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Testing the LS/CMI for Predictive Accuracy: Does Age Matter?

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Testing the LS/CMI for Predictive Accuracy: Does Age Matter?

by

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Abstract

The Level of Service/Case Management Inventory (LS/CMI) is one of the most widely used instruments for assessing recidivism risk and treatment needs in correctional settings. The predictive validity of the measure and its predecessor (LSI-R) has been established in meta-analytic studies and research finds that the scale's accuracy is largely independent of sex, race, and ethnicity. Whether the LS/CMI works equally well for different age groups remains in question. The current study assessed the predictive accuracy of the LS/CMI from a sample of 14,940 adults in custody (AIC) released from an Oregon prison between 2011 and 2017 for three age groups: 18 to 39, 40 to 54, and 55 and older. Study findings indicate that age is an important factor to consider when assessing an AICs risk for recidivism. Older adults in custody (55+) recidivated at significantly lower rates than other age groups. Mean LS/CMI score differences were found by age group. The LS/CMI was found to be equally accurate considering age, as higher risk scores were associated with higher recidivism across ages. However, findings also indicated that going beyond accurate scoring is important. LS/CMI cut-points may not be age-responsive, as similar LS/CMI scores produced differing levels of recidivism by age group. The LS/CMI may overclassify the risk of recidivism for older AICs and LS/CMI cut-points may need to be adjusted considering age. A discussion of the findings and how they can inform local policy and correctional assessment practices more broadly is provided.

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Introduction

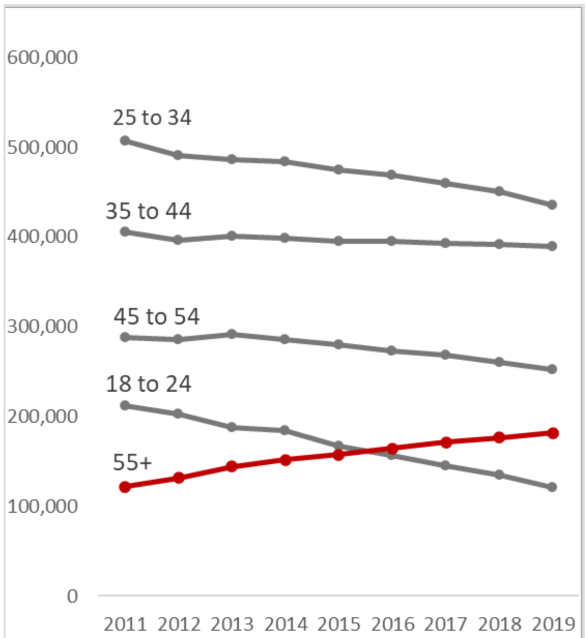
The prison population in the United States is aging. The United States federal and state prison population of adults in custody (AIC) aged 55 or older increased 250% between 1999 and 2014 (Dulisse et al., 2020). The U.S. Bureau of Justice Statistics reported in 2016 a 400% increase in state prison populations of AICs aged 55 and older between 1993 and 2013. At the same time, the younger prison population realized a decrease overall (Carson & Sabol, 2016). In 2015, 19% percent of the federal prison population and 10% percent of the state prison population comprised older[1] adult offenders (Monahan et al., 2017). Why might our prison population be aging? Literature indicates that decarceration rates are shifting in the United States.

According to the U.S. Department of Justice (DOJ) Bureau of Statistics, in the state prison systems, older adults are released from prison at lower rates as compared to younger adults, as Figure 1 demonstrates (BJS, 2021). In 2012 half of the AICs released from state prisons were 25 to 39 years of age and only one-third were 40 or older (Durose & Antenangeli, 2021). Between 2011 and 2019 a 49% increase in state and federal sentencing of adults aged 55 and older was realized, while the state and federal sentencing rates of the population 18-24 decreased by 43% (BJS, 2021). In 2019, there were 181,500 sentenced AICs aged 55 and older in state and federal prisons in the United States (BJS, 2021). Research indicates that a pattern of aging in the prison population is expected to continue to increase over time (Rakes et al., 2018). As such, there is evidence

[1] For this thesis "older" will be referred to as age 55 and older.

of a pattern of aging in the United States prison and parolee populations (Dulisse et al., 2020; Hughes & ten Bensel, 2021; Psick et al., 2017).

Figure 1. *Sentenced state and federal AICs by age and year (BJS, 2021)*



Bows & Westmarland (2018) found that the aging prison population in the United States is correlated with the aging general population. The aging prison and general population can be partially attributed to the age cohort known as the baby boomers. According to Quadagno (2014), the largest age cohort is the baby boomers born 1946-1964, and the second-largest are echo boomers, children of baby boomers born 1977-1994 (Quadagno, 2014, p. 8). The age range of the baby boomers in 2021 is 57-75 years old and the echo boomers are 27-44 years old (Quadagno, 2014, p.8). Between 2010 and 2019 the U.S. population of adults 55 and older saw a 25% increase (U.S. Census Bureau, 2021). Since January 1, 2011, one person every 8 seconds turns 65 (Hooyman et al., 2017, p.21). As a result, the overall population in 2021 is comprised of two age cohorts that are larger and increasing in age. Due to the aging baby boomers, the U.S. Census Bureau projects that for the first time in history, after 2030 the death rate in the United States will be higher than the birth rate (Hooyman et al., 2017, p.18).

The cost of an aging prison population is high. Medical care costs in prison continue to increase as the prison population ages. Special populations such as older AICs, have increased medical needs. Medical care for older AICs is five times more costly, and medication is fourteen times more costly compared to younger AICs (Monahan et al., 2017). Older AICs have a higher rate of chronic illnesses as compared to the non-incarcerated population suggesting an “accelerated aging” process in prison (Greene et al., 2018; Prost et al., 2019). Several studies found that older AICs have significant problems with prison activities of daily living (PADL) such as climbing stairs, climbing to the top bunk, walking to meals, trouble dressing, going to the bathroom, or bathing without help (Greene et al., 2018; Prost et al., 2019; Skarupski et al., 2018). Many older adults need wheelchairs, walkers, or canes, some need portable oxygen, and others cannot hear orders from staff (Greene et al., 2018; Prost et al., 2019; Skarupski et al., 2018). Higher rates of chronic illnesses found in older AICs and increased needs translate into higher prison costs. Age has been identified as a major contributor to increasing healthcare costs in prison (Hughes & ten Bensel, 2021; Monahan et al., 2017; Prost et al., 2019; Psick et al., 2017; Rakes et al., 2018).

While the costs associated with the aging prison population are important to understand, other factors need to be considered. More stringent sanctions implemented through policies in the 1980s and 1990s have resulted in individuals remaining in prison for longer periods and have also reduced opportunities for early release. As an example, an increased rate of imprisonment between 1978 and 1999 was reported by the U.S. DOJ Bureau of Justice Statistics in 2020 (Carson, 2020). In 1978 the imprisonment rate of sentenced AICs age 18 or older under state or federal corrections custody was 183 per 100,000 U.S. residents, as compared to 640 per 100,00 U.S. residents in 1999 (Carson, 2020). More stringent sentencing such as mandatory minimum sentences and decreased opportunities for early release have dramatically increased the rate of imprisonment in the U.S. state and federal prison population within a very short period.

With the rising population of older AICs, concerns are growing that the current correctional practices might not be age responsive. Risk needs assessment (RNA) scales are utilized by the DOC to make decisions about an offender's likelihood of reoffending (risk) and to "inform the type and intensity of correctional interventions" (needs) (Skeem et al., 2016). RNA tool use is mandated in both federal as well as Oregon state statutes (Henning & Labrecque, 2017; Skeem & Lowenkamp, 2016). Oregon DOC utilizes the Level of Service Case Management Inventory (LS/CMI) risk scale to fulfill the legal mandate. Research findings indicate that risk assessment scales might overclassify the risk of recidivism for older AICs (Monahan et al., 2017). The overclassification of older AICs' risk of recidivism may indicate that risk assessment scales might not work well for older AICs. As an example, RNA tool risk factors for reoffending have been found to differ by age band (Fazel et al., 2006; Monahan et al., 2017). Differences in risk factors considering age certainly raise questions about age-responsive correctional risk assessment practices.

In an extensive literature search, only one study evaluated a risk instrument considering age. Results from the study indicate that the Post-Conviction Risk Assessment (PCRA) risk scale had similar predictive accuracy for older versus younger AICs (Monahan et al., 2017). Age did not moderate the relationship between the PCRA score and rearrest (Monahan et al., 2017). Lastly, Monahan et al. (2017) found that the PCRA overclassified the risk of recidivism for older AICs. No studies evaluated the Level of Service Case Management Inventory (LS/CMI) risk scale, considering age.

The limited body of research examining risk instruments in combination with an aging U.S. prison population may have large implications for the DOC. Several studies have confirmed that the lowest rate of reconviction was found in older adult groups (Avieli, 2020; Durose & Cooper, 2005; Fazel et al., 2006). We know very little about older age AICs and risk scales. Therefore, it is important to assess whether current risk assessment practices utilized by the DOC are suitable given what we know about age and recidivism. This study begins by exploring the relationship between age and recidivism and then evaluates the impact of age on the LS/CMI risk assessment tool. In the next section, recidivism in the context of older AICs, theoretical explanations for the reduced rate of recidivism in older AICs, gerontological perspectives on aging AICs, risk scales in correctional programming, and the rising concerns that risk scales such as the LS/CMI may have bias will be discussed.

Literature Review

Evidence that Recidivism and Criminal Behavior Decline with Age

There is an agreement amongst scholars that as age increases both criminal behaviors and recidivism decline (Hirschi & Gottfredson, 1983; Laub & Sampson, 2001; Sampson & Laub, 2005; Hanson, 2006; Wolfe et al., 2016). Research indicates that for all individuals "age has a direct effect on offending" and "life-course desistance is the norm for all" (Sampson & Laub, 2005). Desistance from crime is described as a "decrease in the frequency of offending, a reduction in its diversification (specialization), and a reduction in its seriousness" (Snipes et al., 2019, p.347). Laub & Sampson (2001) found that aging factors such as a decline in physical health or strength, energy, psychological drive, and the reduced need for stimulation are related to desistance from criminal behavior. Hanson (2006) found that the lowest risk of recidivism for sexual offenders was in those aged 60 years and over. In addition, less than 5% of older sexual offenders, sixty years or older, recidivate compared to 20% in their twenties (Hanson, 2006). Durose & Antenangeli (2021) found that 81% of AICs aged 24 years or younger released in 2012 were arrested within five years of release, compared to 74% aged 25-39, and 61% aged 40 or older. In other words, the relative difference in arrests was 24.7% within five years of release, with older AICs having fewer rearrests (Durose & Antenangeli, 2021). For AICs released at age 65 or older, Durose & Antenangeli (2021) found that this age group had 48% fewer arrests than AICs aged 24 years or younger within five years of release.

