$ was seen.

Males. When the males in the construction sample were separated and the scale developed for the full and male sample was correlated with the violent recidivism variable in the construction sample, $r = .210$, $p < .001$.

Females. The female portion of the construction sample created a scale with fewer items on it than the full and male sample. When these items were combined as a scale and correlated with the violent recidivism variable, the correlations proved to be a little bit higher, $r = .224$, $p < .001$.

Validation Sample

Full Sample. The same items generated from the significant item correlations in the construction sample were then combined and correlated with violent recidivism in the validation sample. The correlation decreased a little bit in this sample but still reached a high significance level, $r = .194$, $p < .001$. The male sample dropped in its correlation with violent recidivism, $r = .192$, $p < .001$. When applying this scale to the females in the validation sample, a correlation of, $r = .153$, $p < .001$ was obtained.

Males. The significant items for the male portion of the construction sample were added together and correlated with the violent recidivism variable for the males in the validation sample. Similar to the validation full sample's correlation with the male portion of the validation sample, $r = .192$, $p < .001$.

Females. Contrary to the larger correlation that was found in the female portion of the construction sample, between the significant items and violent recidivism, when the same items were combined as a scale and correlated in the validation sample a smaller correlation was found, $r = .157$, $p < .001$.

Prediction Models Based on the Burgess Technique

Descriptives

Full sample

The significant items that were found using the full sample with the Burgess technique are presented in Table 3.5. With an overall average violent recidivism rate of 11.4%, items that

differed from the average by multiples of 5% (i.e., < 6.4%, > .16.4%) are included in the table. Items that showed the most significant change in score include 2 point scores for A15 (Arrested or charged under 16), A526 (No anti-criminal acquaintances), a 0 score on A527R (No anti-criminal friends), A840 (Specialized assessment for Antisocial pattern), A841 (Early and diverse antisocial behaviour), A841B (Escape History), B110 (Peers outside age range), B25 (Assault on authority figure), B26 (Weapon use), B27 (Fire setting) and B28 (Escapes).The items that were not included in this table did not differ from the average violent recidivism rate by 5% and therefore were not part of the scale.

Table 3.5. Items Predicting Violent Recidivism using the Burgess Technique with the Construction Sample

Item	Value	Full Sample Score	Male Score	Female Score
(N)		(13594)	(11121)	(2473)
A11: Any prior y.o. or adult dispositions	0	-1	-1	-
A12: Two or more prior adult/youth dispositions	1	1	-	-
A13: Three or more prior adult/youth dispositions	1	1	1	-
A14: Three or more present offences	1	1	1	1
A15: Arrested or charged under 16	1	2	1	1
A16: Ever incarcerated upon adjudication	1	1	1	-
A17: Ever punished for institutional misconduct/behaviour report	1	1	1	-
A18: Charge laid, probation breached or parole suspended during prior community supervision	1	1	1	1
A210: Frequently unemployed	1	1	1	-
A211:Never employed for a full year	1	1	1	-
A214: Suspended or expelled at least once	1	1	1	-
A215R: Participation/Performance	3	-1	-1	-
A216R: Peer interactions	3	-1	-1	-
A217R: Authority interactions	1	-	-	1
	3	-	-1	-
A319R: Nonrewarding, parental	3	-1	-1	-
A321: Criminal – Family/Spouse	1	-	1	-
A423R: Could make better use of time	0	1	1	-

	3	-1	-1	-
A526: No anti-criminal acquaintances	1	2	2	1
A527R: No anti-criminal friends	0	2	2	1
	1	1	1	2
	3	-	-1	-
A628R: Supportive of crime	2	-	- 1	1
A629: Unfavourable toward convention	1	1	1	1
A631: Poor, toward supervision/treatment	1	1	1	1
A732: Alcohol problem, ever	1	-	-	1
A734R: Alcohol problem, currently	0	1	1	1
	1	1	-	1
	3	-1	-	-
A735R: Drug problem, currently	0	1	1	-
A736: Law violations	1	-	-	1
A737: Marital/Family	1	1	1	1
A738: School/Work	1	1	1	1
A739: Medical or other clinical indicators	1	1	1	1
A840: Specialized assessment for Antisocial pattern	1	2	1	2
A841: Early and diverse antisocial behaviour	1	2	2	2
A841A: Official record of assault/violence	1	1	-	1
A841B: Escape history	1	2	2	2
A843: A pattern of generalized trouble	1	1	1	1
A843B: 3 or more address changes	1	1	1	-
B11: Clear problems of compliance	1	1	1	1
B14: Threat from third party	1	1	2	-
B16: Anger management deficits	1	1	1	1
B17: Intimidating/Controlling	1	1	1	2
B19: Poor social skills	1	1	1	1
B110: Peers outside age range	1	2	2	-
B111: Racist/sexist behaviour	1	1	-	-
B112: Underachievement	1	1	1	-
B113: Outstanding charges	1	1	1	-
B114: Other	1	1	1	-
B23: Physical assault (extrafamilial)	1	1	1	1
B24: Physical assault (intrafamilial)	1	-	-	1
B25: Assault on authority figure	1	2	2	3
B26: Weapon use	1	2	1	2
B27: Fire setting	1	2	-	-
B28: Escapes/U.A.L.	1	2	2	-

Males

When the Burgess technique was used on the male portion of the construction sample, similar results to the full sample scale were found. Table 3.5 also shows the scale developed from the male group. The average violent recidivism rate was 12.4%. The items that displayed the greatest difference from the mean included a 2 point scores for A526 (No anti-criminal acquaintances), a 0 score on A527R (No anti-criminal friends), A841 (Early and diverse antisocial behaviour), A841B (Escape history), B14 (Threat from a third party), B110 (Peers outside age range), B25 (Assault on authority figure) and B28 (Escapes).

Females

The average rate of violent recidivism among females in the construction sample was 7.0%. Table 3.10 displays the Burgess scale that was developed from the items for the female portion of the sample. As in the male and full sample only the items that were correlated with violent recidivism at $p < .001$ were looked at in the crosstabs to develop this scale. There were many less items in this scale when compared to the ones developed for males and the full sample. A value of 3 was assigned to B25 (Assault on authority figure) and a value of 2 was given for a 0 score on A527R (No anti-criminal friends), A840 (Specialized assessment for Antisocial pattern), A841 (Early and diverse antisocial behaviour), A841B (Escape history) B17(Intimidating/Controlling) and B26 (Weapon use). All other items were not included in this table if they did not differ from the average violent recidivism rate by more than 5%.

Scale Validation

Construction Sample

Full Sample. When the Burgess Scale scores were calculated, added up and correlated with violent recidivism for all the participants in the construction sample there was a significant correlation of $r = .222$, $p < .001$. When the full sample Burgess equation was applied to just the males in the sample, $r = .216$, $p < .001$. The same scale was then applied to only the females in the construction sample and yielded a correlation of, $r = .212$, $p < .001$.

Males. The male Burgess Scale that was generated from the construction sample also demonstrated a fairly high validation with the male participants. Slightly lower than the full

sample, the correlation between the male Burgess scores and violent recidivism was $r = .212$, $p < .001$.

Females. The female portion of the sample generated a Burgess score that was different in scores and number of items than the male and full sample scales. Fewer items that yielded some highly predictive scores provided a correlation of $r = .252$, $p < .001$ when correlated with the violent recidivism variable.

Validation Sample

Full Sample. When the validation sample was used to determine the correlation between the Burgess scale scores and violent recidivism for the full sample there was a slight decrease in the size of the correlation from the construction sample, $r = .195$, $p < .001$. Again the full sample Burgess equation was applied to the males and females and correlated with violent recidivism. Males showed a higher correlation, $r = .189$, $p < .001$ than females did, $r = .159$, $p < .001$, although both were significant.

Males. The correlation of the male portion of the validation sample with its Burgess scale scores had also decreased from the construction sample correlations, and was also less than the correlations for the full sample, $r = .183$, $p < .001$.

Females. The greatest decrease in the validation of the Burgess Scales that were generated from the construction sample came in the female portion of the participants. Compared to the largest correlation in the construction sample validation, the correlation between violent recidivism and the female Burgess score dropped to the lowest correlations for the samples, $r = .168$, $p < .001$.

Prediction Models Based on Subscale Linear Regression

Descriptives

Full sample

The next analysis used to create new scales to predict violent recidivism utilized stepwise linear regression to identify key scales from the LSI-OR. Table 3.6 represents the scales that were added into the regression equation, including the variance accounted for at each step.

Scales were added into the equation if the addition of that variable increased the percentage of variance explained at the $p < .001$ level. The total variance explained by this model was 5.0% and was terminated with 5 steps. This shows that there were nine subscales on the LSI-OR that significantly add to the variance of predicting violent recidivism for the full sample.

Table 3.6. Linear Regression Analysis for LSI-OR Subscales on the Full Construction Sample

Step #	Subscale Entered	b	R	Cumulative R Square	R Square Change	Significant F Change
1	Personal Problems with Criminogenic Potential (B1)	.017	.186	.035	.035	.000
2	Criminal History (A1)	.006	.208	.043	.009	.000
3	History of Perpetration (B2)	.020	.216	.047	.003	.000
4	Substance Abuse (A7)	.006	.220	.048	.002	.000
5	Education/Employment (A2)	.005	.223	.050	.001	.000

Constant = .024

Males

The male sample included linear regression that accounted for 4.6% of the variance in violent recidivism. The regression equation was terminated in five steps, and highlighted five subscales that significantly add to the prediction of violent recidivism. Table 3.7 displays the regression steps for the male portion of the construction sample.

Table 3.7. Linear Regression Analysis for LSI-OR Subscales on the Male Portion of the Construction Sample

Step #	Subscale Entered	b	R	Cumulative R Square	R Square Change	Significant F Change
1	Personal Problems with Criminogenic Potential (B1)	.019	.182	.033	.033	.000
2	Criminal History (A1)	.008	.204	.042	.009	.000
3	History of Perpetration (B2)	.017	.209	.044	.002	.000
4	Education/Employment	.007	.214	.046	.002	.000

(A2)
Constant = .035

Females

The female portion of the sample only had two regression steps to account for 5.3% of the variance in the violent recidivism variable. Table 3.8 displays the two subscales and the addition that each subscale makes in explaining the dependent variable.

Table 3.8. Linear Regression Analysis for LSI-OR Subscales on the Female Portion of the Construction Sample

Step #	Subscale Entered	b	R	Cumulative R Square	R Square Change	Significant F Change
1	History of Perpetration (B2)	.049	.203	.041	.041	.000
2	Substance Abuse (A7)	.013	.231	.053	.012	.000

Constant = .020

Scale Validation

Construction sample

Full Sample. When the linear regression equations were calculated for the subscales of section A and B on the LSI-OR and then correlated with violent recidivism for the full construction sample, they yielded a significant correlation, $r = .223$, $p < .001$. When this equation was applied to males in the construction sample, $r = .215$, $p < .001$ and females yielded an even higher correlation, $r = .229$, $p < .001$.

Males. The male portion of the construction sample had very similar items in its linear regression equation but generated a smaller correlation between violent recidivism and its regression equation than the full sample, $r = .214$, $p < .001$.

Females. The female subsample of the construction sample displayed a higher correlation than the male subsample and full construction sample with its linear regression equation and violent recidivism, $r = .231$, $p < .001$.

Validation sample

Full Sample. When the regression equation generated from the construction sample was applied to the full validation sample there was a decrease in the correlation between violent recidivism and the equation, r = .209, p < .001, from what was generated from the validation of the construction. When the male sample was validated with this equation, the results were also relatively unchanged, $r = .203$, $p < .001$, but the females showed a slight drop in correlation, $r = .177$, $p < .001$.

Males. Similar to the full sample comparisons between the validation and the construction samples, the male participant correlation for the subscale equation was the same as the construction sample validation correlation, $r = .199$, $p < .001$.

Females. Contrary to the previous similarities between the correlations from the validations of the construction and validation samples, the female participants exhibited a lower correlation in the validation sample than in the construction sample, $r = .161$, $p < .001$. As with the Burgess Scale, the female portion of the sample, which indicated the highest correlations in the construction sample, again had the lowest correlation in the validation sample.

Prediction Models Based on Item Linear Regression

Descriptives

Full sample

To further identify items that are predictive of violent recidivism, further linear regression analyses were completed on the individual items of the LSI-OR. Table 3.9 displays the 11 steps and items that were identified as significantly contributing to explaining the variance of the dependent variable. The combination explains 5.9% of the variance in the violent recidivism construct.

Table 3.9. Linear Regression Analysis for LSI-OR Items on the Full Construction Sample

Step #	Item Entered	b	R	Cumulative R Square	R Square Change	Significant F Change
1	A18: Charge laid, probation	.027	.147	.021	.021	.000

	breached or parole suspended during prior community supervision					
2	B16: Anger management deficits	.046	.187	.035	.014	.000
3	A734: Alcohol problem, currently	.050	.205	.042	.007	.000
4	A15: Arrested or charged under 16	.041	.216	.047	.005	.000
5	B23: Physical assault (extrafamilial)	.038	.223	.050	.003	.000
6	A213: Less than regular grade 12 or equivalent	.028	.229	.053	.003	.000
7	B25: Assault on authority figure	.062	.234	.055	.002	.000
8	B113: Outstanding charges	.045	.238	.056	.002	.000
9	A214: Suspended or expelled at least once	.024	.240	.058	.001	.000
10	A215:Participation/Performance (Education)	.020	.242	.058	.001	.000
11	B17: Intimidating/Controlling	.028	.243	.059	.001	.001
Constant = .020						

Males

The male portion of the construction sample took nine steps to generate a regression model that explained the maximum variance. Table 3.10 shows the cumulative R Square as each item was added to the equation, resulting in an overall accounting of 5.3% of the variance in the violent recidivism variable.

Table 3.10. Linear Regression Analysis for LSI-OR Items on the Male Portion of the Construction Sample

Step #	Item Entered	b	R	Cumulative R Square	R Square Change	Significant F Change
1	A18: Charge laid, probation breached or parole suspended during prior community supervision	.030	.146	.021	.021	.000
2	B16: Anger management deficits	.050	.180	.032	.011	.000
3	B23: Physical assault	.041	.193	.037	.005	.000

	(extrafamilial)					
4	A734: Alcohol problem, currently	.043	.204	.042	.004	.000
5	A15: Arrested or charged under 16	.049	.213	.045	.004	.000
6	B113: Outstanding charges	.058	.219	.048	.002	.000
7	A213: Less than regular grade 12 or equivalent	.030	.224	.050	.002	.000
8	B25: Assault on authority figure	.054	.228	.052	.002	.000
9	A215:Participation/Performance (Education)	.027	.231	.053	.001	.000

Constant = .030

Females

Table 3.11 displays the five items that were sequentially entered into the regression equation based on their ability to explain variance in the violent recidivism variable for the female portion of the construction sample. The five items accounted for 8.0% of the variance in the dependent variable.

Table 3.11. Linear Regression Analysis for LSI-OR Items on the Female Portion of the Construction Sample

Step #	Item Entered	b	R	Cumulative R Square	R Square Change	Significant F Change
1	A732: Alcohol problem, ever	.038	.187	.035	.035	.000
2	B16: Anger management deficits	.070	.236	.055	.021	.000
3	B25: Assault on authority figure	.138	.264	.069	.014	.000
4	A213: Less than regular grade 12 or equivalent	.039	.273	.075	.005	.000
5	A734: Alcohol problem, currently	.057	.282	.080	.005	.000

Constant = .000

Scale Validation

Construction sample

Full Sample. When the linear regression was run for the items in the LSI-OR, the 12 items that were identified as being significant for the full sample yielded a fairly high correlation when correlated with violent recidivism, $r = .243$, $p < .001$. When this regression equation was applied to the males in the sample and then correlated with violent recidivism a correlation of $r = .234$, $p < .001$ was obtained. Females in the construction sample exhibited an even higher correlation of $r = .261$, $p < .001$ when the regression equation generated for the full sample was applied to them.

Males. The regression equation that was generated for the males on the construction sample was shorter by three items than the full sample. The correlation of the item regression equation and violent recidivism was larger than for the subscales in the male subsample in the construction sample, $r = .231$, $p < .001$.

Females. The largest correlation found for the scales that were developed is the four item scale generated by linear regression for the females in the construction sample. The validation of this scale yielded a correlation of $r = .282$, $p < .001$.

Validation Sample

Full Sample. The full validation sample also generated a high correlation between the regression equation and violent recidivism, similar to that obtained from the construction sample validation, $r = .214$, $p < .001$. The violent recidivist males of the validation sample correlated with this equation at $r = .208$, $p < .001$. The correlation seen for the females was reduced when the regression equation was applied to the females in the validation sample, $r = .178$, $p < .001$.

Males. When the male participants from the validation sample were used to validate the regression equation generated by the construction sample, again the correlations between the regression equation and violent recidivism were similar to that obtained in the validation in the construction sample males, $r = .206$, $p < .001$.

Females. The same trend seen in the previous female subsample validations for the validations of the other scales was seen in the item linear regression as well. Whereas the validation correlation in the construction sample was the largest one that was obtained, the

correlation between the regression equation and violent recidivism for women had decreased substantially in the validation sample, $r = .179$, $p < .001$.

Summary Tables

To summarize the scales that were developed through each of the statistical techniques, Table 3.12 lists the number of scales or items that were included in each of the generated scales.

Table 3.12. Number of Scales/Items in each Generated Scale

Statistical Method	Full Sample	Male Correlations	Female Correlations
Subscale Correlations	10 scales	10 scales	10 scales
Item Correlations	64 items	61 items	40 items
Burgess Technique	45 items	44 items	28 items
Subscale Linear Regression	5 scales	4 scales	2 scales
Item Linear Regression	11 items	9 items	5 items

Table 3.13 highlights the scales that were used in each of the two techniques that involved using the existing scales on the LSI-OR, and not the items. For more information on how many scales each item was included in, Appendix A illustrates the breakdown of which items were included for which samples. There were three items that were included in all nine of the scales, A734: Alcohol problem, currently, B16: Anger management and B25: Assault on authority figure. There were also three items that were included in eight of the nine scales; A15: Arrested or charged under 16, A18: Charge laid, probation breached or parole suspended during prior community supervision, B23: Physical assault (extrafamilial).

Table 3.13 Scales that were Included in Derived Scales

	Scale Correlations			Scale Linear Regression			TOTAL
Scale	FS	M	F	FS	M	F	
Criminal History (A1)	X	X	X	X	X		**5**
Education/Employment (A2)	X	X	X	X	X		**5**

Family/Marital (A3)	X	X	X				**3**
Leisure/Recreation (A4)	X	X	X				**3**
Companions (A5)	X	X	X				**3**
Procriminal Attitude/Orientation (A6)	X	X	X				**3**
Substance Abuse (A7)	X	X	X	X		X	**5**
Antisocial Pattern (A8)	X	X	X				**3**
Personal Problems with Criminogenic Potential (B1)	X	X	X	X	X		**5**
History of Perpetration (B2)	X	X	X	X	X	X	**6**
Total Number of Scales	**10**	**10**	**10**	**5**	**4**	**2**	

FS = Full Sample, M = Male Sample, F = Female Sample

Table 3.14 summarizes the descriptive statistics for all of the generated scales from the preceding analyses. These statistics are provided for both the construction and validation samples on the full samples and separated by gender.

Table 3.14. Descriptive Statistics for all Generated Scales by Gender and for the Construction and Validation Samples

	Construction				Validation			
(N)	min	max	mean	SD	min	max	mean	SD
A Scale Total								
Full Sample (13594/13433)	0	43	12.56	8.79	0	42	12.50	8.80
Males (11121/10954)	0	43	12.91	8.94	0	42	12.81	8.92
Females (2473/2479)	0	40	10.97	7.92	0	41	11.12	8.10
B Scale Total								
Full Sample (13594/13433)	0	20	2.51	2.36	0	19	2.49	2.32
Males (11121/10954)	0	20	2.67	2.43	0	19	2.65	2.38
Females (2473/2479)	0	13	1.79	1.85	0	14	1.77	1.86
Subscale Correlations								
Full Sample (13594/13433)	0	61	15.06	10.55	0	61	14.99	10.52
Males (11121/10954)	0	61	15.57	11.60	0	61	15.46	10.70
Females (2473/2479)	0	51	12.76	9.18	0	55	12.89	9.38

Item Correlations								
Full Sample (13594/13433)	0	62	15.53	10.85	0	60	15.46	10.84
Males ǂ (11121/10954)	0	62	16.05	11.08	0	60	15.95	11.04
Females‡‡ (2473/2479)	0	53	13.20	9.45	0	58	13.32	9.66
Males (11121/10954)	0	59	15.79	10.93	0	59	15.68	10.89
Females (2473/2479)	0	38	9.35	7.29	0	40	9.45	7.40
Burgess								
Full Sample (13594/13433)	-6	48	5.60	7.67	-6	47	5.55	7.64
Males ǂ (11121/10954)	-6	48	6.11	7.86	-6	47	6.01	7.81
Females‡‡ (2473/2479)	-6	42	3.34	6.27	-6	42	3.49	6.47
Males (11121/10954)	-7	43	4.84	7.15	-7	43	4.75	7.14
Females (2473/2479)	0	32	3.31	4.03	0	30	3.40	4.04
Subscale Regression								
Full Sample (13594/13433)	.024	.521	.112	.070	.024	.504	.111	.069
Males ǂ (11121/10954)	.024	.521	.116	.071	.024	.504	.116	.070
Females‡‡ (2473/2479)	.024	.381	.091	.056	.024	.415	.091	.058
Males (11121/10954)	.035	.517	.124	.070	.035	.502	.124	.070
Females (2473/2479)	.020	.405	.070	.059	.020	.405	.070	.058
Item Regression								
Full Sample (13594/13433)	.020	.429	.114	.077	.020	.429	.113	.077
Males ǂ (11121/10954)	.020	.429	.119	.079	.020	.429	.119	.079
Females‡‡ (2473/2479)	.020	.429	.090	.065	.020	.429	.090	.067
Males (11121/10954)	.030	.412	.124	.076	.030	.412	.124	.070
Females (2473/2479)	.000	.342	.070	.072	.009	.342	.068	.073

ǂ = scale developed from the full sample being validated only on the male participants

‡‡= scale developed from the full sample being validated only on the female participants

*** p < .001, ** p < .01, * p < .05

Table 3.15 summarizes the predictive validity correlations for all of the scales generated from the construction sample in the preceding analyses. In order to examine possible shrinkage in predictive validity, these correlations are provided for both the construction and validation samples on the total participants in each sample as well as by gender.

Table 3.15. Correlations between the Generated Scales and Violent Recidivism for the Construction and Validation Samples

	Construction			Validation		
(N) Type of Scale	Full Sample (13594)	Males (11121)	Females (2473)	Full Sample (13433)	Males (10954)	Females (2479)
A Scale Total	.202***	.199***	.193***	.181***	.182***	.139***
B Scale Total	.207***	.199***	.212***	.197***	.188***	.171***
Subscale Correlations	.215***	.210***	.209***	.195***	.193***	.154***
Item Correlations	.215***	.210***	.210***	.194***	.192***	.153***
Male Scale‡		.210***			.192***	
Female Scale‡‡			.224***			.157***
Burgess	.222***	.216***	.212***	.195***	.189***	.159***
Male Scale‡		.212***			.183***	
Female Scale‡‡			.252***			.168***
Subscale Regression	.223***	.215***	.229***.	.209***	.203***	.177***
Male Scale‡		.214***			.199***	
Female Scale‡‡			.231***			.161***
Item Regression	.243***	.234***	.261***	.214***	.208***	.178***
Male Scale‡		.231***			.206***	
Female Scale‡‡			.282***			.179***

‡ = male sample derived scale being validated only on the male participants

‡‡= the female sample derived scale being validated only on the female participants

*** p < .001, ** p < .01, * p < .05

Corresponding to the predictive validity correlations summarized in Table 3.15, the AUC values for each of the scales in the male, female and full samples in both the construction and validation samples are presented in Table 3.16. For those interested in viewing the ROC curves associated with the validation sample AUCs, they are located in Appendix B – F.

Table 3.16. AUC Coefficients for the Generated Scales with Confidence Intervals (CI) for the Construction and Validation Samples

	Construction			Validation		
Full Sample						
(N)	Full Sample (13594)	Low CI	High CI	Full Sample (13433)	Low CI	High CI
Type of Scale						
A Scale Total	.677***	.664	.691	.663***	.649	.677
B Scale Total	.671***	.656	.685	.663***	.648	.677
Subscale Correlations	.687***	.674	.701	.673***	.659	.687
Item Correlations	.688***	.674	.701	.673***	.659	.687
Males‡	.678***	.664	.693	.664***	.650	.679
Females‡‡	.722***	.685	.759	.696***	.651	.741
Burgess	.695***	.681	.708	.676***	.662	.690
Males‡	.684***	.670	.698	.663***	.648	.677
Females‡‡	.718***	.680	.756	.707***	.662	.751
Subscale Regression	.693***	.679	.706	.681***	.667	.695
Males‡	.681***	.666	.695	.668***	.653	.683
Females‡‡	.732***	.694	.770	.710***	.665	.756
Item Regression	.706***	.693	.720	.683***	.668	.697
Males‡	.693***	.678	.707	.670***	.655	.685
Females‡‡	.756***	.719	.792	.700***	.651	.749
Male Sample						
(N)	Males (11121)	Low CI	High CI	Males (10954)	Low CI	High CI
A Scale Total	.669***	.655	.684	.656***	.641	.671
B Scale Total	.660***	.644	.675	.649***	.633	.664
Subscale Correlations	.678***	.663	.692	.664***	.650	.679
Item Correlations	.678***	.664	.693	.665***	.650	.679
Burgess	.681***	.667	.696	.657***	.642	.672
Subscale Regression	.680***	.665	.695	.665***	.650	.680
Item Regression	.689***	.675	.704	.669***	.653	.684
Female Sample						
(N)	Females (2473)	Low CI	High CI	Females (2479)	Low CI	High CI

A Scale Total	.705***	.668	.743	.680***	.634	.726
B Scale Total	.698***	.656	.740	.694***	.646	.742
Subscale Correlations	.719***	.683	.756	.694***	.648	.739
Item Correlations	.728***	.691	.766	.699***	.654	.744
Burgess	.750***	.712	.787	.705***	.660	.751
Subscale Regression	.734***	.695	.773	.686***	.639	.733
Item Regression	.780***	.747	.813	.689***	.636	.741

ǂ = scale developed from the full sample being validated only on the male participants

ǂǂ = scale developed from the full sample being validated only on the female participants

*** p < .001, ** p < .01, * p < .05

Linear Regression Model versus Original Scale

Also, in order to confirm the capacity of the full sample item linear regression scale to predict more variance of the violent recidivism variable than the A or B scale individually or the A and B scales together, Appendix G presents a series of linear regression analyses.

