


THE ROLE OF AGE IN RISK ASSESSMENT AND CLASSIFICATION


by

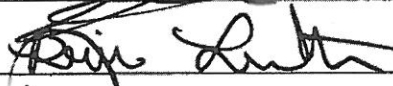
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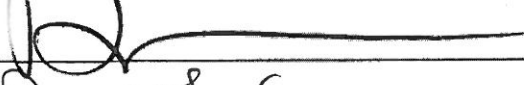


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DEDICATION

This effort is dedicated to my parents, whose unwavering strength and unconditional support have allowed me to pursue my passions.

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TABLE OF CONTENTS

	Page
List of Tables	vii
LIST OF FIGURES	viii
Abstract.....	ix
Introduction.....	1
Literature Analysis.....	9
The Age-Crime Relationship	9
Criminological Theory – Attempts to Explain “Why”	11
Lambda versus Involvement.....	14
Risk Assessment, Classification, and Prediction	16
Risk Assessment.....	16
Risk Classification.....	18
Risk Prediction	18
Ethical Concerns – The Problem of Prediction (and Assessment).....	19
Systematic Biases	21
False Positives and Negatives.....	21
Ethical Concerns with the Use of Age in Risk Classification	22
Past Policy Responses Relating to Age.....	23
The Current State – Age Omitted as a Predictor.....	25
Research Methodology	26
Data	27
Variables and Key Measures.....	28
Principal Independent Variable – Age.....	28
Risk of Reoffending.....	28
Recidivism.....	29
Demographics Variables.....	29
Approach.....	30

Limitations	31
Analyses and Results	32
Discussion and Conclusions	44
Recommendations	48
Future Research.....	49
References.....	51

LIST OF TABLES

Table	Page
Table 1: Demographic Characteristics of the Sample (n=10,749).....	33
Table 2: Criminal History Risk, Total Risk Score, and Recidivism by Age Bands	34
Table 3: Criminal History Risk, Total Risk Score, and Recidivism by Age Categories ..	34
Table 4: Pearson Correlations and AUC between LSI-R Scores/Age Measures and Recidivism	38
Table 5: Spearman Correlations between LSI-R Classifications, Age Groups, and Recidivism	38
Table 6: Logistic Regression Models--LSI-R Total Score	39
Table 7: Logistic Regression Models--Criminal History Risk Score	40
Table 8: Criminal History Risk, Total Risk Score, and Recidivism by Age Categories ..	41
Table 9: Risk Distributions--Original Classifications and Classifications with Age Added	42
Table 10: Correlations with Recidivism--Original Scores and Scores with Age Added..	43

LIST OF FIGURES

Figure	Page
Figure 1: Mean Criminal History Score by Age Bands	35
Figure 2: Mean LSI-R Total Score by Age Bands.....	36
Figure 3: Mean Recidivism Probability by Age Bands	37

ABSTRACT

THE ROLE OF AGE IN RISK ASSESSMENT AND CLASSIFICATION

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Corresponding with the movement towards evidence-based crime policy, risk assessment instruments now guide correctional practice more than ever before. Despite the fact that the age-crime relationship is a longstanding truth within criminology and criminal justice, current age is not a factor which informs assessed risk on the majority of currently used risk tools. This thesis explores whether incorporating age into risk assessment techniques could lead to potential improvements in predicting future offending behavior. The data analyzed comes from one state's department of corrections; information from risk assessments is used in combination with current age to assess the degree to which age matters in predicting future offending. The findings suggest that risk tools would do a more complete job measuring "risk" if current age was incorporated into the scoring of assessments. Lastly, limitations and future research into this topic are discussed.

INTRODUCTION

In recent years, as the demand for evidence-based practices has increased, so too has the use of actuarial risk assessment instruments in criminal justice system decision-making (Hyatt, Bergstrom, & Chanenson, 2011). Such tools rely on the statistical relationships of prior occurrences to inform prospective decision-making (Silver & Miller, 2002). Corresponding with the evidence-based policy movement, actuarial assessment tools are increasingly relied upon in correctional settings. In a correctional context, risk assessment techniques are justified on the grounds of their effectiveness, generally measured through an aggregate reduction in recidivism (Palmer, 1984; Andrews & Bonta, 2010b; Taxman, 1998). While justified on effectiveness grounds, equity or ethical concerns have historically rendered the inclusion of demographic factors impermissible. Characteristics such as sex, race, and age are consistently omitted when assessing one's risk of reoffending. The present research explores potentially incorporating age into one such risk assessment tool. Specifically, if young individuals are more likely to reoffend, is it truly appropriate to ignore age when assessing risk on equity grounds?

Within the field of criminology, there are few agreed upon facts; the age-crime relationship represents one clear exception (Huebner & Berg, 2011; Pritchard, 1979). The literature is clear that age is one of the best predictors of offending on the aggregate

(Quetelet, 1831/1984; Farrington, 1986; Greenberg, 1985; Moffitt, 1993; Sampson & Laub, 1993). Offending behavior tends to peak during the teenage years and then steadily taper-off from there (Moffitt, 1993; Patterson, DeBarse, & Ramsey, 1989). Chapter 2 includes a brief discussion of the major developmental theories of crime in an effort to frame the argument pertaining to why age is a theoretically relevant construct. While various explanations exist in the literature as to the causes of this relationship (Hirschi & Gottfredson, 1983; Sampson & Laub, 1993), these explanations are not the central focus of the present research. The existence of this relationship is, however, of critical importance – young offenders commit a disproportionate share of crime (Langan & Levin, 2002; Wolfgang, Figlio, & Sellin, 1972; Farrington, 1986).

The Risk-Need-Responsivity framework (Andrews & Bonta, 2010a) has emerged as the principal evidence-based framework for implementing correctional research into practice (Polaschek, 2012; Ward, Melsner, & Yates, 2007). In corrections, risk assessment and classification tools measure an individual's probability of reoffending. Correctional and probation officers use the risk "score" to match individuals to the appropriate level of control and services (Andrews & Bonta, 2010a). The RNR framework (Andrews, Bonta, & Hoge, 1990; Andrews & Bonta, 2010a; Andrews, Bonta, & Wormith, 2006) has three central components. First, the risk principle advocates for matching intensity of service to the risk of reoffending. Second, the need principle advocates that treatment target dynamic need factors related to offending behavior. Finally, the responsivity principle suggests individuals with specific dynamic need factors should be appropriately matched to interventions designed to match their learning style and to target said need domain.

Empirical assessments of the RNR model typically find that the four risk factors, of those typically included in fourth generation assessments, “most highly” correlated with offending to be: criminal history risk, attitudes/orientation, emotional/personal, and companions/peers (Andrews and Dowden, 2006). Of these “big four” only criminal history risk is a static construct; it cannot change. More specifically, it can remain the same or worsen but has no potential to improve. The other three factors are termed “criminogenic needs” (Andrews & Bonta, 2010a) because they are both highly correlated with offending and are subject to improvement. The present research is concerned with the implications of relying, in part, on the one static factor – criminal history risk – and its interaction with an individual’s age. Prior research (Forst, 1983; Farrington, 1986) suggests that age may in fact be a better predictor of future offending behavior than even criminal history yet age is omitted from the majority of risk assessment instruments.

At present, the most up-to-date large-scale recidivism study is the Bureau of Justice Statistics (BJS) recidivism study of prisoners released in 1994. The BJS recidivism study tracked 272,111 prisoners released from state prisons in fifteen different states (Langan & Levin, 2002). Four different recidivism measures – rearrest, reconviction, returned to prison with a new prison sentence, returned to prison at all – consistently suggest that younger offenders are more likely to recidivate (Langan & Levin, 2002). However, the risk principle of the RNR model potentially underestimates risk for youthful offenders by ignoring age.

While there was no shortage of academic discussion regarding the use of demographic variables when risk assessment and classification was in its early stages (Gottfredson, 1987), this largely normative debate has since gone silent. The equity concern is that the omission of age from assessment tools potentially means that young offenders have a diminished chance of receiving treatment services. The RNR model, and consequent risk assessment and classification, presently guides which individuals receive treatment or programming. Precisely, if young people are more likely to offend but also less likely to be classified as “high risk” than their older counterparts, are current practices rendered unfair in the effort to remain impartial?

While a variety of risk assessments are used in correctional settings (e.g., Wisconsin Risk tool, ORAS, COMPAS), the Level of Service Inventory-Revised (LSI-R) is the tool that was developed by Andrews, Bonta, and colleagues. The LSI-R is the most widely used and studied correctional risk assessment instrument so it is the most appropriate choice for the present research. The precise technique used to classify individuals into a given risk level varies between assessment instruments. However, the empirical literature suggests that past offending behavior is likely the strongest predictor of future offending. The LSI-R measures criminal history risk through a ten item scale.¹

As stated above, the age-crime curve is one of the most well-established truths in the field of criminology and age is one of the best predictors of future offending (Quetelet, 1831/1984; Forst, 1983; Blumstein, Cohen, & Farrington, 1988a; Piquero,

¹ The items included in the criminal history scale include: any prior adult convictions, two or more prior convictions, three or more prior convictions, three or more present offenses, arrested under age 16, prior incarceration, escape history from a correctional facility, punished for institutional misconduct, any violation of prior community supervision, and any official record of assault or violence (Lowenkamp, Holsinger, Brusman-Lovins, & Latessa, 2004).