Wolfe et al. (2016) found that criminal offending declines with each year of increasing age partially attributable to cognitive and physical decline associated with aging processes, which decreases the propensity for criminal offending (Wolfe et al., 2016). Desistance from crime in older AICs can be attributed to fear of death in prison and a general disillusionment with a life of criminal behavior (Avieli, 2020). Several studies confirm that the lowest rate of reconviction was found to be in older adult groups (Avieli, 2020; Durose & Cooper, 2005; Fazel et al., 2006). Maturation, strong social bonds, marriage, stable employment, and transformation of personal identity are all associated with aging and play a role in desistance from criminal behavior (Laub & Sampson, 2001; Sampson & Laub, 2005).

Criminology Theoretical Explanations for Desistance from Crime

Developmental or life-course (DLC) theorists help us to better understand crime over the life course and desistance from criminal behavior. DLC scholarly findings indicate that most individuals “age out” of crime by their late 30’s or early 40’s (Bohm & Vogel, 2015, p. 198; Boisvert et al., 2021; Hirschi & Gottfredson, 1983; Laub & Sampson, 2001; Snipes et al., 2019). Research is limited when considering older AICs and patterns of desistance from crime. Desistance from crime in older AICs is one of the areas that we know the least about in criminology. By comparison, an abundance of research exists focused on the onset of criminal behavior (Laub & Sampson, 2001). Maruna (2001) eloquently states that desistance can be defined as the “maintenance of crime-free behavior in the face of life’s obstacles and frustrations” (Maruna, 2001, p. 26). It is important to note that desistance can happen at any time in the lifespan, but through maturation processes, adults simply have been found to mature out of crime (Hirschi & Gottfredson, 1983; Laub & Sampson, 2001; Sampson & Laub, 2003; Snipes et al., 2019).

Theoretical frameworks such as Sampson and Laub's age-graded theory of informal social control can help us to better understand adult criminal behavior and desistance from crime. The age-graded theory of informal social control indicates that stability, life events, and social bonds such as a good marriage, stable work, physical and psychological aging processes, a realization associated with the costs and benefits of crime, and personal transformation are all factors that reduce the likelihood of criminal behavior (Laub & Sampson, 2001; Snipes et al., 2019). When examining desistance from crime, Laub & Sampson (2001) suggest that in future research a delineation between crime types and offender characteristics should be in place to control measurement conditions. In addition, antisocial behavioral attributes such as heavy alcohol use or drug use are also important indicators of criminality and should be considered when examining desistance from a life of crime (Laub & Sampson, 2001).

To understand an older AICs risk of recidivism, environmental factors and criminal propensity must be considered. Macro-sociological criminology theories such as Agnew's General Strain Theory (GST), posit that negative events or strain can elicit a higher likelihood of criminal behavior (Liu et al., 2021). Importantly, GST concedes that not all individuals who experience strain (i.e., negative stimuli, loss, failure to achieve valued goals) engage in criminal activity (Bohm & Vogel, 2015, p. 109). Agnew (2013) states that coping strategies, circumstances around strain, and the type of strain are important to consider when testing a higher likelihood of criminal behavior. Special populations such as older AICs, through a process of maturation and personal transformation as demonstrated by Sampson and Laub's age-graded theory of informal social control, may have a higher likelihood of managing strain more productively as compared to younger AICs.

Agnew (2013) posits that anger is an emotion that "occupies a special place in GST" as it "energizes the individual for action" (Agnew, 2013). Past studies have often tested GST on adolescent or younger AICs. More recently, Liu et al. (2021) tested Agnew's GST on former AICs released from state prisons in Ohio, Illinois, and Texas with an average age of 36 ranging between 18 and 65 years of age. Liu et al. (2021) found that anger as a negative stimulus was not associated with criminal propensity. More importantly, the Liu et al. (2021) findings indicate that older AICs had a lower level of criminal propensity and that a "1-year increase in age was associated with a 0.03 unit decrease in criminal propensity" (Liu et al., 2021). Thereby, older AICs have a lower propensity for criminal behavior when compared to younger AICs, supporting the assertion that older AICs have a lower risk of recidivism.

Gerontological Perspectives on Aging

Gerontology scholars agree that as we age we become more diverse, not more alike (Saxon et al., 2015, p.5). Age diversification happens in part as a result of lifestyle. Both the physiological and mental well-being of an individual is dependent upon lifestyle (i.e., regular exercise, proper nutrition, not smoking, and stress management). An individual's lifestyle is considered the most important risk factor associated with morbidity and mortality (Braveman & Gottlieb, 2014; Saxon et al., 2015, p.2). Therefore, it is important to understand the impact that the prison lifestyle has on older AICs.

The prison lifestyle is particularly unhealthy due to limited opportunities for physical activity, poor diet, and difficulties in delivering age-appropriate health care (Skarupski et al., 2018). Older AICs have an increased risk of comorbidities and poorer health outcomes (Skarupski et al, 2018). Particularly concerning are findings indicating that a process of premature aging is associated with incarceration (Dulisse et al., 2020; Holland et al., 2021; Hughes & ten Bensel, 2021; Rakes et al., 2018; Skarupski et al., 2018). Scholarship widely supports the idea that oxidative stress can shorten telomeres (i.e., protective DNA protein at the end of chromosomes) and is a sign of cellular senescence affecting morbidity and mortality (Braveman & Gottlieb, 2014; Epel et al., 2004). Epel et al. (2004) found that chronic stress impacts oxidative processes, and even perceived stress significantly impacts telomere length and accelerates cellular aging. Therefore, older AICs with a mean age of 59 have been found to experience geriatric health conditions comparable to community older adults aged 75 or older (Greene et al., 2018). The evidence of a rapid decline in health in older AICs is evident in both criminology and epidemiology research (Dulisse et al., 2020; Skarupski et al., 2018). The effect of accelerated aging processes associated with the prison lifestyle may need to be considered as they may influence the likelihood of recidivism.

Aging processes are an accumulation of the biological, psychological, and social (biopsychosocial) factors that affect the individual over the life course (Alkema & Alley, 2006; Boisvert et al., 2021; Dannefer & Settersen, 2010; Saxon et al., 2015, p.2). From a gerontological lens, incarceration would be considered a biopsychosocial factor in aging. Incarceration breaks family ties and increases social isolation, and many scholars agree has a damaging and lasting effect on mental and physical health (Umberson & Thomeer, 2020). Creating biopsychosocial profiles to better assess desistance from criminal behavior and the risk of recidivism in criminological research is only beginning to emerge (Boisvert et al., 2021). Utilization of the biopsychosocial perspective will help to build a better understanding of older AICs, expand the body of knowledge on desistance from criminal behavior, and help create risk instruments that are more age-response.

According to the World Health Organization, ageism or age bias is a recognized social pathology rooted in how we think, feel, and act towards older adults (WHO, 2022). Ageism is deleterious to older adults. Ageism is associated with poorer mental and physical well-being, shortens life span, and contributes to poverty and financial insecurity (Chrisler et al., 2016; Mayo et al., 2021; Monahan et al., 2020; WHO, 2022). A key pillar of the United Nations Decade of Healthy Aging initiative includes ending age-based discrimination (WHO, 2022). Ageism must be recognized and eliminated not only in the general population but also within the criminal justice system. Systemic ageism directly affects the physical and mental well-being of every individual. Therefore, we must better understand if age biases exist in criminal justice corrections processes such as risk instruments.

RNR in Correctional Programming

One of the most common methods to predict the risk of reoffending is based on the Risk, Need, and Responsivity (RNR) model developed by Andrews, Bonta, and Hoge

(1990). The model is based on the principles of Risks, Needs, and Responsivity (Andrews et al., 1990). Risk is associated with a higher level of service and is an outcome of an assessment process targeted at an individual (Andrews et al., 1990). Needs and/or criminogenic need factors are associated with outcomes related to stability (Andrews et al., 1990). Responsivity is associated with the interventions utilized to target an individual's needs or risks (Andrews et al., 1990). Needs assessments and risk management processes are utilized by the criminal justice system to reduce the risk of recidivism by implementing a plan that may include restrictions, expectations, supervision, monitoring, and treatment (Henning & Labrecque, 2017). RNR tools are designed such that correctional interventions are aversive. The overall objective of RNR is to target supervision plans to individual risks and needs to decrease reoffending. This raises the question, are RNR individualized supervision plans age-responsive?

We know very little about how well RNR tools work when considering age. What we do know is that research indicates older AICs recidivate at lower rates than other age groups (Avieli, 2020; Durose & Antenangeli, 2021; Durose & Cooper, 2005; Fazel et al., 2006; Hanson, 2006; Liu et al., 2021; Sampson & Laub, 2005; Wolfe et al., 2016). In addition, we know that older AICs may have unique and potentially higher needs as compared to younger populations (i.e., health care, age-appropriate housing). Monahan et al. (2017) found that older AICs had lower risk scores. Given that older AICs have higher unique needs, are lower risk scale results limiting age-appropriate services and are therefore not age-responsive? This study argues that the potential needs unique to older

AICs may not be captured in risk scales.

LS/CMI: Most Widely Used RNR Instrument

RNR is a management strategy supported by risk scales such as the Level of Service/Case Management Inventory (LS/CMI). The LS/CMI is one of the most widely used RNR fourth-generation risk assessment instruments and was originally developed in Canada and released in 2004 (Andrews, Bonta & Wormith, 2006; Labrecque, Campbell, et al., 2018; Olver, Stockdale & Wormith, 2014; Singh et al., 2018). The LS/CMI is used for risk assessment and needs planning within the criminal justice system to include pretrial release, parole, sentencing, setting correctional custody levels, community supervision, and setting conditions of release. The LS/CMI is based upon a Central Eight of risk/needs factors consisting of 43 items that are grounded in General Personality and Cognitive Social Learning theory (GPCSL) (Andrews et al., 1990; Ghasemi et al., 2021; Labrecque, Campbell, et al., 2018; Olver, Stockdale & Wormith, 2014; Singh et al., 2018).

The overall predictive validity of the measures in the LS/CMI, and its predecessor the LSI-R, has been established in meta-analysis studies (Andrews & Bonta, 1995; Olver, Stockdale, & Wormith, 2014; Smith et al., 2009). In the meta-analysis examination of the predictive accuracy of the LS scales completed by Olver, Stockdale, & Wormith (2014) it was found that the LS/CMI scale accuracy was largely independent of sex, race, and ethnicity. To be included in this meta-analysis, the studies were required to have a comparison that included sex, race, or ethnicity plus (a) a measure of recidivism outcome in the institution or community and (b) sufficient information or data to compute predictive validity effect size using Pearson *r* or a point biserial correlation *r* (Olver, Stockdale, & Wormith, 2014). The final sample size included 128 LS studies. As mentioned, the LS/CMI scale accuracy was found to be predictive of recidivism (Olver, Stockdale, & Wormith, 2014). Age was not tested in the meta-analysis suggesting a gap in the literature.