The Female Sample

Viewing the summary tables, it is apparent that the validation correlations in the female sample are lower than those in the construction sample. The full and male samples remain similar in both of their validations, whereas the females show a tendency to decrease. This pattern suggests that there may have been an unexpected difference in the construction and validation female samples that is causing the differences. Indeed, when reviewing Table 3.2, it was noticed that for females, the correlations for the construction sample for the A and B scales were much higher than those for the validation sample in spite of the fact that the A and B scales were created some years ago, quite independent of the current construction sample. Therefore, there may be differences between the construction and validation samples of women that caused the A and B scales on the LSI-OR to be more predictive for the construction sample than for the validation sample. Table 3.17 represents the additional comparisons that were done between the two female groups to identify where the differences in the sample may have occurred.

It is important to note that no significant differences were found in the female samples when compared based on ethnicity [χ^2 (3) = 3.098, p =.377, *ns*], age [χ^2 (4) = 4.244, p =.374, *ns*], region [χ^2 (3) = 1.589, p =.662, *ns*], final risk level [χ^2 (4) = 1.840, p =.765, *ns*], original offence [χ^2

(7) = 5.274, p =.627, *ns*] or general recidivism [χ^2 (1) = .213, p = .644, *ns*]. There were also no significant differences found between the groups on community sentence length (t(4950) = .405, p = .685, *ns*), custodial sentence length (t(4950) = .323, p = .747, *ns*), followup time (t(4950) = .359, p = .720, *ns*) or total LSI-OR score (t(4950) = -.665, p = .506, *ns*). Although the samples were very similar on these variables, a significant difference in the number of violent recidivists in the groups may have been the cause of the shrinkage in the validation correlations.

Even though the sample was randomly split, the construction sample had a violent recidivism rate of 7.0% and the validation sample had a significantly lower rate of 5.0%, χ^2 (1) = 8.673, $p < .01$. Further investigation into the recidivism offence severities also show a significant chi square, χ^2 (6) = 13.737, $p < .05$. As well, the number of assault charges (χ^2 (1) = 5.732, $p < .05$) and miscellaneous offences against the person (χ^2 (1) = 3.857, $p < .05$) were significantly larger in the construction sample than in the validation sample. These significant differences between the two subgroups may provide an explanation as to why there are smaller correlations seen in the female validation sample when compared to the construction sample validations. Although ROC is believed to be less sensitive to variations in the outcome variable (Rice & Harris, 2005) a decrement in the item linear regression model for women was still quite substantial (i.e., .780 - .689). However, it remained slightly higher than the corresponding ROC for males on the validation sample (.669).

Table 3.17. Construction and Validation Sample Comparisons for the Female Participants

	Frequency [*n (%)*]		
	Construction Sample	Validation Sample	Chi square or t test sig
Overall total	2473 (49.9%)	2479 (50.1%)	-
Ethnicity			χ^2 (3) = 3.098, p =.377, *ns*
Aboriginal	210 (8.5%)	216 (8.7 %)	
Black	148 (6.0%)	162 (6.5%)	
White	1397 (56.5%)	1372 (55.3%)	
Other	168 (6.8%)	197 (7.9 %)	
Missing	550 (22.2%)	535 (21.5%)	
Age at admission			χ^2 (4) = 4.244, p =.374, *ns*
25 & Under	749 (30.3%)	790 (31.9%)	
26 – 35	664 (26.8%)	691 (27.9 %)	

36 - 45	708 (28.6%)	649 (26.2%)	
46 – 55	267 (10.8%)	262 (10.6%)	
56 +	85 (3.4%)	86 (3.5%)	
Average Sentence Length (days)			
Community	408.1 (*SD* = 228.1)	405.41 (*SD* = 241.7)	$t(4950) = .405$, $p = .685$, *ns*
Custodial	10.0 (*SD* = 51.0)	9.6 (*SD* = 46.7)	$t(4950) = .323$, $p = .747$, *ns*
Region			$\chi^2(3) = 1.589$, $p = .662$, *ns*
Central	815 (33.0%)	826 (33.3%)	
Eastern	488 (19.7%)	483 (19.5%)	
Northern	423 (17.1%)	451 (18.2%)	
Western	718 (29.0%)	689 (27.8%)	
Missing	29 (1.2 %)	30 (1.2%)	
Followup Time (days)	1602.4(SD = 131.1)	1601.1 (SD = 131.4)	$t(4950) = .359$, $p = .720$, *ns*
Average LSI Score	10.97 (*SD* = 7.9)	11.12 (*SD* = 8.1)	$t(4950) = -.665$, $p = .506$, *ns*
Final Risk Level			$\chi^2(4) = 1.840$, $p = .765$, *ns*
1	498 (20.1%)	502 (20.3%)	
2	723 (29.2%)	685 (27.6%)	
3	876 (35.4%)	902 (36.4%)	
4	309 (12.5%)	316 (12.7%)	
5	67 (2.7%)	74 (3.0%)	
Offence Severity for Initial Offence			$\chi^2(7) = 5.274$, $p = .627$, *ns*
Homicide and related	3 (.1%)	3 (.1%)	
Serious violent	15 (.6%)	19 (.8%)	
Violent sexual	1 (.0%)	2 (.1%)	
Non-violent sexual	6 (.2%)	7 (.3%)	
Weapons	19 (.8%)	25 (1.0%)	
Misc. against the person	102 (4.1%)	77 (3.1%)	
Assault and related	680 (27.5%)	682 (27.5%)	
Nonviolent	1647 (66.6%)	1664 (67.1%)	
Offence Severity for Recidivism Offence			$\chi^2(6) = 13.737$, $p < .05$
Homicide and related	0 (0%)	0 (0%)	no difference
Serious violent	5 (.2%)	8 (0.3%)	$\chi^2(1) = .687$, $p = .407$, *ns*
Violent sexual	0 (0%)	0 (0%)	no difference
Non-violent sexual	2 (.1%)	0 (0%)	$\chi^2(1) = 2.006$, $p = .157$, *ns*
Weapons	5 (.2%)	3 (0.1%)	$\chi^2(1) = .506$, $p = .477$, *ns*
Misc. against the person	42 (1.7%)	26 (1.0%)	$\chi^2(1) = 3.857$, $p < .05$
Assault and related	124 (5.0%)	90 (3.6%)	$\chi^2(1) = 5.732$, $p < .05$
Nonviolent	544 (22.0%)	582 (23.5%)	$\chi^2(1) = 1.543$, $p = .214$, *ns*
No recidivism	1751 (70.8%)	1770 (71.4%)	
General Recidivists	722 (29.2%)	709 (28.6%)	$\chi^2(1) = .213$, $p = .644$, *ns*
Violent Recidivists	174 (7.0%)	125 (5.0%)	$\chi^2(1) = 8.673$, $p < .01$

Risk Levels

Risk Levels Derived from Full Sample Item Linear Regression

The table representing the linear regression equations for the full, male and female samples is located in Appendix H. As shown in Tables 3.15 and 3.16, by a small margin, the highest predictive correlations and AUCs are obtained through the use of the full scale item linear regression analysis. In accordance with the LSI tradition, risk levels were assigned to offenders based on the sample item linear regression scale. These risk levels were determined by dividing the linear regression scores from the construction sample into 5 equal portions along the range of the scale, to obtain five sections to classify offenders in very high, high, medium, low and very low risk categories. Table 3.18 displays the risk levels and linear regression scores on the full sample item linear regression scale that would classify offenders in each category. It is noted that more than half of the construction and validation samples fall into the very low risk category. This is because of the highly skewed distribution of scores on the violence prediction variable (skewness = .986)

Table 3.18. Numbers of Offenders Classified in each Risk Category for the Construction and Validation Samples

	Construction			Validation		
(N) Risk Levels	Full Sample (13594)	Males (11121)	Females (2473)	Full Sample (13433)	Males (10954)	Females (2479)
Very Low (lowest - .1018)						
# of Offenders	7233	5593	1640	7174	5509	1665
% of Sample	53.2	50.3	66.3	53.4	50.3	67.2
Low (.1019 - .1836)						
# of Offenders	4001	3403	598	3940	3366	574
% of Sample	29.4	30.6	24.2	29.3	30.7	23.2
Medium (.1837 - .2654)						
# of Offenders	1649	1464	185	1616	1441	175
% of Sample	12.1	13.2	7.5	12.0	13.2	7.1
High (.2655 - .3472)						
# of Offenders	592	551	41	574	520	54

% of Sample	4.4	5.0	1.7	4.3	4.7	2.2
Very High (.3473 - highest)						
# of Offenders	119	110	9	129	118	11
% of Sample	.9	1.0	.4	1.0	1.1	.4

Chi squares

The previous table describes the distribution of offenders into each risk category, Table 3.19 provides the violent recidivism percentages that occur in each risk level by construction and validation sample and by gender.

Table 3.19. Violent Recidivism Percentages when the Validation and Construction Samples are Separated into Risk Levels Derived from the Full Sample Item Linear Regression Analysis

	Very Low	Low	Medium	High	Very High	**TOTAL**
Construction Sample						
Full Sample (13594)						
Total Number in Risk Level	7233	4001	1649	592	119	13594
Number of Violent Recidivates	412	533	381	178	46	1550
% Violent Recidivism	5.7	13.3	23.1	30.1	38.7	11.4
Males (11121)						
Total Number in Risk Level	5593	3403	1464	551	110	11121
Number of Violent Recidivates	356	476	334	168	42	1376
% Violent Recidivism	6.4	14.0	22.8	30.5	38.2	12.4
Females (2473)						
Total Number in Risk Level	1640	598	185	41	9	2473
Number of Violent Recidivates	56	57	47	10	4	174
% Violent Recidivism	3.4	9.5	25.4	24.4	44.4	7.0
Validation Sample						
Full Sample (13433)						
Total Number in Risk Level	7174	3940	1616	574	129	13433
Number of Violent Recidivates	454	504	328	168	41	1495
% Violent Recidivism	6.3	12.8	20.3	29.3	31.8	11.1
Males (10954)						
Total Number in Risk Level	5509	3366	1441	520	118	10954
Number of Violent Recidivates	410	458	304	161	37	1370
% Violent Recidivism	7.4	13.6	21.1	31.0	31.4	12.5
Females (2479)						
Total Number in Risk Level	1665	574	175	54	11	2479

Number of Violent Recidivates	44	46	24	7	4	125
% Violent Recidivism	2.6	8.0	13.7	13.0	36.4	5.0

Chi squares of the risk levels were analyzed with violent recidivism to determine how well the five categories were corresponded to an accurate stratification of offenders who differed from each other on violent recidivism. The full construction [$\chi^2(4) = 762.9$, $p < .001$] and validation [$\chi^2(4) = 562.1$, $p < .001$] samples both had significant chi squares, as did the males in the construction [$\chi^2(4) = 576.0$, $p < .001$] and validation [$\chi^2(4) = 430.2$, $p < .001$] samples. Also displaying significant differences between the risk levels were the females in both the construction [$\chi^2(4) = 172.1$, $p < .001$] and validation samples [$\chi^2(4) = 87.7$, $p < .001$].

AUC

When plotting the ROC curve for the risk levels that were generated on the full sample, it was found that the construction sample had an AUC = .684, $p < .001$, with a 95% confidence interval ranging from .670 to .699. Males in the construction sample displayed an AUC = .674, $p < .001$ with a 95% confidence interval from .658 to .690. The females in the construction sample had a slightly higher AUC at .713, $p < .001$, but an overlapping confidence interval including .669 to .757.

The ROC plots for the validation sample were also highly significant. The full validation sample had an AUC = .659, $p < .001$, CI = .644 - .674. Males in the validation sample showed a slightly smaller AUC = .648, $p < .001$, CI = .632 - .664, and females had a marginally higher AUC = .685, $p < .001$ with a larger CI = .633 - .736.

Survival analysis

When the survival analysis was completed for the five derived risk levels, it is apparent that the very high risk offenders have a lower survival time. Figure 3.1 displays the survival curves for the five risk levels for the construction sample using Cox Regression analysis. Only the survival curves for the full construction and full validation samples are presented within the text to demonstrate the general trend of the figures. Appendix I presents the survival curves for the male and the female subsamples for both the construction and validation samples.

Figure 3.1. Survival Analysis on the Five Risk Levels Developed by Taking Five Equal Sections of the Range of Scores from the Full Sample Item Linear Regression Scale for the Construction Sample

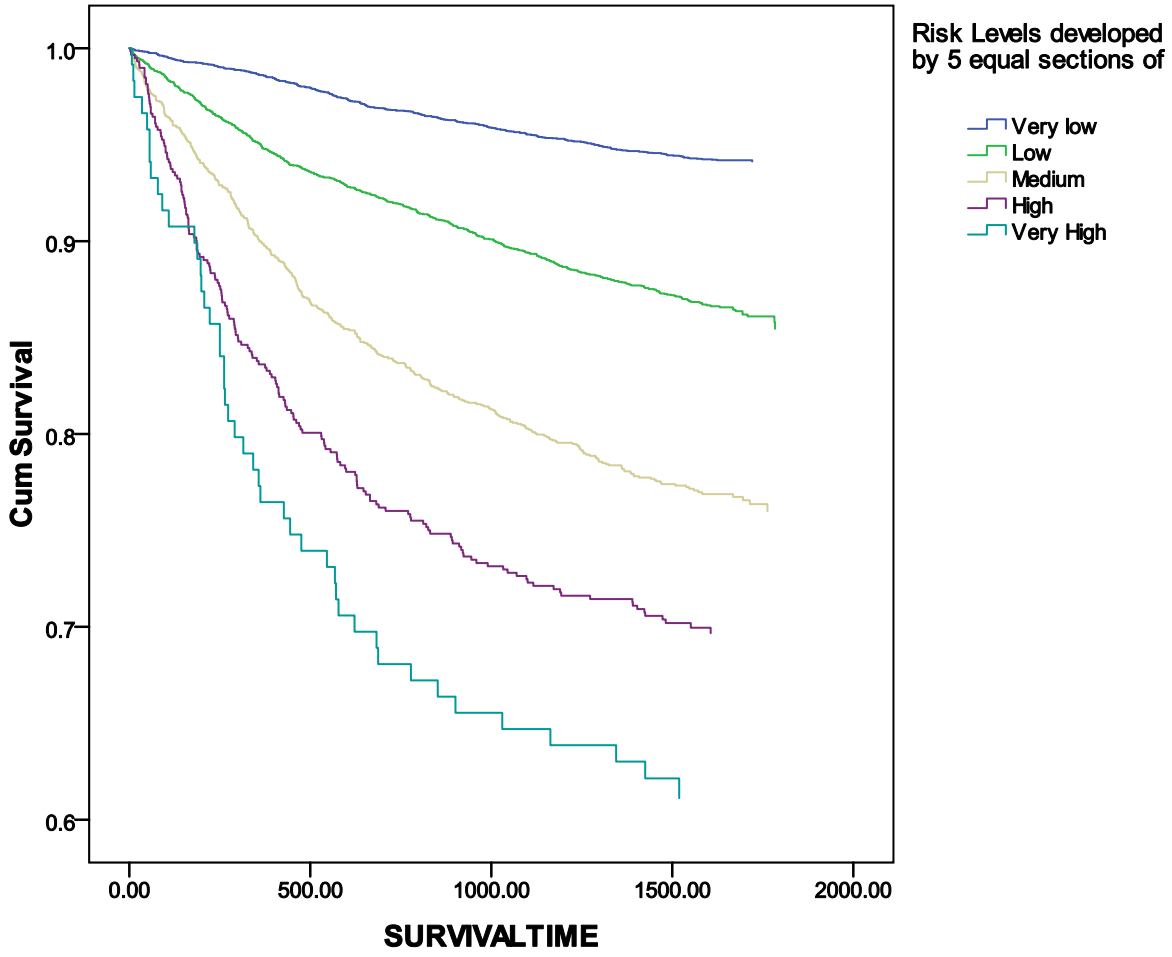
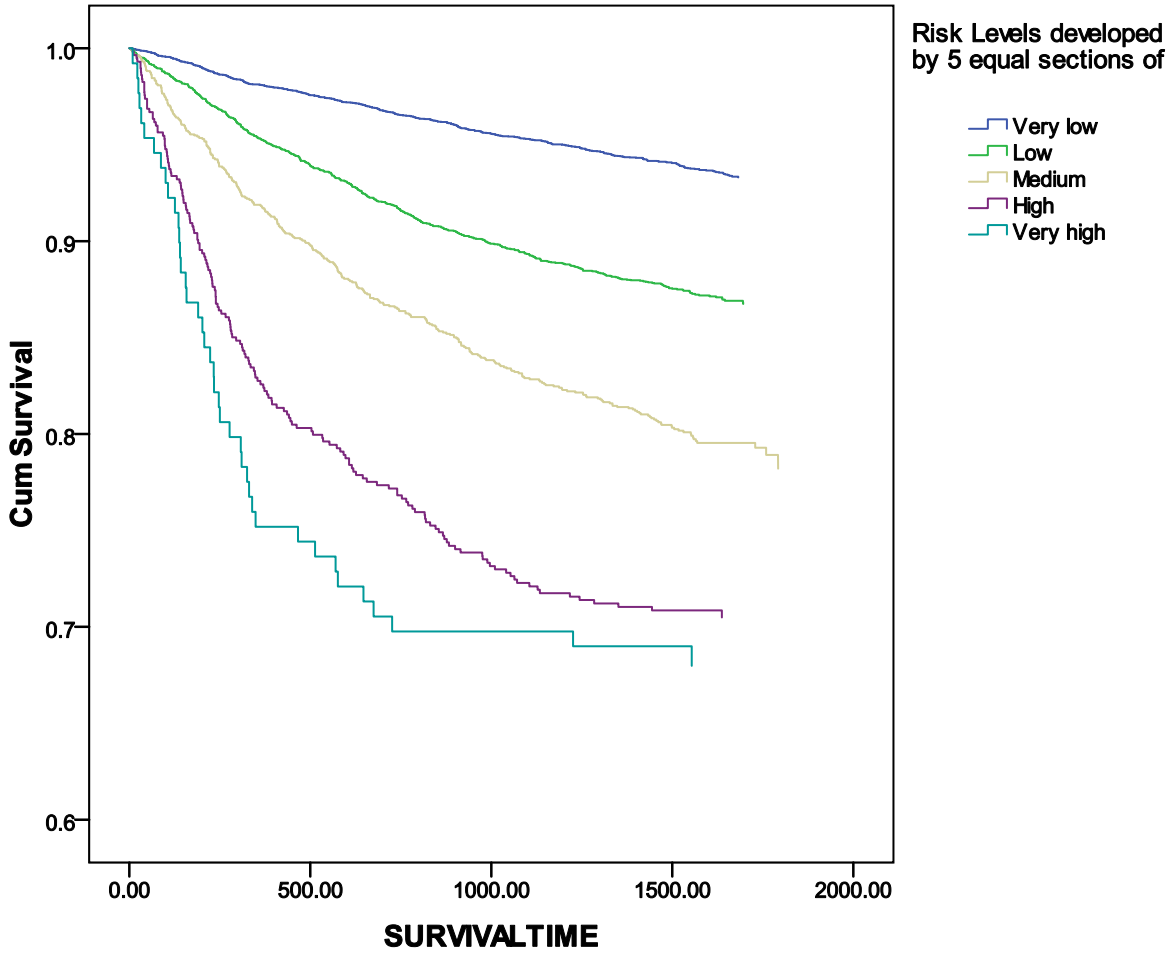


Figure 3.2. Survival Analysis on the Five Risk Levels Developed by Taking Five Equal Sections of the Range of Scores from the Full Sample Item Linear Regression Scale for the Validation Sample



Pre-existing Risk Levels Based on LSI-OR A Scale Score

Chi squares

In order to compare the results of the derived scale cutoffs with the A Scale risk levels that are currently in place with the LSI-OR, Table 3.20 displays the violent recidivism percentages that were obtained using the A Scale risk levels.

Table 3.20. Violent Recidivism Percentages when the Validation and Construction Samples are Separated into the Current LSI-OR A Scale Risk Levels

	Very Low (1-4)	Low (5 - 10)	Medium (11 – 19)	High (20– 29)	Very High (30 +)
Construction Sample					
Full Sample (13594)					
Total Number in Risk Level	2670	3962	4110	2106	738
Number of Violent Recidivates	105	302	533	407	203
% Violent Recidivism	3.9	7.6	13.0	19.3	27.5
Males (11121)					
Total Number in Risk Level	2118	3126	3389	1817	671
Number of Violent Recidivates	95	260	473	360	188
% Violent Recidivism	4.5	8.3	14.0	19.8	28.0
Females (2473)					
Total Number in Risk Level	560	836	721	289	67
Number of Violent Recidivates	10	42	60	47	12
% Violent Recidivism	1.8	5.0	8.3	16.3	22.4
Validation Sample					
Full Sample (13433)					
Total Number in Risk Level	2694	3943	3991	2068	737
Number of Violent Recidivates	103	322	514	376	180
% Violent Recidivism	3.8	8.2	12.9	18.2	24.4
Males (10954)					
Total Number in Risk Level	2115	3132	3286	1762	659
Number of Violent Recidivates	93	295	468	342	172
% Violent Recidivism	4.4	9.4	14.2	19.4	26.1
Females (2479)					
Total Number in Risk Level	579	811	705	306	78
Number of Violent Recidivates	10	27	46	34	8
% Violent Recidivism	1.7	3.3	6.5	11.1	10.3

The chi squares that were calculated for the risk levels that had previously been determined on the A Scale, also proved to show significant differences between the groups. The full construction [$\chi^2(4) = 534.7$, $p < .01$] and validation [$\chi^2(4) = 428.4$, $p < .01$] samples both had significant chi squares, as did the males in the construction [$\chi^2(4) = 421.0$, $p < .01$] and validation [$\chi^2(4) = 351.5$, $p < .01$] samples. Also displaying significant differences between the risk levels were the females in both the construction [$\chi^2(4) = 92.4$, $p < .01$] and validation samples [$\chi^2(4) = 49.5$, $p < .01$].

AUC

When plotting the ROC curves for the risk levels that were pre-existing on the A scales, it was found that the construction sample had an AUC = .668, $p < .001$ with a confidence interval ranging from .654 to .682. Males in the construction sample had an AUC = .660, $p < .001$, CI = .645 - .675 and females again had a higher AUC = .692, $p < .001$, CI = .653 - .732.

Showing a slight drop, when the ROC curves were plotted for the validation sample the AUC = .655, $p < .001$ with a confidence interval spanning from .641 to .670. Males in the validation sample decreased to AUC = .649, $p < .001$, CI = .634 - .664 and females were AUC = .672, $p < .001$, CI = .625 - .719.

Survival analysis

Figures 3.3 and 3.4 display the survival curves that were created for the full samples of the construction and validation samples when divided into the five risk levels that exists for the A scales. These curves are available for comparison against the survival curves that were presented for the risk levels that were generated from the full sample item linear regression scale. Male and female survival curves for the construction and validation sample are available in Appendix J.

In addition, cutoffs based on equal proportions of offenders in the five risk levels (approximately 20%) were also used to create another set of risk categories. The results of these analyses are presented in Appendix K.