Farrington, & Blumstein, 2007). However, this piece of highly relevant information is omitted from most validated risk assessment instruments. Typically, the argument for omitting demographic characteristics (e.g., age, sex, and race) is one built upon ethical or equity grounds. Individuals cannot control demographic factors; put differently, this trait is not the result of a choice made by an individual (Farrington, 1986; Gottfredson, 1987). Additionally, demographics are omitted to prevent extralegal biases from entering into risk prediction.

However, if risk is measured exclusively by criminal history, then two individuals with the same offending history, one 22 years of age and one 52 years old, are assessed as equally likely to reoffend. The age-crime curve fundamentally contradicts such a notion. There are examples in risk prediction and assessment which implicitly acknowledge the relevance of age (e.g., a different tool is used for individuals under 18, the Static-99 uses current age in risk assessment) so the present suggestion is not altogether new.

The scope of this thesis is largely limited to one specific correctional application of the use of such risk assessments – the matching of treatment programs and interventions to justice-involved individuals. While risk classification has been used in other correctional situations throughout history, these other applications (e.g., selective incapacitation) are widely seen as failed experiments (Greenwood & Abrahamse, 1982; Auerhahn, 1999; Auerhahn, 2006; Gottfredson & Gottfredson, 1994). Incumbent in this notion of identifying and incapacitating those career criminals, is the argument that those with a high rate of offending will continue to offend. Since virtually all inmates will eventually be released back into society (Travis, 2005), rehabilitative programs ought to

play a central role in reducing future crime (i.e., preventing recidivism). Unfortunately, preventing crime is not as simple as merely incarcerating the criminals, as some scholars have suggested (*see* van Dine, Conrad, & Dinitz, 1979; Visher, 1987).

Focusing only on treatment matching (grounded in the RNR model), as opposed to other forms of correctional risk prediction, is consistent with the view of many leading correctional scholars (Andrews, 1990; Clear, 1988; Gendreau, 1996). Todd Clear (1988), a leading proponent of the need for rehabilitation in corrections, made this point almost twenty-five years ago, “The choice is not so much whether or not to use prediction approaches in corrections, but when and how to use them. And it is essential that their limitations be understood” (p. 3). While certainly correct that the limitations of risk assessment must be understood, omitting variables such as age may well further limit the predictive ability of such tools in the quest to remain ethical.

The central question relates to the nature of the interaction effect between an offender’s age and their probability of being categorized as a given risk level. Specifically, because an offender is young, it is less likely that he or she will have as severe a criminal history, *ceteris paribus*, as an individual who poses the same true risk of reoffending but is older. Simply, the younger offender has not had the opportunity to amass an adult criminal record. This point necessitates a crucial distinction; true risk and assessed risk are often quite different. From a statistical standpoint, the most logical way to frame this distinction centers on two vital measurement terms: signal and noise (Silver, 2012). The signal of a statistic is the true value; in this example, the signal is the true risk of reoffending an individual poses. Noise can be viewed as the misspecification or

mismeasurement, which subsequently leads to incorrect predictions. In this example, there is ample noise; risk assessment techniques do an imperfect job assessing risk so it is really just a collection of proxy measures (Silver, 2012). The omission of the most salient predictor – age – is a glaring error from both a statistical and ethical standpoint.

Put differently, youthful offenders are hypothesized to act more like moderate or high-risk offenders while systematically more likely to be classified as low risk when relying on a typical actuarial assessment instrument. This results in individuals who are in the prime of their offending careers (Quetelet, 1831/1984; Blumstein et al., 1988a, 1988b; Farrington, 1986; Nagin, 2005) being under-classified. The apparent complement is that older offenders are classified as higher risk than their true risk. This is because criminal history never goes away, or even decreases, in standard actuarial assessment instruments. Many of these older offenders, who have often aged-out of their offending careers or desisted (Nagin, 2005; Maruna, 2001), resultantly occupy some portion of the limited amount of scarce treatment slots. The recent work of Blumstein and Nakamura (2009) attempts to address this significant issue, asking how long after an individual commits their last offense does their risk of reoffending return to that of someone of the same age without any history of offending. Their findings suggest that after some period of crime-free behavior, an individual's estimated rate of offending returns to that of a non-offender of the same age. The desistance literature also makes clear that the offending behavior of individuals with a criminal history will not persist indefinitely (Maruna, 2001; Warr, 1998; Laub & Sampson, 2001). Risk assessment instruments fail to account for this likely possibility.

The main research question at hand is whether including age in risk assessment instruments improves their predictive validity and reliability of the risk assessment instrument. If so, are the ethical concerns with using age too great to preclude its inclusion? The next chapter analyzes the relevant literature pertaining to the age-crime relationship and risk assessment and classification in search of the theoretical explanations suggesting either that age is or is not appropriate in calculating risk level.

LITERATURE ANALYSIS

The current research asks if risk assessment and subsequent classification would be more effective if the current age of an individual were included in the analysis.

Analyzed below is the extant literature concerning: the age-crime relationship; the differences between assessment, classification and prediction; and the ethical concerns relating to the decision to include demographic variables, such as age, in assessment instruments in order to situate the present argument in the existing scholarship.

The Age-Crime Relationship

Criminological research into the relationship between age and crime dates back almost two centuries. In 1831, Belgian scientist and criminologist Adolph Quetelet published *Of the Development of the Propensity to Crime*. The central findings of this research suggest that age and sex are the two factors most highly related to offending behavior. Quetelet (1831/1984) represents the first substantive empirical contribution to the scholarship surrounding the age-crime relationship.

More than a century after Quetelet published his findings, the Gluecks wrote *Predicting Delinquency and Crime* (1959) and added to the body of literature suggesting that young males are responsible for more than their share of crime. The Gluecks studied 500 delinquent boys and matched them to a control sample of 500 non-delinquents in the Boston area. They sought to study the causes of offending among the delinquent cohort

(Gleuck & Glueck, 1959). Their findings suggest that delinquent boys were more likely to feel unloved and act impulsively. The data collected by Sheldon and Eleanor Glueck has been analyzed in recent research surrounding age and its relationship to criminal involvement (*e.g.*, Sampson & Laub, 1993) and is consistent with suggestions that low self-control is essential in predicting criminality (Gottfredson & Hirschi, 1990).

In another groundbreaking study, Wolfgang, Figlio, and Sellin (1972) followed a birth cohort of Philadelphia boys into adulthood. This study had two central findings: adolescent boys and young men are responsible for a disproportionate amount of crime and a small percent of this birth cohort (about 5%) were responsible for about half of the crime. This study was later used as support for why selective incapacitation as a potentially feasible crime control strategy.

David Greenburg (1977; 1985; 1992), more recently, made significant contributions to the research literature surrounding age and crime. Greenburg (1977) investigates the age structure of society and its relationship to crime. The author argues that the changing age structure of society in modern times leads to more juveniles committing serious offenses. This argument appears to provide preliminary support for a central hypothesis of Moffitt (1993): the discrepancy between biological age and social age is responsible for a great deal of adolescent delinquency. While it is well-understood that young people commit more than their share of crime, methodological deficiencies make a definitive answer to causal questions not yet possible (*see* Blumstein, Cohen, & Farrington, 1988b; Lauritsen, 1998). But is it possible to make valid inferences about individual behavior from aggregate level data? (Piquero, Farrington, & Blumstein, 2003).

Criminological Theory – Attempts to Explain “Why”

Few agreed-upon empirically established facts exist within the field of criminology. One notable exception to this rule – the age-crime curve – shows how offending behavior, on the aggregate, varies with age. Evidence supporting this relationship is long-established (Quetelet, 1831/1984; Cloward & Ohlin, 1960; Matza, 1964; Wolfgang, Figlio, & Sellin, 1987; Farrington, 1986; Greenberg, 1985). Throughout the more recent development of criminological theory development, competing explanations for the age-crime relationship are offered (Moffitt, 1993; Sampson & Laub, 1993; Gottfredson & Hirschi, 1990; Patterson, DeBarse, & Ramsey, 1989). A review of the most prominent criminological theories follows. Stated simply, the extant literature is remarkably consistent in showing that youthful² offenders are responsible for a disproportionately large amount of crime.

Early attempts to explain offending behavior centered on either sociological or interpersonal explanations; crime was the result of social forces exerted on the individual or an individual-level deficiency, which caused them to choose to offend (Matza, 1964; Robins, 1978). Hirschi (1969) argues that insufficient social bonds are the reason individuals are not restrained from offending. Social control theory, as it has been termed, provides the groundwork for some of the more recent theoretical explanations, namely Sampson and Laub’s (1993) age-graded theory of crime.

The recent literature pertaining to the explanation of the age-crime relationship develops through one of two frameworks. Broadly, theories are either general or

² The precise definition of youthful varies throughout the literature. Certainly young adults are to be considered in this subgroup of youthful offenders.

developmental. General theories attempt to explain why some individuals commit crime and other do not (Gottfredson & Hirschi, 1990) while developmental theories endeavor to explain how and why offending behavior changes over a person's lifetime (Patterson et al., 1989; Moffitt, 1993; Sampson & Laub, 1993).