The LS/CMI was fully adopted in Oregon in 2010 (Radakrishnan et al., 2019). Comprehensive annual training is provided by the DOC in Oregon. According to Radakrishnan et al. (2019), Oregon LS/CMI assessments are completed both before incarceration release and may occur in community corrections shortly after release from prison. In addition, most AICs will have a reassessment approximately one year following release from prison while under community corrections custody. LS/CMI assessments must be conducted within 60 days after the start of supervision (Radakrishnan et al., 2019). According to the DOC in Oregon, upon prison intake, every AIC receives a full LS/CMI. Oregon also utilizes the Public Safety Checklist (PSC), a state-specific risk instrument used post-incarceration in community corrections. Our study sample includes the initial post-incarceration LS/CMI assessment, so it is important to consider the PSC impact. According to the Oregon DOC (2021), the PSC utilizes criminal history and demographic data to assess the risk of recidivism. The PSC defines low risk as less than 25%, medium risk as greater than or equal to 25% and less than 42%, and high risk as greater than 42% (OR DOC, 2021). Radakrishnan et al. (2019) state that only if a PSC score results in a “Medium” or “High” a subsequent LS/CMI will be administered in community corrections.

Increasing Concerns: Risk Scales Including the LS/CMI, May Be Biased

There are growing concerns that risk scales "may exacerbate unwarranted and unjust disparities" (Skeem & Lowenkamp, 2016). Scholars are becoming increasingly concerned that demographic characteristics of adults (i.e., race, ethnicity, gender) are weak predictors of recidivism (Monahan et al., 2017; Skeem, Monahan, & Lowenkamp, 2016). Whiteacre (2006) states that more research is required to better understand risk instruments and the potential for bias in classifications. While risk scales have been tested and initial findings indicate good predictive validity considering race and sex (Smith, Cullen & Latessa, 2009; Olver, Stockdale & Wormith, 2014), research considering age remains a gap.

Special populations, such as older AICs, present some unique assessment challenges in predicting reoffending. Fazel et al. (2006) found that risk factors for reoffending differ when considering age and raises questions about the applicability of risk assessments applied similarly across all ages. In addition, risk instruments have been designed for AICs in their late twenties and thirties (mean age = 32) which can cause issues with results (Singh et. al., 2011). Bucklen et al. (n.d.) argue that risk instruments currently used in the field require improvement and are largely outdated, inefficient, and less effective than they should be. Similarly, Campagna, Hsieh, & Campbell (2019) argue that risk assessment tools should not be used off the shelf but rather be refined and tailored to the local population. Farrall (2021) states that risk assessment instruments need to consider strengths and not just focus on the deficits associated with an individual. Risk assessment tools such as the LS/CMI should be locally normalized, have more clearly defined and operationalized dynamic risk and protective factors, embrace individual strengths and be routinely re-validated (Bucklen et al., n.d.; Campagna, Hsieh, & Campbell, 2019; Farrall, 2021; Guay et al. 2020; Gordon et al., 2015).

Several scholars have argued that some risk instruments that are not weighted might overclassify reoffending rates for older adults and underestimate for younger adults (Hanson, 2006; Helmus et al., 2012; Monahan et al., 2017). The LS/CMI does not use weighting in its assessment process (Taxman, 2017, p.344), which might present an instrument accuracy issue. Ghasemi et al. (2021) found that newer approaches, such as machine learning (ML) algorithms, were shown to improve LS/CMI overall predictive accuracy significantly. Several studies suggest that age should be reviewed separately, and categories should be weighted differently based on risks (Campagna, Hsieh, & Campbell, 2019; Hanson, 2006; Helmus et al., 2012; Monahan et al., 2017; Singh et al., 2011).

RNR assessments may score older AICs at higher risk due to criminal history, but older AICs may have physical limitations and patterns of desistance that cannot be easily captured by risk instruments such as the LS/CMI (Taxman, 2017, p.364). Radakrishnan et al. (2019) found that community corrections officers in Oregon noted that the LS/CMI does not capture mental health or past trauma information, as compared to the Women's Risk Needs Assessment (WRNA), and as such does not provide critical insights that would provide better supervision and case management planning. Finally, Giguère & Lussier (2016) found that outside of static factors, the majority of criminogenic needs factors have limited predictive value and raise questions about the use of risk assessments in case management.

It is important to understand LS/CMI predictive validity as risk and need scores directly affect individuals in custody, institutions, and society. LS/CMI scores impact the AIC level of supervision assigned, rehabilitative services provided, AIC level of restrictiveness, and lastly the cost and effectiveness of crime prevention (Andrews et al., 2011). As the prison population continues to age, the factors associated with aging will become more prevalent and may need to be considered differently in assessment processes. As such, this may present an opportunity for more research examining RNR tools, age bias, desistance from crime, and older AICs.

Current Study: Research Questions and Hypotheses

This study aims to understand the relationship between age and recidivism and the predictive accuracy of the LS/CMI considering age. Criminology literature is limited, and we have very little understanding of older AICs in custodial settings. There is still a considerable debate surrounding at what age an AIC is considered an "older" adult offender. There appears to be no universal definition of "older" adult offenders in criminal justice literature (Hughes & ten Bensel, 2021). Bows & Westmarland (2018) state that in criminal justice literature, "older" ranges between 45 to 65 years old. A review of the Bureau of Justice Statistics (BJS) reveals that some age scales define older starting as early as 40 years of age (Alper, 2018). The National Institute of Corrections uses age 50 to define older or elderly (Dulisse et al., 2020). However, the National Commission on Correctional Health Care uses age 55 years old (Dulisse et al., 2020). Monahan et al. (2017) defined older as equal to or greater than age 41. Psick et al. (2017) state that incarcerated adults 50 and older are known as older or "prison boomers".

In contrast to criminological literature, developmental psychologists generally agree that 18 to 24 is considered young adulthood, 35 to 44 is considered middle adulthood, and 45 years and older is considered late adulthood (Arnett, 2000; Ellison et al., 2016). Gerontology and geriatric scholars suggest age categories differentiating older adults (65 and older) into three categories of young-old (65-74), middle-old (75-84), and oldest-old (85+). Some criminal justice literature was found and aligned with the developmental psychology perspective that "older" adulthood begins at age 45 (Bows & Westmarland, 2018; Ellison et al., 2016, Rakes et al., 2018). We know that prison is associated with accelerated aging processes resulting in deleterious health outcomes (Greene et al., 2018; Prost et al., 2019). As an agreed-upon definition of older AIC is remiss in literature and considering prison lifestyle health outcomes, we aligned the definition of older AIC in this study with The National Commission on Correctional Health Care's definition of 55 and older.

Several studies have referenced the need for more research targeting older age offenders and risk assessment factors for reoffending (Fazel et al., 2006; Monahan et al., 2017; Rakes et al., 2018; Singh et al., 2011; Taxman, 2017). In this study, we follow the scholarly precedent set by Monahan et al. (2017) evaluating the PCRA risk scale considering age. The current study begins by analyzing the relationship between age and recidivism. Then moves toward understanding LS/CMI mean scores and if they are different when age is considered. This study then evaluates the predictive accuracy of the LS/CMI scale considering age. Lastly, the study evaluates if age moderates the relationship between the LS/CMI and recidivism. The research questions for this study are:

RQ1: *What is the relationship between age and recidivism?*

H1: Research suggests that an inverse relationship exists between age and recidivism (Bohm & Vogel, 2015, p. 198; Hirschi & Gottfredson, 1983; Laub & Sampson, 2001; Snipes et al., 2019). It is unclear if the same relationship will be found in this study's sample (i.e., as age increases recidivism will decrease). It is hypothesized that this study will have similar findings to the body of research on age and recidivism. As such, it is expected that a difference in recidivism will be found when comparing younger AICs (18-39) to older AICs (55+) and middle-aged AICs (40-54) to older (55+) AICs.

RQ2: *Does the LS/CMI yield mean score differences by age group?*

H2: The LS/CMI is utilized to determine the likelihood of recidivism and assesses treatment needs. Research suggests that when considering older AICs, risk scales may produce scoring differences as older AICs have unique needs and may also present a differing level of risk *compared* to other age groups (Taxman, 2017, p.364). No studies have specifically tested the LS/CMI to understand if scoring differences are present considering age. Thus, it is unclear if this study will produce differing scores considering age. It is hypothesized that given the implications that older AICs have more unique needs and different levels of risk considering age, it is expected that mean LS/CMI score differences will be found when comparing younger AICs (18-39) to older AICs (55+) and middle-aged AICs (40-54) to older (55+) AICs.

RQ3*: Is the LS/CMI equally predictive of recidivism considering age?*

H3: Research suggests that the LS/CMI is equally predictive of recidivism when considering race and sex (Olver, Stockdale & Wormith, 2014; Smith, Cullen & Latessa, 2009). It is unclear if the LS/CMI will be equally predictive of recidivism considering age, as it has not yet been tested. We know that as age increases, recidivism decreases. What is not clear is if LS/CMI scores are truly representative of the likelihood of recidivism and level of case planning needs by age group. AUC analyses are considered the gold standard for testing the predictive accuracy of risk scales (Andrews et al., 2012; DeMichele et al., 2020; Helmus & Babchishin, 2017; Mossman, 2013; Radakrishnan et al., 2019, Skeem & Lowenkamp, 2016; Tsao & Chu, 2021). Concerns are mounting as the AUC standard should perhaps not be taken in isolation, and other factors such as risk category cut-points may need to be considered in association with age. As an example, an LS/CMI score for a younger AIC (18-39) may mean something different compared to an older AIC (55+). While the concerns are growing about risk scale accuracy and age, the only literature precedent on LS/CMI scale accuracy to date is for race and sex. Therefore, it is expected that the LS/CMI will be equally predictive of recidivism when comparing younger AICs (18-39) to older AICs (55+) and middle-aged AICs (40-54) to older (55+) AICs.

RQ4*: Does age moderate the relationship between the LS/CMI and recidivism?*

H4: Monahan et al. (2017) research findings indicate that age does not moderate the relationship between the PCRA risk scale and rearrest. Concerns have been raised that the moderating effect may need to be considered in the context of mean score differences (Monahan et al., 2017; Skeem et al., 2016). It is expected that risk scale scores may lead to differing levels of recidivism due to a lower base rate for older AICs. Therefore, a moderation analysis could potentially indicate no moderation, and yet scale application (i.e., scale cut points) may continue to be of concern (Monahan et al., 2017; Skeem et al., 2016). It is unclear if age will moderate the relationship between the LS/CMI and recidivism as it has not yet been tested. While the concerns are growing and several questions remain about risk scale application, by following the precedent set by Monahan et al. (2017), it is expected that age will not moderate the relationship between the LS/CMI and reoffending.