Figure 3.3. Survival Analysis on the Existing Five Risk Levels for the A Scale of the LSI-OR for the Full Construction Sample

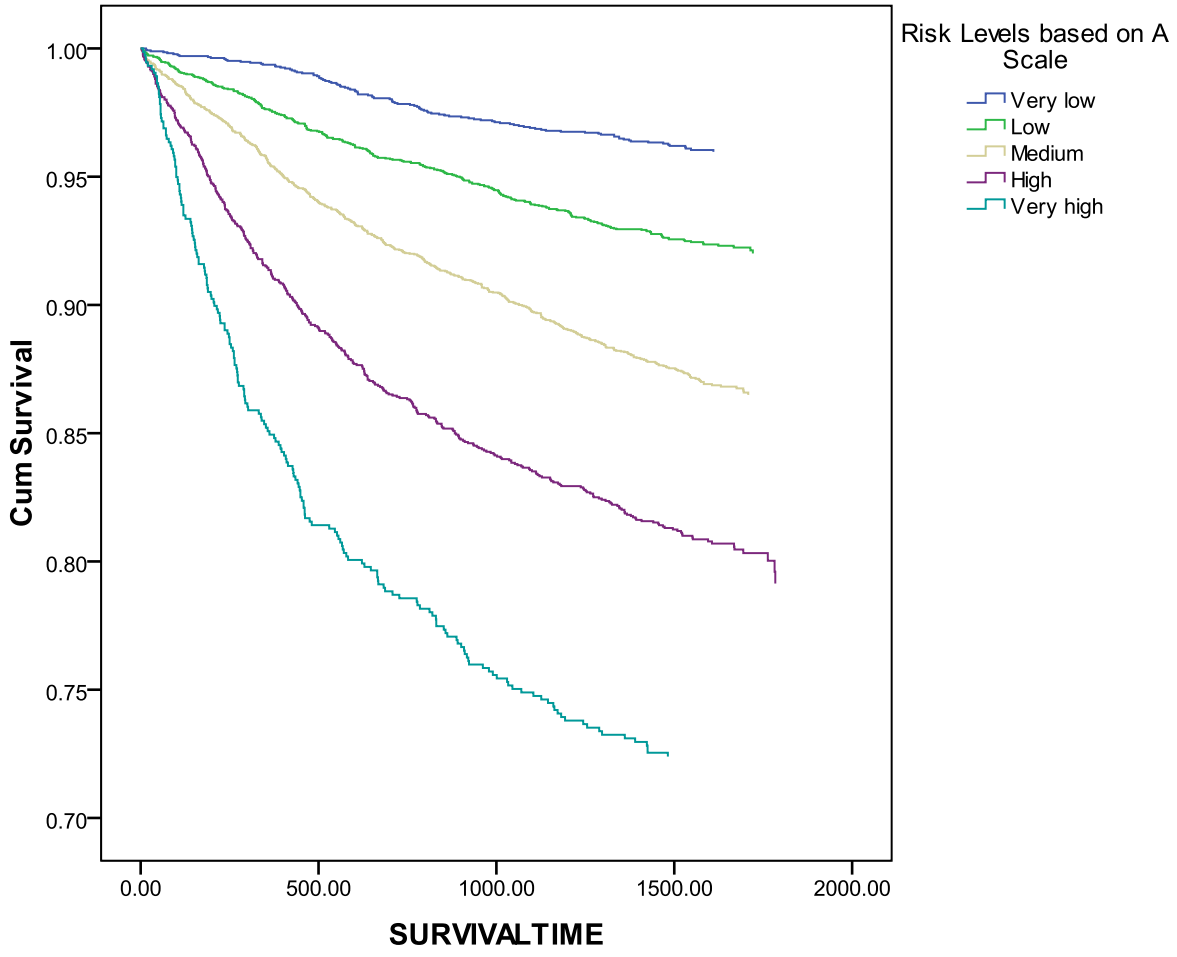
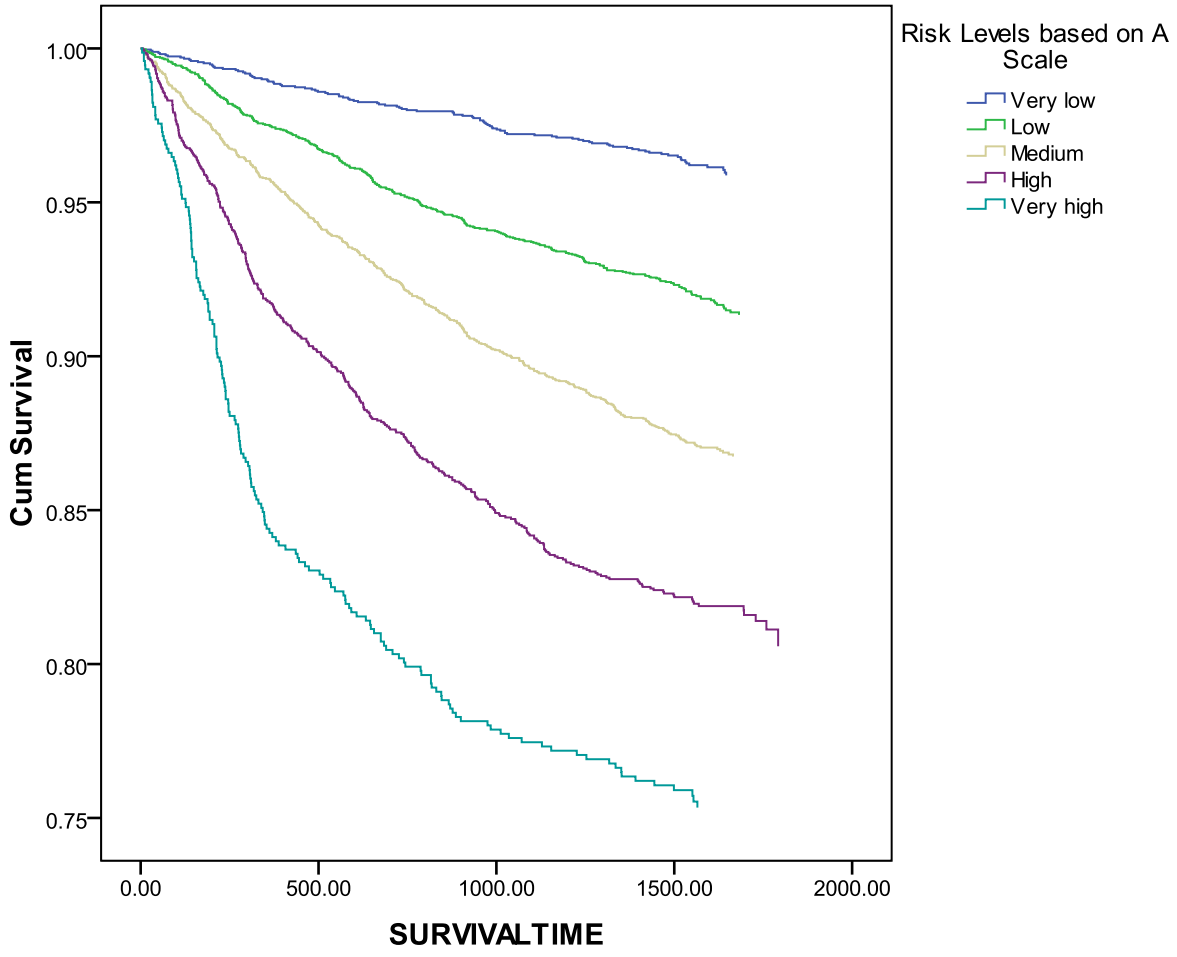


Figure 3.4. Survival Analysis on the Existing Five Risk Levels for the A Scale of the LSI-OR for the Full Validation Sample



The general pattern of the survival curves show that as the risk level increases, the time that it takes the offender to recidivate decreases.

CHAPTER 4

DISCUSSION

The accurate prediction of violent recidivism is an important aspect of risk assessment because of its implications for preventing violent crime. The LSI and its derivates (LSI-R, LS/CMI, LSI-OR) are some of the most widely used risk assessment tools in Canada. Previous literature indicated that these measures are capable of predicting violent recidivism, even though they were not initially designed for this function (Girard & Wormith, 2004; Mills & Kroner, 2006; Campbell, French & Gendreau, 2009). This literature is summarized in a recent chapter by Andrews, Bonta and Wormith (2009). Since the LSI-OR was successful in predicting violent recidivism, the present study was conducted using five different statistical procedures, to identify items or scales from the existing measure that were most predictive of an offender having a violent recidivism offense after a four to five year followup.

The goal of this study was to identify the most significant predictors of violent recidivism and combine them to develop new scales. These new scales were created and validated for the full sample, as well as the male and female portions of the group to determine whether separate measures were more appropriate for different genders. By highlighting the most important factors to consider when assessing an offender's likelihood to commit future violent crime, it was the intention of this study to produce a theoretically derived and clinically valuable tool to aid in the prediction of violent recidivism.

This discussion begins with an explanation of the process used in creating the definition of violent recidivism and comparisons to the definitions and base rates seen in previous literature are made. Results based on each of the five statistical techniques are then reviewed. The techniques are compared and conclusions are drawn about which method yielded the tools with the greatest predictive validity and ease of use. As well, the scales developed for males and females are analyzed to determine if and how they differ from each other and what, if any, benefits would accrue from utilizing gender-specific scales in this context. The scale demonstrating the best predictive validity and ease of use is identified, and its advantages and disadvantages discussed. The predictive validities of scales that have been previously developed to assess violent recidivism are presented and common items that occur in those scales and the

ones developed in this research are highlighted. Two techniques used to develop risk levels on the recommended scale are then discussed. In conclusion, recommendations for the use of an LSI-based violence prediction scale are made, a review of the limitations of this study is presented, and directions for further research are identified.

Defining Violent Recidivism and Base Rate Issues

The violent recidivism variable used in this project differed from the one used in previous research (Mills & Kroner, 2006; Girard & Wormith, 2004). Initially, offenses against the person that included homicide and related offenses, serious violent offenses, sexual offenses, weapons offenses, miscellaneous offenses against the person, assault and related offenses, and arson/property damage offenses, were to be included as violent recidivism offense categories for the current study. Some of these categories are unquestionably violent, whereas others became somewhat ambiguous, as analyses of offense circumstances were completed. It was determined that some of them should not be considered violent. For example, weapons offenses included charges such as, improper storage of a firearm, which may have been the result of a hunting rifle not being correctly kept. As well, the arson and property damage offenses included minor property offenses, such as graffiti. When a frequency analysis of these offense categories was completed, it was found that the majority of arson offenses indeed were minor property offenses that could not be considered violent. Clearly, the developed scales were not meant to predict this kind of behaviour. Therefore, the category of arson/property offenses was not included in the definition of violent recidivism in our study. Alternatively, the most common weapons offense was carrying a concealed weapon, which did have a violent connotation to it. Therefore, this offense category was included in our violent recidivism variable.

In comparison to previous literature, there were differences in base rates and definitions of violent recidivism. In the sample used for this study, the general and violent recidivism rates were 36.0% and 11.3%, respectively. A general recidivism rate of 54.4% and a violent recidivism rate of 24.1% were reported by Girard and Wormith (2004). The reasons for these discrepancies are probably due to differences between the samples. Girard and Wormith (2004) had a sample of 630 males who were mostly institutional offenders (72.1%). The sample in the current study consisted of an entire year (2004) cohort, which totaled 27,027 offenders and included both males and females, of which the majority was community offenders (81.7%). As

well, the average LSI-OR scores differed between the studies, with a much higher total score in the Girard and Wormith (2004) study, indicating higher risk offenders were included, most being custodial. Girard and Wormith (2004) also included arson and property damage offenses as part of their definition of violent recidivism, which was not included in this study. This may have inflated their violent recidivism rate, although these offenses may not have actually been violent.

Similar differences were found between the violent offense definition and violent recidivism rates in the Mills and Kroner (2006) study. Their definition of violent offenses included uttering threats, assault, sexual assault, armed robbery, and robbery with violence. A violent recidivism rate of 29% found in the 209 incarcerated males was again much higher than the sample that was used in our study.

It may be useful for future research to code all offenses in the *Canadian Criminal Code* as violent or nonviolent. This would enable forensic researchers to be consistent in their operational definition of violent recidivism in this kind of study. The final violent recidivism variable used in this study included the following offense categories as identified by the Ontario ministry: homicide and related offenses, serious violent offenses, sexual offenses, weapons offenses, miscellaneous offenses against the person and assault and related offenses.

Comparison of Statistical Techniques[1]

Prediction Models Based on Scale Correlations

The statistical methods used in this study varied greatly in theory and sophistication. Basic correlational analyses involving the A and B scales with violent recidivism provided predictive indicators that only differed slightly from the total LSI-OR scores. All of the 10 subscales from the A and B sections were significantly correlated with violent recidivism. A scale that employs all 10 subscales is the same as taking the sum of the A and B scale totals. This technique generated the smallest validation correlations with violent recidivism.

Prediction Models Based on Item Correlations

[1] For this section of the Discussion, the reader is referred to Table 3.15, which summarized the validation finding for each of the prediction scales derived from all five statistical techniques.

When a scale was developed based on highly significant ($p < .001$) correlations of individual items in each sample, the majority of items within the A and B sections qualified for inclusion. However, using this technique, the number of items differed quite substantially between the full and male sample (64 and 61 items respectively) and the female sample (40 items). There were different scales developed for each of the full, male and female sections, with females having 24 fewer items than the full sample. Although these scales were simple to calculate, as the process involved the simple addition of the significant items, the ease of use was not facilitated by the large number of items/scales that were included. Calculating the total LSI-OR score and correlating it with violent recidivism would provide a similar statistic. In addition, this technique provided moderate correlations with violent recidivism in relation to the other schemes.

Prediction Models Based on Burgess Technique

The Burgess technique provided scales that contained similar items to the previous approach, but the item weightings were different. The Burgess technique resulted in scales that generated predictive validities that were close to those obtained for the scale and item correlational scales. The utility of the Burgess scales had to be questioned because the different weightings of the items created a substantial amount of work when they were applied to the validation sample. For example, each of the many items in these scales had to be recoded into different variables prior to being added into the prediction scale. This was one of the most labour intensive techniques to use, and did not provide the largest predictive validity.

Prediction Models Based on Subscale Linear Regression

The subscale linear regression technique yielded the least number of factors in its scales. Only five of the 10 subscales from the A and B sections were included in the full sample scales and only two were included when the female sample was considered. The linear regression was completed by using a stepwise method, with a *p*-value inclusion criterion of less than .001 and an exclusion criterion of more than .10. For the full sample, the linear regression analysis terminated in five steps. The predictive validity for the full sample was generated by taking the constant and b weights of the regression model, and creating an equation that produced a number that as it increased in size, would indicate a higher risk for violent recidivism.

The male portion of the sample generated four subscales, whereas the female sample had only two subscales and these were all also scales that were part of the full sample equation. The correlations with violent recidivism for these scales were marginally better for this technique in comparison to the previous three.

Prediction Models Based on Item Linear Regression

The last statistical technique used to generate the violence prediction scales was a stepwise linear regression analysis using the items within the A and B sections. This method was the most highly correlated with violent recidivism and provided the greatest ease of use. The same parameters of inclusion that were used for the scale linear regression was used in this method, with a *p*-value inclusion criterion of less than .001 and the item being removed from the scale if the value was greater than .10. Again, the scale total was calculated by using the constant and b weights from the regression analyses to create a regression equation involving the items identified in each step of this technique. Predictive validity was obtained by correlating the fractional numbers that were yielded by these equations with the violent recidivism variable.

Stepwise regression is typically used to identify a set of variables that are useful in predicting the dependent variable, and eliminating variables that do not provide additional predictive information to those already in the subset (Tabachnick & Fidell. 2007). Stepwise regression was used in this study to develop a scale that included items which significantly contributed to the prediction of violent recidivism in a group of offenders. Due to the nature of stepwise linear regression, not all variables that were highly associated with violent recidivism were selected to be in the scale, only those that significantly explained additional variance in the construct of violent recidivism were included. As many of the items in the LSI-OR are highly correlated with each other, there was overlap in the variance in violent recidivism explained by the items. Only those items able to explain unique variance and provide incremental validity to the already included items were entered into the regression equation.

Limitations to this approach often include that it capitalizes on chance and overfits data (Tabachnick & Fidell, 2007), but with the large, representative sample that was available in this study, these issues are not prominent. The use of this technique provided a statistically-derived

instrument that exceeds the predictive validity of the existing subscales on the LSI-OR, as well as the other violence prediction scales that were generated in this study.

The scale developed from the stepwise linear regression analysis based on the full sample provided an 11 item model. This scale's correlation with violent recidivism in the validation sample was the greatest of all the scales (.214). This scale also provided the largest validation correlation with violent recidivism for the male sample (.208) and was comparable to the highest female sample correlation (.178 vs. .179). The male portion of the sample yielded a nine item and the females generated a five item scale that both demonstrated greater predictive validity than the other techniques for their respective samples.

Discussion of the Most Commonly Found Subscales, Items and the Most Useful Technique[2]

The subscales that were included in each of the two methods (scale correlation and linear regression using scales) that used the subscales to generate violence prediction tools are reviewed below. As predicted from previous literature (Girard & Wormith, 2004), the History of Perpetration (B2) subscale of the LSI-OR proved to be the best predictor of violent recidivism in the scale statistical analyses and was included in all of the generated scales. It is commonly accepted that indicators of past criminal behaviour in general are predictive of future violent offenses (Monahan, 1981).

From the nine scales that were created from the individual items of the LSI-OR, using three different statistical techniques, three items were selected for all nine. Item A734, indicating the presence of a current alcohol problem, was included in all nine scales, as was item B16, from the Specific Risk/Need History subscale, which identifies if an offender has anger management deficits and item B25, indicating a history of assault on an authority figure. These three items make sense for their inclusion in scales that predict future violent offenses. Current alcohol abuse, anger management deficits and a history of violence against authority figures are the most consistently predictive items for all of the derived scales.

[2] Reader is referred to Table 3.13 for subscales and Appendix H for items.

As the sophistication of the statistical techniques increased the number of items/scales in the developed scales decreased and the predictive validity correlations that the generated scales had with violent recidivism marginally increased. It is beneficial to have a more succinct tool, as it allows for ease of administration and provides a scale that can be administered in minutes if one is not required to complete the full LSI-OR.

The stepwise linear regression subscale analyses provided larger correlations with violent recidivism than those for the scale or item correlation techniques or the Burgess method, but the inclusion of the scales as opposed to items, did not seem ideal as there was no evidence that all items in each of the subscales were relevant to the prediction of violent recidivism. The last technique, using linear regression equations based on the items of the LSI-OR, demonstrated the greatest ease of use, based on the number of items generated, and most accurately predicted violent recidivism in our sample. However, it is acknowledged that there was not a great degree of variation in the predictive validity coefficients between these techniques.

The eleven items that emerged from the stepwise item linear regression technique came from the General Risk/Need (A subscales) factor scales of the LSI-OR (six items), and from the Specific Risk/Need (B subscales) scales (five items). There were three items from the Personal Problems with Criminogenic Potential (B1) subscale, with offenders having outstanding charges (item B113), intimidating/controlling behaviour (item B17) or anger management issues (item B16) being more likely to recidivate violently. Another three items were generated from the Education/Employment (A2) subscale, offender who had less than a grade 12 education (item A213), were suspended or expelled from school at least once (item A214) and showed low participation or performance in their school or work (item A215) had higher scores on the violent recidivism prediction scale.

The item with the largest b weight, B25, history of assault on an authority figure came from the History of Perpetration subscale (B2) as well as, B23, indicates a history of extrafamilial physical assault. Two more items came from the Criminal History subscale (A1), being arrested or charged under 16 (item A15) and A18, having a charge laid, probation breached or parole suspended during prior community supervision. There was one item from the Substance Abuse (A7) subscale, as a current alcohol problem (item A734) was also a significant item on this scale. All of these items came from the five subscales that were generated from the

scale linear regression technique; the item linear regression method was able to refine the scale to include only the significant items from each of the subscales that predicts violent recidivism. It is apparent from this scale that these personal problems, when mixed with low education, a criminal history, especially one involving assault, and current alcohol abuse are the most significant items on the LSI-OR that identifies offenders who are likely to recidivate violently.

Previous literature suggested the History subscale (B2) of the LSI-OR would provide the most useful items when creating a scale to predict violent recidivism (Girard & Wormith, 2004). Although there were two significant items from this subscale in the derived linear regression scale, the History subscale only provided a small percent (2 of 11 items, 18.2%) of the final scale. It is worth noting that the other subscale that measures Criminal History (A1) also had two items that were included on the full sample item linear regression scale. Overall four of the 11 (36.4%) items that were generated by the item linear regression technique were related to offender's criminal history. This is supported by previous literature that showed that past crime; especially a history of violent crime (e.g., items B23: Physical Assault (extrafamilial), and B25: Assault on authority figure, that were included in the final scale) is the most important correlate of future violence prediction (Monahan, 1981).

Comparison of Full Sample, Males and Females

Full Sample

The full sample provided the prediction scales that displayed the most robust correlations with violent recidivism. The scale generated based on correlations with the subscales, did not differ between the male-only and female-only samples, because all of the subscales were significantly correlated for both of the samples. The full validation sample correlation for this scale with violent recidivism was the largest obtained with this scale, using any of the samples. The scales developed on the full sample had the largest correlations for the item correlation and Burgess techniques as well. There were more significant items for the full sample derivations of the scales, than those created on the male or female sample.

The linear regression analysis technique used with both the subscales and items on the full sample, demonstrated higher correlations with violent recidivism than the scales created on the male or female-only samples. The item linear regression scale that was derived from the full

sample provided the largest correlation seen in the validation sample. Due to the statistical evidence supporting the scales derived and validated on the full sample as having the largest correlations with violent recidivism, the full sample, especially the item linear regression derived scale, shows the most promising predictive performance.

Males

The males in this database made up almost 82% of the full sample, so it is not surprising that the scales derived from the male portion of the sample were similar to those of the full sample. Again, small increases in predictive validity were seen with the scales developed from the linear regression analyses when compared to the correlational or Burgess techniques.

The male sample's linear regression derived scales showed marginally lower correlations with violent recidivism in the validation sample, than those for the scales that were developed on the full sample. It makes sense to utilize the scale that produces the largest correlation with violent recidivism, even if that difference is marginal. With the male sample, as in the full sample, the best scale to predict violent recidivism was the item linear regression scale developed on the full sample.

Females

The scales developed on the female sample generated fewer items than the full or male samples. The smaller number of items may indicate that there are less diverse reasons why women reoffend violently, when compared to males. In spite of having fewer items, there was little difference in predictive validity when violent recidivism in the female sample was correlated with the scales derived from the full sample.

The subscale correlation technique produced the only scale that was exactly the same as both the full and male sample derived scales. Again, small gains in predictive validity were seen as the sophistication of the technique increased, but female predictive validities in the validation sample were substantially less than those presented for males.

The female derived item linear regression scale showed a validation correlation that was virtually the same as the full sample derived item linear regression scale. Therefore, because very little predictive validity would be added by using the female sample derived scale, it was

recommended that the full sample derived item linear regression scale would be the most beneficial and parsimonious to use with offenders of both genders, at least in the jurisdiction from which these data were obtained.

When comparing the full and female sample item linear regression equations there is one item that is included on the female scale, that is not in the full sample or male scales; item A732, which indicates whether the offender ever had an alcohol problem. A current alcohol problem shows an even larger b weight for females than the full sample or males. It may be that substance abuse (current or past) may be more important in explaining factors related to violent recidivism for female offenders (two of the five items come from subscale A7, Substance Abuse), although the inclusion of this factor did not improve the predictive validity of the female item linear regression equation substantially over the full sample item linear regression scale. Examining how substance abuse affects women in regards to violent recidivism may be an area for future research.

Current research suggests additional support for the importance of substance abuse in predicting female recidivism (Huebner, DeJong & Cobbina, 2009; Van Voorhis, Wright, Salisbury & Bauman, 2010). Huebner et al. (2009) also found that education level and institutional misconduct were significant predictors of recidivism, as women with a high school diploma and lower levels of problem behaviour were less likely to reoffend. These items are reflected in the item linear regression scale that was developed on the full sample. Further evidence to support the inclusion of these factors in a recidivism prediction scales is found in Van Voorhis, et al. (2010). They also suggest the inclusion of gender responsive additions to the current risk assessment addressing areas such as economic, parental and mental health needs. Additional research may identify these, or other salient variables that may enhance the prediction of violent recidivism in women.

Identification of the Full Sample Linear Regression Scale as Demonstrating the Best Predictive Validity

Advantages of the Full Sample Linear Regression Scale

Out of the 15 violence prediction scales that were generated using the five techniques, the 11 item linear regression scale that was developed on the full sample is the one that is

recommended for further use. There are several benefits to using this scale, including the ease of use that such a short scale offers and the ability to use it for both males and females. Creating a scale, from the items of a widely used assessment tool that is routinely being administered to all adult offenders in the province of Ontario will create an easy transition to predicting violent recidivism, as all the needed data will already have been collected. Therefore it is recommended that the linear regression equation be applied to the existing database, using the b weights and constant that was developed from the construction sample, so that values predicting violent recidivism can be obtained. This would easily be achieved because the LSI-OR item data are captured in the ministry's offender database. However, periodic replications of the scale's predictive validity for violent recidivism should be conducted on subsequent cohorts.

In addition, the value of being able to predict violent recidivism will be a benefit for the justice system. Identifying those offenders who may need increased supervision when released to the public or higher intensity treatment programs is important information as it may prevent violent crime from occurring. Although some of the items identified through this technique involve historic factors, there are also some directions for treatment in the dynamic factors that are subject to change. Anger management deficits, a current alcohol problem and less than a grade 12 education are items that can be affected by intervention. Providing anger management programs, alcohol addiction treatment and encouraging further education are treatment objectives that may reduce the amount of violent recidivism. Research should be conducted on changes in these items and the impact of such change on recidivism.

The Use of the Full Sample Linear Regression Scale for Females

One of the disadvantages that come from using the scale developed on the full sample linear regression technique is a criticism that is inherent in using a scale derived on a mixed sample of mostly male participants to classify female offenders. As highlighted in the literature review, there has been much debate on the topic of gender-specific measures (Hannah-Moffat, 2004, Blanchette & Brown, 2006) and the need for tools that are derived specifically for females, taking their needs into consideration. However, the scales that were derived from female offenders did not provide a significantly better predictive validity than those generated from the full sample. As shown in the validation sample, the difference in correlations with violent recidivism was negligible when the scale derived on the female only sample was compared to the

one derived from the full sample. There were larger differences between the construction sample correlations but with the smaller female sample, prediction schemes based on women only are subject to more shrinkage upon cross-validation. The significantly smaller violent recidivism base rate in the validation sample may have had an impact on these results as well.

There is also evidence to suggest the low rate of violent recidivism seen in our female sample differs from previous research. In a dissertation looking at the prediction of risk with females using the LSI-OR, there is a large difference in violent recidivism base rate from our female sample (Rettinger, 1998). Although using a similar violent recidivism definition (offenses involving crimes against persons, e.g., murder, manslaughter, infanticide, attempted murder, wounding, rape, sexual assault, assault and robbery) to our study, this sample of 441 provincially sentenced adult female offenders had a violent recidivism rate of 14.3% over a 4 year and nine month follow up period. The construction (violent recidivism = 7%) and validation (violent recidivism = 5%) female samples in our study had much lower violent recidivism rates, although a similar followup. It is proposed that a difference in the sample breakdown of community (54.2% in Rettinger, 1998 vs. 94.0% in this study) and institutional offenders (45.8% in Rettinger, 1998 vs. 6.0% in this study) is the most plausible explanation for these discrepancies. The low violent recidivism rate for the females in this study may have affected the validity of the female-derived scales.

In addition, it could be argued that because the original LSI-OR was created on a sample that was mostly male, it might be missing relevant items that would predict female violent recidivism. In this case, an optimal scale predicting violent recidivism in females would not be created from the existing items on the LSI-OR regardless of the statistical techniques used. Previous research shows that this might not the case, with evidence suggesting the LSI-OR is an excellent predictor of recidivism for females (Rettinger, 1998; Brews, 2009).

Although additional factors, such as victimization, relationships and parental stress have been suggested to be more salient for female offenders (Benda, 2005; Koons, Burrow, Morash & Bynum, 1997), there is not sufficient evidence to confirm that including these needs will further contribute to the prediction of recidivism in general, and violent recidivism specifically (Rettinger & Andrews, 2010; Salisbury et al., 2009). In a recent study, Rettinger and Andrews (2010) examined the predictive validity of the central eight gender neutral risk factors that

characterize the LS/CMI, in relation to supplementary factors that have been suggested by gender-specific perspectives. Examples of these additional factors included parental stress, victimization history and emotional distress. Although these were important variables, as many female offenders identified a history of victimization and high emotional distress, these items did not add incrementally to the prediction of general or violent recidivism above the central eight factors. These findings reinforce the applicability of the full sample item linear regression scale to predict violent recidivism in female populations, as the addition of further items may not increase predictive validity. This does not suggest that gender is irrelevant to the principles of RNR. Gender is included as a responsivity factor on the LS/CMI and plays a role in tailoring service plans to offenders in order to optimize their learning and treatment success.

Comparison of the LSI-OR Item Linear Regression Scale to Other Violence Prediction Scales

A popular tool specifically developed to assess future violence is the VRAG (Quinsey, et al., 1998). Although this scale was originally developed, using the Burgess technique, for a male psychiatric population and shows high correlations with violent recidivism in this population, it also displayed robust predictive validity (ranging from r = .26 to .28) in multiple studies with offenders who had no mental disorders (Harris, Rice & Quinsey, 1993; Snowden, et al., 2007; Mills, et al., 2007; Campbell, et al., 2009). This is a 12 item tool that includes items such as the offender's age at index offence, and the extent of victim injury and gender. Some items are similar to the 11 items that were generated for the violence prediction scale in this study. Failure on prior conditional release and criminal history are examples of factors that are included in both scales. Alcohol problems and school maladjustment items on both scales are similar as well. Where the VRAG differs from the scale developed from this study, is in its inclusion of diagnoses of personality disorders, schizophrenia, and scores on the PCL-R.