In their *General Theory of Crime*, Gottfredson and Hirschi (1990) posit that a single latent trait, low self-control, resulting primarily from improper childrearing practices, is the causal mechanism best able to explain criminal behavior. The General Theory holds that this latent trait persists through the life course. After considering the age-crime curve, critics questioned why offending declines after adolescence if the latent trait remains. The authors believe that low self-control does persist but that most individuals begin to substitute with other analogous acts (e.g., drinking, risky sexual encounters).

Patterson and colleagues (1989) marked the beginning of a new theoretical approach to explain the change in offending behavior over the life course. This developmental theory acknowledged that offending patterns could not be entirely explained through one factor (low self-control) but rather it changed with maturation. This introduction of the developmental perspective laid the groundwork for a variety of theories in this vein.

Developmental criminology drastically evolved when Moffitt (1993) proposed her dual-taxonomy, carefully elaborating on the precise distinctions between adolescent-limited and life-course persistent offenders. A central theoretical contribution to the discipline, Moffitt's dual taxonomy is a targeted attempt to reconcile the following two

seemingly conflicting facts: most (virtually all) adults displaying antisocial behavior were antisocial juveniles but in the majority of juveniles displaying antisocial behavior, it did not persist into adulthood (Moffitt, 1993; Robins, 1978; Pritchard, 1979). Incorporating two different offending trajectories, Moffitt was able to differentiate between age-appropriate adolescent deviance and those whose offending behavior would persist into adulthood (i.e., those with persistent low self-control).

With their age-graded theory, Sampson and Laub (1993) also contribute profoundly to the extant literature pertaining to the explanation of criminal behavior. The most intuitive manner to explain their theory is that it is social-control theory (Hirschi, 1969) without ignoring the developmental (Patterson et al., 1989) nature of criminality. Sampson and Laub (1993) explain that societal bonds are what keep individuals from offending, rather than some underlying latent trait. However, they address the age-crime relationship by saying that the relevant bonds change as one ages. While bonds to parents, teachers, or siblings are likely responsible for preventing offending early in life, these factors evolve. A prosocial marriage or job can potentially provide a transition or “turning-point” for an individual who was offending earlier in their development.

The argument that young offenders commit more crime comes with a necessary corollary; older individuals are responsible for relatively less crime. This process of desistance, or ceasing offending behavior, has received drastically increased research attention since the late 1990s (Warr, 1998; Maruna, 2001; Laub, Nagin, & Sampson, 1998; Laub & Sampson, 2001). However, the desistance process is not accounted for when a risk instrument assesses risk through criminal history. Once an individual has a

criminal history, this will never go away. The concept of redemption (Blumstein & Nakamura, 2009) suggests that after a crime-free period of time, criminal history becomes less predictive of future crime. Nevertheless, crime-free periods of time do not reduce one's criminal history score.

The discussion of developmental versus general theories leads directly to two theoretical explanations central to the desistance literature – Blumstein and colleagues' (1988a, 1988b) notion of Lambda (rate of offending) versus criminal involvement.

Lambda versus Involvement

The preceding sections detail the theories which attempt to explain why young people commit more than their share of crime, as compared to older individuals. The following discussion represents the corresponding “how” pertaining to this phenomenon. In order for young offenders to commit more than their share of crime, offending must correspondingly decrease at some point in the life course. However, the current section focuses on the two different mechanisms that can potentially bring about this reduction. Alfred Blumstein and his colleagues first brought this discussion to the forefront, differentiating between involvement and rate of offending.

The first explanation for offending decreasing with age – termed involvement – suggests that some individuals who offended early in life refrain entirely from offending behavior as they age. That is, many delinquent juveniles do not go on to commit crime as adults. This explanation is consistent with Moffitt's (1993) model of the adolescent limited offender. The second explanation – a decline in the rate of offending (initially termed lambda by Blumstein and colleagues) – is consistent with Gottfredson and Hirschi

(1990) and their General Theory of Crime. Individuals committing crime early in life due to low self-control begin to offend less frequently during the course of their maturation. As impulsive teenagers enter and move through their twenties, criminal behavior decreases. Various explanations have been proffered for this “aging-out” process. Newly developed prosocial bonds act as informal social controls (Hirschi, 1969); individuals may begin to internalize societal norms and modify behavior accordingly (Sampson & Laub, 1993); the underlying latent trait still persists (low self-control) but manifests itself through other analogous acts (drinking, drug-use, gambling, etc.) which are no longer criminal in adulthood (Gottfredson & Hirschi, 1990). This phenomenon, termed desistance, continues to receive considerable research attention in various applications (Blumstein et al., 1988a, 1988b; Maruna, 2001; Laub & Sampson, 2001; Piquero et al., 2003, 2007; Blumstein & Nakamura, 2009).

Though the majority of research is hampered by methodological shortcomings³ (Lauritsen, 1998; Blumstein et al., 1988; Gottfredson and Hirschi, 1986; Greenberg, 1992), findings suggest that both factors matter. That is, offending decreases on the aggregate with age because both those individuals offending are doing so less frequently and because some individuals have stopped their offending behavior all together.

Incumbent in the argument that criminal offending is less likely as individuals age is one major difficulty alluded to above – the criminal justice system aims to intervene when people are caught breaking the law. When an individual is arrested, tried, and

³ These methodological difficulties include: a potential incapacitation effect (i.e., offending decreases because the criminals have already been incarcerated); the inability to answer questions of a causal nature with cross-sectional data; offenders improving their ability to commit crime without getting apprehended with maturation; substitution of property and nonviolent offending behavior for violent crime which is less likely to receive the limited time and resources of police.

convicted of a criminal offense, one of two things typically happen: probation or imprisonment. When an individual is imprisoned, the ability to commit new criminal offenses is curbed. For less serious offenses, when an individual receives probation, he is under justice system surveillance in the community. This has one of two potential results: individuals stop offending as a result of the increased monitoring or apprehension occurs resulting from a subsequent offense due to the increased monitoring. In any of these three potential scenarios, one thing is true; the criminal justice system makes it less likely that individuals offend as they age. In conclusion, it is impossible to fully determine, at least with current approaches to data collection, the extent to which the criminal justice system impacts rate of offending (λ) and/or involvement both at the individual and system level of analysis.

Risk Assessment, Classification, and Prediction

The evidence-based movement within the criminal justice system has brought about an increased reliance on risk assessment, classification, and prediction. These three terms are sometimes inappropriately used interchangeably; in reality, each is a distinct concept or process. In correctional applications, all three terms frequently relate to the broader concept of estimating the risk on an individual engaging in future criminal behavior. The current section aims to explain each one and then draw distinctions between the three.

Risk Assessment

Risk assessment is the practice of using actuarial assessment tools to approximate an individual's probability of engaging in a future activity (Bonta, 2002; Andrews, Bonta,

& Wormith, 2006; Andrews & Bonta, 2010a; Clements, 1996). Don Gottfredson (1987) implicitly acknowledged that the role of risk assessment in criminal justice is to do one of two things: classify or predict. Risk assessment in criminal justice settings has gone through four distinct developmental stages (Andrews, Bonta, & Wormith, 2006). First generation risk assessment typically consisted of professional judgment without any formal structure or assessment tool. Second generation risk assessments, while an improvement because they were empirically related to the likelihood of reoffending, were largely atheoretical. Additionally, second generation tools measured primarily static factors; static factors cannot be targeted for improvement through correctional intervention. Third generation tools measure both static and dynamic risk factors. Static risk is typically operationalized through variables relating to criminal history (e.g., number of prior arrests, incarcerations, failures on supervision). Dynamic risk factors, also termed needs, included on third and fourth generation assessment instruments measure constructs like: substance abuse/dependence; antisocial personality, peers, and values; educational and employment deficiencies; and housing instability (Andrews & Bonta, 2010a). Fourth generation tools represent an improvement over third in that they include a case management component (Andrews, Bonta, & Wormith, 2006).

There are known problems with and critiques of risk assessment techniques used by correctional agencies (Baird, 2009; Silver & Miller, 2002; Gottfredson & Moriarty, 2006). More specifically, there is a longstanding and ongoing dialogue about the appropriate application of risk assessment techniques in corrections (Andrews, 1990; Clear 1988; Austin, 2003; Baird, 2009). In other words, at what stages in the criminal

justice system should risk assessments be relied upon? Previously, risk assessments have been used at the sentencing phase, at the parole/release stage and within community corrections.

Risk Classification

Once risk has been measured using an actuarial assessment instrument, one of two things typically follows; the first option is classification. Stated simply, classification is the process of assigning individuals or items into like groups. Risk classification has been extensively covered in the criminal justice literature (*see* Glaser, 1987; Sechrest, 1987; Andrews & Dowden, 2006; Clear & Gallagher, 1985). Typically, the purpose of classification strategies is to respond similarly to the individuals who comprise a given risk level. For instance, from a public safety perspective, it would seem appropriate to incarcerate individuals who will likely commit future crime (high risk) while monitoring low risk individuals in the community (i.e., probation).