Methodology

Sample

The fully de-identified secondary dataset in this study came from the Oregon Department of Corrections (DOC). The dataset was comprised of AICs released from a DOC state facility between 2011 and 2017. In total, there were 32,780 cases in the data. Variables such as demographic information, date of release, crimes currently served, convictions, arrest history, visitation history, disciplinary history, administrative segregation, LS/CMI assessment, PSC assessment, and recidivism data were included in the dataset.

This study started with 32,780 cases of AICs released from an Oregon prison facility between 2011 and 2017. In total, 17,840 cases were removed from 32,780 cases of AICs as follows. AICs who died while incarcerated (released upon death) or died while on community supervision with less than three full years for recidivism from the data sample (n=292) were removed. Cases with two or more releases in the sample (n=2,808) were also removed. Where an LS/CMI was available shortly before or after index release, the first assessment was retained. AICs incarcerated for less than 90 days (n=151) were removed from the sample. AICs under the age of 18 or if age was missing were removed from the sample (n=45). Next, an examination was performed to assess if an LS/CMI assessment was within 365 days before the index release or within 30 days after release. AICs that did not have an LS/CMI in this period were removed from the sample (n=14,354). If multiple assessments were available, the LS/CMI closest to the index release date (before or after release) was selected. This generated a full sample of

14,940 AICs with an LS/CMI shortly before (0 to 365 days) or after (0 to 30 days) index release.

Given the high loss of cases resulting from the selection process, an analysis to document how our final sample of 14,940 compared to the 17,840 cases that were excluded was conducted. The demographic characteristics of the full sample and cases removed sample are in Table 1. The mean age of the AICs in the full sample at release from prison was 35.9 (SD = 10.9), ranging from 18 to 85 years of age. AICs 55 or older comprised 6.2% of the sample cases. AICs aged 25 to 34 comprised 36.4% of the cases. The majority of AICs were white (77.6%) and male (84.9%). The majority of cases were from the Metro region comprising 65.7% of the sample. The mean length of stay for index incarceration in months was 25.5 (SD=32.9).

The demographic characteristics of the cases removed sample indicate that the mean AIC mean age was 37.8 (SD=12.0). The majority of AICs were white (73.4%) and male (89.1%). The majority of cases were from the Metro region comprising 58.1% of the sample. The mean length of stay for index incarceration in months was 39.5 (SD=42.8). In addition, differences were found between the full sample and the cases removed sample in the Chi-square ($\chi 2$) tests and the independent samples t-tests conducted. As an example, the full sample had fewer sex offenses (5.7%) when compared to the cases removed sample (17.5%). Therefore, it is unclear if the full sample would fully generalize as there were significant differences found. These results will be discussed at greater length in the limitations section of the discussion.

Table 1. *Descriptive statistics for the full sample (n=14,940) and cases removed (n=17,840)*

Demographic Factors	Full Sample % or M	Cases Removed % or M	t or χ^2
Age (SD)	35.9 (10.9)	37.8 (12.0)	14.9***
Sex (Male)	84.9%	89.1%	130.2***
Race (White)	77.6%	73.4%	75.8***
Length of stay in months (SD)	25.5 (32.9)	39.5 (42.8)	32.6***
Region (Metro)	65.7%	58.1%	197.4***
Most Serious Offense			1,218.4***
Property	32.1%	24.9%	
Person	28.5%	29.0%	
Other	15.9%	11.2%	
Drug Sale/Manufacture	13.8%	13.7%	
Sex offense	5.7%	17.5%	
Driving	3.9%	3.6%	

*$p < .05$. **$p < .01$. ***$p < .001$

Procedures

A primary goal of this study is to analyze the predictive accuracy of the LS/CMI for older AICs as compared to middle-aged and younger AICs. A direct comparison is complicated, as the possibility that older AICs differ from younger AICs is evident. For example, a higher proportion of older AICs may be serving time for sexual offenses, while younger AICs may be serving time for drugs or property offenses. Any age difference in the predictive utility of the LS/CMI might therefore be a function of an index crime (i.e., confounding variable) rather than age. To address this possibility, a case-control matching process was utilized to help ensure analysis outcomes are associated with age rather than being affected by confounding variables (Monahan et al., 2017).

The case-control matching process began by generating a variable labeled ID in Excel and then assigned to each of the 14,940 cases. The new variable ID was then merged into the full sample in SPSS as a case ID unique identifier. Two age category variables were created: age category 1 = younger (18-39) and older (55+), age category 2 = middle (40-54) and older (55+). Each age category variable was run separately through the case-control matching process (i.e., two rounds of case-control matching). Age category 1 was matched first. In SPSS under the data menu, the case-control matching process function was utilized. Variables matched were sex, race, LOS in quartiles, region, and the most serious offense. The match tolerances were set to zero for each variable to ensure a perfect match. The group indicator = age category 1 and the case ID = ID. The label for Match ID variables = Matchid. The name for the “Matchgroup” variable = MatchID_Var. The additional output option was chosen to instruct SPSS to form a new temp SPSS file of matches (Matchid=1). Next from the data menu in SPSS, the select cases function was selected and conditions satisfied were set to “does not equal zero” to eliminate all data not matched. A temp SPSS file of Matchid cases = 0 was created. From the data menu the option to merge files was selected and the add cases option. The temp SPSS file Matchid = 1 was selected to create a new case-control matched file for the first age category 1 group younger (18-39) and older (55+). The entire process was then repeated to create a second file for the age category 2 group middle (40-54) and older 55+).

In the age category 1 group case-control matching process, 922 exact matches resulted for younger aged AICs (18-39) and 922 for older aged AICs (55+). Ten cases were unmatched during the matching process due to missing data and eliminated by SPSS resulting in a file total of n = 1,844 cases. In the case-control matching process for age category 2, 911 exact matches were found for the middle-aged AICs (40-54) and 911 for older aged AICs (55+). Twenty-one cases were unmatched during the SPSS process and eliminated due to missing data resulting in a file total of n=1,822 cases.

There were significant differences found initially in the full sample of AICs and the case-control matching process provided a more unbiased comparison between younger (18-39 and older (55+) AICs and middle-aged (40-54) and older (55+) AICs. Table 2 results from the full sample compared to the case-control matched sample findings indicate that sex, race, LOS in quartiles, region, and the most serious offense variables no longer suggest any significant differences between AICs age groups. As an example, the composition of the most serious offense category was significantly different with older aged AICs more likely to be sex offenders (14.3%) than younger (4.2%) or middle-aged (5.1%) AICs in the full sample. In addition, significant differences were found in the sex, race, and length of stay (LOS) in months. Some differences were also found in the metro region as well. The case-control matching process helped to mitigate any potential issues of confounding variables in the results.

Table 2. *Characteristics of younger, middle, and older AICs in full and matched samples (1 of 2)*

	Full sample (n=10,793)			Matched sample (n=1,844)		
	Younger (18-39)	Older (55+)		Younger (18-39)	Older (55+)	
Demographic Factors	% or M	% or M	t or χ^2	% or M	% or M	t or χ^2
Age (SD)	29.3 (5.5)	59.9 (5.1)	164.4***	22.3 (3.3)	59.9 (5.1)	187.6***
Sex (Male)	84.8%	89.9%	17.9***	90.5%	90.5%	-
Race (White)	75.6%	80.5%	11.04***	81.1%	81.1%	-
LOS[a] continuous (SD)	22.7 (24.3)	39.5 (53.1)	17.5***	23.9 (20.2)	39.6 (53.3)	8.4***
LOS[a] quartiles (SD)			65.9***			-
90 to 291 days	25.4%	23.5%		23.3%	23.3%	
292 to 391 days	25.8%	19.4%		19.5%	19.5%	
392 to 824 days	25.5%	22.2%		22.0%	22.0%	
825+ days	23.3%	34.9%		35.1%	35.1%	
Region (Metro)	65.0%	65.6%	0.1	65.4%	65.4%	-
Most Serious Offense			269.0***			-
Property	32.6%	20.4%		20.4%	20.4%	
Person	30.2%	26.2%		26.5%	26.5%	
Other	15.9%	14.6%		14.6%	14.6%	
Drug Sale/Manufacture	13.5%	15.8%		15.9%	15.9%	
Sex offense	5.2%	14.3%		14.1%	14.1%	
Driving	2.6%	8.8%		8.5%	8.5%	

[a] LOS = Length of stay in months

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

Table 2. *Characteristics of younger, middle, and older AICs in full and matched samples (2 of 2)*

	Full sample (n=5,079)			Matched sample (n=1,822)		
	Middle (40-54) % or M	Older (55+) % or M	t or χ^2	Middle (40-54) % or M	Older (55+) % or M	t or χ^2
Age (SD)	46.1 (4.2)	59.9 (5.1)	87.8***	41.8 (2.5)	59.9 (5.1)	96.9***
Sex (Male)	84.0%	89.9%	21.2***	90.5%	90.5%	-
Race (White)	81.6%	80.5%	0.6	82.0%	82.0%	-
LOS[a] continuous (SD)	29.1 (42.4)	39.5 (53.1)	17.5***	36.0 (47.0)	39.8 (53.4)	1.6**
LOS[a] quartiles (SD)			28.0***			-
90 to 291 days	24.5%	23.5%		23.3%	23.3%	
292 to 391 days	24.3%	19.4%		19.3%	19.3%	
392 to 824 days	24.6%	22.2%		22.1%	22.1%	
825+ days	26.6%	34.9%		35.3%	35.3%	
Region (Metro)	67.5%	65.6%	1.3	66.1%	66.1%	-
Most Serious Offense			151.1***			-
Property	33.5%	20.4%		20.5%	20.5%	
Person	25.2%	26.2%		26.5%	26.5%	
Other	16.1%	14.6%		14.7%	14.7%	
Drug Sale/Manufacture	14.1%	15.8%		15.5%	15.5%	
Sex offense	5.1%	14.3%		14.1%	14.1%	
Driving	6.0%	8.8%		8.8%	8.8%	

[a] LOS = Length of stay in months

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

Measures

Dependent Variable

The dependent variable (DV) for this study is an arrest in Oregon for a new criminal offense within 3 years (1,096 days) of index release from prison coded as 1= occurred and 0= did not occur. Arrests resulting from probation or parole violations were excluded.

Independent Variables

Age (Primary IV)

Age at index date of release was utilized to delineate older versus younger individuals released from prison. Following the Monahan et al. (2017) study which tested the PCRA risk scale considering age, three age groups were created based on the continuous age variable in the full sample. Separate comparisons were run on the continuous age variable and resulted in two data files with age group comparisons. The first file defined younger adults (18-39) coded = 0, and older adults (55+) coded = 1. The second data file defined middle-aged adults (40-54) were coded = 0, and older adults (55+) were coded = 1.