The Violence Risk Scale (VRS; Wong & Gordon, 1998 – 2003) is a 26 item tool that was developed for use on high risk/needs violent offenders. It consists of six static items that reflect the criminal history of the offender and 20 dynamic items that assess such areas as antisocial attitudes and associates (Wong & Gordon, 2006). Again, criminal history items are similar to the ones included on the scale that was developed in this study, as well as substance abuse and emotion regulation, which may relate to our item identifying anger management issues. This

scale has also demonstrated excellent predictive validity (r = .28 to .40) increasing as the length of followup increased (Wong & Gordon, 2006).

A third tool used to assess future violent behaviour is the HCR-20 (Webster, Eaves, Douglas & Wintrup, 1995), which also shows high correlations with violent recidivism (r = .25 to .37; Mills, et al., 2007; Campbell, et al., 2009). This instrument differs from the others, as it uses a clinical judgment approach to risk assessment, using the 20 items scale as a guide to classify the offender as a low, medium or high risk to reoffend. The items on this scale are broken down into historical, clinical and risk management factors, with the historical section containing items such as prior supervision failure and substance abuse problems. Also included are previous violence and young age at first violent incident. These items are also comparable to items generated for the scale developed in this study.

Drawing from previous assessment tools that have demonstrated their ability in predicting violent recidivism, several of the 11 items that were selected for this scale also appear on these other measures. The importance of criminal history is reinforced by all the instruments, and the inclusion of substance abuse and supervision failure are included on each. As well, education performance and emotions regulation are important. One component that is reflected on the other tools but not included on the LSI-OR scale is a diagnosis of mental illness or personality disorder. It will be interesting to see how the exclusion of this factor relates to the differences in predictive validity for the LSI-OR scale. Although these measures were developed on varying offender populations with different theoretical perspectives and goals in mind, they have all evidence supporting their usefulness in predicting future violence and contain common items that are related to future violence.

Risk Levels

After demonstrating that the item linear regression technique provided scales that showed the greatest correlations with violent recidivism, and selecting the full sample item linear regression scale as the most useful scale to use, risk levels, developed from the linear regression values were created in order to classify offenders into five risk levels representing their likelihood to reoffend violently. In a prior study that utilized different methods to develop risk levels for female groups on the LSI-OR, it was found that the ROC curves for both the technique

that used equal percentages of offenders to define each risk level and the recursive partitioning method (in which groups are developed to emphasize their differences) were only slightly superior to the original risk level partitions (Brews, 2009). The risk levels that are suggested in the LSI-OR manual as well as the two techniques that were used in our study are presented here, with similar results on the ROC curves.

Pre-existing Risk Levels from the A Scale

Risk levels based on participant scores on the A scale are found in the existing LSI-OR (Andrews, Bonta & Wormith, 1995). Developed by the scale's creators, these cutoffs assign offenders into five risk levels for general recidivism. For the purposes of this study, these risk levels are examined in respect to violent recidivism. The majority of offenders (79.1%) were classified in the very low, low and medium risk categories, and their violent recidivism rates were much lower than for the high and very high risk categories.

Risk Levels Developed from Dividing the Range of Full Sample Item Linear Regression Scores into Five Equal Sections

New violence risk levels were developed based on the full sample item linear regression values. There is no definitive best method to create risk levels, therefore two techniques were presented in this study. Due to the adoption of the full sample item linear regression equation as the most predictive scale, risk levels were only developed using the full sample, not separating the sample into males and females, as in previous statistical analyses.

One method of creating risk levels is to divide the range of scores on the item linear regression equation into five equal sections to create very low, low, medium, high and very high risk categories. In this scheme, even more offenders fell into the very low to medium risk categories (94.7%) and recidivism rates increased systematically as risk level increased. The majority of the sample was in the very low risk category with scores that fell in the lowest fifth of the range of the linear regression values. Even though over half of the sample was in the very low risk category, only a small portion of that sample recidivated violently. In the very high risk classification, over 30% of the sample was convicted of violent recidivism offenses. However, one is reminded that the base rate of violent recidivism in the study was 11.3%. The chi squares

and AUC values for the risk levels were highly significant and the survival curves demonstrated the expected trajectories, similar to those generated for the pre-existing A scale risk levels.

Risk Levels Developed from Separating Full Sample into Five Percentiles Based on Scores from the Full Sample Item Linear Regression Scores

Another method of creating risk levels for newly derived scale involves separating the sample into five equal percentiles containing approximately the same number of participants. Therefore the very low risk level would include all values that the bottom 20% of the sample obtained, the low risk level from 21 to 40%, and so on. These results (Appendix K) show similar numbers of offenders in each of the five risk levels and an increasing number of violent recidivists in the high and very high risk categories. Again the chi squares and the AUC values were all highly significant, indicating significant differences between the groups on violent recidivism. As well, the survival curves show shorter survival times for offenders classified in the higher risk categories.

Each approach has its benefits. One position is that the distribution of offenders into risk levels should reflect the base rate of the criterion behaviour. Therefore, with a low base rate for violent recidivism, most offenders should fall into the lower risk categories. Using this approach, the number of very high risk cases approximates the number of violent recidivists in the sample and the recidivism rate in the high risk groups should be relatively high, hence the term 'high risk' should be reasonably accurate. On the other hand, the advantage of spreading offenders equally across risk levels conveys the message that the offender's risk level places him or her in a relative range of risk among the offender population. For example, a medium risk offender is in the 40 to 60th *percentile* among offenders in terms of his/her risk for violent recidivism. However, the actual probability of them recidivating is likely to be quite low (i.e., in the current study, 8.9%). Both of these risk level derivation techniques provide significant statistical classifications and have their advantages, but in the equal range risk levels the descriptor 'high risk' is a better reflection of the small number, who actually do pose a high risk of reoffending violently. This may be a better choice, taking into account the small number of offenders who do pose a very high risk of violent recidivism, and the amount of resources that should be devoted to these offenders, as compared to other, lower risk offenders.

Conclusions

This study succeeded in identifying items on a widely used risk assessment measure that are predictive of an offender's likelihood to violently reoffend when in the community. This contribution to the literature will provide parole decision-makers and offender program managers with information about criminogenic needs that are more predictive of violent recidivism, and therefore may be more important to target in programming. Due to the LSI-OR being a popular tool already in use within the province of Ontario, and its derivate, the LS/CMI, widely used in many other jurisdictions, being able to utilize the item linear regression scale, derived from the pre-existing items will be useful, as system-wide use of the tool is already in place.

Statistically determining the content of a violence prediction scale, using multiple methods, should be of value to the offender prediction literature. Examining which criminogenic factors were the most likely to predict violent offenses show which items on the LSI-OR are identified by each of the statistical techniques. An item's correlation with violent recidivism and the number of times that it was chosen to be part of the violence prediction scales speak to its ability to identify offenders that will recidivate violently. As well, by randomly splitting the large, archival database, both a construction and validation sample were obtained from the same group of offenders. The examination of the scales' content in addition to the statistical technique comparisons in this study provides useful evidence for criminal justice workers to aid in their treatment and release decisions. The study also offered an opportunity to examine the value of commonly used statistical techniques to derive the optimal prediction scale. It was seen that as the sophistication of the techniques increased, the usefulness of the scale also increased. Item linear regression was the statistical method that proved to be the most succinct, with an easy to use tool that provided the best predictive validity for our sample. However, one is reminded that the differences in predictive validity between the different construction methods were quite small. In fact it is somewhat surprising that more advanced multivariate approaches did not generate a scale that was much better than the scales developed from the more crude statistical techniques.

A third element that this project added to the literature is information on the differences between violent recidivism predictors for males and females. A salient issue in criminal justice in Canada is that risk assessment of females routinely use tools that were normed on male samples.

Some argue that the differences are negligible (Gendreau, Little & Goggin, 1996), but others call for gender-sensitive instruments that have been created on female samples (Hannah-Moffat, 2004; Blanchette & Brown, 2006). By generating violence prediction scales for both males and females from a common cohort, the current study offered an opportunity to compare their content and determine if there are items that are more predictive for females than males. Although the scales developed on the female-only sample had fewer items, most of the same items were included in the male and full sample scales. An exception is the inclusion of the item that identifies if an offender has ever had an alcohol problem in the female item linear regression scale. This may provide some indication that substance abuse, both past and present, may be a more important predictor for females than for males. The further development of gendered pathway theories and additional studies that examine how these factors affect violent recidivism for females will be needed to draw any substantial conclusions.

Predictive coefficients were examined for each scale to determine if gender provided a significant variation in a scale's ability to predict violent recidivism. There was a very small range in predictive validity for all the scales that were developed in this study, whether for female, male or full sample, with most of the confidence intervals for the AUC values overlapping. This suggests that although there were marginal differences as the sophistication of the scale derivation technique increased, the scales predicted violent recidivism at virtually the same level. Our results support previous literature suggesting that the LSI-OR does provide accurate prediction of violent recidivism for both males and females.

Limitations

Most of the limitations in this study stem from the nature of the database that was used to derive and validate the scales. First, as data were obtained from an existing database, there was no way to control for the quality of the administration of the LSI-ORs that were completed over 5 years ago. Similarly, it was impossible to control or assess the accuracy of data entry into the ministry database, although some safeguards were built into the data entry software. Third, recidivism was identified only if it occurred in the province of Ontario. This limitation means that information about whether the offender committed further crimes in other provinces was not available. Fourth, like other studies that are designed to assess the predictive validity of a risk assessment scale for violence, nonviolent recidivism was ignored. This strategy neglects the fact

that at least some offenders who recidivated only in a nonviolent fashion are incarcerated and hence no longer eligible to recidivate, at least in the community, if they were in custody during any part of the followup period. It is reasonable to assume that each of these limitations may have reduced the predictive validity results that were obtained in this study as they entail the introduction of error variance into either the independent (LSI-OR) or dependent (recidivism) variables.

A limitation that may have affected the predictive validity correlations for the female sample was, what appears to be, a randomly produced difference in the violent recidivism rates for women in the construction and validation samples. The lower recidivism rate, or base rate, for women in the validation sample may be responsible for the shrinkage in predictive validity that was found between the construction and validation samples. This appears to be a coincidence of the randomization process. Additionally, as we were only using items from the LSI-OR, which was developed on a mostly male sample, it is quite possible that some items that are especially salient to predicting violent recidivism for women were not available for inclusion in the developed scales.

Finally, although there is evidence to suggest that other violence risk assessment tools are able to predict well when applied to samples in other areas of the world (e.g., Sjostedt & Langstrom, 2002; Grann, Belfrage & Tengstrom, 2000), there is no guarantee that the violence scale developed in this study from items on the LSI-OR will be equally transferable to other jurisdictions and countries. Although the sample was very large, it was generated from one provincial jurisdiction in Canada over a single year. Therefore, it is recommended that caution be used before applying this assessment tool in all populations. Replications of predictive validity as well as cross validation of the measure should be conducted before its use in new samples.

Future Directions for Research

To begin, future directions for research in this field may focus on creating a consistent and accepted definition of violent crimes based on the *Canadian Criminal Code* for researchers working in this area. Having a standard for those doing research on violence and risk assessment would eliminate the discrepancies in the literature on defining violent recidivism, and would provide, in our view, a more 'pure' grouping of offenses that are defined and accepted as violent.

The most important next step in this line of research is to replicate the current study with one or more of the violence risk scales and associated risk levels developed in this study in other jurisdictions, both nationally and internationally. It would also be interesting to study the other versions of the LSI and how they might generate other violence risk scales developed from those in the current sample. Due to the majority of the cohort used in this study being community offenders who were very low risk to reoffend, our violent recidivism rates were very low. Additional research may focus on the use of this scale with higher risk offenders, to determine if there are differences in predictive validity for very high risk offenders compared to offenders who pose only moderate risk of recidivism.

It would also be interesting to analyze the gender differences in violent recidivism more deeply. It was apparent in this study that there were fewer items that were generated on the scales when only the female sample was used. Although the female sample was quite large in comparison to most studies of female offenders, it was still considerably smaller than the male sample. Therefore, the linear regression analyses that were applied to the female sample had less power. This may explain why fewer predictive items were identified for women than men. Investigating whether there are fewer factors involved in a women committing violent crime or the factors most salient to females are not reflected in this measure are important research directions because we still lack an understanding about the different possible pathways.

REFERENCES

Andrews, D.A., & Bonta, J. (1995). *The Level of Service Inventory – Revised.* Toronto, Canada: Multi-Health Systems.

Andrews, D.A., & Bonta, J. (2003). *The psychology of criminal conduct* (3rd ed.). Cincinnati, OH: Anderson Publishing.

Andrews, D.A., Bonta, J., & Hoge, R.D. (1990). Classification for effective rehabilitation: Rediscovering psychology. *Criminal Justice and Behaviour, 17,* 19 – 52.

Andrews, D.A., Bonta, J., & Wormith, J.S. (1995). *Level of Service Inventory – Ontario Revision (LSI-OR): Interview and scoring guide.* Toronto, Canada: Ontario Ministry of the Solicitor General and Correctional Services.

Andrews, D.A., Bonta, J., & Wormith, J.S. (2001). *The Level of Service Inventory – Saskatchewan Youth Edition.* Toronto, Canada: Multi-Health Systems.

Andrews, D.A., Bonta, J., & Wormith, J.S. (2004). *The Level of Service/Case Management Inventory (LS/CMI).* Toronto, Canada: Multi-Health Systems.

Andrews, D.A., Bonta, J., & Wormith, J.S. (2006). The recent past and near future of risk and/or need assessment. *Crime and Delinquency, 52*(1), 7-27.

Andrews, D.A., Bonta, J. & Wormith, J.S. (2009). The Level of Service (LS) Assessment of Adults and Older Adolescents. In R.K. Otto & K.S. Douglas (Eds.), *Handbook of Violence Risk Assessment* (pp.199-225). London, UK: Routledge.

Andrews, D.A., Hoge, R.D., & Leschied, A.W. (2002). *The Youth Level of Service and Case Management Inventory.* Toronto, Canada: Multi-Health Systems.

Benda, B.B. (2005). Gender differences in life-course theory of recidivism: A survival analysis. *International Journal of Offender Therapy and Comparative Criminology 49*(3), 325 – 342.

Blanchette, K., & Brown, S.L. (2006). *The assessment and treatment of women offenders.* Etobicoke, ON: John Wiley & Sons.

Bonta, J. (1996). Risk-needs assessment and treatment. In A.T. Harland (Ed.), *Choosing correctional options that work: Defining the demand and evaluating the supply* (pp. 18 – 32). Thousand Oaks, CA: Sage Publications, Inc.

Bonta, J., & Motiuk, L.L. (1985). Utilization of an interview-based classification instrument, A study of correctional halfway houses. *Criminal Justice and Behaviour, 12,* 333-352.

Bonta, J., & Motiuk, L.L. (1987). The diversion of incarcerated offenders to correctional halfway houses. *Journal of Research in Crime and Delinquency, 24,* 302-323.

Brennan, T., & Oliver, W.L. (2000). *Evaluation of reliability and validity of COMPAS scales: National aggregate sample.* Traverse City, MI: Northpointe Institute for Public Management.

Brews, A.L. (2009). *The Level of Service Inventory and female offenders: Addressing issues of reliability and predictive validity*. Unpublished master's thesis, University of Saskatchewan, Saskatoon, Saskatchewan, Canada.

Campbell, M.A., French, S., & Gendreau, P. (2009). The prediction of violence in adult offenders: A meta-analytic comparison of instruments and methods of assessment. *Criminal Justice and Behaviour, 36*(6), 567-590.

Clements, C.B. (1996). Offender Classification: Two decades of progress. *Criminal Justice and Behaviour, 23*(1), 121-143.

Farrington, D.P., & Tarling R. (Eds.) (1985). Prediction in criminology. Albany, NY: State University of New York Press.

Gendreau, P., Goggin, C., & Smith, P. (2002). Is the PCL-R really the "unparalleled" measure of offender risk? A lesson in knowledge cumulation. *Criminal Justice and Behaviour, 29,* 397-426.

Gendreau, P., Little, T., & Goggin, C. (1996). A meta-analysis of the predictors of adult offender recidivism: What works? *Criminology, 34,* 575–607.

Girard, L., & Wormith, J.S. (2004). The predictive validity of the Level of Service Inventory - Ontario Revision on general and violent recidivism among various offender groups. *Criminal Justice and Behaviour, 31*(2), 150 –181.

Grann, M., Belfrage, H., & Tengstrom, A. (2000). Actuarial assessment of risk for violence: Predictive validity of the VRAG and the historical part of the HCR-20. *Criminal Justice and Behavior, 27*(97), 97-114.

Grisso, T., & Appelbaum, P.S. (1993). Structuring the debate about ethical predictions of future violence. *Law and Human Behaviour, 17*(4), 482-485.

Hannah-Moffat, K. (2004). Gendering risk at what cost: Negotiations of gender and risk in Canadian women's prisons. *Feminism & Psychology, 14*(2), 243 – 249.

Hare, R. D. (1990). *The Hare Psychopathy Checklist-Revised.* Toronto, Canada: Multi-Health Systems.

Harris, G.T., Rice, M.E., & Quinsey, V. L. (1993). Violent recidivism of mentally disordered offenders: The development of a statistical prediction instrument. *Criminal Justice and Behaviour, 20*(4), 315 – 335.

Holtfretter, K., & Cupp, R. (2007). Gender and risk assessment: The empirical status of the LSI-R for women. *Journal of Contemporary Criminal Justice, 23*(4), 363 – 382.

Huebner, B.M., DeJong, C. & Cobbina, J. (2010). Women coming home: Long-term patterns of recidivism. *Justice Quarterly, 27*(2), 225 – 254.

Koons,B.A., Burrow, J.D., Morash, M., & Bynum, T. (1997). Expert and offender perceptions of program elements linked to successful outcomes for incarcerated women. *Crime & Delinquency, 43*(4), 512 – 532.

Litwack, T. R. (1993). On the ethics of dangerousness assessments. *Law and Human Behaviour, 17*(4), 479-482.

Low, S. M. (2001). The edge and the center: Gated communities and the discourse of urban fear. *American Anthropologist, 103,* 45-58.

Mills, J.F., & Kroner, D.G. (2006). The effect of discordance among violence and general recidivism risk estimates on predictive accuracy. *Criminal Behaviour and Mental Health, 16,* 155-166.

Mills, J.F., Kroner, D.G., & Hemmati, T. (2007). The validity of violence risk estimates: An issue of item performance. *Psychological Services, 4*(1), 1 – 12.

Monahan, J. (1981). The clinical prediction of violent behaviour [Monograph]. *Crime and Delinquency Issues: A Monograph Series.* Rockville, MD: National Institute of Mental Health.

Motiuk, L.L. (1997). Classification for correctional programming: The Offender Intake Assessment (OIA) process. *Forum on Corrections Research, 9,* 18-22.

National Council on Crime and Delinquency. (2004). *Correctional assessment and intervention system.* Oakland, CA: Author.

Nuffield, J. (1982). Parole decision-making in Canada: Research towards decision guidelines. Ottawa, Canada: Ministry of the Solicitor General of Canada.

Quinsey, V.L. (1980). The baserate problem and the prediction of dangerousness: A reappraisal. *Journal of Psychiatry and Law, 8,* 329-340.

Quinsey, V.L., & Ambtman, R. (1979). Variables affecting psychiatrists' and teachers' assessment of the dangerousness of mentally ill offenders. *Journal of Consulting and Clinical Psychology, 47*(2), 353-362.

Quinsey, V.L., Harris, G.T., Rice, M.E., & Cormier, C.A. (1998). *Violent offenders: Appraising and managing risk.* Washington, DC: American Psychological Association.

Rettinger, L.J. (1998) *A recidivism follow-up study investigating risk and need within a sample of provincially sentenced women.* Unpublished doctoral dissertation, Carleton University, Ottawa, Ontario.

Rettinger L.J. & Andrews, D.A. (2010). General risk and need, gender specificity, and the recidivism of female offenders. *Criminal Justice and Behaviour, 37*(1), 29 – 46.

Rice, M.E., & Harris, G.T. (1995). Violent recidivism: Assessing predictive validity. *Journal of Consulting and Clinical Psychology, 63*(5), 737-748.

Rice, M.E., & Harris, G.T. (2005). Comparing effect sizes of in follow-up studies: ROC area, Cohen's *d*, and *r*. *Law and Human Behaviour, 29*(5), 615 – 620.

Rountree, P.W., & Land, K.C. (1996). Perceived risk versus fear of crime: Empirical evidence of conceptually distinct reactions in survey data. *Social Forces, 74*(4), 1353 – 1376.

Salisbury, E.J., Van Voorhis, P., & Spiropoulos, G.V. (2009). The predictive validity of a gender-responsive needs assessment: An exploratory study. *Crime & Delinquency, 55*(4), 550 – 585.

Shah, S.A. (1978). Dangerousness: A paradigm for exploring some issues in law and psychology. *American Psychologist, 33*(3), 224-238.

Sjostedt, G., & Langstrom, N. (2002). Assessment of risk for criminal recidivism among rapists: A comparison of four different measures. *Psychology, Crime & Law, 8*(1), 25-40.

Snowden, R.J., Gray, N.S., Taylor, J, & MacCulloch, M.J. (2007). Actuarial prediction of violent recidivism in mentally disordered offenders. *Psychological Medicine, 37*(11), 1539 – 1549.

Stasiuk, E., Winter, K., & Nixon, B. (1996). Awaiting trial: Accused persons remanded to custody. Toronto: Ontario Ministry of Correctional Services.

Steadman, H.J. (1983). Predicting dangerousness among the mentally ill: Art, magic and science. *International Journal of Law and Psychiatry, 6*(3-4), 381-390.

Tabachnick, B.G., & Fidell, L.S. (2007). *Using multivariate statistics*(5th ed.). Boston, MA: Pearson Education, Inc.

Van Voorhis, P., Wright, E.M., Salisbury, E., & Bauman, A. (2010). Women's risk factors and their contributions to existing risk/needs assessment: The current status of a gender-responsive supplement. *Criminal Justice and Behaviour, 37*(3), 261 – 288.

Webster, C.D., Douglas, K.S., Eaves, D., & Hart, S.D. (1997). *HCR-20: Assessing risk for violence (version 2).* Vancouver, Canada: Simon Fraser University.

Wong, S.C.P., & Gordon, A. (1998 – 2003). *Violence Risk Scale.* University of Saskatchewan, Saskatoon, Saskatchewan, Canada.

Wong, S.C.P., & Gordon, A. (2006). The validity and reliability of the Violence Risk Scale: A treatment-friendly violence risk assessment tool. *Psychology, Public Policy and Law, 12*(3), 279 – 309.

Wormith, J.S. (1997). Research to practice: Applying risk/needs assessment to offender classification. *Forum on Corrections Research, 9,* 26-31.

Wormith, J.S., Olver, M.E., Stevenson, H.E., & Girard L. (2007). The long-term prediction of offender recidivism using diagnostic, personality, and risk/need approaches to offender assessment. *Psychological Services, 4*(4), 287 – 305.