Risk Prediction

Risk prediction has been defined as the process of estimating the likelihood of a future state or occurrence (Gottfredson, 1987). In the past, risk prediction has been misused in criminal justice settings as a rationale for sentencing length and severity (Austin, 2003). Since prediction is an imperfect science (i.e., the prediction is frequently incorrect), it should not be used to determine the extent to which an individual is punished. Don Andrews (1990) said it best, over twenty years ago: “In brief, let seriousness of the offense determine severity of punishment, *and* let risk determine intensive rehabilitative effort (emphasis in original)” (p. 517). The section below dealing

with past policy responses makes two things clear: the RNR model is not a risk prediction framework, but one focused on classification, and the justice system must refrain from using risk assessment instruments for prediction.

Ethical Concerns – The Problem of Prediction (and Assessment)

This section represents an effort to differentiate the normative concerns relating to criminal justice risk prediction techniques, more generally, from those specific to the risk principle of RNR. With regard to actuarial risk prediction, one scholarly disagreement is centered on methodology (Gottfredson et al., 2006; Silver & Miller, 2002; Clear, 1988). Although on average, these prediction methods perform better than chance (50-50), they are in no way exact predictors. They can range in precision from approximately 40-70% accurate (Gottfredson & Moriarty, 2006). With regard to different applications, it makes sense that the permissible margin for error will vary accordingly based on some collective assessment of the worth of a false positive or negative in a given situation. For instance, it is viewed as a great impingement on one's human rights to be deprived liberty (incarcerated) if there is any chance that the individual is innocent.

A parallel argument exists in risk prediction. If we use risk prediction to determine sentence severity, the potential emerges that an offender will receive too harsh or lenient a sentence in relation to their probability of reoffending. This is not an acceptable use of prediction as it relates to corrections (Auerhahn, 1999). However, if we let seriousness of the offense dictate sentence severity, and only use risk of reoffending to determine what treatment an offender is subjected to (Andrews, 1990), doesn't the acceptable margin of error change? The current argument is that an erroneous

assessment in this scenario is a much less worrisome violation of one's liberty. The magnitude of liberty violation coming about if already incarcerated offenders receive some treatment program, which does not lengthen their sentence, on the grounds that they are assessed as being a high risk of reoffending when in fact they are not can be debated. It is the reverse of this situation, a high risk offender being classified as low risk and resultantly deprived of programming, which appears especially problematic.

The strength of correctional risk prediction tools is to distinguish between groups (Gendreau, 1996). These tools do a better job when asked to label a group of offenders as high risk of reoffending. Conversely, if you knew that 80% of high risk offenders (hypothetically) will reoffend and then were presented with five high risk offenders, such risk prediction would be of little or no help in determining which one of the five would not reoffend. Auerhahn (1999) indicates this limitation has been understood for almost fifteen years now: "What this means is that while we can predict with some confidence that a certain proportion of offenders will be career criminals or high-rate offenders, prediction to the level of individual offenders is very difficult" (p. 708). This explains why selective incapacitation has little chance of reducing crime while subjecting all high-risk offenders to programming is the most cost-effective method of allocating spaces in treatment. A guiding principle can be synthesized from this example: use risk assessments to distinguish between groups but be wary about using them to distinguish between individuals within a specific risk group or level.

Systematic Biases

In presently used fourth generation risk assessment tools, current age is not normed into the instrument. Resultantly, there is a substantial risk that the LSI-R, and similar such instruments, introduce systematic bias. In other words, a young offender of a given risk score poses a higher true risk of reoffending than an older individual with the identical risk score. An apt parallel exists pertaining to women and “gender neutral” assessment instruments. Salisbury and colleagues (2009) suggest that standard risk assessment tools may systematically overstate female risk, which would produce undesirable consequences both in terms of costs and effective outcomes. This means that while gender-blind assessment instruments may well distinguish between females of different risk levels, they might very well overstate the risk of a female reoffending in comparison to a male offender of the same risk level. The same issues pertain to age; a twenty five year old, with the same total risk score as a forty five year old, is more likely to continue his offending behavior.

False Positives and Negatives

A central ethical concern with risk assessment tools and subsequent classification or prediction is the potential for false positives and negatives. Stated simply, a false positive occurs when an individual who is unlikely to reoffend is classified as a higher risk level than his or her true risk level. A false negative is the opposite – labeling an individual who poses a high risk of reoffending as a lower risk than his or her true risk (Silver & Miller, 2002). Although incorrect classification is cause for pause, it must be compared to the next best alternative. Additionally, tools can be systematically normed so as to increase or decrease the likelihood of a false positive or a false negative.

Ethical Concerns with the Use of Age in Risk Classification

There are substantial fairness issues relating to the use of criminal history alone as a component of the proxy measure which is relied on to estimate the probability of reoffending. When relying on the RNR model to determine who warrants a space in a treatment program, first-time offenders (those without any criminal history) are more likely to be passed over. We know that first time offenders are more likely to be younger than individuals with prior offending records. So from an age perspective, first timers are more likely to offend again. (Nagin, 2005). We also know that young individuals are more likely to be first time offenders (Piquero et al., 2007). However, extending Auerhahn (1999), we do not know who among this large group of first-time offenders will be the ones who do in fact reoffend. Using criminal history risk as a component of risk score makes it less likely that offenders earlier in their careers will be placed into correctional programming. Instead, relying on criminal history, not until offenders reoffend are they likely eligible for treatment as part of their sentence.

First, the relationship between age and risk level must be unpacked. Since age is unable to be altered or adjusted by anything other than the passage of time, it only makes sense to view the age of an individual as an independent (x) variable in this discussion. Risk level is clearly the dependent (or outcome) variable, as a number of factors, one being age, are components which have some impact on an individual's risk level. The work of Daniel Nagin and colleagues on trajectories of offending maintains that an individual goes through distinct, rather predictable, stages of offending behavior. Generally, a given individual is most likely to offend during his late teens and early

twenties (Nagin, 2005). However, a first-time offender by definition will not have a criminal history and this point brings with it important implications.

The current study aims to test if the LSI-R generally, and the criminal history subscale specifically, does an incomplete job operationalizing risk of future reoffending by ignoring current age. In this study, this is not a matter up for normative debate; rather, it is an empirical question. If we were doing a complete job (which is of course impossible) risk assessments of an individual's likelihood to reoffend would always be correct. However, we understand that this technique does an imperfect job but we use it anyway (Latessa, 2004). A life course theory of criminology suggests that many of these "hardened offenders" have actually already aged-out of crime (Laub & Sampson, 1993). The risk principle, as it currently exists, may result in the systematic diversion of treatment services away from younger offenders (in favor of older offenders). Trajectories of criminal offending (Nagin, 2005) suggest once he or she reaches a certain age, an individual will become increasingly likely to desist from crime (Laub et al., 1993). It is first necessary to determine how long an ex-offender must remain crime-free so their risk of offending returns to the age-appropriate level for someone without a history of offending.

Past Policy Responses Relating to Age

In response to a multitude of criminal justice problems including, but not limited to, prison overcrowding, rising crime rates, and both deterrence and rehabilitation being viewed as ineffective crime control strategies, a promising new approach emerged during the early 1980s. This novel approach – termed selective incapacitation – sought to

identify high-risk individuals early in their offending trajectories and incapacitate them for longer periods of time (Greenwood & Abrahamse, 1982; Forst, 1983, 1984; Auerhahn, 1999). In this instance, the policy was to sentence offenders more harshly in an effort to control crime and more efficiently allocate prison space (Forst, 1983, 1984).

Unfortunately, this policy response was unsuccessful (Greenwood & Turner, 1987). Some leading correctional scholars were aware of the inchoate logical flaws from the inception but could not prevent this proposed solution (see Shannon, 1985; Von Hirsch & Gottfredson, 1983; Cohen, 1983) while others were supportive at first but quickly saw the inadequacies of such an approach (Greenwood & Turner, 1987).

Succinctly, assessment instruments do a moderately effective job of identifying high risk individuals but are unable to distinguish between said individuals. This led to the problem of false positives (i.e., low risk offenders being classified and subsequently sentenced as if they were high risk).

This accumulated knowledge suggests that a single risk assessment is likely not appropriate for all stages along the criminal justice system. In the development of the Ohio Risk Assessment System (ORAS), Latessa and colleagues (2010) explicitly acknowledge this fact. The ORAS is technically a suite of four tools, each one designed for use at a different stage: pre-trial, community supervision, institutional intake, and community reentry. Through this framework, the present argument can be properly understood. Inclusion of age in two of these two stages (pre-trial and intake) could produce results alarmingly similar to those stemming from attempts at selective incapacitation. However, the risk of overexposing younger justice involved individuals to

programming and treatment is less worrisome from an ethical standpoint. This could mean assigning treatment to young people who are high need but lower risk because they lack a criminal history.

The Current State – Age Omitted as a Predictor

Presently, in fourth generation assessment instruments, age is collected as a demographic variable but does not impact risk score. Age is categorized with other “demographic variables” which are ethically barred from inclusion (Gottfredson, 1987). One state’s department of corrections has already designed their own risk instrument which does include age when scoring risk. Their approach accomplishes two very important tasks: young people get a risk increase, and after a certain age, risk points begin to get subtracted. In another vein, the Static-99 is another relevant point of discussion. The Static-99 is the risk assessment tool used for sex offenders and *does* include current age in the scoring scheme (Hanson & Thornton, 1999). This example is slightly different because the underlying cause of sexual offending does decrease, as a result of biology, as one ages.