LS/CMI Score(s)

AICs released with an existing LS/CMI assessment completed shortly before (0 to 365 days) or after (0 to 30 days) the index release date were analyzed. The LS/CMI Central Eight factors include criminal history (eight items), education/employment (nine items), family/marital (four items), leisure/recreation (two items), companion (four items), alcohol/drug problems (eight items), pro-criminal attitude/orientation (four items), and antisocial patterns (four items) (Andrews et al., 1990; Guay et al., 2020; Olver, Stockdale & Wormith, 2014; Radakrishnan et al., 2019; Singh et al., 2018). Each domain has a range of possible points which is equal to the number of questions within each domain (Guay et al., 2020; Orsini et al., n.d.). The criminal history (score range 0-8), education/employment (score range 0-9), family/marital (score range 0-4), leisure/recreation (score range 0-2), companion (score range 0-4), alcohol/drug problems (score range 0-8), pro-criminal attitude/orientation (score range 0-4), and antisocial patterns (score range 0-4). The total number of possible points is equal to 43 points (Guay et al., 2020; Orsini et al., n.d.).

Analytical Plan

This study utilized IBM SPSS statistics to analyze the data. To answer the first research question (RQ1) the full sample was utilized to understand the relationship between age and recidivism. Descriptive statistics, bivariate correlation analysis utilizing Person's correlation coefficient, and a Chi-square ($\chi 2$) test of association were performed. A binary logistic regression analysis was performed to understand the predicted probability of rearrest. The predicted probability of rearrest was compared to age as a continuous measure and then graphed in a scatter plot. Descriptive statistics and Chi-square ($\chi 2$) analyses were conducted on the case-control matched younger (18-39) and older (55+) sample, as well as the case-control matched middle-aged (40-54) and older (55+) sample.

To examine research question two (RQ2), regarding the LS/CMI yield mean score differences by age group, independent samples t-tests were performed. Age groupings of younger (18-39) versus older (55+) and middle-aged (40-54) and older (55+) were compared to the LS/CMI total score and the subscales (i.e., criminal history, education/employment, family/marital, leisure/recreation, companions, alcohol/drug problem, pro-criminal attitude, antisocial patterns). In addition, an analysis of variance, or ANOVA, was conducted to understand the variance between groups. The ANOVA test *F-statistic* was captured to identify whether group means differed. Cohen's d was calculated to understand the standardized mean difference effect size between age groups.

To examine if the LS/CMI is equally predictive of recidivism considering age (RQ3), a Receiver Operation Characteristic (ROC) or Area Under the Curve (AUC) analysis was conducted. The AUC analysis is the standard and most commonly used statistic for assessing risk scales (Andrews et al., 2012; DeMichele et al., 2020; Helmus & Babchishin, 2017; Mossman, 2013; Radakrishnan et al., 2019, Skeem & Lowenkamp, 2016; Tsao & Chu, 2021). AUC values are considered an excellent measure for testing risk instruments, as they are not influenced by varying rates of offending across groups (Skeem & Lowenkamp, 2016). AUCs range from 0 to 1.0, with 0 being a perfect negative prediction and 1.0 perfect positive prediction (Tsao & Chu, 2021). According to Rice and Harris (2005), AUCs of .71 or greater are considered strong, between .64 to .71 is considered moderate, and .56 to .64 is considered weak. Most risk instruments have an AUC or accuracy level that generally falls in the range of .65 to .75 (Brennan et al., 2009), or rather a moderate to strong predictive accuracy.

To answer research question four (RQ4) binary logistic regression analysis was performed to examine if age moderates the relationship between the LS/CMI and recidivism. The moderator regression analysis model utilized in this study followed the *Standards for Educational and Psychological Testing* (American Educational Research Association, American Psychological Association, & National Council on Measurement in Education, 2014), in line with previous risk instrument studies (DeMichele et al., 2020; Monahan et al., 2017; Skeem et al., 2016). Younger (18-39) and older (55+) AICs and middle-aged (40-54) and older (55+) AICs were compared to evaluate if age moderates the relationship between the LS/CMI and recidivism. To understand LS/CMI test bias in the risk instrument, a bivariate analysis testing significant $\chi 2$ differences between models 2 and 3 (intercept) and models 3 and 4 (slope) were analyzed (Aguinis et al., 2010; Monahan et al., 2017; Skeem et al., 2016). Finally, a crosstabulation analysis was conducted and then graphed in Excel to better understand the association of recidivism, age, and LS/CMI risk category cut points.

Lastly, the application of risk scale cut points raised some concerns (Monahan et al., 2017; Skeem et al., 2016). Considering that older AICs may recidivate at lower rates than younger or middle-aged AICs, an additional analysis step was taken. A positive-predictive value (PPV) and negative-predictive value (NPV) analysis was completed. Crosstabulation results were placed in a table to understand the differences in recidivism by age group based on LS/CMI risk categories. Overall, the PPV and NPV analysis was utilized to further evaluate if the LS/CMI scores overclassify the risk of recidivism for older AICs (55+).

Findings

RQ1: *What is the relationship between age and recidivism?*

As shown in Table 3, of the 14,940 cases in the full sample, 29.1% of AICs 55 and older were rearrested, significantly less than other age groups. More specifically, older AICs 55+ recidivated 27.1% less than AICs 18 to 24, and 16.4% less than AICs 40-54 years of age. The Pearson's r correlation coefficient indicates that when age is tested as a continuous variable, age has a significant negative effect on rearrest ($r = -.163$; $p < .001$). Figure 2 reveals that the probability of rearrest decreased significantly as a function of age, $\chi2$ (1, N = 14,940) = 399.7, $p < .001$. Fifty-two percent of the 14,940 AICs in the sample recidivated within three years of release from prison. Lastly, A chi-square ($\chi2$) analysis was performed with age as a categorical variable testing recidivism rates for the three age groups. Findings also indicate that recidivism decreased significantly as a function of age, $\chi2$ (2, N = 14,940) = 332.7, $p < .001$. This means that as age increases recidivism decreases. Thus, validating the RQ1 hypothesis that the risk of recidivism would decrease with increasing age.

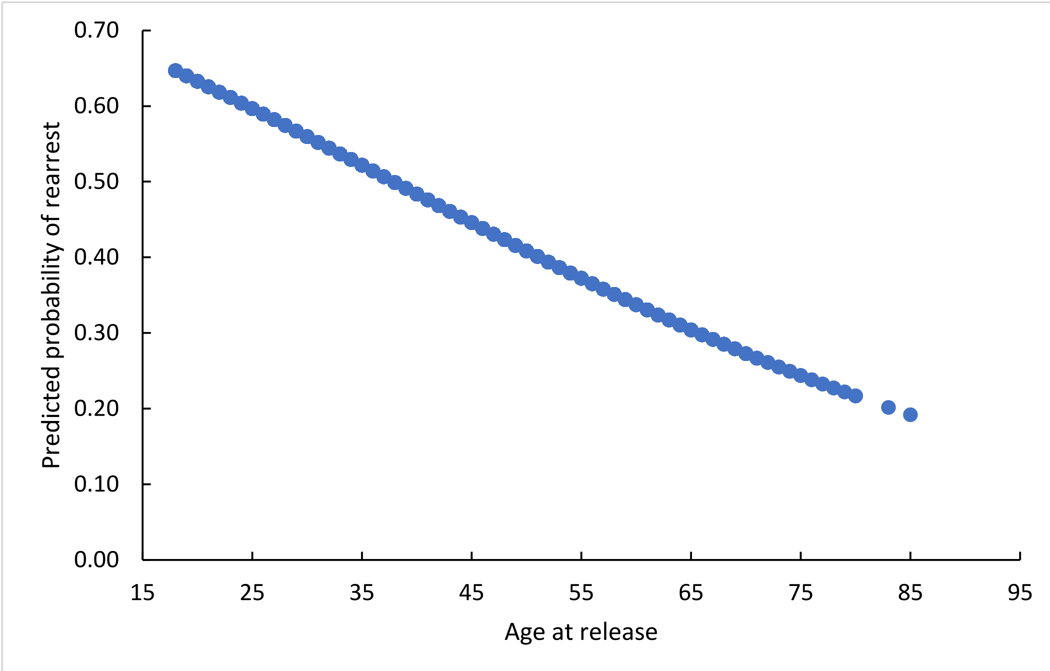
Table 3. *AICs rearrested by age group (N=14,940)*

Age Group	Percent Re-Arrested	r^a
Full Sample		-.163***
Younger (18-39)	56.2%	
Middle (40-54)	45.5%	
Older (55+)	29.1%	

*$p < .05$. **$p < .01$. ***$p < .001$

[a]Pearson correlation

Figure 2. *Predicted probability of rearrest by age at release, full sample (N=14,940)*



The above analyses do not control for confounding variables (i.e., sex, race, LOS in quartiles, region, and the most serious offense) that might differ between younger, middle-aged, and older AICs. Table 4 findings utilized the case-control matched samples of younger (18-39) versus older (55+) and middle-aged (40-54) versus older (55+) to understand the association between age and rearrest. A chi-square ($\chi 2$) analysis was performed with age as a categorical variable of younger (18-39) versus older (55+) testing recidivism rates for the two age groups. Findings indicate that recidivism decreased significantly as a function of age, $\chi 2$ (1, N = 1,844) = 135.4, $p < .001$. Similarly, the chi-square ($\chi 2$) analysis for the middle-aged (40-54) versus older (55+) AICs produced a statistically significant result $\chi 2$ (1, N = 1,844) = 49.5, $p < .001$.

Table 4: *AICs rearrested by age group. Younger 18-39 v. Older 55+ (N=1,844). Middle 40-54 v. Older 55+ (N=1,822)*

Age Group	Percent Re-Arrested	$\chi 2$
Matched Sample Younger v. Older		135.4***
Younger (18-39)	55.9%	
Older (55+)	29.1%	
Matched Sample Middle v. Older		49.5***
Middle (40-54)	45.0%	
Older (55+)	29.1%	

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

RQ2: *Does the LS/CMI yield mean score differences by age group?*

The second aim of this study was to assess the mean score differences for younger (18-39) versus older (55+) AICS and middle-aged (40-54) versus older (55+) AICs. It was hypothesized that mean score differences would be found between age groups. The results found in Table 5 indicate that significant LS/CMI mean score differences were found between younger and older age AICs, except for criminal history and leisure/recreation categories which were not significantly different. Younger AICs have a higher LS/CMI total score than older AICs, F (1, N = 1,844) = 38.25, p < .001. However, the Cohen's d for the standardized mean difference effect size was small (d = -.29). According to Cohen (1988), minimum d values of .2 are defined as a small effect, .5 is a medium effect, and a large effect is .8. The education/employment measure difference between younger (18-39) and older (55) AICs was the largest F (1, N = 1,844) = 239.72, p < .001. The education/employment measure also had a medium to large negative effect (d = -.72) when considering age. This may suggest that older AICs have fewer education/employment needs compared to younger AICs. It could be hypothesized that maturation processes may help to stabilize employment for older AICs and education might not be as critical. Except for education/employment, the differences between younger (18-39) and older (55+) AICs across the LS/CMI sub-domains were small (*d* = -.35 to .23).