APPENDIX A

BREAKDOWN OF ITEM INCLUSION IN THE NINE GENERATED ITEMS SCALES

Table A.1. Items that were Included in Derived Scales

Item	Item Correlations			Burgess Technique			Item Linear Regression			TOTAL
	FS	M	F	FS	M	F	FS	M	F	
A11: Any prior y.o. or adult dispositions	X	X	X	X	X					**5**
A12: Two or more prior adult/youth dispositions	X	X	X	X						**4**
A13: Three or more prior adult/youth dispositions	X	X	X	X	X					**5**
A14: Three or more present offences	X	X		X	X	X				**5**
A15: Arrested or charged under 16	X	X	X	X	X	X	X	X		**8**
A16: Ever incarcerated upon adjudication	X	X	X	X	X					**5**
A17: Ever punished for institutional misconduct/behaviour report	X	X		X	X					**4**
A18: Charge laid, probation breached or parole suspended during prior community supervision	X	X	X	X	X	X	X	X		**8**
A29: Currently unemployed	X	X	X							**3**
A210: Frequently unemployed	X	X	X	X	X					**5**
A211:Never employed for a full year	X	X	X	X	X					**5**
A212: Less than regular grade 10 or equivalent	X	X	X							**3**
A213: Less than regular grade 12 or equivalent	X	X	X				X	X	X	**6**
A214: Suspended or expelled at least once	X	X	X	X	X		X			**6**
A215: Participation/Performance	X	X	X	X	X		X	X		**7**
A216: Peer interactions	X	X	X	X	X					**5**
A217: Authority interactions	X	X	X		X	X				**5**
A318: Dissatisfaction with marital or equivalent situation	X	X								**2**
A319: Nonrewarding, parental	X	X		X	X					**4**
A320: Nonrewarding, other relatives	X	X	X							**3**
A321: Criminal – Family/Spouse	X	X	X		X					**4**
A422: No recent participation in organized activity	X	X								**2**
A423: Could make better use of time	X	X	X	X	X					**5**
A524: Some criminal acquaintances	X	X	X							**3**

A525: Some criminal friends	X	X								**2**
A526: No anti-criminal acquaintances	X	X		X	X	X				**5**
A527: No anti-criminal friends	X	X	X	X	X	X				**6**
A628: Supportive of crime	X	X	X		X	X				**5**
A629: Unfavourable toward convention	X	X	X	X	X	X				**6**
A630: Poor, toward sentence/offence	X	X								**2**
A631: Poor, toward supervision/treatment	X	X		X	X	X				**5**
A732: Alcohol problem, ever	X	X	X			X			X	**5**
A733: Drug problem, ever	X	X	X							**3**
A734: Alcohol problem, currently	X	X	X	X	X	X	X	X	X	**9**
A735: Drug problem, currently	X	X		X	X					**4**
A736: Law violations	X	X	X			X				**4**
A737: Marital/Family	X	X	X	X	X	X				**6**
A738: School/Work	X	X		X	X	X				**5**
A739: Medical or other clinical indicators	X	X	X	X	X	X				**6**
A840: Specialized assessment for Antisocial pattern	X	X		X	X	X				**5**
A841: Early and diverse antisocial behaviour	X	X	X	X	X	X				**6**
A841A: Official record of assault/violence	X	X	X	X		X				**5**
A841B: Escape history	X	X	X	X		X				**5**
A842: Criminal attitude	X	X	X							**3**
A843: A pattern of generalized trouble	X	X	X	X	X	X				**6**
A843A: Financial problems	X	X								**2**
A843B: 3 or more address changes	X	X		X	X					**4**
B11: Clear problems of compliance	X	X	X	X	X	X				**6**
B14: Threat from third party	X	X		X	X					**4**
B15: Problem-solving/self-management skill deficits	X	X								**2**
B16: Anger management deficits	X	X	X	X	X	X	X	X	X	**9**
B17: Intimidating/Controlling	X	X	X	X	X	X	X			**7**
B19: Poor social skills	X	X		X	X	X				**5**
B110: Peers outside age range	X	X		X	X					**4**
B111: Racist/sexist behaviour	X			X						**2**
B112: Underachievement	X	X			X					**3**
B113: Outstanding charges	X	X		X	X		X	X		**6**
B114: Other	X			X	X					**3**
B23: Physical assault (extrafamilial)	X	X	X	X	X	X	X	X		**8**
B24: Physical assault (intrafamilial)	X	X	X			X				**4**
B25: Assault on authority figure	X	X	X	X	X	X	X	X	X	**9**
B26: Weapon use	X	X	X	X	X	X				**6**

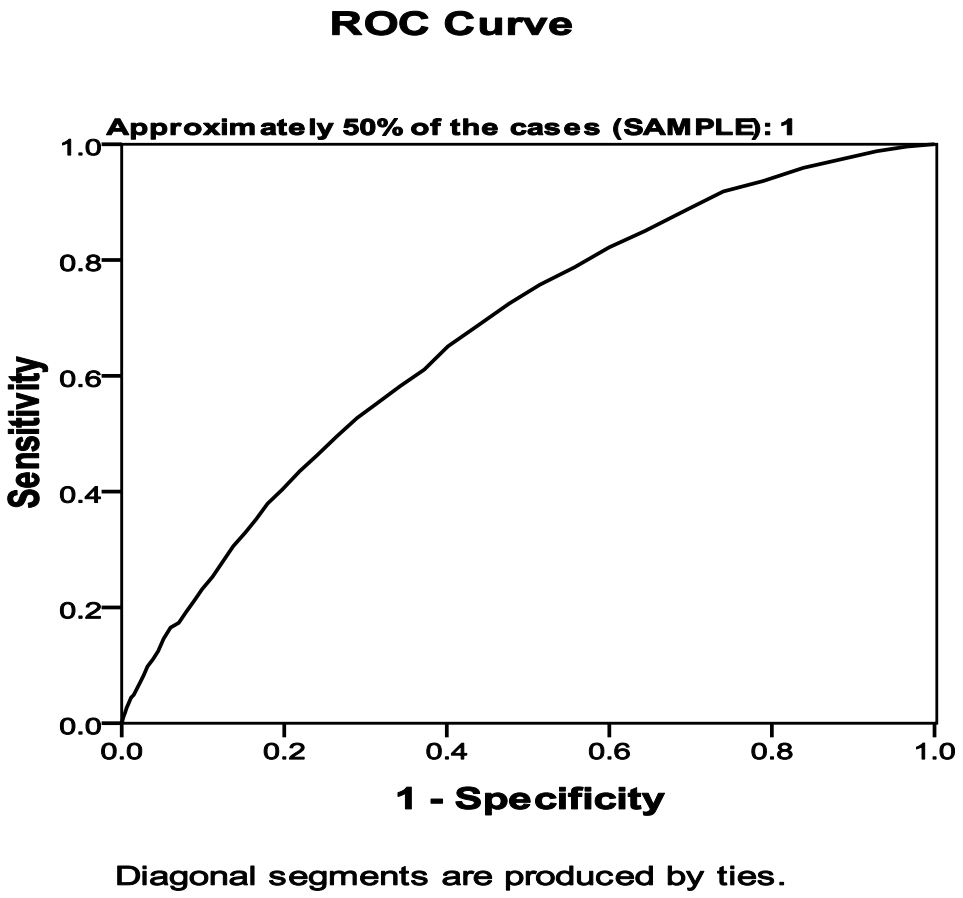
B27: Fire setting	X		X		**2**
B28: Escapes/U.A.L.	X	X	X	X	**4**
B29: Impaired driving	X				**1**

FS = Full Sample, M = Male Sample, F = Female Sample

APPENDIX B

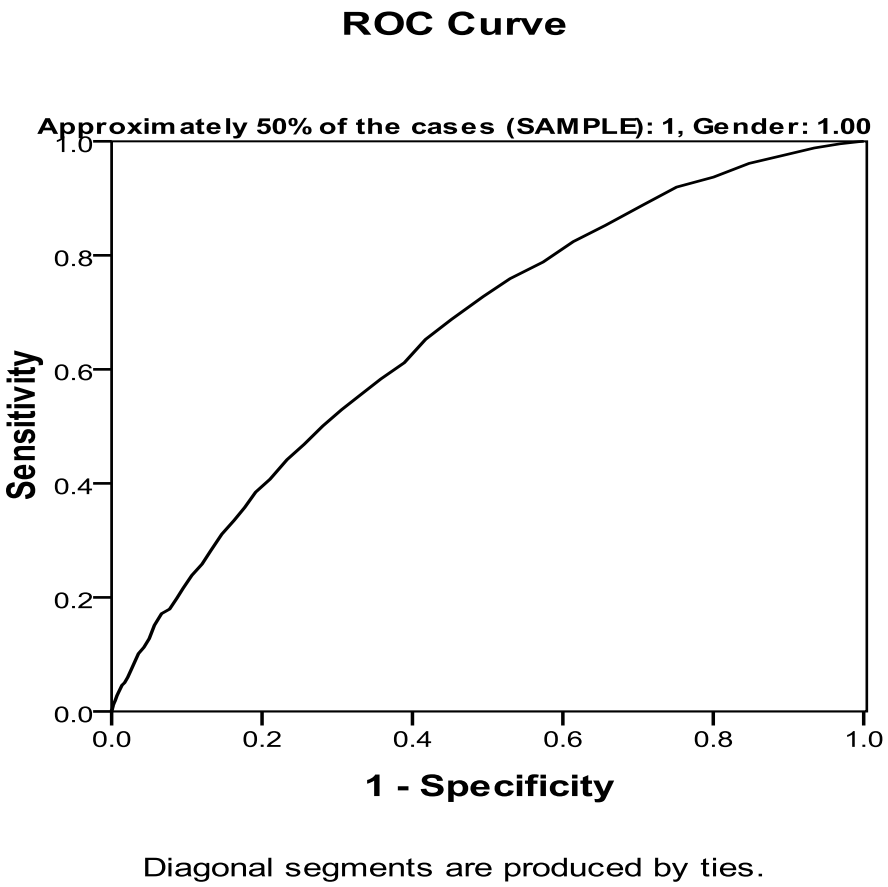
ROC CURVES FOR SUBSCALE CORRELATIONS SCALES

Figure B.1. Full Validation Sample with the Subscale Correlations Scale.



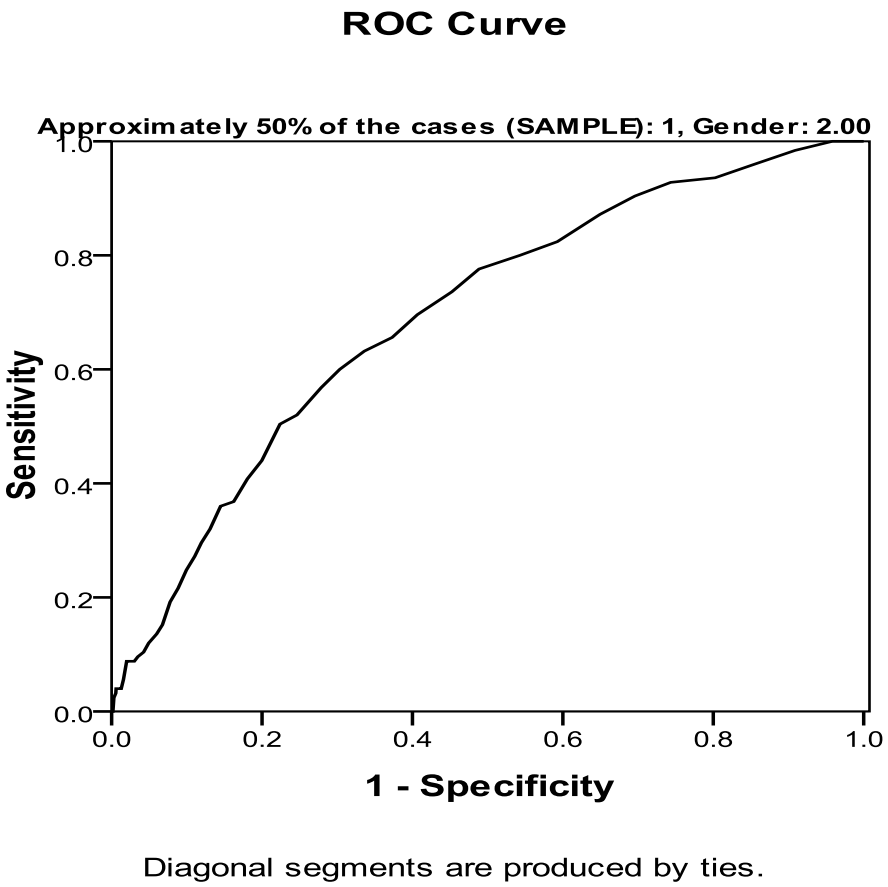
Full Sample AUC = .673, $p < .001$

Figure B.2. Male Validation Sample with the Male Subscale Correlation Scale.



Male Sample AUC = .664, $p < .001$

Figure B.3. Female Validation Sample with the Female Subscale Correlation Scale.

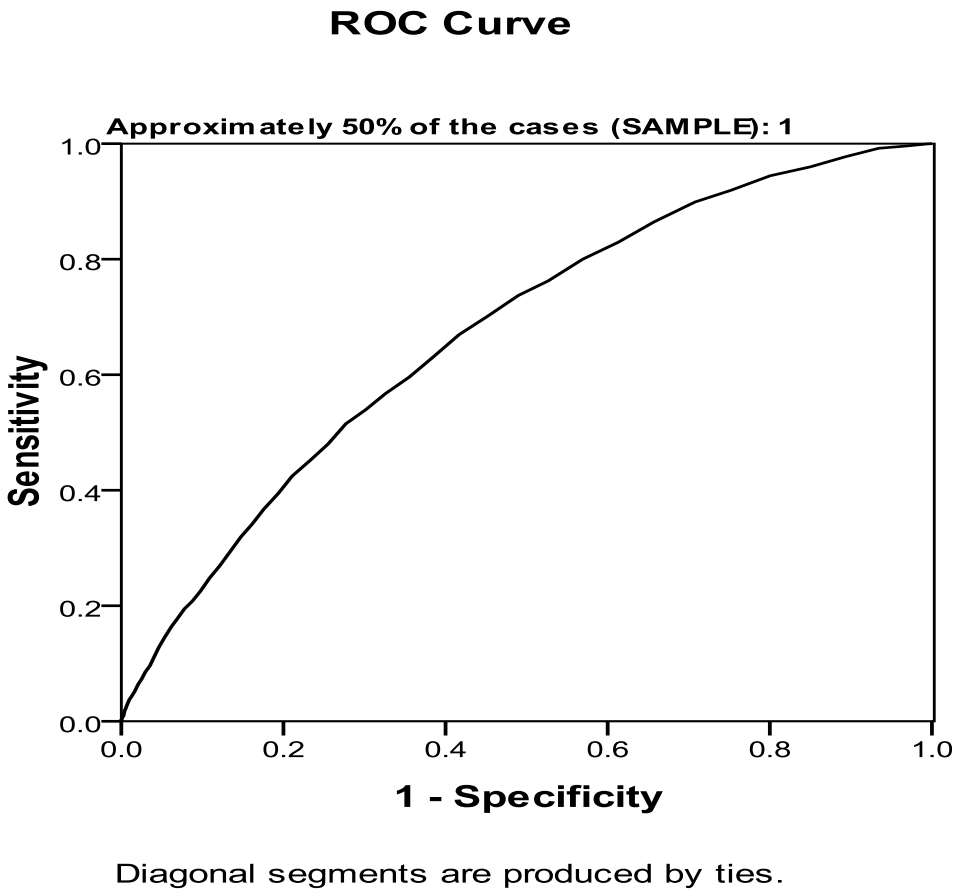


Female Sample AUC = .694, $p < .001$

APPENDIX C

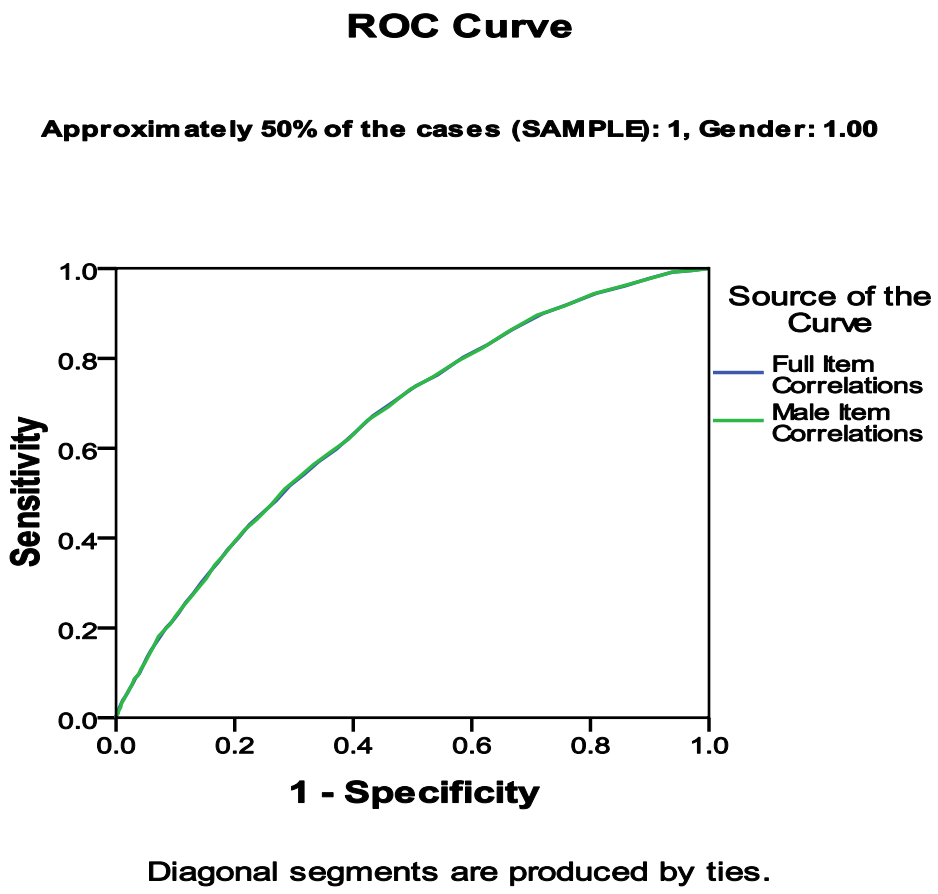
ROC CURVES FOR ITEM CORRELATIONS SCALES

Figure C.1. Full Validation Sample with Full Sample Item Scale



Full Scale AUC = .673, $p < .001$

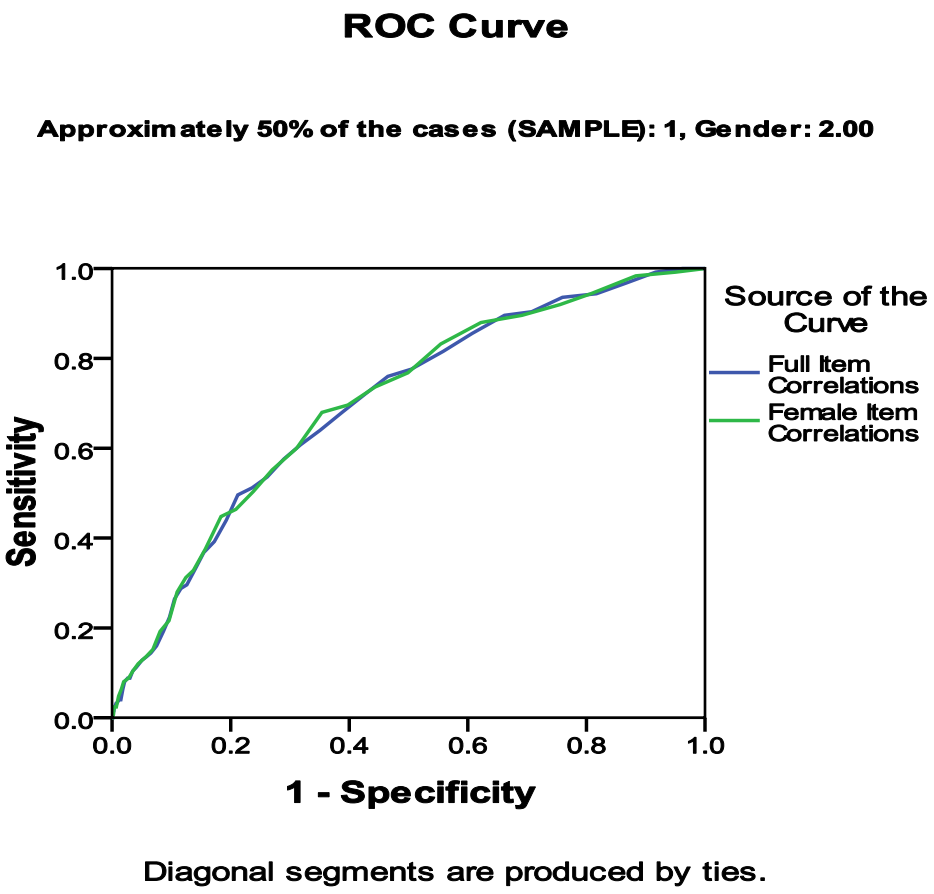
Figure C.2. Male Validation Sample with Male Item Correlation and Full Sample Correlation Scales.



Full Scale AUC = .664, $p < .001$

Male Scale AUC = .665, $p < .001$

Figure C.3. Female Validation Sample with Female Item Correlation and Full Sample Correlation Scales



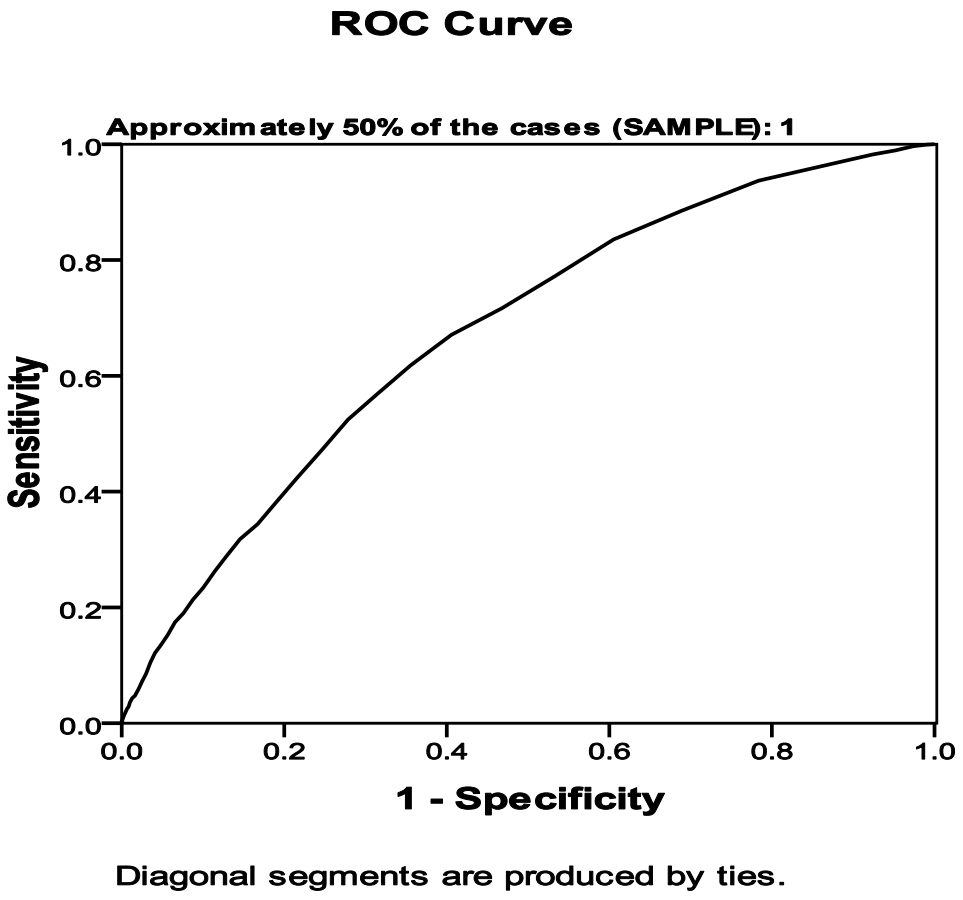
Full Scale AUC = .696, $p < .001$

Female Scale AUC = .699, $p < .001$

APPENDIX D

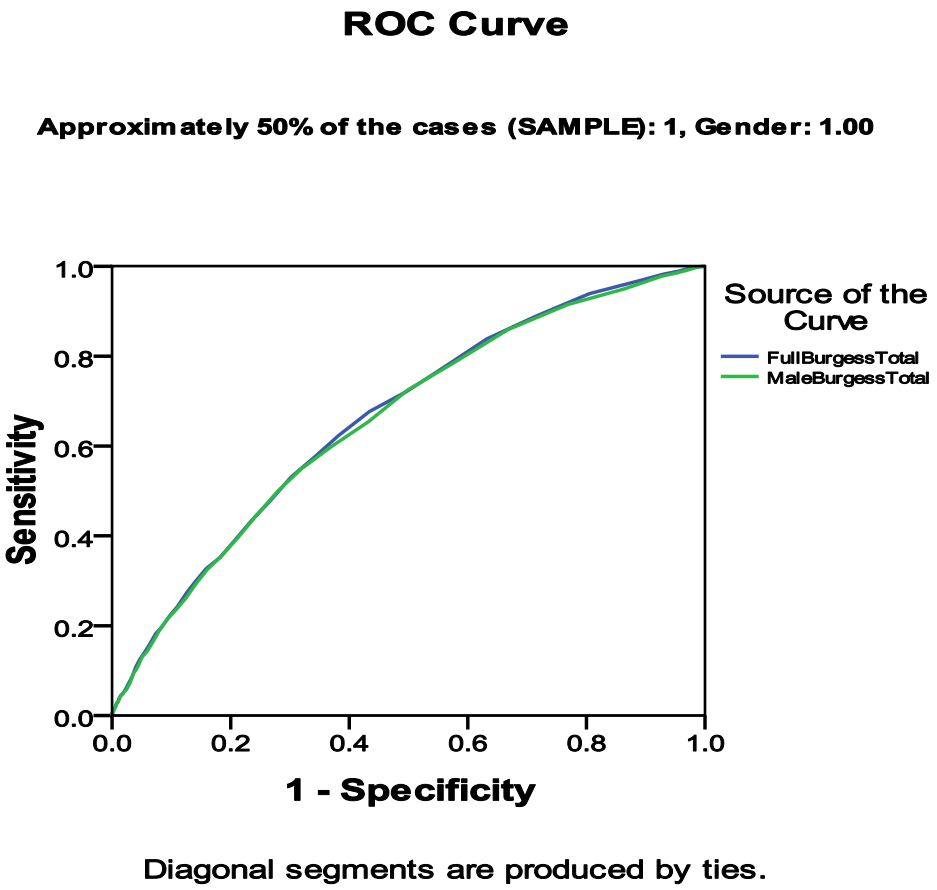
ROC CURVES FOR BURGESS SCALES

Figure D.1. Full Validation Sample with Full Sample Burgess Scale



Full Scale AUC = .676, $p < .001$

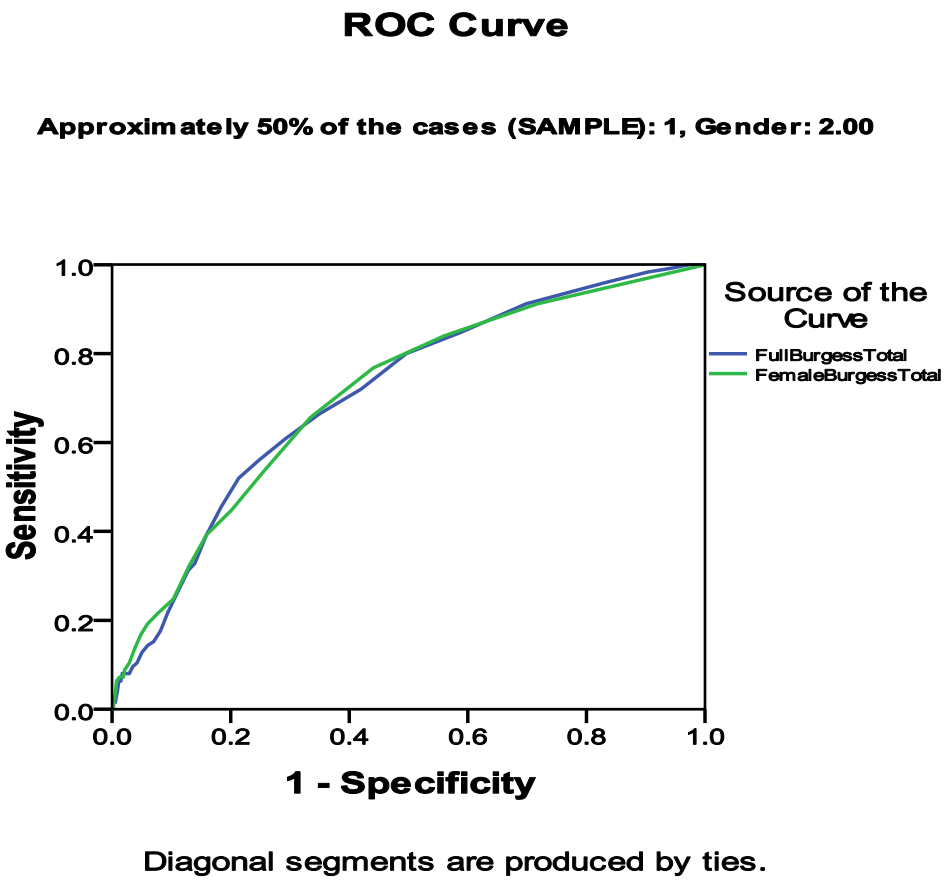
Figure D.2. Male Validation Sample with Full Sample Burgess and Male Sample Burgess Scales



Full Scale AUC = .663, $p < .001$

Male Scale AUC = .657, $p < .001$

Figure D.3. Female Validation Sample with Full Sample Burgess and Female Sample Burgess Scales