Age is unmistakably different than both sex and race – it changes predictably and constantly (Portillo, 2010). Like a dynamic risk factor, age changes; like a static factor, it cannot be altered. While age is not the result of a choice made by an individual, it is without question a dynamic factor. Therefore, it fits into its own category and ought to be treated as different than sex or race. However, the argument here is that age is not the type of demographic variable which must be barred from inclusion on ethical grounds; its inclusion on the Static-99 lends initial, yet very tangible, support to this claim.

RESEARCH METHODOLOGY

From the previous chapter, two points are clear: age historically relates to offending and most actuarial assessments used to assess the risk of future criminal behavior do not include a variable which concretely accounts for current age. The present research seeks to answer the following question: would risk assessment and classification instruments, such as the Level of Service Inventory-Revised (LSI-R), be better able to predict reoffending behavior if an individual's current age was used as an independent variable? Extending the approach of Austin and colleagues (2003), the present research will primarily rely on logistic regression modeling to assess the degree to which a risk assessment that includes age can more effectively predict recidivism as compared to those that rely on criminal history and/or dynamic need factors alone.

Various sub-questions must first be explored in the effort to attempt to answer the global question raised above. First, how does the inclusion of age in risk classification alter the prevalence rates of a given risk classification within various age groups? For instance, the sole reliance on criminal history as a risk measure is hypothesized to under-classify younger individuals since they have not had the time to amass enough of a criminal history to be classified as high risk. Therefore, it is expected that including age will move younger offenders to a higher risk level, which is theoretically consistent with the age-crime curve. A second question relates to age and its interaction with recidivism

likelihood. Across age groups, are individuals of a given risk level equally likely to recidivate? A finding that within risk levels, younger individuals are more likely to recidivate would provide empirical support for the age-crime relationship. Additionally, this would suggest that the inclusion of age as a predictor variable would improve the predictive capacity of classification techniques. Lastly, it would suggest that presently employed assessments systematically underestimate the risk level for youthful offenders.

Data

The data used in this study comes from a Midwestern state's department of corrections between the years 2005 and 2008. Individuals included in the analyses must meet the following minimum criteria: have a complete LSI-R assessment; have been under supervision in the community for up to a 36-month follow-up period so as to permit tracking three-year recidivism outcomes; have valid date of birth data so current age can be computed. Individuals who do not meet the above criteria are not included in the database; the analysis sample consists of 11,146 formerly incarcerated individuals.

The central variables used in the included analyses are: a completed LSI-R assessment with complete risk and need information, date released onto community supervision (representing the date an individual is eligible to recidivate), a dichotomous indicator of recidivism, current age of individual, and an individual's sex. The recidivism measure is a composite indicator which includes any new conviction or a return to incarceration.⁴ The specific research questions explored in this thesis are:

⁴ In this dataset, individuals released from prison were far more likely to be technically violated and subsequently returned to incarceration than to receive a new conviction. As such, the composite measure of recidivism was most appropriate. A full justification for this approach can be found in the extant literature (*see* Huebner & Berg, 2011).

1. How do criminal history risk (computed with LSI-R items 1-10) and LSI-R total risk scores vary by age? Specifically, are younger individuals less likely to have amassed a criminal history?
2. How does the inclusion of age in risk assessment impact the age distributions in given risk classification categories?
3. Does the inclusion of age when determining an individual's risk level improve the predictive ability of the LSI-R to estimate the likelihood of reoffending behavior?

Variables and Key Measures

Principal Independent Variable – Age

The central variable of interest was age at time of LSI-R assessment. The age variable was computed as the difference between an individual's date of birth and the date of LSI-R intake assessment. From a theoretical standpoint, it would have been preferable to use release date, as opposed to assessment date, to compute the age variable. Regrettably, release date was missing for approximately 15% of the sample, so the decision was made to use age at LSI-R assessment. Additionally, since the current research question is concerned with the potential of adding age to risk assessment, it makes theoretical sense to use the age at the time of assessment.

Risk of Reoffending

Using data from completed LSI-R assessments, risk of reoffending is operationalized in two different ways. First, risk is measured using the criminal history subscale of the LSI-R assessment. The criminal history subscale, a ten-item instrument, can take on values between zero and ten. The second measure of recidivism risk is LSI-R total score, a 54-item instrument, which contains the criminal history subscale as well as

additional measures of dynamic need factors. The total score measure is a considered a global measure of risk because it accounts for these additional dynamic risk factors.

Recidivism

In this study, recidivism was tracked for three years following release from a secure facility. A composite measure of recidivism was used which included either a new conviction or a return to incarceration. After exploring the potential of using only a new conviction to measure recidivism, the choice was made to use the composite measure. The three-year reconviction rate was only 20.1%; this rate was especially low in comparison to the findings from the extant literature. However, the return to incarceration rate was much higher, at 52.9%. This discrepancy suggested the potential that this jurisdiction was using technical violations as a means of addressing new crimes, as well as true technical violations. It requires fewer scarce resources to technically violate a former prisoner than to pursue new charges and a subsequent new conviction. The potential existence of this practice is unsettling from a due process standpoint; it also suggested a need to use a more inclusive measure of recidivism than simply reconviction. In the current sample, the global recidivism rate was 57.0%.

Demographics Variables

Demographic characteristics will be included in the models as control variables. The dichotomous indicators included are sex (coded as 0=female) and race/ethnicity (coded as 0=white). Prior research suggests the need to include demographics as control variables in regression models.

Approach

With the type and nature of the research questions at hand, and the related choice of the dataset used in this analysis, regression modeling appears most appropriate. When analyzing a dichotomous dependent variable, as is the case when looking at recidivism, binary logistic regression is the appropriate choice. The iterative process of building subsequent models is an effective technique for observing the relative improvement gained from including additional variables. The change in the log-likelihood from one model to the next quantifies this approximate improvement. In its raw form, the present dataset was not conducive to analysis. In order to generate the regression models, preliminary steps were first required, discussed below.

In order to create an analytic file, or a “clean” dataset, two characteristics were needed: each individual was only represented once in the data and all individuals included in the dataset had complete age and LSI-R assessment information. For individuals with multiple LSI-R assessments, the decision rule was to use the first complete assessment. This rationale allowed the fewest number of cases to be removed from the data and also allowed the longest duration to track recidivism for individuals who were assessed more than once. Using SPSS, the data was first restructured so that each unique identification number represented one, and only one, line in the data. Once restructured, cases missing necessary variables were removed. In order to ensure that data was missing at random and not missing systematically, comparative analyses were conducted between those cases removed and those remaining. The differences between the two subsamples were substantively small which suggests that the removal of missing data was unlikely to produce systematically biased findings.

The study assesses the predictive and incremental validity of demographics, criminal history risk (static risk), LSI-R total risk, the “Central Eight” criminogenic needs (dynamic risk) (Andrews & Bonta, 2010a), and most centrally, age at LSI-R assessment. An important feature of the current study is the use of a dataset that includes the entire correctional population released from an individual state in the United States for a four-year period. The sheer size of the dataset suggests generalizability of the findings concerning the predictive utility of age, pertaining to reoffending behavior.

Limitations

One unavoidable limitation results from using logistic regression. While there are approximate goodness-of-fit measures (e.g., Pseudo R^2 , log likelihood ratio, 2x2 contingency table), there is not a traditional R^2 to approximate goodness-of-fit. As a result, the findings present both the negative log likelihood and the Nagelkerke R^2 .

Additionally, while the criminal history subscale of the LSI-R was available, an individual’s actual offending history (i.e., rap sheet) was not available. If an event-based criminal history measure was available, an approximate age-specific measure of Lambda could be calculated to measure how rate of offending varied over the life-course.

ANALYSES AND RESULTS

This thesis explores two central questions relating to age and risk assessment and classification. First, how do risk assessment scores and recidivism rates vary across age? Secondly, would risk assessment tools better predict reoffending behavior if age was an included variable? The construction of the present chapter reflects this distinction. The relationship between current assessment instruments and age comprises the initial section; the first set of analyses and findings provide a justification for the need to conduct the second set of analyses.

The second section proposes an initial, hypothetical technique for incorporating age into assessment practices. The approach I use to incorporate age into assessment scoring is theoretically informed. From a psychometric standpoint, I do not suggest that this technique represents the “ideal” approach. Rather it represents an exploration of how adding age to assessment could potentially improve classification. The second section represents an exploration of, rather than a proposed solution to, the question of if and how age might potentially be incorporated into assessment tools moving forward. Table 1 displays the demographic characteristics of the analysis sample.