Table 5. *LS/CMI mean scores, SD for younger 18-39 versus older adults 55+ (N=1,844)*

Measures	Possible Range	Younger (18-39)		Older (55+)		Younger versus Older		
		M	*SD*	*M*	*SD*	*Diff.*	*F*	*d*
LS/CMI Total Score	0 - 43	22.74	7.74	20.56	7.35	-2.17	38.25***	-.29
Criminal History	0 - 8	4.86	1.97	5.02	1.77	.16	3.39	.09
Education/Employment	0 - 9	5.48	2.38	3.73	2.46	-1.75	239.72***	-.72
Family/Marital	0 - 4	1.58	1.15	1.88	1.14	.30	31.82***	.26
Leisure/Recreation	0 - 2	1.47	.78	1.41	.80	-.06	2.44	-.08
Companions	0 - 4	2.79	1.22	2.55	1.27	-.24	17.45***	-.19
Alcohol/Drug Problem	0 - 8	3.38	2.47	2.86	2.33	-.52	21.30***	-.22
Procriminal Attitude	0 - 4	1.33	1.37	1.64	1.35	.31	23.69***	.23
Antisocial Patterns	0 - 4	1.85	1.12	1.47	1.07	-.38	56.06***	-.35

*$p < .05$. **$p < .01$. ***$p < .001$

The results found in Table 6 indicate significant LS/CMI mean score differences between middle-aged (40-54) and older (55+) AICs. Middle-aged AICs were found to have a significantly higher LS/CMI total score than older AICs, F (1, N = 1,822) = 37.24, $p < .001$. However, the Cohen's *d* for the standardized mean difference effect size was small (*d* = -.29). The family/marital, leisure/recreation, and pro-criminal attitude scores were not significantly different when comparing middle-aged AICs to older AICs. In contrast to the younger (18-39) and older (55+) aged AICs analysis, the criminal history score for middle-aged AICs was significantly different (higher) to the older aged AICs, F (1, N = 1,822) = 35.25, $p < .001$. Again, similar to the total score, the Cohen's *d* for the standardized mean difference effect size for criminal history was small (*d* = -.29).

Overall, the differences between middle-aged (40-54) and older (55+) AICs across the LS/CMI sub-domains were small (*d* = -.38 to .07).

Table 6. *LS/CMI mean scores, SD for middle 40-54 versus older adults 55+ (N=1,822)*

Measures	Possible Range	Middle (40-54)		Older (55+)		Younger versus Older		
		M	*SD*	*M*	*SD*	*Diff.*	*F*	*d*
LS/CMI Total Score	0 - 43	22.69	7.16	20.62	7.33	-2.07	37.24***	-.29
Criminal History	0 - 8	5.51	1.65	5.03	1.78	-.48	35.25***	-.29
Education/Employment	0 - 9	4.62	2.21	3.74	2.46	-.88	64.70***	-.38
Family/Marital	0 - 4	1.81	1.20	1.88	1.14	.07	1.86	.06
Leisure/Recreation	0 - 2	1.43	.78	1.42	.80	-.01	.11	-.01
Companions	0 - 4	2.71	1.27	2.55	1.28	-.16	7.32**	-.13
Alcohol/Drug Problem	0 - 8	3.39	2.40	2.87	2.32	-.52	22.04***	-.22
Procriminal Attitude	0 - 4	1.56	1.34	1.65	1.35	.09	1.85	.07
Antisocial Patterns	0 - 4	1.66	1.11	1.48	1.07	-.18	12.59***	-.17

*$p < .05$. **$p < .01$. ***$p < .001$

RQ3*: Is the LS/CMI equally predictive of recidivism considering age?*

To test the third research question (RQ3) in line with previous risk scale tests, an AUC analysis was conducted (Hanley & McNeil, 1982; Monahan et al., 2017). The LS/CMI total score and all of the central eight domains were analyzed by age groupings utilizing the case-control matched samples. It was hypothesized that LS/CMI would be equally predictive of recidivism for both older versus middle-aged and older versus younger aged AICs. As shown in Table 7, the AUCs were all comparable between the younger and older AICs except for criminal history, $Z = 2.54$, $p < .01$. Given the larger sample size a more stringent threshold was utilized of $p < .001$ rather than $p < .05$. As mentioned, according to Rice and Harris (2005) an AUC of .71 or greater is considered strong, between .64 to .71 is considered moderate, and .56 to .64 is considered weak.

AUC values in Table 7 ranged from .55 to .66 for younger AICs and .55 to .68 for older AICs suggesting overall weak to moderate predictive utility.

Table 7. *LS/CMI AUC and Z scores for younger 18-39 versus older 55+ (N=1,844)*

Measures	Younger (18-39)	Older (55+)	Younger versus Older	
	AUC	AUC	AUC Diff.	z
LS/CMI Total Score	.66	.68	.02	.89
Criminal History	.62	.68	.07	2.54**
Education/Employment	.62	.60	.00	0.01
Family/Marital	.56	.57	.01	.39
Leisure/Recreation	.55	.57	.02	.73
Companions	.59	.58	-.01	-.36
Alcohol/Drug Problem	.61	.63	.02	.83
Procriminal Attitude	.60	.55	-.05	-1.81
Antisocial Patterns	.60	.62	-.01	-.22

*$p < .05$. **$p < .01$. ***$p < .001$

In Table 8, the results indicate that all AUC differences between middle-aged (40-54) and older (55+) AICs were comparable at the criteria level of $p < .001$, except for the LS/CMI total score, $Z = 1.98$, $p < .05$. Given the larger sample size, a more stringent threshold was utilized of $p < .001$ rather than $p < .05$. AUC values in Table 8 ranged from .52 to .66 for middle-aged AICs and .55 to .69 for older AICs suggesting weak to moderate predictive utility.

Table 8. *LS/CMI AUC and Z scores for middle 40-54 versus older 55+ (N=1,822)*

Measures	Middle (40-54)	Older (55+)	Middle versus Older	
	AUC	AUC	AUC Diff.	z
LS/CMI Total Score	.63	.68	.05	1.98*
Criminal History	.66	.69	.03	1.08
Education/Employment	.58	.61	.03	.91
Family/Marital	.52	.57	.05	1.64
Leisure/Recreation	.54	.57	.03	.88
Companions	.58	.58	.00	-.16
Alcohol/Drug Problem	.58	.63	.05	1.76
Procriminal Attitude	.53	.55	.02	.70
Antisocial Patterns	.60	.62	.02	.71

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

While the above analyses provide evidence that the LS/CMI has good predictive utility, further questions remain. Older AICs aged 55+ were found to have lower rates of recidivism than younger (18-39) or middle-aged (40-54) AICs. This suggests that while the LS/CMI is predictively accurate as reported in the AUC analysis, there is more to be considered. It could be hypothesized that the LS/CMI can be predictively accurate yet not applied correctly. Unpacking these analyses' outcomes may suggest that perhaps the risk category cut-points are not appropriately applied.

***RQ4**: Does age moderate the relationship between the LS/CMI and recidivism?*

To examine the fourth research question (RQ4), a series of logistic regression models were developed to test if age moderates the relationship between the LS/CMI and recidivism. Based on the outcomes of Monahan et al. (2017), it was hypothesized that age would not moderate the relationship between the LS/CMI total score and recidivism. The results are summarized in Table 9 for younger (18-39) and older (55+) aged AICs and in

Table 10 for middle-aged (40-54) and older (55+) aged AICs. Both Tables 9 and 10 follow a similar method with Model 1 only using age and Model 2 only using the LS/CMI total scores to predict rearrest. In Model 3 age and the LS/CMI total score were used to predict rearrest. Model 4 included age, the LS/CMI total score, and the interactions between age and the LS/CMI total score. Overall, age was not found to moderate the relationship between the LS/CMI and rearrest[2].

In Table 9 findings indicate that the slope of the relationship between the LS/CMI total score and rearrest is similar across age groups (younger versus older) and not significant. Model 3 was statistically significant, χ 2 (2) = 283.86, *p* < .001, and explained 19% (Nagelkerke R^2) of the variation in the outcome, rearrest. When comparing Model 3 and Model 4 (slope), age does not significantly moderate the LS/CMI total score in predicting rearrest, $\Delta\chi^2$ (1) = 1.30, *ns*. When comparing Model 2 and 3 (intercept), findings indicate that age adds significant incremental value to the LS/CMI in predicting rearrest, $\Delta\chi^2$ (1) = 106.72, *p* < .001. The intercept of the relationship between the LS/CMI total score and rearrest decreases with increasing age.

[2] The LS/CMI total score and rearrest were also tested with age coded continuously (Monahan et al., 2017) and coded as a quadratic, both squared and cubed. Similar results were found, age did not moderate the relationship between the LS/CMI total score and rearrest, and the results were not significant. The LS/CMI eight sub-domains (criminal history, education/employment, family/marital, leisure/recreation, companion, alcohol/drug problems, pro-criminal attitude/orientation, antisocial patterns), and rearrest were also tested with age younger v. older and middle-aged v. older. Findings indicated that age did not moderate the relationship between any of the sub-domain relationships and rearrest, with one exception. The younger (18-29) v. older (55+) logistic regression test findings indicated that age moderated the relationship between criminal history and rearrest, χ 2 (3) = 269.79, p < .001.

Table 9. *Logistic regression model of LS/CMI total score and age (N=1,844)*

	Recidivism							
	Model 1		Model 2		Model 3		Model 4	
	OR	[95% CI]	*OR*	[95% CI]	*OR*	[95% CI]	*OR*	[95% CI]
Age (Younger 18-39)	.32***	[.27-.39]			.35***	[0.29-0.43]	.24***	[.12-.48]
LS/CMI Total Score			1.09***	[1.08-1.11]	1.09***	[1.07-1.10]	1.08***	[1.06-1.10]
LS/CMI Total Score x Age							1.02	[.99-1.05]
(Constant)	1.27***		.11***		.20***		.23***	
Model $\chi 2$	137.30***		177.14***		283.86***		285.16***	
Nagelkerke R^2	.10		.12		.19		.19	

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

Table 10 findings are comparable to Table 9 and indicate that the slope of the relationship between the LS/CMI score and rearrest is similar across age groups (middle-aged versus older) and not significant. Model 3 was statistically significant, χ 2 (2) = 176.71, $p < .001$, and explained 13% (Nagelkerke R^2) of the variation in the outcome, rearrest. When comparing Model 3 and Model 4 (slope), age does not significantly moderate the LS/CMI total score in predicting rearrest, $\Delta\chi^2$ (1) = 3.02, *ns*. When comparing Model 2 and 3 (intercept), findings indicate that age adds significant incremental value to the LS/CMI in predicting rearrest, $\Delta\chi^2$ (1) = 31.84, $p < .001$. The intercept of the relationship between the LS/CMI total score and rearrest decreased with increasing age.