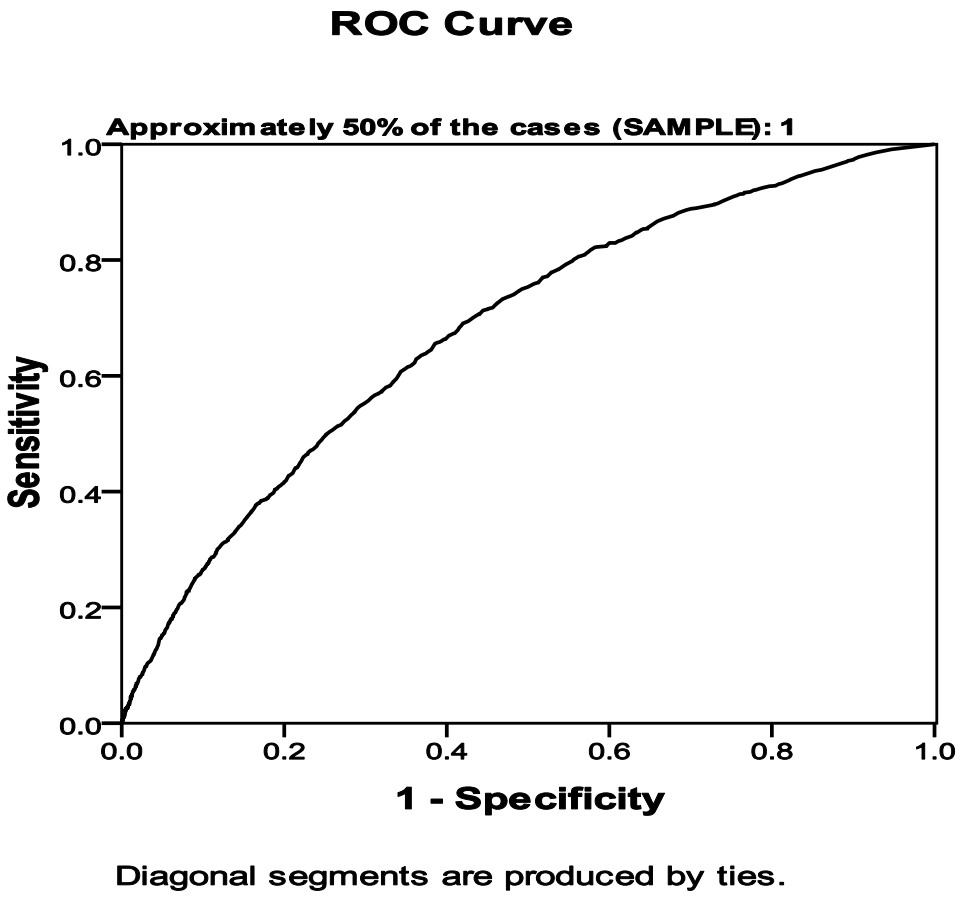
Full Scale AUC = .707, p < .001

Female Scale AUC = .705, p <.001

APPENDIX E

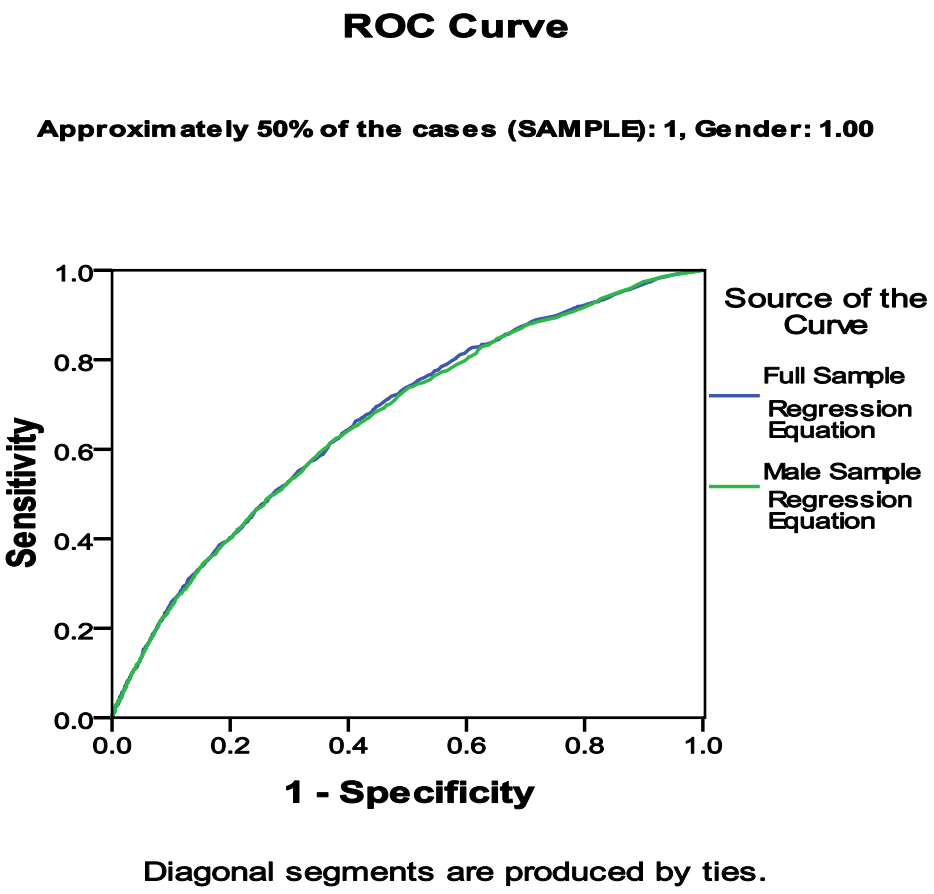
ROC CURVES FOR SUBSCALE LINEAR REGRESSION SCALES

Figure E.1. Full Validation Sample with the Full Subscale Linear Regression Scale



Full Scale AUC = .681, $p < .001$

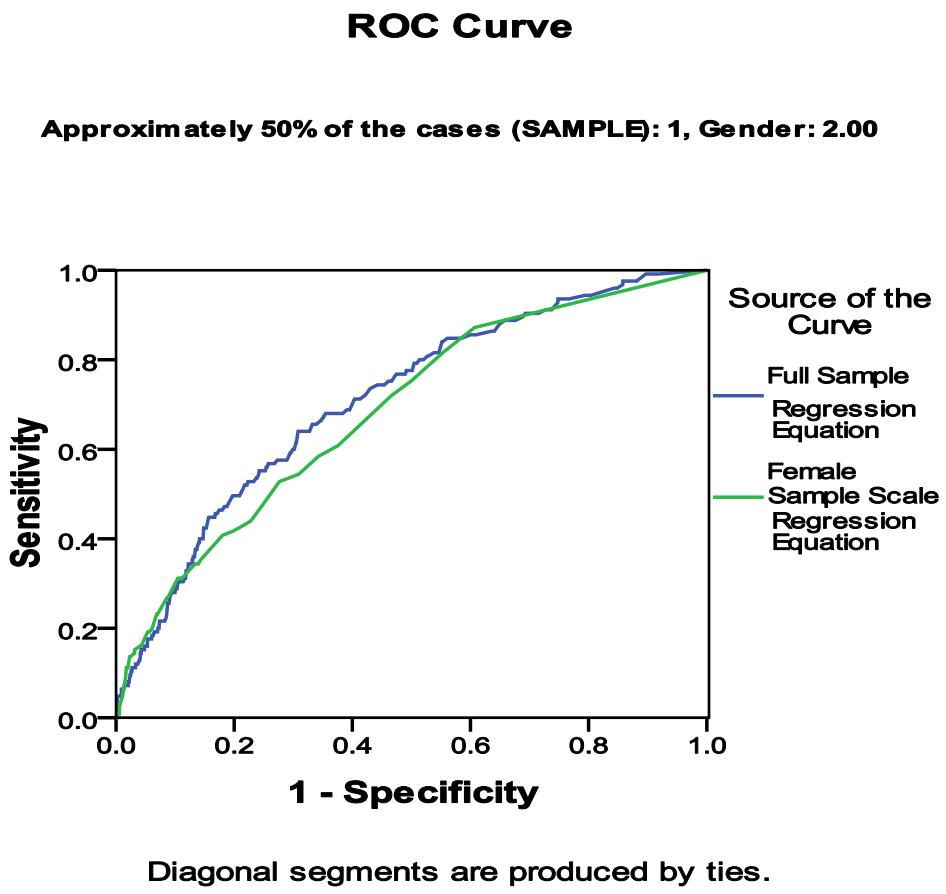
Figure E.2. Male Validation Sample with Full Subscale and Male Subscale Linear Regression Scales



Full Scale AUC = .668, $p < .001$

Male Scale AUC = .665, $p < .001$

Figure E.3. Female Validation Sample with Full Subscale and Female Subscale Linear Regression Scales



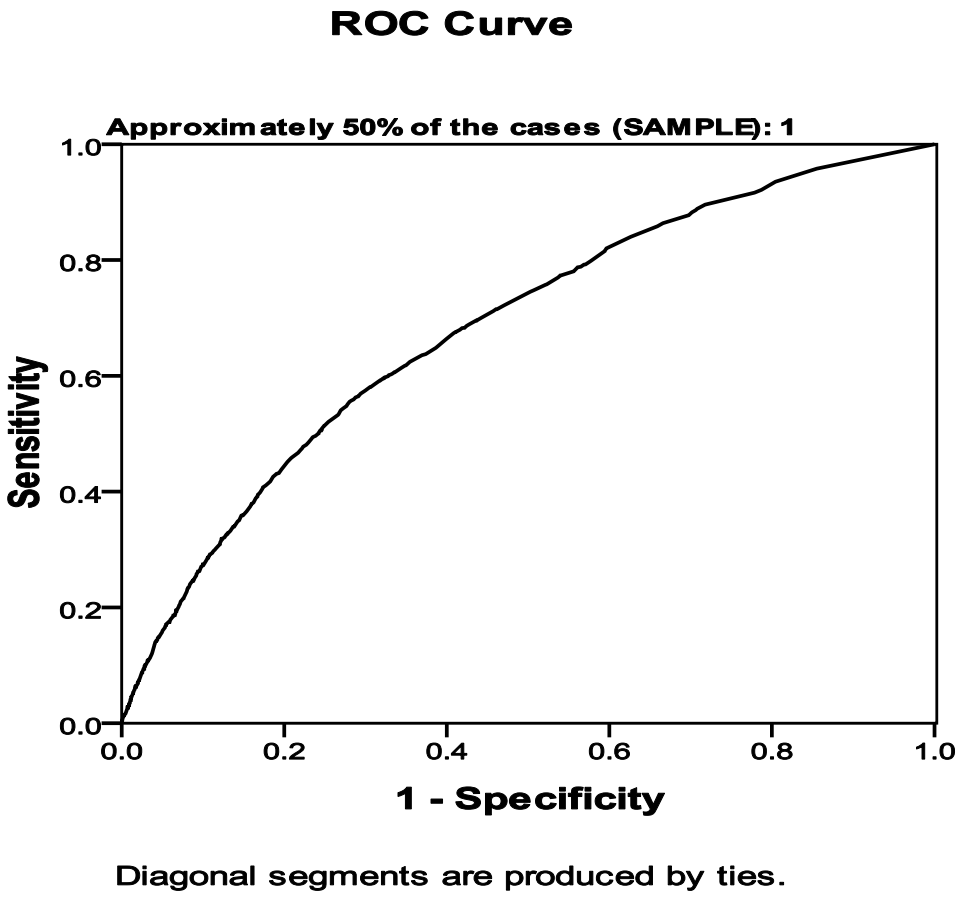
Full Scale AUC = .710, $p < .001$

Female Scale AUC = .686, $p < .001$

APPENDIX F

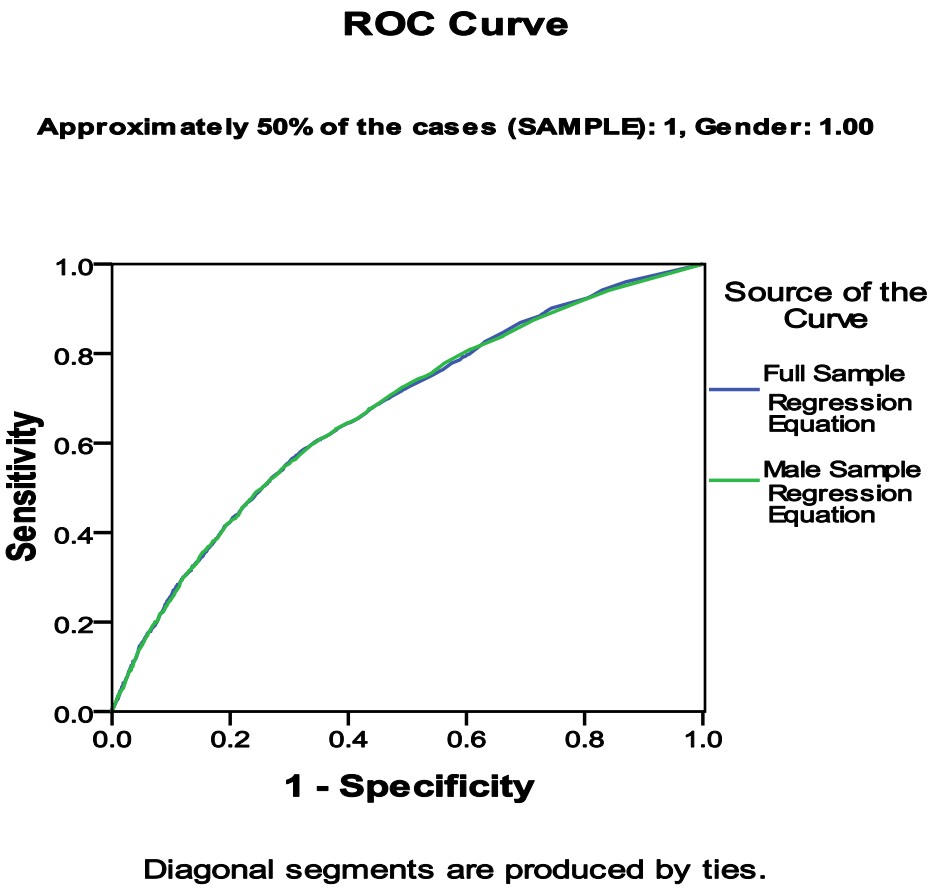
ROC CURVES FOR ITEM LINEAR REGRESSION SCALES

Figure F.1. Full Validation Sample with Full Sample Item Linear Regression Scale



Full Scale AUC = .683, $p < .001$

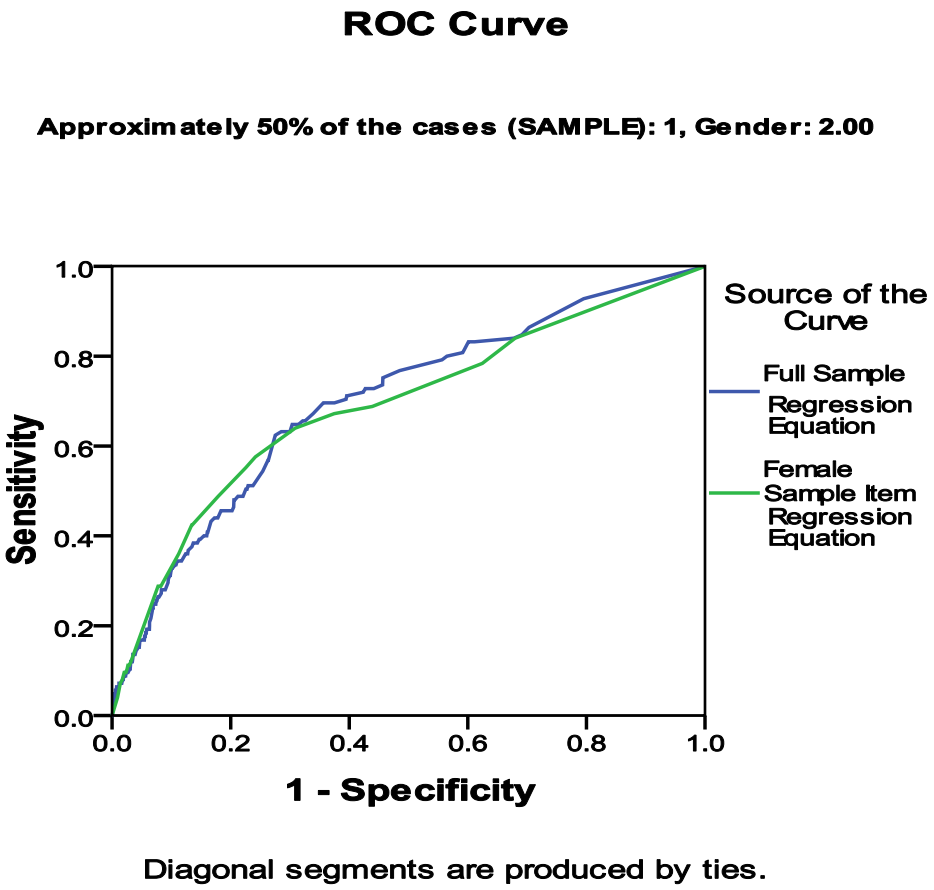
Figure F.2. Male Validation Sample with Full Item and Male Item Linear Regression Scales



Full Scale AUC = .670, $p < .001$

Male Scale AUC = .669, $p < .001$

Figure F.3. Female Validation Sample with Full Item and Female Item Linear Regression Scales



Full Scale AUC = .700, $p < .001$

Female Scale AUC = .689, $p < .001$

APPENDIX G

ENTER LINEAR REGRESSION ANALYSES TO TEST FULL SAMPLE ITEM LINEAR REGRESSION SCALE AGAINST EXISTING A SCALE, B SCALE AND A + B SCALE

Three linear regression analyses were completed, using the enter method to determine whether the item linear regression equation that was developed on the full sample explained more variance in the construct of violent recidivism than the existing scales. Table G.1 – G.3 displays the regression coefficient tables that were obtained when the linear regression scales for the full sample and the pre-existing A scale, B scale and A + B total were entered into a linear regression analysis with the construction sample. Tables G.4 – G.6 show the tables for the males of the construction sample and Tables G.7 – G.9 represents the coefficients for the females of the construction sample.

Tables G.10 – G.12 displays the linear regression coefficients tables for the validation samples with the same linear regression analyses. Tables G. 13 – G. 15 display the coefficients for the males of the validation sample and G.16 – G.18 shows the coefficients for the females of the validation sample.

Table G.1. Enter Method Linear Regression Analysis Comparing the Pre-existing A Scale to the Generated Item Linear Regression Scale for the Full Construction Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	-.003	.005		-.540	.589	-.012	.007			
A Scales Total	.001	.000	.032	2.409	.016	.000	.002	.202	.021	.020
Full Sample Item Linear Regression Equation	.899	.055	.218	16.467	.000	.792	1.007	.243	.140	.137

Table G.2. Enter Method Linear Regression Analysis Comparing the Pre-existing B Scale to the Generated Item Linear Regression Scale for the Full Construction Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	.002	.005		.319	.749	-.008	.011			
B Scales Total	.005	.002	.037	2.699	.007	.001	.009	.207	.023	.022
Full Sample Item Linear Regression Equation	.881	.056	.214	15.615	.000	.770	.992	.243	.133	.130

Table G.3. Enter Method Linear Regression Analysis Comparing the A + B Scales to the Generated Item Linear Regression Scale for the Full Construction Sample

Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1	(Constant)	-.003	.005		-.546	.585	-.012	.007			
	ABTOTAL	.001	.000	.043	2.892	.004	.000	.002	.215	.025	.024
	Full Sample Item Linear Regression Equation	.856	.061	.208	14.054	.000	.737	.976	.243	.120	.117

Table G.4. Enter Method Linear Regression Analysis Comparing the Pre-existing A Scale to the Generated Item Linear Regression Scale for the Male Construction Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	.004	.006		.772	.440	-.007	.015			
A Scales Total	.001	.001	.039	2.650	.008	.000	.003	.199	.025	.024
Full Sample Item Linear Regression Equation	.848	.062	.203	13.595	.000	.725	.970	.234	.128	.125

Table G.5. Enter Method Linear Regression Analysis Comparing the Pre-existing B Scale to the Generated Item Linear Regression Scale for the Male Construction Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	.009	.006		1.614	.106	-.002	.020			
B Scales Total	.005	.002	.034	2.261	.024	.001	.009	.199	.021	.021
Full Sample Item Linear Regression Equation	.863	.064	.206	13.538	.000	.738	.988	.234	.127	.125

Table G.6. Enter Method Linear Regression Analysis Comparing the A + B Scales to the Generated Item Linear Regression Scale Developed for Male Construction Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	.005	.006		.816	.414	-.006	.016			
ABTOTAL	.002	.001	.050	3.013	.003	.001	.003	.210	.029	.028
Full Sample Item Linear Regression Equation	.803	.070	.192	11.542	.000	.667	.939	.234	.109	.106

Table G.7. Enter Method Linear Regression Analysis Comparing the Pre-Existing A Scale to the Generated Item Linear Regression Scale for the Female Construction Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	-.023	.009		-2.583	.010	-.041	-.006			
A Scales Total	.000	.001	.005	.189	.850	-.002	.002	.193	.004	.004
Full Sample Item Linear Regression Equation	1.012	.112	.257	9.076	.000	.793	1.231	.261	.180	.176

Table G.8. Enter Method Linear Regression Analysis Comparing the Pre-Existing B Scale to the Generated Item Linear Regression Scale for the Female Construction Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	-.022	.009		-2.559	.011	-.039	-.005			
B Scales Total	.005	.004	.036	1.216	.224	-.003	.013	.212	.024	.024
Full Sample Item Linear Regression Equation	.921	.116	.234	7.954	.000	.694	1.149	.261	.158	.154

Table G.9. Enter Method Linear Regression Analysis Comparing the A + B Scales to the Generated Item Linear Regression Scale for the Female Construction Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	-.024	.009		-2.668	.008	-.041	-.006			
ABTOTAL	.000	.001	.013	.435	.664	-.001	.002	.209	.009	.008
Full Sample Item Linear Regression Equation	.986	.122	.251	8.090	.000	.747	1.225	.261	.161	.157

Table G.10. Enter Method Linear Regression Analysis Comparing the Pre-existing A Scale to the Generated Item Linear Regression Scale for the Full Validation Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	.009	.005		1.878	.060	.000	.019			
A Scales Total	.001	.000	.039	2.943	.003	.000	.002	.181	.025	.025
Full Sample Item Linear Regression Equation	.747	.054	.184	13.863	.000	.642	.853	.214	.119	.117

Table G.11. Enter Method Linear Regression Analysis Comparing the Pre-existing B Scale to the Generated Item Linear Regression Scale for the Full Validation Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	.015	.005		3.086	.002	.005	.024			
B Scales Total	.010	.002	.074	5.384	.000	.006	.014	.197	.046	.045
Full Sample Item Linear Regression Equation	.633	.056	.156	11.372	.000	.524	.742	.214	.098	.096

Table G.12. Enter Method Linear Regression Analysis Comparing the A + B Scales to the Generated Item Linear Regression Scale Developed from the Full Validation Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	.009	.005		1.767	.077	.000	.018			
ABTOTAL	.002	.000	.059	4.005	.000	.001	.003	.195	.035	.034
Full Sample Item Linear Regression Equation	.673	.060	.166	11.259	.000	.556	.791	.214	.097	.095

Table G.13. Enter Method Linear Regression Analysis Comparing the A Scale to the Generated Item Linear Regression Scale for the Male Validation Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	.017	.006		2.961	.003	.006	.028			
A Scales Total	.002	.001	.050	3.325	.001	.001	.003	.182	.032	.031
Full Sample Item Linear Regression Equation	.711	.063	.169	11.307	.000	.588	.834	.208	.107	.106

Table G.14. Enter Method Linear Regression Analysis Comparing the B Scale to the Generated Item Linear Regression Scale for the Male Validation Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	.023	.006		4.071	.000	.012	.034			
B Scales Total	.009	.002	.064	4.189	.000	.005	.013	.188	.040	.039
Full Sample Item Linear Regression Equation	.662	.064	.157	10.345	.000	.537	.788	.208	.098	.097

Table G.15. Enter Method Linear Regression Analysis Comparing the A + B Scales to the Generated Item Linear Regression Scale for the Male Validation Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	.017	.006		2.947	.003	.006	.028			
ABTOTAL	.002	.001	.068	4.090	.000	.001	.003	.193	.039	.038
Full Sample Item Linear Regression Equation	.639	.070	.152	9.154	.000	.502	.775	.208	.087	.085

Table G.16. Enter Method Linear Regression Analysis Comparing the A Scale to the Generated Item Linear Regression Scale for the Female Validation Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	-.004	.008		-.461	.645	-.019	.011			
A Scales Total	.001	.001	.021	.734	.463	.000	.002	.139	.015	.015
Full Sample Item Linear Regression Equation	.531	.094	.163	5.662	.000	.347	.716	.178	.113	.112

Table G.17. Enter Method Linear Regression Analysis Comparing the B Scale to the Generated Item Linear Regression Scale for the Female Validation Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	.000	.007		-.084	.933	-.015	.014			
B Scales Total	.010	.004	.086	2.857	.004	.003	.017	.171	.057	.056
Full Sample Item Linear Regression Equation	.370	.098	.113	3.770	.000	.178	.563	.178	.076	.074

Table G.18. Enter Method Linear Regression Analysis Comparing the A + B Scales to the Generated Item Linear Regression Scale for the Female Validation Sample

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	-.005	.008		-.609	.543	-.019	.010			
ABTOTAL	.001	.001	.040	1.278	.201	.000	.002	.154	.026	.025
Full Sample Item Linear Regression Equation	.480	.102	.147	4.694	.000	.279	.681	.178	.094	.093

APPENDIX H

ITEM LINEAR REGRESSION EQUATIONS FOR FULL, MALE AND FEMALE SAMPLES

Table H.1. Item Linear Regression Equations for Full, Male and Female Samples

Item Entered	Full Sample	Males	Females
Constant	.020	.030	.000
		b weights	
A15: Arrested or charged under 16	.041	.049	-
A18: Charge laid, probation breached or parole suspended during prior community supervision	.027	.030	-
A213: Less than regular grade 12 or equivalent	.028	.030	.039
A214: Suspended or expelled at least once	.024	-	-
A215:Participation/Performance (Education)	.020	.027	-
A732: Alcohol problem, ever	-	-	.038
A734: Alcohol problem, currently	.050	.043	.057
B16: Anger management deficits	.046	.050	.070
B17: Intimidating/Controlling	.028	-	-
B113: Outstanding charges	.045	.058	-
B23: Physical assault (extrafamilial)	.038	.041	-
B25: Assault on authority figure	.062	.054	.138

APPENDIX I

SURVIVAL ANALYSES FOR THE MALES AND FEMALES IN THE CONSTRUCTION AND VALIDATION SAMPLES ON THE FIVE RISK LEVELS THAT WERE DERIVED FROM THE FULL SAMPLE LINEAR REGRESSION SCALE