Table 1: Demographic Characteristics of the Sample (n=10,749)

Variable	Percentages
Sex	
Male	89.6
Female	10.4
Race/Ethnicity	
White	62.9
Black	26.6
Hispanic	8.5
Other	2.0
Age Category	
16-27	28.0
28-35	22.5
36-42	20.0
43 and older	28.4
Mean Age	35.9
LSI-R Risk Level	
High	2.3
Moderate/High	11.4
Moderate	38.4
Low/Moderate	38.4
Low	9.5

The first set of analyses conducted assesses the degree to which the age-crime relationship is exhibited in this dataset. The last column in Table 2 suggests the presence of the age-crime relationship in the analysis dataset. In older age groups, the likelihood of recidivism decreases steadily. In Table 2, column 3 shows that criminal history increases steadily until the late thirties and then begins to decline. The present sample is comprised of individuals who are being released from prison onto community supervision (probation or parole). It is impossible to empirically assess the degree to which the reason criminal history begins to taper off in the early thirties. It is very plausible that this tapering off of criminal history scores is a result of selection bias. In other words,

individuals with severe criminal histories are no longer being released at this point in their criminal career. Middle aged offenders are not the focus of the present research, which seeks to assess the extent to which young offenders are underclassified. Next, the analyses presented assess the following questions: how does LSI-R total risk score and criminal history risk score (computed with LSI-R items 1-10) vary by age and specifically, is risk being systematically underestimated for younger individuals?

Table 2: Criminal History Risk, Total Risk Score, and Recidivism by Age Bands

Ages	Prevalence Rate	Criminal History Score	Total LSI-R Score	Recidivism Rate
18–19	1.1	4.05	24.92	0.800
20–21	3.9	5.18	26.63	0.765
22–23	6.9	5.87	26.27	0.702
24–25	8.2	6.16	25.65	0.668
26–27	7.9	6.35	25.55	0.632
28–29	7.0	6.26	24.42	0.599
30–32	8.1	6.46	24.62	0.588
33–35	8.4	6.34	24.16	0.570
36–38	8.5	6.35	24.35	0.575
39–41	8.5	6.21	23.88	0.550
42–45	11.9	6.17	23.44	0.516
46–49	9.0	6.08	23.30	0.481
50–54	5.8	5.83	22.23	0.437
55–59	2.7	5.56	21.89	0.355
60–65	1.5	5.58	20.27	0.293
Above 65	0.6	4.64	17.78	0.109

Table 3: Criminal History Risk, Total Risk Score, and Recidivism by Age Categories

Age Groups	Prevalence Rate	Criminal History Score	Total LSI-R Score	Recidivism Rate
17–24	16.0	5.61	26.10	0.721
25–30	21.7	6.33	25.17	0.623
31–39	24.8	6.35	24.24	0.576
40–49	27.0	6.14	23.49	0.507
50 and above	10.5	5.66	21.62	0.378

Figures 1, 2, and 3 graphically display the data included in Table 2. Figure 1 illustrates how criminal history score is lowest for individuals in their late teens and early twenties. From this point, it consistently increases until an individual reaches his or her early to mid-thirties. After this point, criminal history score begins to decline. It is difficult to know for certain why criminal history begins to decline after the mid-thirties, one potential explanation is an incapacitation effect. If an individual was in prison for the preceding time period, it would not have been possible to be in the community and committing more crimes. The portion of Figure 1 which displays data on offenders in their twenties does suggest that younger individuals are less likely to have amassed a lengthy criminal history.

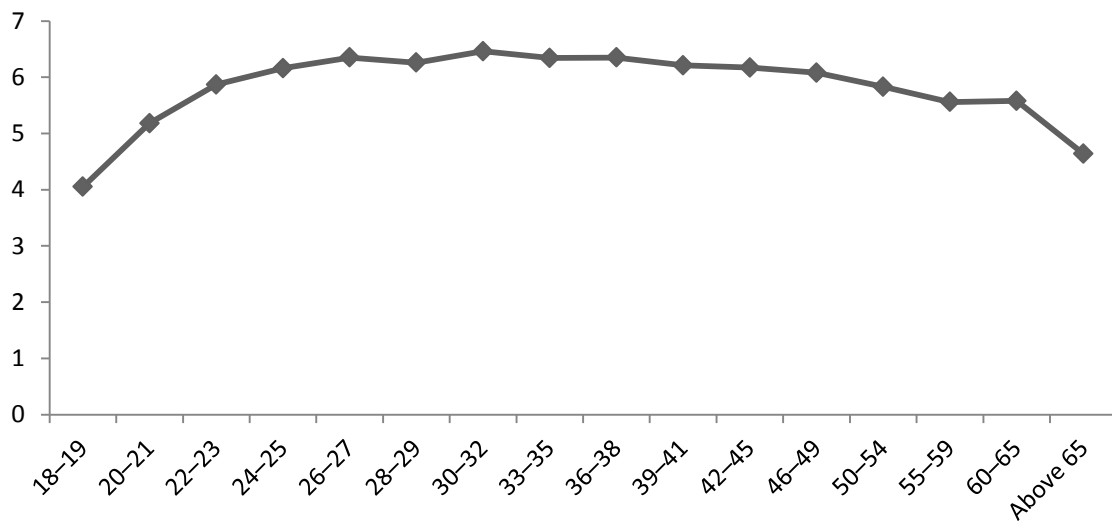


Figure 1: Mean Criminal History Score by Age Bands

Figure 2 displays LSI-R total risk by the same age bands. Total risk declines consistently as individuals age. This suggests that dynamic risk factors are correlated with age (i.e., younger people present with more need factors). Potentially, the inclusion of dynamic factors helps norm the tool in an age-appropriate manner.

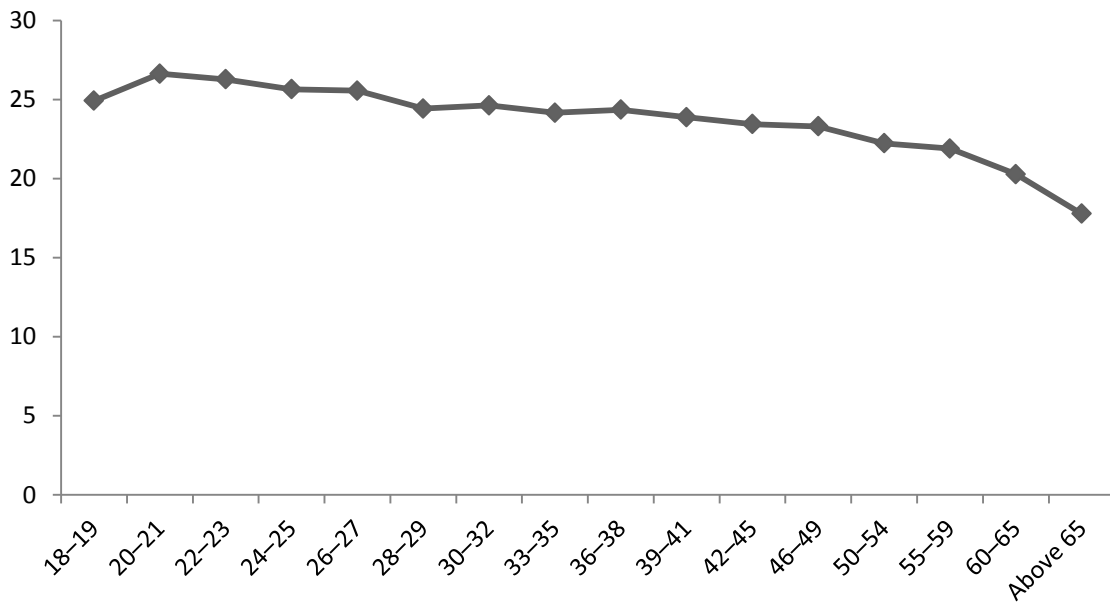


Figure 2: Mean LSI-R Total Score by Age Bands

Finally, Figure 3 shows how recidivism rates vary by age. Consistent with the age-crime curve, the probability of recidivism decreases as individuals become older. However, if the LSI-R was doing a more complete job capturing “true risk” Figures 2 and 3 would appear much more similar. The finding that Figure 2 is virtually flat, in comparison to Figure 3 suggests that while the likelihood of recidivism declines drastically as time passes, the average risk score of an individual does not decrease

accordingly. In fact, from age 20 to age 40, the average LSI-R score decreases by about three points. When the instrument can take on a range of values from zero to fifty-four, a three point decline is quite small. However, over that same time period, the likelihood of recidivism decreases by more than 20%.