Table 10. *Logistic regression model of LS/CMI total score and age (N=1,822)*

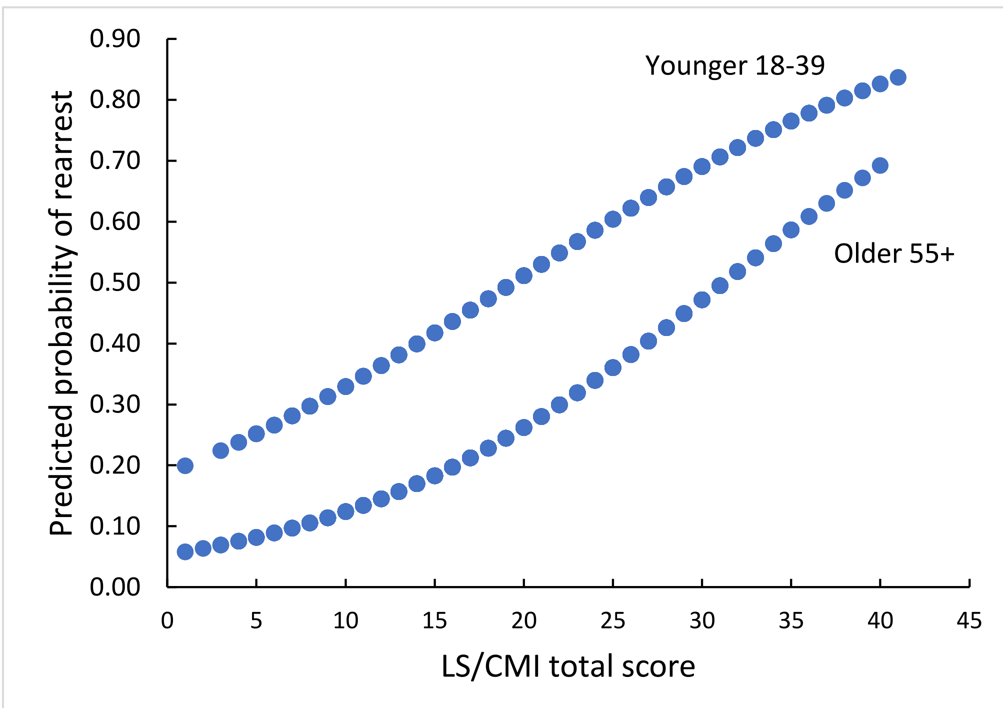
	Recidivism							
	Model 1		Model 2		Model 3		Model 4	
	OR	[95% CI]	*OR*	[95% CI]	*OR*	[95% CI]	*OR*	[95% CI]
Age (Middle 40-54)	.50***	[.41-.61]			.56***	[.46-.69]	.31***	[.15-.63]
LS/CMI Total Score			1.09***	[1.07-1.10]	1.08***	[1.07-1.10]	1.07***	[1.05-1.09]
LS/CMI Total Score x Age							1.03	[.99-1.06]
(Constant)	.82**		.09***		.13***		.17***	
Model χ2	49.77***		144.88***		176.71***		179.73***	
Nagelkerke R^2	.04		.10		.13		.13	

*$p < .05$. **$p < .01$. ***$p < .001$

Figure 3, Panels A and B help to further illustrate the relationship between the LS/CMI total score and rearrest. As the predicted probability of rearrest increases and age decreases, the LS/CMI total score may overclassify rearrest for older AICs. An interesting finding in Figure 3, Panel A is the line of the younger AIC predicted probably of rearrest and the LS/CMI total score shows a somewhat curvilinear relationship. This may indicate that the relationship is less linear and more dynamic with the concept of recidivism. Overall, the findings indicate that a strong association exists between age, the LS/CMI total score, and rearrest.

Figure 3. *Predicted probability of rearrest by LS/CMI total score. Panel A = younger 18-39 and older 55+ (N=1,844). Panel B = middle-aged 40-54 and older 55+ (N=1,822)*

A



B

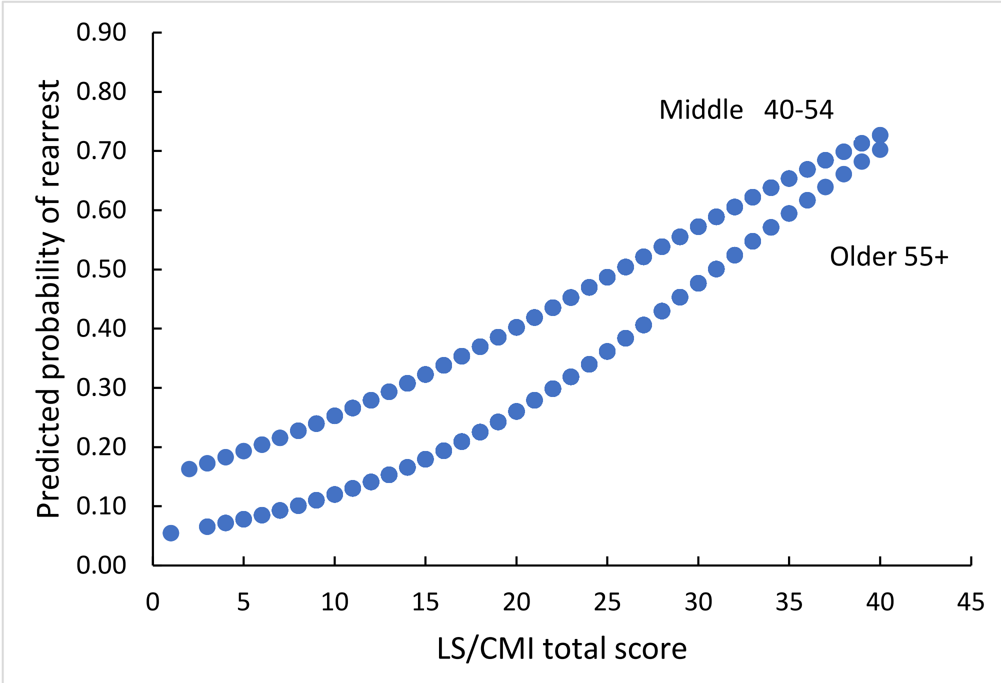
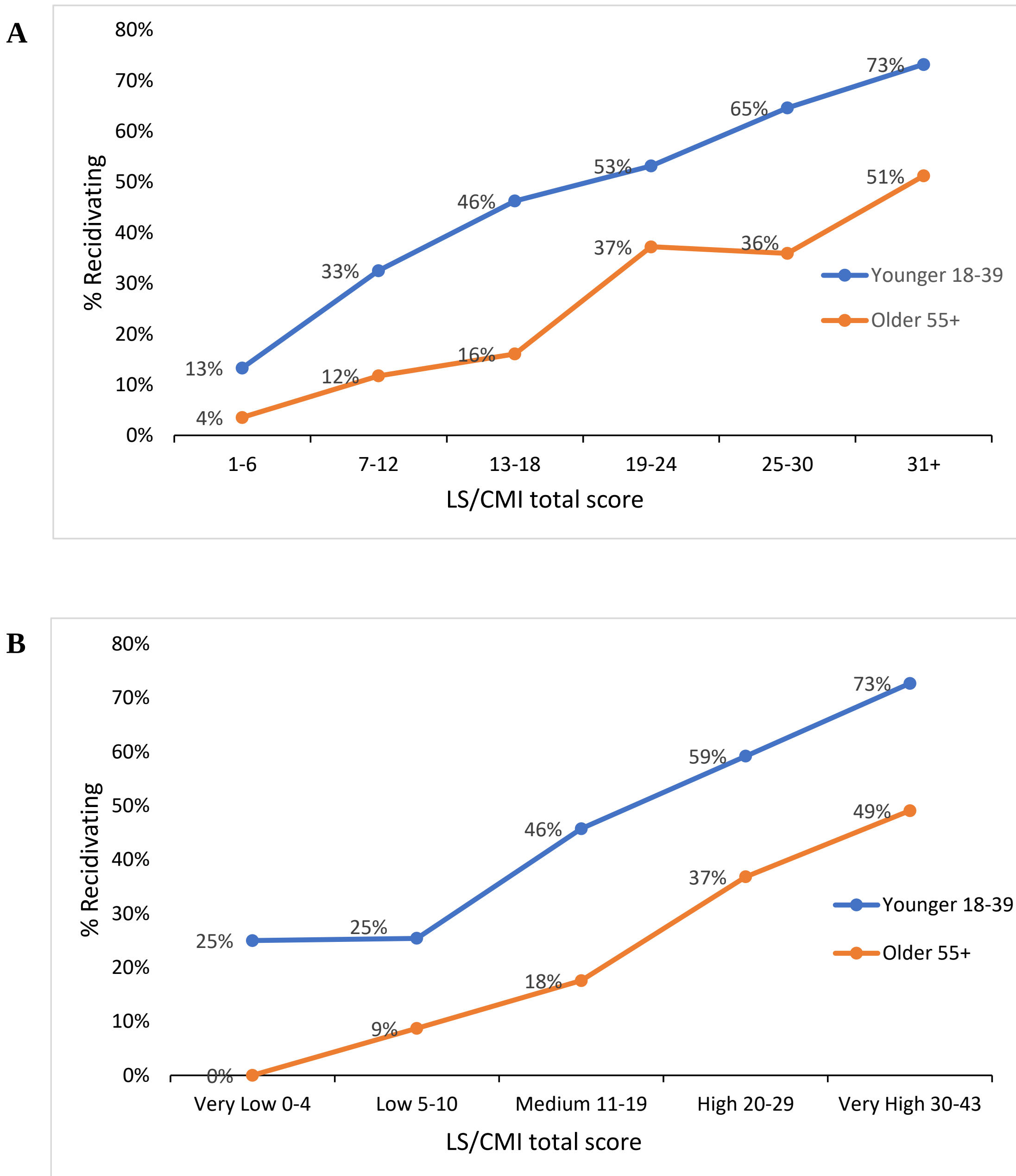


Figure 4 and Figure 5 provide a more visual summary of the predictive fairness and mean score differences. Both Figure 4 and Figure 5 demonstrate results of the LS/CMI continuous scores (A) and risk categories (B) of very low (0-4), low (5-10), medium (11-19), high (20-29), and very high (30-43). The results indicate that older AICs recidivated at a much lower rate than younger or middle-aged AICs. In figure 4 (A), younger AICs scoring 25-30 points were found to recidivate 65% as compared to older AICs at 36%. In Figure 4 (B), younger AICs were found to recidivate at 46% as compared to older AICs at 18%. This raises the concern that while the LS/CMI may indicate risk trajectories correctly, the application of risk scale cut-points would indicate that the LS/CMI may not be age-responsive.