Figure I.1. Survival Curve for Males of the Construction Sample when Separated by the Risk Levels Derived from the Full Sample Linear Regression Scale

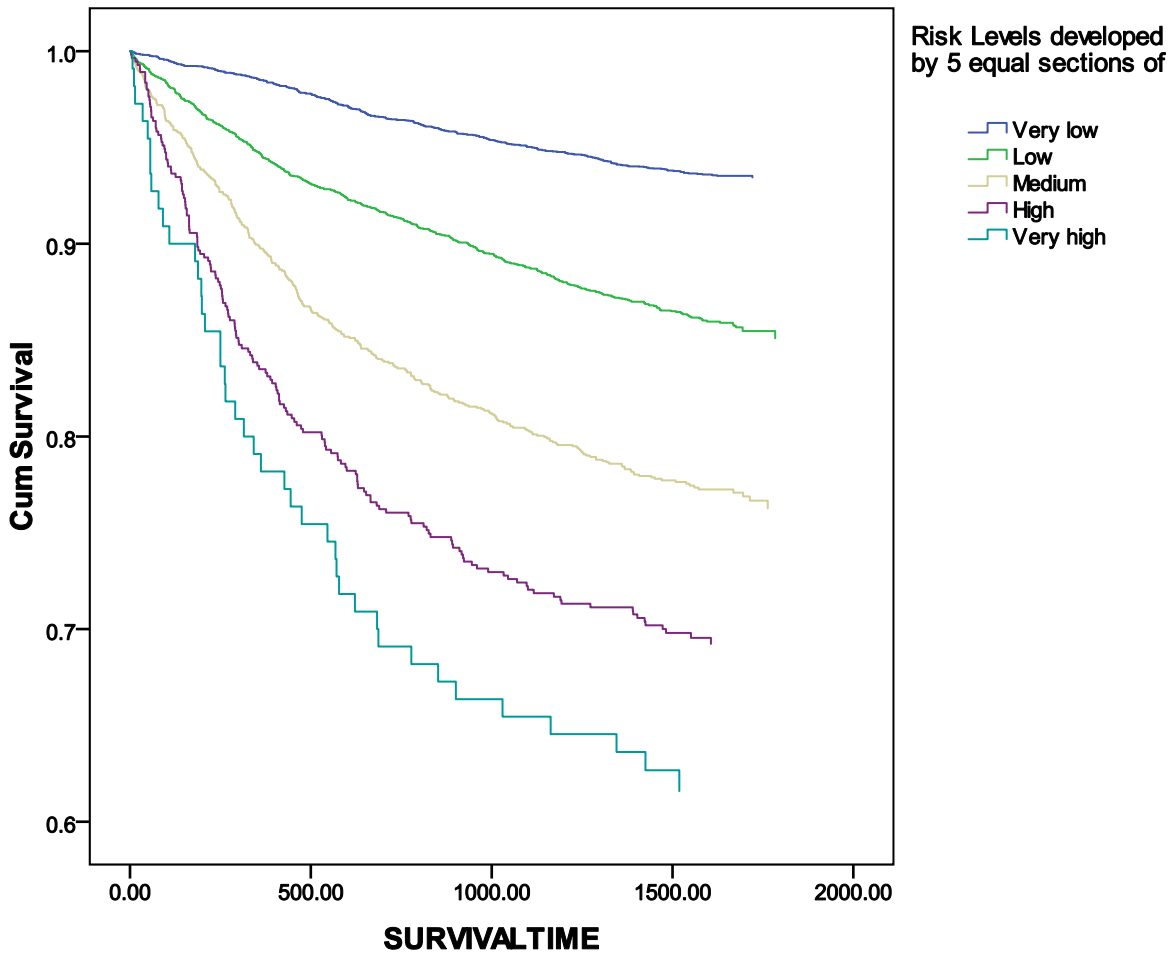


Figure I.2. Survival Curve for Females of the Construction Sample when Separated by the Risk Levels Derived from the Full Sample Linear Regression Scale

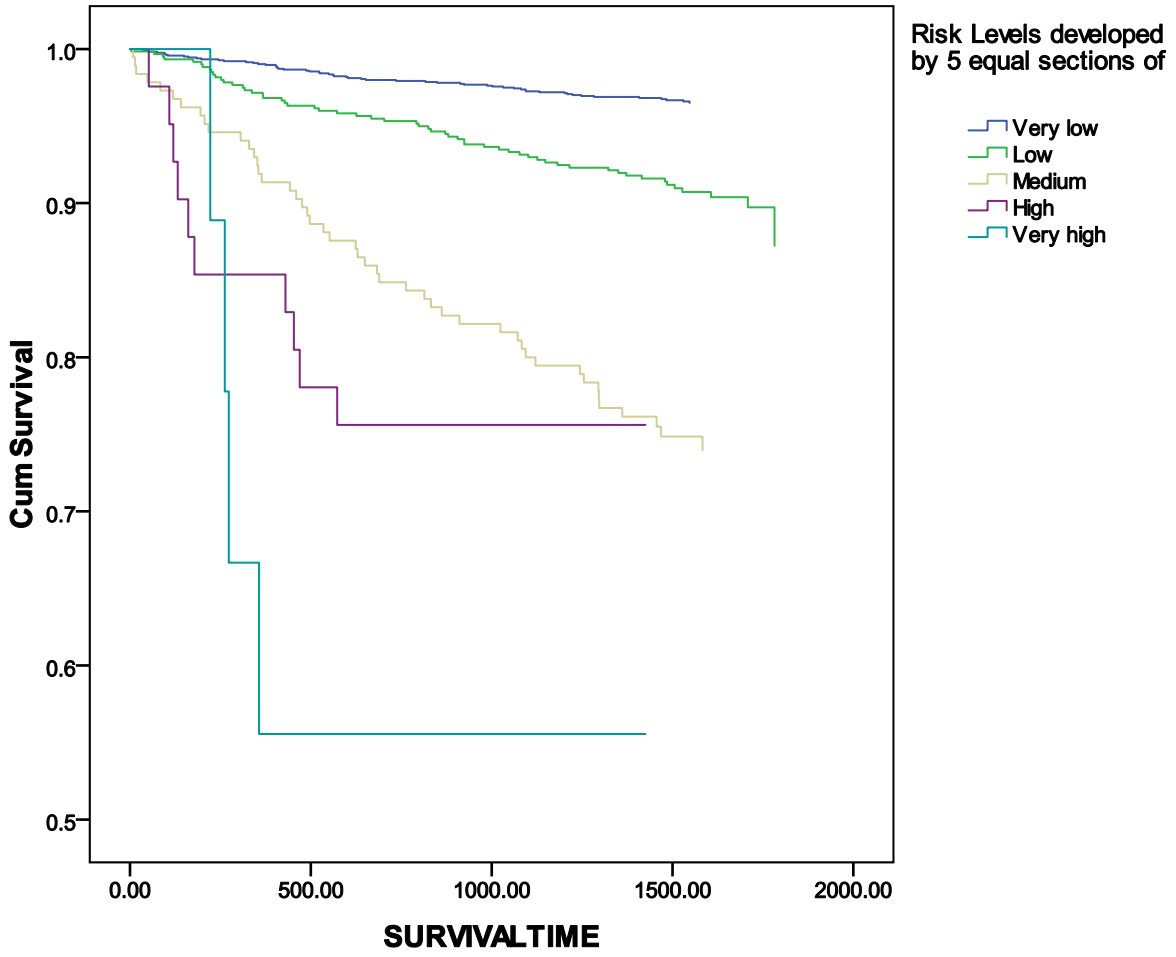


Figure I.3. Survival Curve for Males of the Validation Sample when Separated by the Risk Levels Derived from the Full Sample Linear Regression Scale

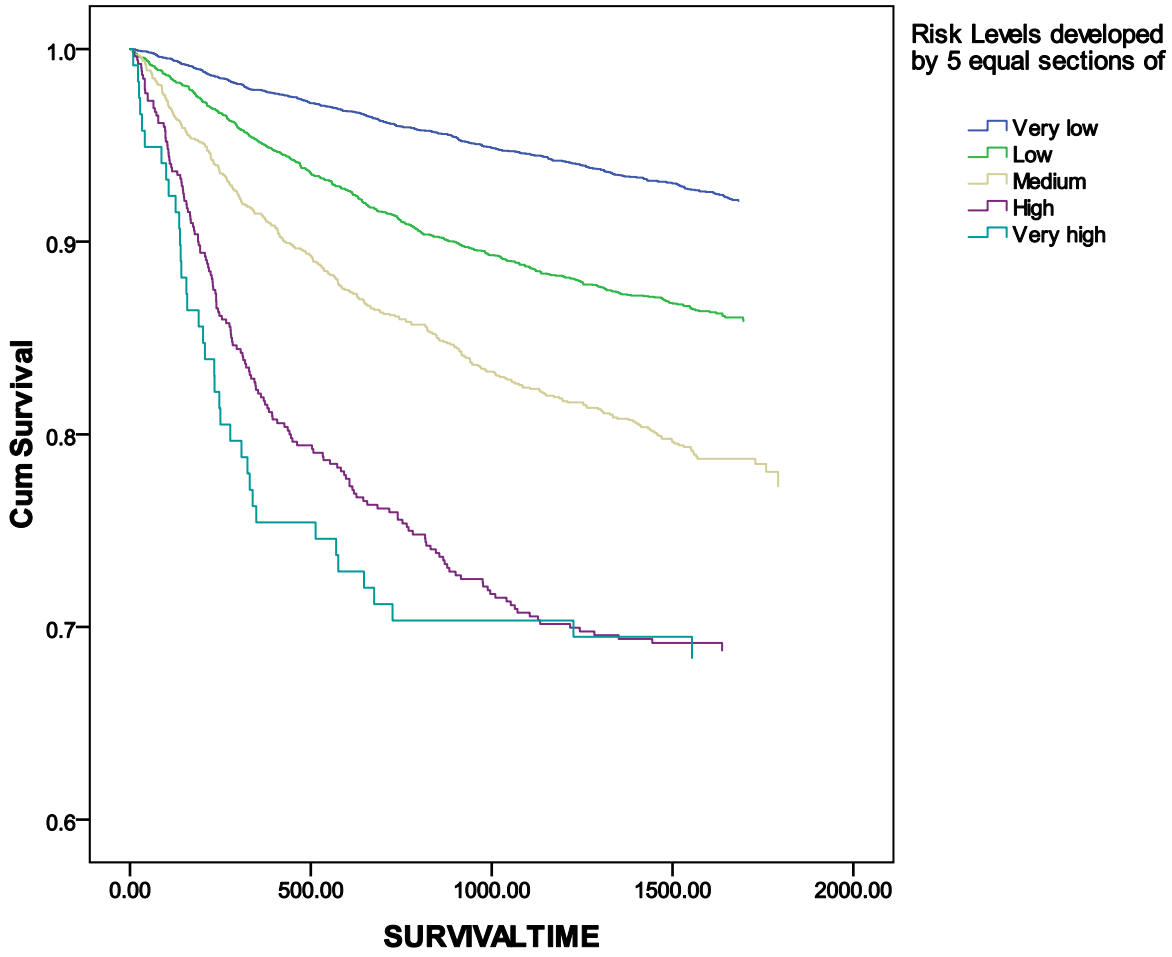
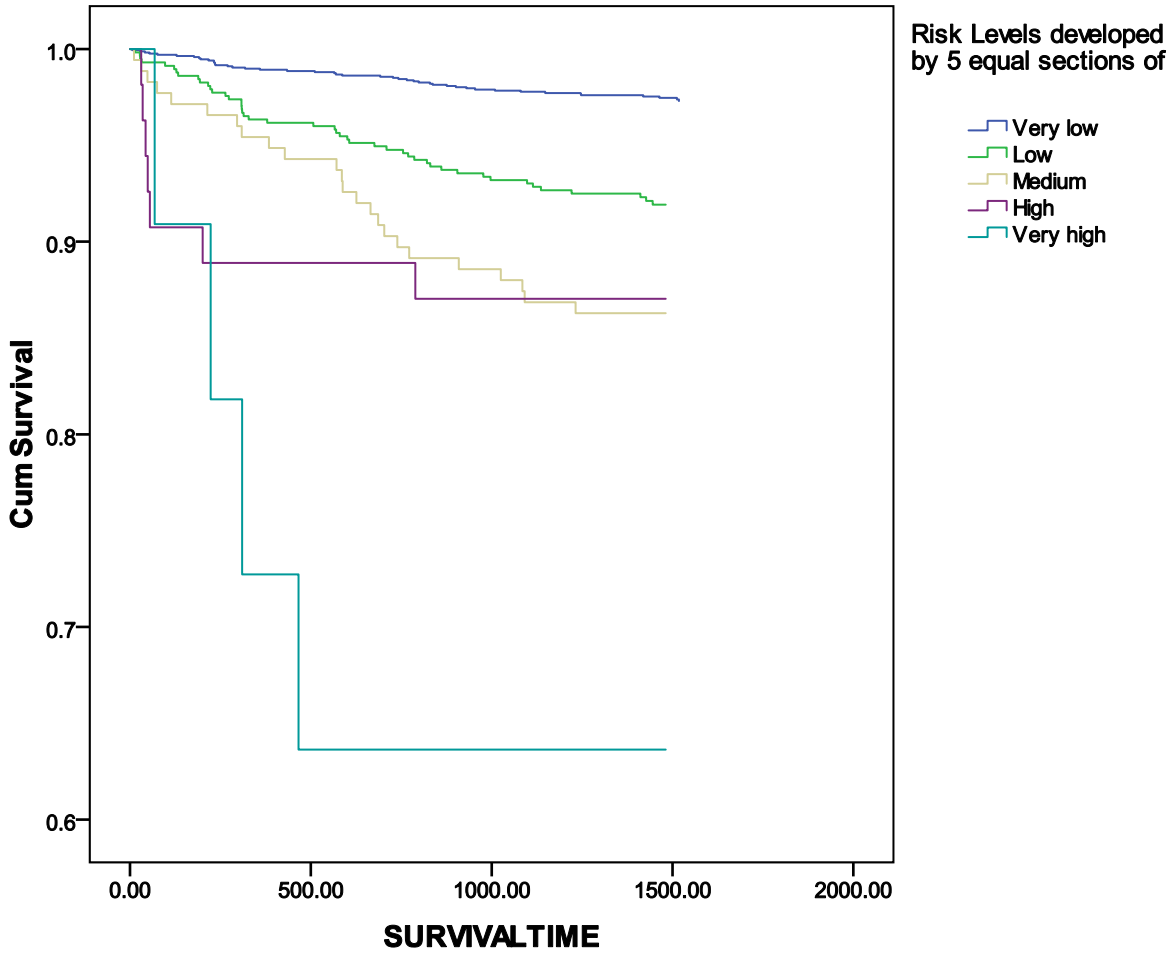


Figure I.4. Survival Curve for Females of the Validation Sample when Separated by the Risk Levels Derived from the Full Sample Linear Regression Scale



APPENDIX J

SURVIVAL ANALYSES FOR THE MALES AND FEMALES IN THE CONSTRUCTION AND VALIDATION SAMPLES ON THE PRE-EXISTING FIVE RISK LEVELS ON THE A SCALE

Figure J.1. Survival Curve for Males of the Construction Sample when Separated by the Pre-Existing A Scale Risk Levels

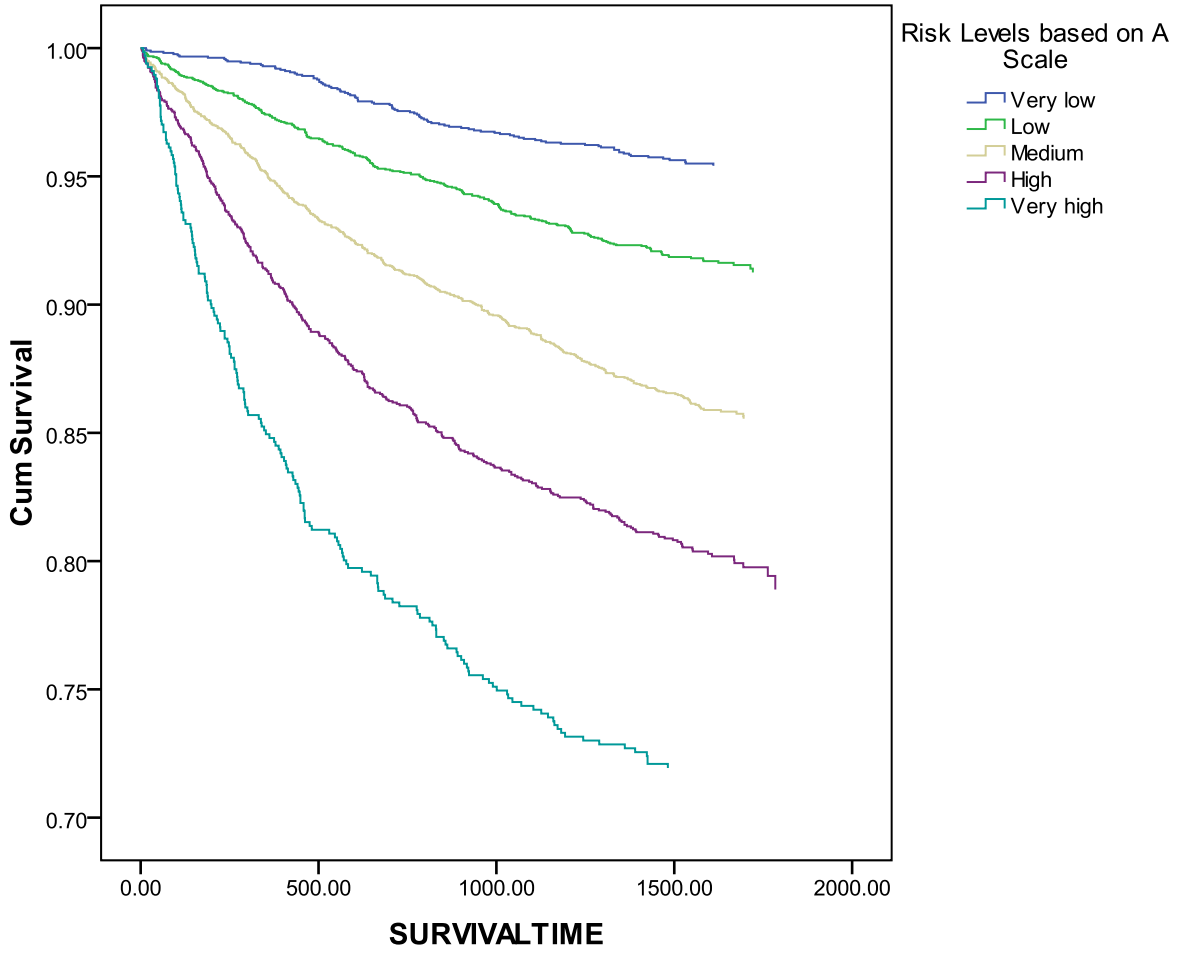


Figure J.2. Survival Curve for Females of the Construction Sample when Separated by the Pre-Existing A Scale Risk Levels

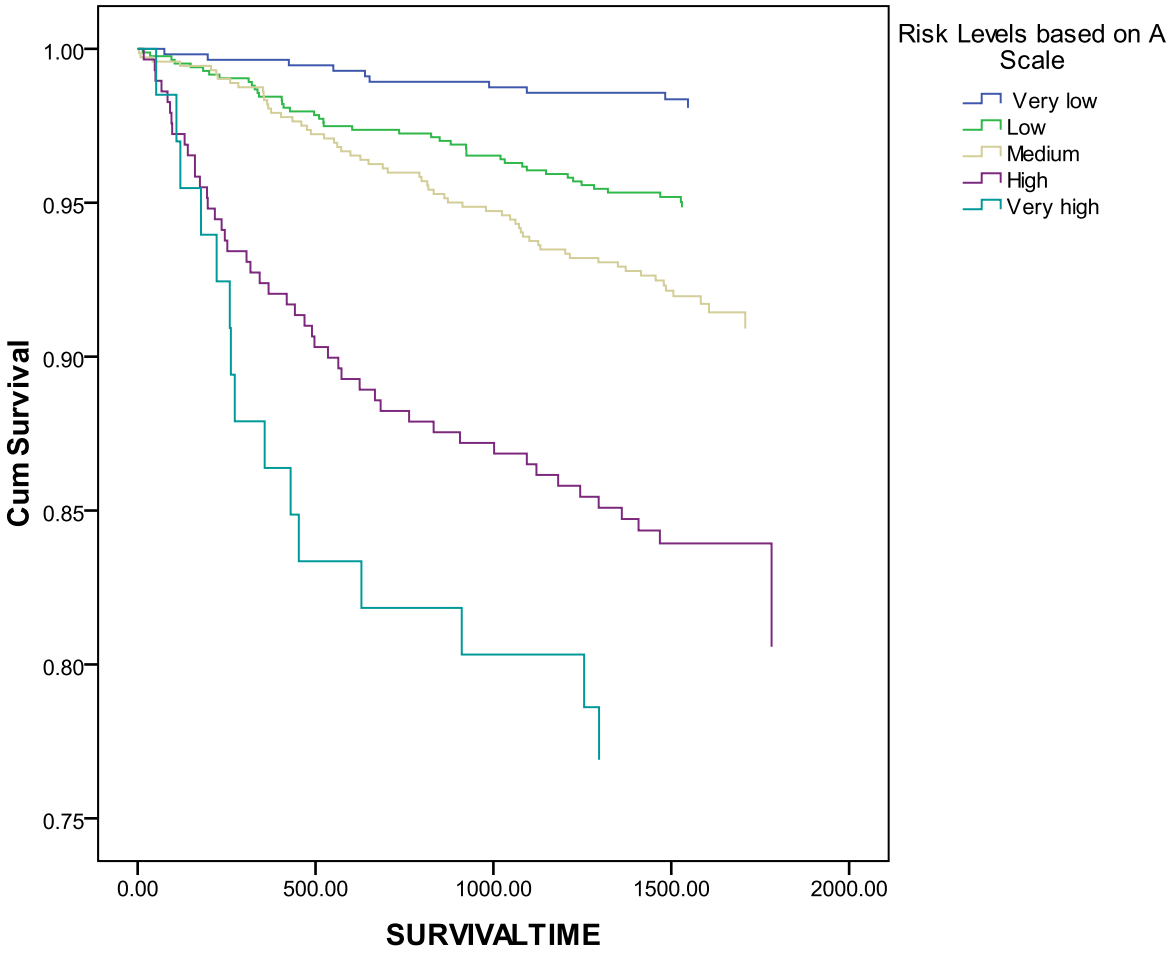


Figure J.3. Survival Curve for Males of the Validation Sample when Separated by the Pre-Existing A Scale Risk Levels

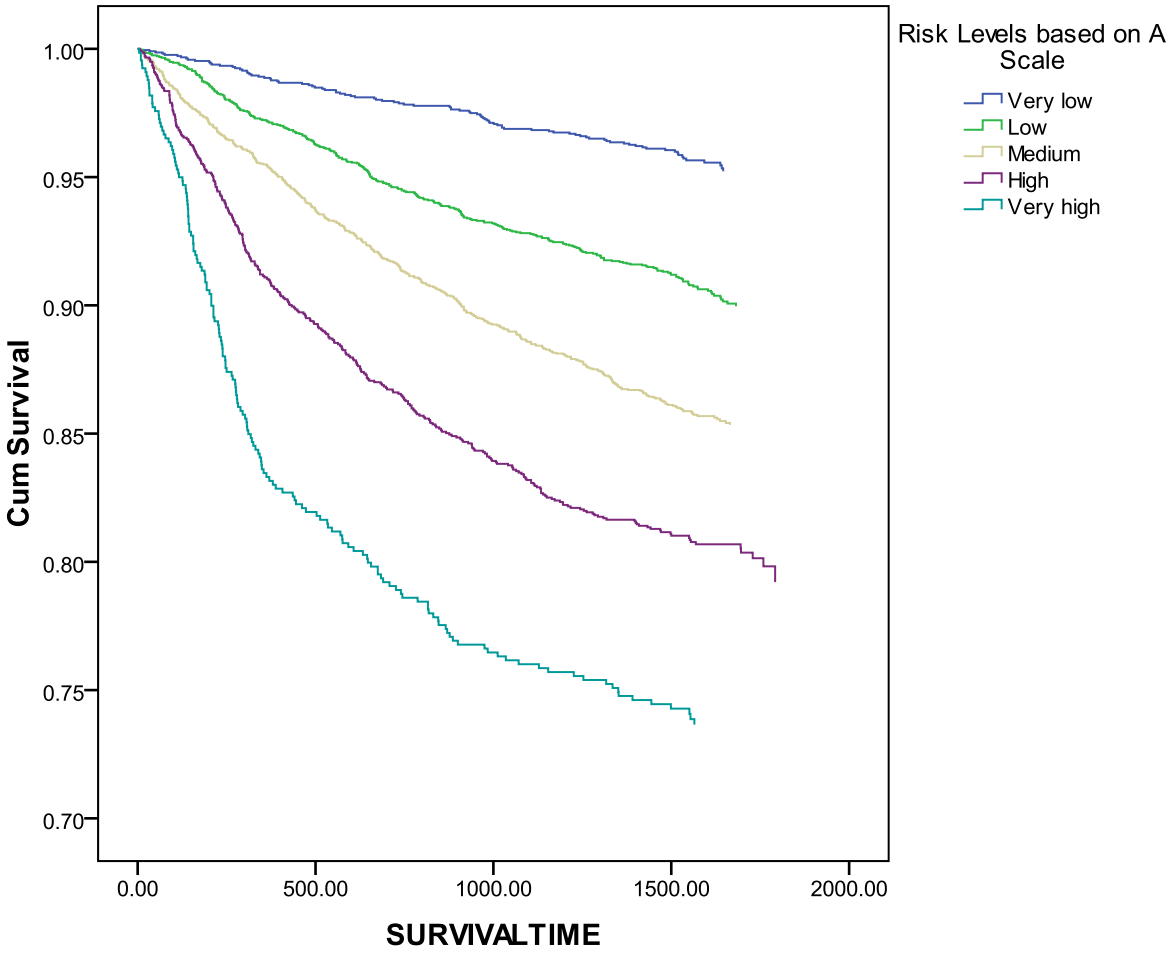
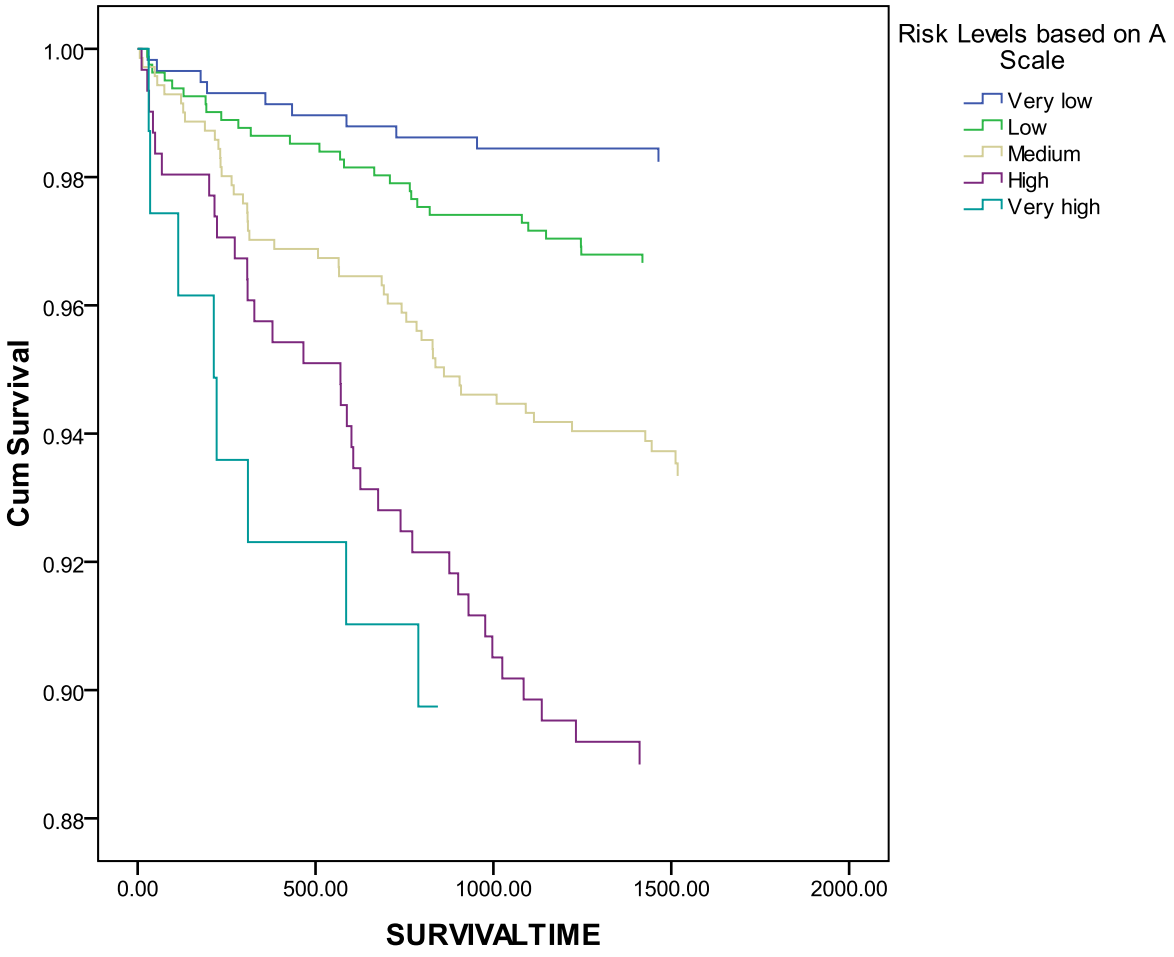


Figure J.4. Survival Curve for Females of the Validation Sample when Separated by the Pre-Existing A Scale Risk Levels



APPENDIX K

RISK LEVELS DERIVED FROM PERCENTILES OF THE FULL SAMPLE LINEAR REGRESSION TECHNIQUE

These risk levels are determined by dividing the linear regression scores from the construction sample into five equal percentiles to classify offenders into very high, high, medium, low and very low risk categories. Table K.1 displays the risk levels and linear regression scores on the full sample item linear regression scale that would classify offenders in each category. The violent recidivism in each group is presented as a percentage of the sample.