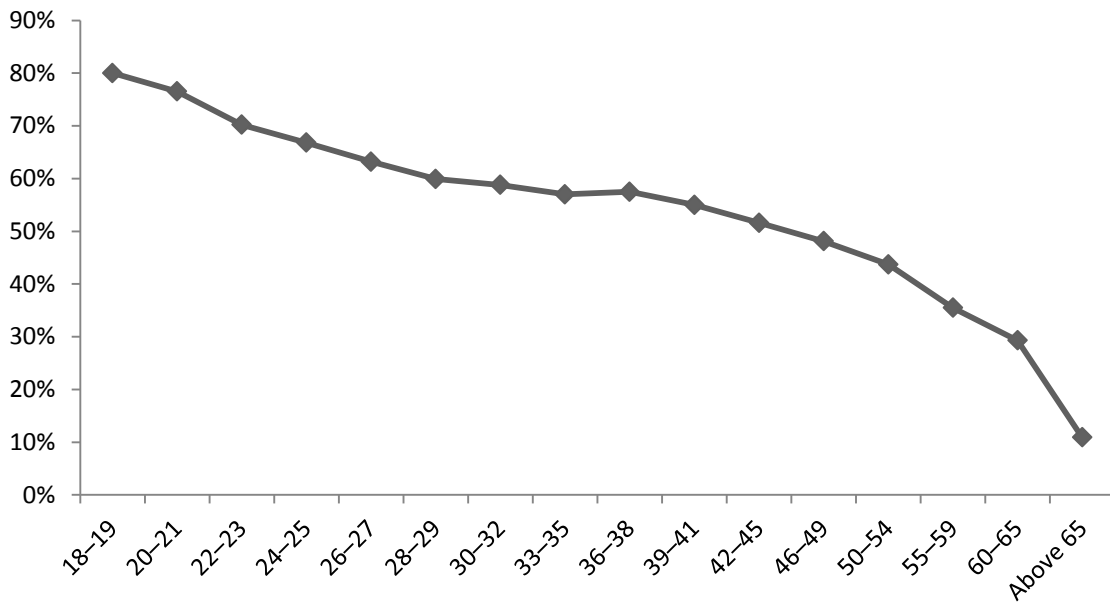


Figure 3: Mean Recidivism Probability by Age Bands

Table 4 (below) lends further empirical support to the question underlying the central argument – risk assessments would be more effective if age was included. While both criminal history risk score and total risk score are significantly related ($p < .001$) to recidivism, so too is age. Total risk score emerges as the best predictor of recidivism. However, both measures of age (i.e., age as a continuous measure and age collapsed into the groups indicated in Tables 2 and 3) predict recidivism as well as criminal history.

Table 4: Pearson Correlations and AUC between LSI-R Scores/Age Measures and Recidivism

Variable	Correlation <i>r</i>	ROC Analysis AUC
<i>Total Risk Score</i>	.318***	.686***
<i>Criminal History Score</i>	.194***	.618***
<i>Age</i>	-.198***	.389***
<i>Age Groups</i>	-.194***	.390***

* p < .05; ** p < .01; *** p < .001

While risk scores, as continuous measures, are important, so too are risk levels.

Table 5 (below) displays the Spearman correlations between the relevant categorical variables: risk classification, age groups, and recidivism. Again, total risk is most highly correlated with recidivism; age group and criminal history are also highly correlated with recidivism. This lends further support to the argument that criminal history and age together would provide an improved risk measure over history alone.

Table 5: Spearman Correlations between LSI-R Classifications, Age Groups, and Recidivism

Variable	<i>Recidivism</i>	<i>Total Risk Classifications</i>	<i>Criminal History Group</i>	<i>Age Groups</i>
<i>Recidivism</i>	x	–	–	–
<i>Total Risk</i>	.297***	x	–	–
<i>Criminal History</i>	.187***	.403***	x	–
<i>Age Groups</i>	-.189***	-.141***	-.015	x

* p < .05; ** p < .01; *** p < .001

A comparison of how well the two risk measures and age predicted recidivism outcomes comprises the final stage in the first section of the analyses. In order to assess this relationship, a series of logistic regression models were conducted. The two regression models are included as Tables 6 and 7. The first series of models displays the capacity of LSI-R total score in predicting recidivism. The first iterations include only LSI-R score and age; sex and race/ethnicity are added in iteration two; the final model included dynamic risk factors as well. Table 7 follows the same pattern but uses criminal history risk score instead of LSI-R total score.

Table 6: Logistic Regression Models--LSI-R Total Score

	Iteration 1				Iteration 2				Iteration 3			
	β	SE	Sig	OR	β	SE	Sig	OR	β	SE	Sig	OR
<i>LSI-R Total Score</i>	.083	.003	<.001	1.087	.083	.003	<.001	1.086	.117	.005	<.001	1.125
<i>Age</i>	-.032	.002	<.001	.969	-.030	.002	<.001	.970	-.033	.002	<.001	.968
<i>Sex (0=female)</i>					.100	.068	.142	1.105	.105	.069	.126	1.111
<i>Race/Eth (0=white)</i>					.313	.044	<.001	1.368	.326	.044	<.001	1.386
<i>Alc./Drug Flag</i>									-.172	.065	.009	.842
<i>Attitude Flag</i>									-.146	.053	.006	.864
<i>Crim. Peers Flag</i>									-.043	.048	.367	.958
<i>Edu/Emp Flag</i>									-.391	.056	<.001	.676
<i>Emot./Pers. Flag</i>									-.345	.074	<.001	.708
<i>Family/Mar. Flag</i>									.117	.005	<.001	1.125
<i>Leisure Flag</i>									-.033	.002	<.001	.968
-2 Log Likelihood				13,290				13,238				13,159
Nagelkerke R²				0.164				0.170				0.178

First, in both models, adding the age variable increases predictive capacity. Age is a statistically significant variable in both models. The addition of demographics in iteration 2 and dichotomous indicators of dynamic risk factors in iteration 3 adds little to the overall model fit. This clearly suggests two different things. First, from an empirical

perspective, there is preliminary evidence that age warrants inclusion in assessment instruments. Second, the addition of dynamic factors in iteration 3 improves model 2 but does little to improve model 1. This makes sense from a theoretical standpoint since total risk score already takes these variables into account.

Table 7: Logistic Regression Models--Criminal History Risk Score

	Iteration 1				Iteration 2				Iteration 3			
	β	SE	Sig	OR	β	SE	Sig	OR	β	SE	Sig	OR
<i>Criminal History</i>	.228	.012	<.001	1.256	.226	.012	<.001	1.254	.186	.012	<.001	1.204
<i>Age</i>	-.040	.002	<.001	.961	-.038	.002	<.001	.963	-.033	.002	<.001	.967
<i>Sex (0=female)</i>					-.083	.066	.213	.921	-.061	.068	.375	.941
<i>Race/Eth (0=white)</i>					.325	.043	<.001	1.384	.315	.044	<.001	1.371
<i>Alc./Drug Flag</i>									.478	.058	<.001	1.613
<i>Attitude Flag</i>									.259	.049	<.001	1.296
<i>Crim. Peers Flag</i>									.247	.045	<.001	1.280
<i>Edu./Emp. Flag</i>									.178	.047	<.001	1.195
<i>Emot./Pers. Flag</i>									.162	.069	.019	1.176
<i>Family/Mar. Flag</i>									.165	.052	.002	1.179
<i>Leisure Flag</i>									.217	.045	<.001	1.243
-2 Log Likelihood				13,854				13,794				13,422
Nagelkerke R²				0.101				0.107				0.149

The second central question is concerned with how the inclusion of age in risk scoring can impact predictive capacity and age distributions into different risk categories. The first step was to determine an approach for reweighting the risk scores while incorporating age. Criminal history score ranges from 1 through 10 on the LSI-R. After studying the age distributions and age specific recidivism rates, consulting the tool of a correctional jurisdiction that does factor in current age, and recoding history scores in numerous different ways, I settled on the reweighting scheme displayed in Table 8. Based on an individual's current age, the corresponding number of points was added (or

subtracted) to the criminal history score. Then, scores needed to be recoded so they still were in the original range of possible values; any score below zero was recoded to be equal zero and any score about ten was recoded to be equal to ten. The same process was carried out for LSI-R total score (which ranges from 0 through 54); and again any score below zero was recoded to be zero and any score above 54 was recoded to be 54.

Table 8: Criminal History Risk, Total Risk Score, and Recidivism by Age Categories

Ages	Prevalence Rate	Criminal History Score Adjustment	Total LSI-R Score Adjustment
18–19	1.1	+5	+8
20–21	3.9	+5	+7
22–23	6.9	+4	+6
24–25	8.2	+3	+5
26–27	7.9	+3	+4
28–29	7.0	+2	+3
30–32	8.1	+2	+2
33–35	8.4	+1	+1
36–38	8.5	+1	0
39–41	8.5	0	-1
42–45	11.9	-1	-2
46–49	9.0	-2	-3
50–54	5.8	-3	-4
55–59	2.7	-4	-5
60–65	1.5	-5	-6
Above 65	0.6	-6	-7

Table 9 shows the classifications into risk groups for both total score and criminal history score using the initial scoring technique and the scoring technique with age added. Classification was done using the jurisdiction validated cutoff points. It was beyond the scope of this project to revalidate the cutoff points for the new risk measures which incorporate age. Adding age to both measures had the same impact on the distributions –

it moved people out of the middle of the distribution in the direction of one of the two extremes – but was more pronounced with the criminal history scoring. This makes sense because the age adjustment comprised a bigger portion of the history score (with a maximum value of ten) than the total score (with a maximum value of 54). While the recidivism predictions were largely the same for total score with and without age, the criminal history classifications were better able to distinguish between low and moderate risk individuals once age was included.