Table K.1. Numbers of Offenders Classified in each Risk Category for the Construction and Validation Samples

	Construction			Validation		
(N) Risk Levels	Full Sample (13594)	Males (11121)	Females (2473)	Full Sample (13433)	Males (10954)	Females (2479)
Very Low (lowest - .1018)						
# of Offenders	2697	1987	710	2767	1988	779
% of Sample	19.8	17.9	28.7	20.6	18.1	31.4
Low (.1019 - .1836)						
# of Offenders	2535	1963	572	2426	1874	552
% of Sample	18.6	17.7	23.1	18.1	17.1	22.3
Medium (.1837 - .2654)						
# of Offenders	2921	2399	522	2873	2381	492
% of Sample	21.5	21.6	21.1	21.4	21.7	19.8
High (.2655 - .3472)						
# of Offenders	2720	2344	376	2693	2330	363
% of Sample	20.0	21.1	15.2	20.0	21.3	14.6
Very High (.3273 - highest)						
# of Offenders	2721	2428	293	2674	2381	293
% of Sample	20.0	21.8	11.8	19.9	21.7	11.8

1. Chi Squares

The number of participants in the previous table gives us a good idea of how many offenders were classified into each category. Table K.2 provides the violent recidivism percentages that occur in each risk level.

Table K.2. Violent Recidivism Percentages when the Validation and Construction Samples are Separated into Risk Levels Derived from the Full Sample Item Linear Regression Analysis

	Very Low	Low	Medium	High	Very High
Construction Sample					
Full Sample (13594)					
Total Number in Risk Level	2697	2535	2921	2720	2721
Number of Violent Recidivates	91	157	257	385	660
% Violent Recidivism	3.4	6.2	8.8	14.2	24.3
Males (11121)					
Total Number in Risk Level	1987	1963	2399	2344	2428
Number of Violent Recidivates	82	134	223	346	591
% Violent Recidivism	4.1	6.8	9.3	14.8	24.3
Females (2473)					
Total Number in Risk Level	710	572	522	376	293
Number of Violent Recidivates	9	23	34	39	69
% Violent Recidivism	1.3	4.0	6.5	10.4	23.5
Validation Sample					
Full Sample (13433)					
Total Number in Risk Level	2767	2426	2873	2693	2674
Number of Violent Recidivates	125	160	259	345	606
% Violent Recidivism	4.5	6.6	9.0	12.8	22.7
Males (10954)					
Total Number in Risk Level	1988	1874	2381	2330	2381
Number of Violent Recidivates	105	147	234	320	564
% Violent Recidivism	5.3	7.8	9.8	13.7	23.7
Females (2479)					
Total Number in Risk Level	779	552	492	363	293
Number of Violent Recidivates	20	13	25	25	42
% Violent Recidivism	2.6	2.4	5.1	6.9	14.3

Chi squares of the risk levels were analyzed with violent recidivism to determine whether the five categories were providing accurate stratification of offenders who differed from each other on violent recidivism. The full construction [$\chi^2(4) = 725.2$, $p < .001$] and validation [$\chi^2(4) =$

553.0, $p < .001$] samples both had significant chi squares, as did the males in the construction [$\chi^2(4) = 534.4$, $p < .001$] and validation [$\chi^2(4) = 422.9$, $p < .001$] samples. Also displaying significant differences between the risk levels were the females in both the construction [$\chi^2(4) = 172.8$, $p < .001$] and validation samples [$\chi^2(4) = 73.7$, $p < .001$].

2. AUC

When plotting the ROC curve for the risk levels that were generated on the full sample, it was found that the construction sample had an AUC = .696, $p < .001$, with a 95% confidence interval ranging from .683 to .710. Males in the construction sample displayed an AUC = .681, $p < .001$ with a 95% confidence interval from .667 to .696. The females in the construction sample had a little bit higher AUC at .754, $p < .001$, but an overlapping confidence interval including .718 to .790.

The ROC plots for the validation sample were also highly significant. The full validation sample had an AUC = .672, $p < .001$, CI = .657 - .686. Males in the validation sample showed a bit smaller AUC = .659, $p < .001$, CI = .644 - .674, and females had a marginally higher AUC = .684, $p < .001$ with a larger CI = .633 - .734.

3. Survival Analysis

When the survival analysis was completed for the five derived risk levels, it is apparent that the very high risk offenders have a lower survival time. Figures K.1 – K.3 displays the survival curves for the five risk levels for the full, male and females of the construction sample using Cox Regression analysis and Figures K.4 – K.6 display those for the validation sample.

Figure K.1. Survival Analysis on the Five Risk Levels Developed by Taking Five Percentiles of the Scores from the Full Sample Item Linear Regression Scale for the Construction Sample

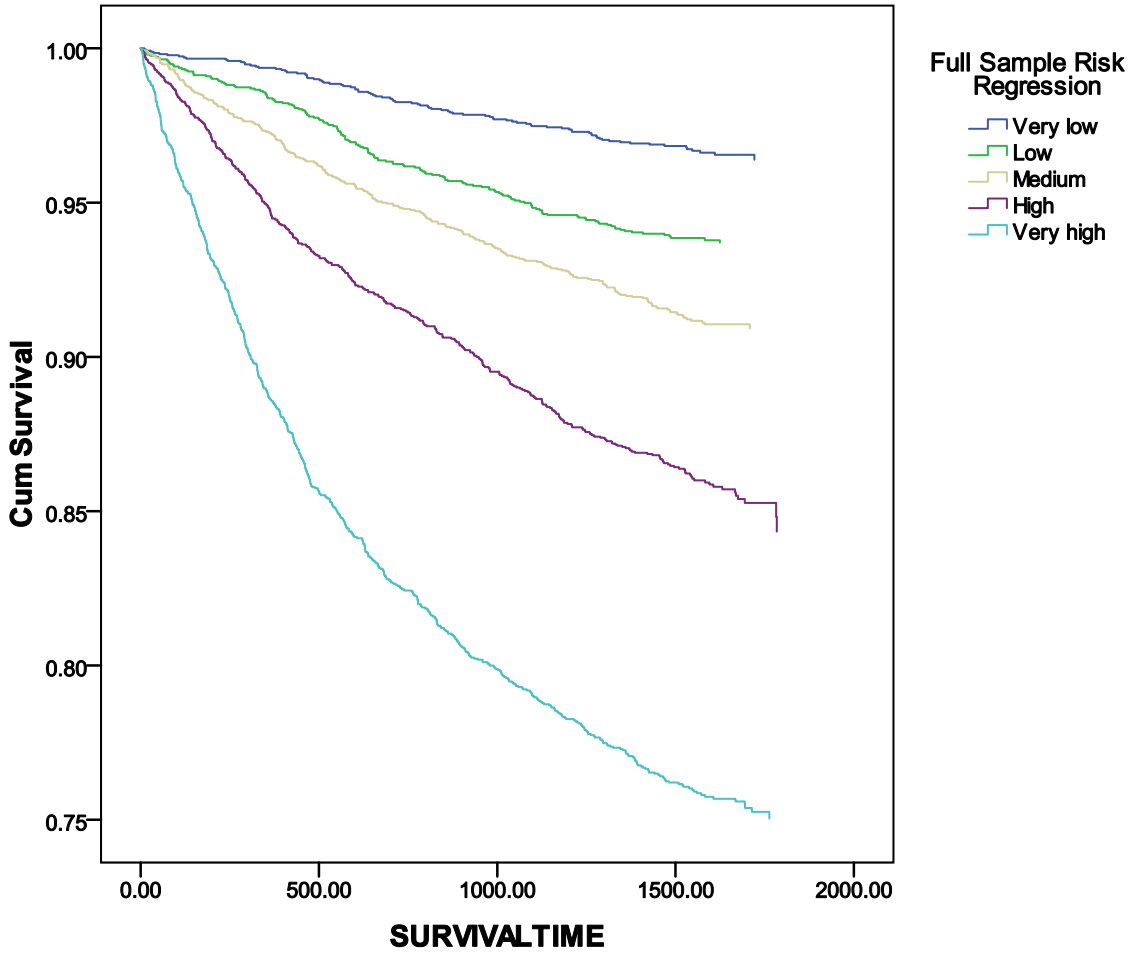


Figure K.2. Survival Analysis on the Five Risk Levels Developed by Taking Five Percentiles of the Scores from the Full Sample Item Linear Regression Scale for the Males of the Construction Sample

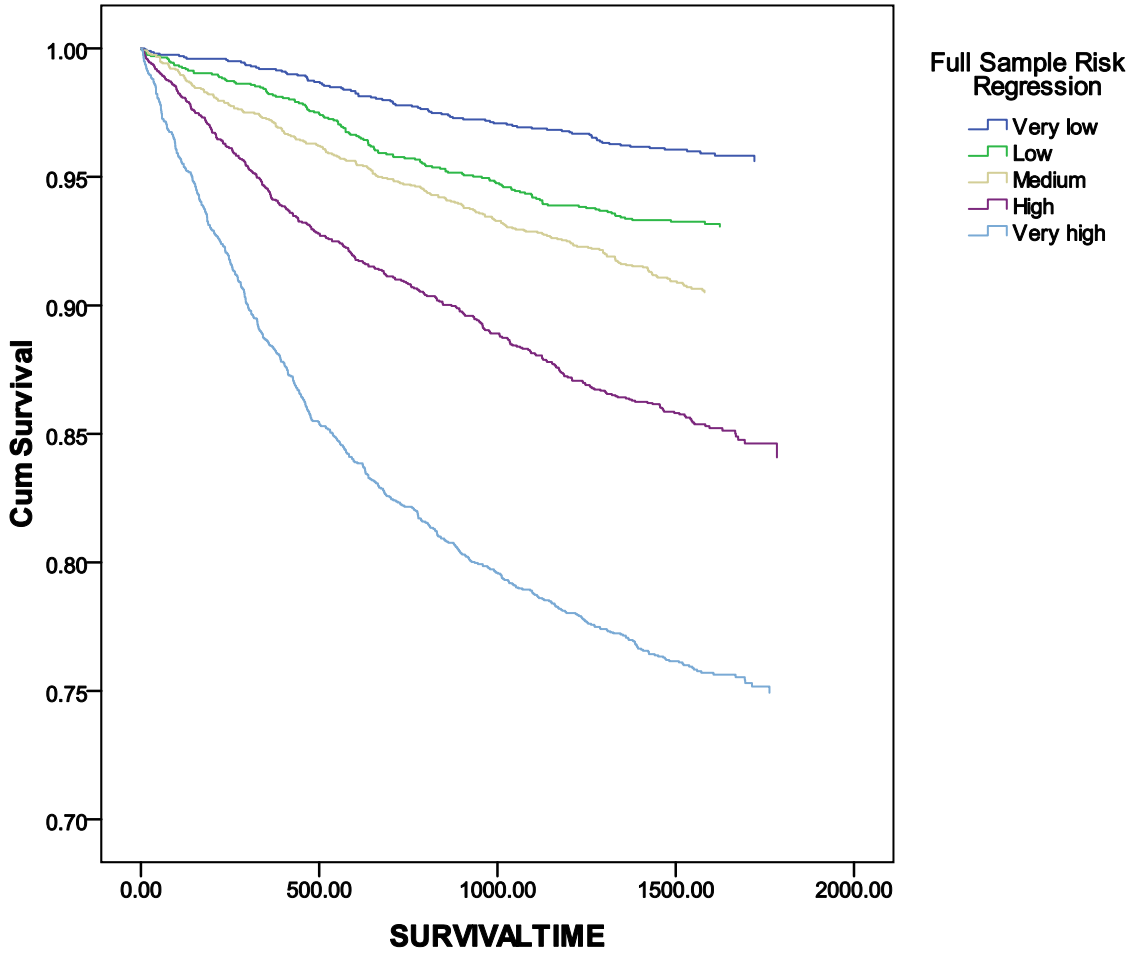


Figure K.3. Survival Analysis on the Five Risk Levels Developed by Taking Five Percentiles of the Scores from the Full Sample Item Linear Regression Scale for the Females of the Construction Sample

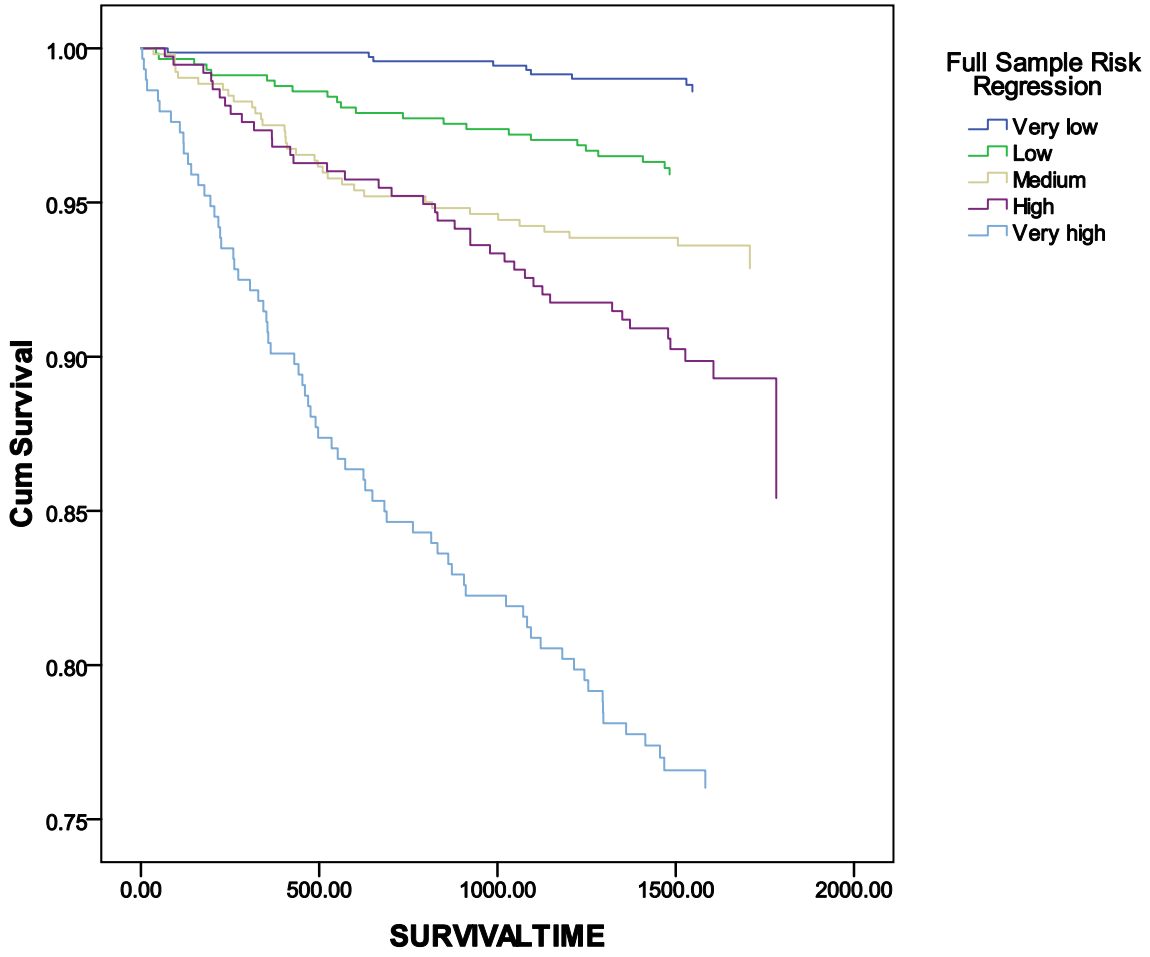


Figure K.4. Survival Analysis on the Five Risk Levels Developed by Taking Five Percentiles of the Scores from the Full Sample Item Linear Regression Scale for the Validation Sample

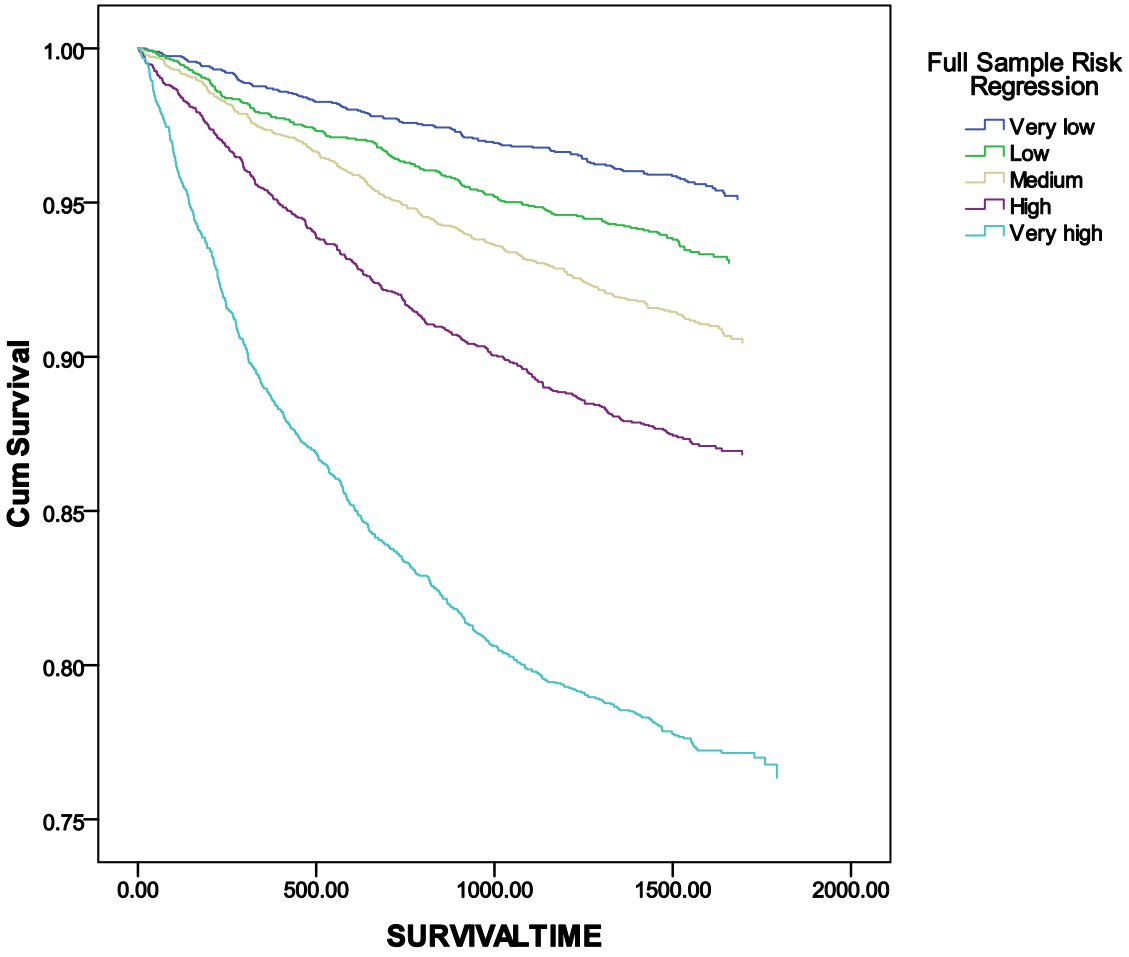


Figure K.5. Survival Analysis on the Five Risk Levels Developed by Taking Five Percentiles of the Scores from the Full Sample Item Linear Regression Scale for the Males of the Validation Sample

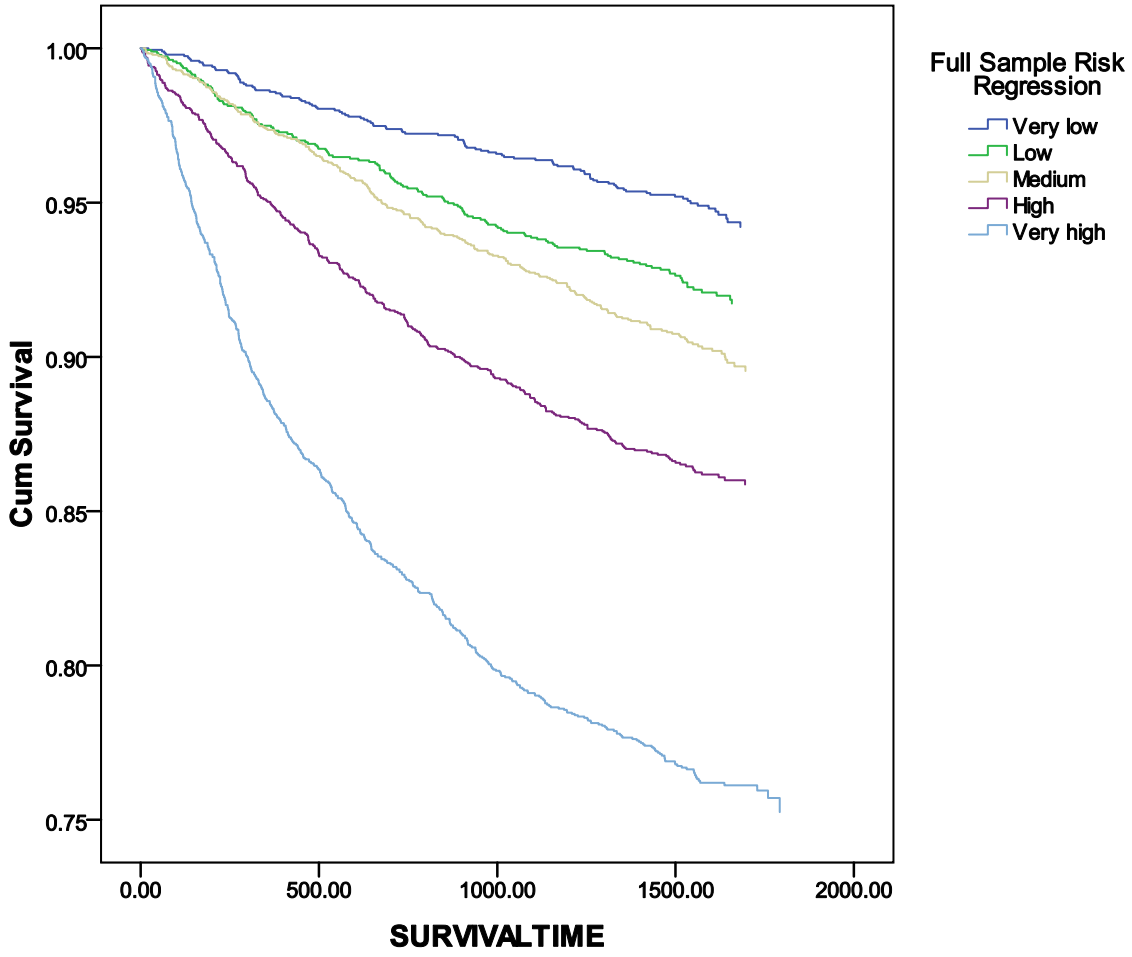


Figure K.6. Survival Analysis on the Five Risk Levels Developed by Taking Five Percentiles of the Scores from the Full Sample Item Linear Regression Scale for the Females of the Validation Sample