Table 9: Risk Distributions--Original Classifications and Classifications with Age Added

Variable	Initial Scoring		Scoring with Age Added	
	<u>Prevalence</u>	<u>Recidivism</u>	<u>Prevalence</u>	<u>Recidivism</u>
Criminal History Risk Level				
High	45.1	67.0	45.8	68.6
Moderate	46.5	49.5	23.2	56.3
Low	8.4	44.6	31.0	40.4
LSI-R Total Risk Level				
High	2.3	82.7	5.4	80.7
Moderate/High	11.4	75.3	14.0	76.2
Moderate	38.4	67.1	36.4	66.7
Low/Moderate	38.4	48.1	33.0	45.9
Low	9.5	23.6	11.2	22.3

Note: Table values reflect percentages

The point-biserial correlation coefficients, and the corresponding significance values, are reported below in Table 10. Since the sample size is very large, even relationships which appear substantively small rise to the level of statistical significance ($p < .05$). However, a more stringent p-value is reported to indicate that the magnitude of the predictive capacity is sizable. Adding age to both LSI-R total score and criminal

history score improved the relationship with recidivism. However, the improvement was much greater with criminal history, as compared to total score. There are certainly other approaches for adding age into risk scoring but the approach used here mimics that used by the only correctional jurisdiction, to my knowledge, presently incorporating current age in assessment practice. The inclusion of criminal history as a central component in assessment tools, without accounting for age, may be biasing assessment practices in the direction of diverting young offenders out of treatment and programming placements.

Table 10: Correlations with Recidivism--Original Scores and Scores with Age Added

Variable	Initial Scoring	Scoring with Age Added
Criminal History Risk Level		
Pearson Correlation (r)	.194	.272
Significance (2-tailed)	<.0001	<.0001
LSI-R Total Risk Level		
Pearson Correlation (r)	.318	.347
Significance (2-tailed)	<.0001	<.0001

DISCUSSION AND CONCLUSIONS

Within criminology, the age-crime curve represents one of few empirical facts. In the current time-period characterized by evidence-based practice, the RNR framework is considered a “best practice” for correctional case management. However the LSI-R, the proprietary tool designed by the creators of the RNR framework, does not incorporate the current age of an individual. The present research represents an exploration into whether the addition of age is relevant from an empirical perspective. There are equity and ethical concerns with either including or omitting age from assessment practices; however, that conversation is moot if the addition of age is of little empirical value. Chapter 4 provides preliminary evidence that age does improve the predictive capacity of the LSI-R. This suggests a need to potentially revisit the relevant equity discussion as correctional jurisdictions increasingly rely on assessment tools to inform case management practices.

In the present correctional framework, one centered around risk mitigation and recidivism reduction (Cullen, 2012), an improvement in predictive ability of assessment tools is potentially of great value. This new “rehabilitative” school is centered on goals like cost-effectiveness and reducing prison crowding. Since the risk mitigation framework is justified around the ideal of helping citizens or taxpayers, rather than criminals or offenders, it was successful in avoiding some of the criticism from the “get

tough” folk (Cullen, 2012). Adding age into assessment practices represents a potentially viable approach to reduce the likelihood of recidivism for younger offenders.

The literature pertaining to risk assessment typically includes age in the larger category of demographic variables. It is taken as a given that it is ethically impermissible to include demographic variables in risk assessment and classification (Tonry, 1987); this is logical after the failed experiment of selective incapacitation. While age is a demographic variable it is fundamentally different than race/ethnicity and sex for it changes predictably and constantly. In the literature, an implicit distinction emerges between different categories of demographic characteristics – age and the rest (e.g., race/ethnicity and sex). However, when examples of such characteristics are presented, the list consistently includes race, ethnicity, and sex but rarely (see Gottfredson & Gottfredson, 1986; Gottfredson, 1987; but see Farrington, 1987) mentions age.

A wide range of characteristics (in addition to criminal history) factor into the calculation of an individual’s likelihood of reoffending including: substance use disorder, educational and employment barriers, antisocial personality and values, procriminal peers, and financial problems. Depending on the assessment tool at-hand, the sample being studied, and the recidivism measure being used, these assessments range greatly in their predictive accuracy (Gottfredson, 1987; Gottfredson & Gottfredson, 1986; Silver & Miller, 2002; Gottfredson & Moriarty, 2006). The nature of the problem is rather straightforward. Younger individuals (who tend to act like moderate or high risk offenders) may potentially be classified at too low a risk level because they have not had the time to build a criminal history.

Stemming from the failure of selective incapacitation, there emerged a consensus that targeting young offenders was inappropriate from the standpoints of justice, fairness, effectiveness, and cost-effectiveness. However, in the current instance, the policy does not seek to sentence young individuals more harshly. Rather, the policy is to match high-risk individuals to higher intensity treatment interventions (Palmer, 1991). Previous failures to sentence based on age must not be the basis for keeping age out of the equation and potentially depriving young offenders of correctional programming.

A change in approach is needed: age belongs in its own theoretical category because it is neither static (it obviously changes) nor amenable to change (impossible to age faster or slower). Andrews and Bonta (2010a) have long been distinguishing between static and dynamic factors; static factors are not amenable to change while dynamic factors are. Within individuals, age changes predictably and at a constant rate but cannot be targeted through intervention. This raises another question pertaining to the inclusion criteria for specific variables. Are factors included or excluded because they are a result of choices made by the individual or solely because they can be affected by intervention? A third option exists – that there is no systematic reason for the present inclusion/exclusion decision – and this topic must be revisited.

The relevant normative question regarding age leads to some very tough criminal justice calculus. More specifically, we must decide if we prioritize improved outcomes for a given individual more or less than improved macro-level outcomes (overall reduction in reoffending). The logic of this point is not terribly clear and often overlooked. First, adding current age into the risk prediction strategy outline above will

allow precious programming resources to be diverted away from older offenders who have already desisted from their criminal offending. After a certain age, perhaps forty, an individual's assessed criminal history risk score should be able to be incrementally reduced for every span of time (say one year) without committing a criminal activity. One such technique for reducing the criminal history of individuals was proposed in Chapter 4. Then instead of criminal history being a static risk factor, it would be transformed into a time-sensitive dynamic factor.

The RNR model says treatment and programming resources should be focused on individuals classified as high risk. And we know past offending is the best predictor of future offending (Gottfredson & Gottfredson, 1986). However, this is not to say that either that it is an exact predictor of future offending. There will be individuals classified as high risk who will desist from criminal activity entirely and there will be individuals classified as low risk who do reoffend. What we already know is that the first group (high risk; does not reoffend) tends to be comprised of older individuals and the second group (low risk; does reoffend) tends to be comprised youthful offenders. This effort, and related such attempts, has the potential to improve prediction practices, reduce recidivism on the aggregate, and improve the outcomes of individual first-time offenders. Treatment matching in an effort to reduce reoffending is appropriate so long as the severity or amount of punishment is not impacted by the results of risk assessment tools.

Austin (2006) cites prior research findings which have led researchers to advocate for the addition of variables such as age: "These findings led the researchers to recommend that some of the LSI-R items be combined with other non-LSI-R factors, like

current age and sex, to provide for a better risk instrument” (p. 60). Additionally, the Static-99 uses current age when assessing risk for sex offenders (Hanson & Thornton, 1999). So the argument advanced within is not new altogether.

Recommendations

The major contribution of the present research is quite basic from a theoretical perspective: age is neither truly static nor dynamic. Instead it changes of its own accord. Moving forward, age ought to be viewed as such and not ignored from assessment practices simply because it is unethical to include “demographic” factors. In order to advance assessment practices, age should be treated in a manner consistent with the redemption research of Blumstein and Nakamura (2009). That is, if an individual has not offended for some amount of time, his or her criminal history should begin to be erased. Additionally, young offenders must not be diverted from treatment programs simply because they have not had the opportunity to develop a criminal history.

Building off the research in life-course and developmental criminology, risk assessment techniques would likely be aided if knowledge relating to trajectories of offending and desistance were included in classification. It is well-known that age is a relevant factor as to the likelihood of ones future offending. It ought to play a role in the calculation of one’s reoffending risk. Stated differently, we know past offending is the best known predictor of future offending, but it is not the only one. Blumstein and Nakamura (2009) bring this point to the forefront in their discussion pertaining to redemption. The desistance literature also makes clear that the offending behavior of

individuals with a criminal history will not persist indefinitely (Maruna, 2001; Warr, 1998; Laub & Sampson, 2001).

Future Research

In the future, I plan to analyze data which includes the individual LSI-R items in an effort to determine if specific items are less likely to be present for young offenders. This is similar to the approach used by Austin and colleagues (2003). This research will also better inform the appropriate technique to use in the effort to begin to include age in assessment instruments. The present research was an exploration into whether age was relevant to risk, outside of the factors already measured. The analyses conducted suggest that it appears to be. Future work on this topic will replicate these analyses in other samples of individuals returning to the community from prison.

Another interesting question pertains to the risk principle of the Risk-Need-Responsivity framework. The RNR framework shows that the greatest recidivism reductions are accomplished when high risk individuals are placed into programming. In the future, I plan to compare “high risk” individuals over the age of forty who both did and did not receive some correctional treatment or programming. If the RNR framework is correct, those who received programming should have improved future outcomes. However, if the LSI-R is over classifying the risk of reoffending for older individuals, this finding may not come to fruition. Instead, if individuals who have already aged-out of offending behavior are placed in treatment and then do not reoffend, this would cause a false treatment effect.

Lastly, I intend to conduct diagnostic analyses which will be useful in assessing the most appropriate method for inclusion of age as a variable which goes into assessment scoring. As stated above, the purpose of the present research was not to solve the problem of how to incorporate age into assessment practices. Rather, the goal was to assess if this specific problem relating to age and risk of recidivism was present at all. My findings suggest that correctional risk assessment practices and corresponding case management techniques could be improved if the current age of an individual was not omitted altogether.

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