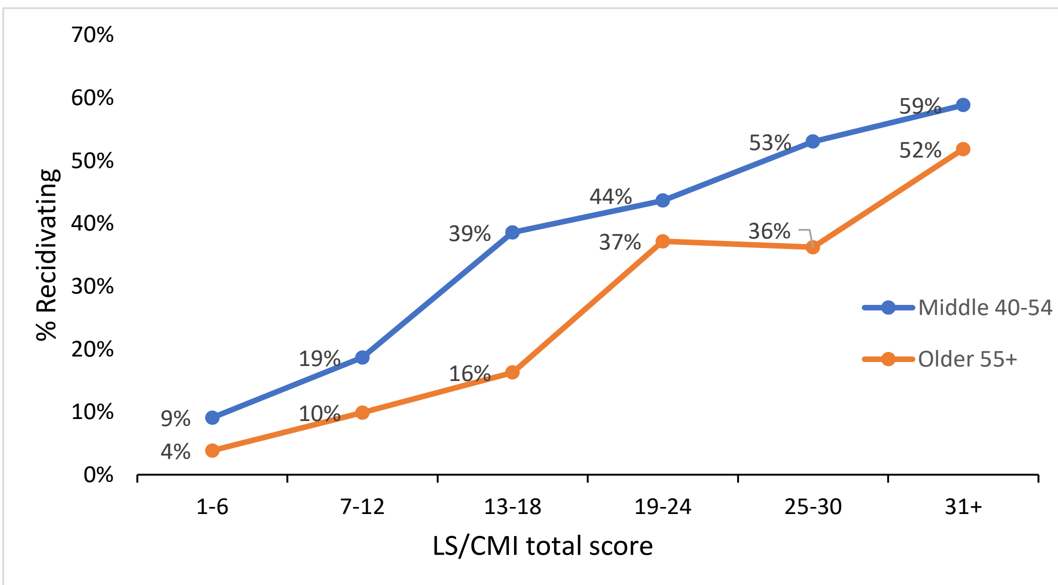
Figure 4. *LS/CMI total scores and recidivism by age group, younger versus older (N=1,844). Panel A = continuous scores. Panel B = risk categories.*



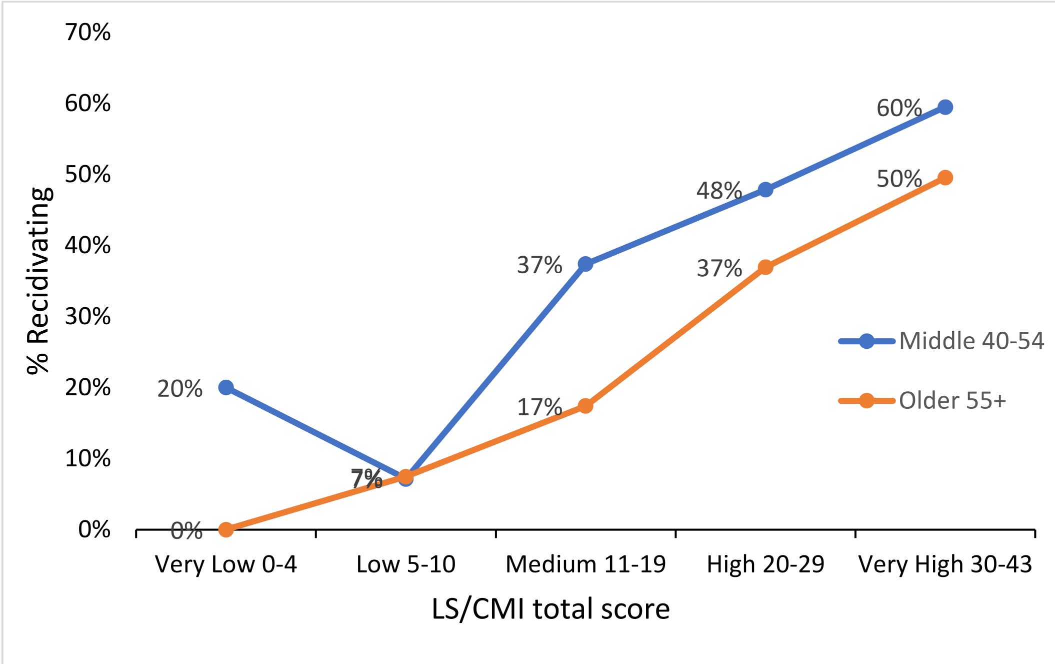
Similarly, in Figures 5 (A) and (B) middle-aged AICs recidivated at higher rates than older AICs. This may suggest that the LS/CMI score overclassifies recidivism in older AICs. As an example, a medium score (11-19) resulted in 37% recidivating for middle-aged AICs as compared to 17% in the older AIC population. As such, a score for a younger or middle-aged AIC means something very different compared to an older AIC. As mentioned, both Figures 4 and 5 suggest that the LS/CMI cut-points may not be age-responsive, as similar LS/CMI scores produce differing levels of recidivism by age group. As an example, a high-risk score (20-29) for older adults indicates 37% recidivating by comparison middle-aged adults with 37% recidivism are scored as medium risk. Overclassifying by one category in the LS/CMI level of risk (i.e., high-risk score versus medium-risk score) has important implications for both sanctions and case planning.

Figure 5. *LS/CMI total scores and recidivism by age group, middle versus older (N=1,822). Panel A = continuous scores. Panel B = risk categories.*

A



B



Lastly, a positive-predictive value (PPV) and negative-predictive value (NPV) analysis was completed to fully extend the understanding of the LS/CMI accuracy in predicting recidivists. The case-control matched samples for younger AICs (18-39) versus older AICs (55+) and middle-aged (40-54) versus older AICs (55+) were analyzed. Table 11 results indicate that the scale accuracy in predicting recidivists in the older AIC population (PPV) is 23.9% lower than younger AICs and 11.3% lower when compared to middle-aged AICs. The PPV and NPV analyses further demonstrate that LS/CMI scores are not accurate due to scale cut-points that are not age-responsive. As such, the LS/CMI may overclassify recidivism for older AICs.

Table 11. *PPV and NPV LS/CMI results for younger 18-39 versus older adults 55+ (N=1,844) and middle 40-54 versus older adults 55+ (N=1,822)*

Measures	Younger (18-39)	Older (55+)	Middle (40-54)	Older (55+)
Overall accuracy of scale	61.6%	59.0%	56.3%	59.2%
PPV - Accuracy in predicting recidivists	63.4%	39.5%	51.0%	39.7%
NPV - Accuracy in predicting non-recidivists	58.2%	84.5%	67.1%	84.8%
Sensitivity - % of recidivists accurately identified	73.8%	76.9%	75.9%	77.4%
Specificity - % of non-recidivists accurately identified	46.2%	51.7%	40.3%	51.7%
LS/CMI total score AUC	.66	.68	.63	.68

Discussion

The LS/CMI is widely used across the U.S. criminal justice system and yet we know very little about how the risk scale performs considering age. Developmental or life-course theories help us to understand that with age criminal propensity declines. Therefore, it was surprising that no empirical research was found testing the LS/CMI risk scale considering age. Risk instruments such as the LS/CMI are central to correctional management processes. Risk assessments set sanction decisions and provide offenders with focused resources to reduce the risk of recidivism in the future. The criminal justice system will maximize its resources by focusing on offenders with the highest risk and by applying resources to the offenders with the highest levels of need. Age is an important factor to consider when assessing an AICs risk for recidivism. This study's findings indicate that age matters.

In this study, a comparable sample of AICs released from an Oregon prison facility between 2011 and 2017 was used to examine the relationship between age and recidivism and if the LS/CMI is equally predictive of recidivism considering age. Following the research methods utilized by Monahan et al. (2017) and Skeem et al. (2016), several research questions were asked to investigate further the relationship between age, recidivism, the LS/CMI, and age. While scholarship has confirmed that as individuals age recidivism declines, it was unclear if scholarship findings would apply to this study's Oregon sample. The first research question (RQ1) investigated the relationship between age and recidivism. It was expected that age would have an inverse relationship with recidivism, and differences in recidivism would be found when comparing younger (18-39) and older (55+) AICs and middle-aged (40-54) and older (55+) AICs. Findings indicated that recidivism decreased significantly as a function of age. In addition, a strong negative linear relationship between age and the predicted probability of rearrest was found. These findings lend support to the existing body of research that: older AICs recidivate at significantly lower rates than other age groups.

The second aim of the study (RQ2) was to test if LS/CMI mean score differences would be found when comparing younger (18-39) and older (55+) AICs and middle-aged (40-54) and older (55+) AICs. Older AICs were found to have significantly lower mean LS/CMI total scores than younger or middle-aged AICs. The findings support the hypothesis that: mean score differences would be found between age groups. While mean score differences were important to understand, questions about accuracy and equity remained unanswered. As an example, lower LS/CMI mean scores in needs categories for older AICs may indicate that the amount or type of resources available may be limited. Older AICs may be denied critical resources such as housing or healthcare due to a lower risk score. In contrast, it is also conceivable that unnecessarily strict sanctions may be applied when considering that older AICs recidivate at significantly lower rates than other age groups.

Next, to further investigate the accuracy of the LS/CMI considering age (RQ3) an AUC analysis was performed. The AUC analysis findings indicated that the greater majority of the AUC differences between the younger (18-39) and older (55+) AICs and middle-aged (40-54) and older (55+) AICs were not statistically significant. As expected, the LS/CMI was largely equal in predictive accuracy when comparing age groups, thus supporting the hypothesis. Findings indicated AUC values ranging between .52 to .69 suggesting weak to moderate LS/CMI predictive utility (Rice and Harris, 2005). More importantly, and similarly to Monahan et al. (2017), this study found that the AUC analysis may not reveal the entire story related to age, risk assessment accuracy, and patterns of recidivism. Special populations such as older (55+) AICs, present assessment challenges for the criminal justice corrections system. Older AICs potentially have higher needs but may not receive critical resources (i.e., health care, housing) due to lower risk scale scores. In contrast, older AICs might score high risk but may not require stricter sanctions (i.e., monitoring, supervision) due to declining health, for example. Scholars argue that a risk instrument "can perfectly measure risk across groups" and yet be unfairly applied as risk category cut-points result in disparate impacts (Monahan et al., 2017; Skeem et al., 2016). Therefore, going beyond accurate scoring or predictive accuracy was considered to be important in this study.

A series of logistic regression models were developed (i.e., LS/CMI total score, subdomains, age groups, age as a continuous variable, and age quadratics) to test if age moderates the relationship between the LS/CMI and recidivism (RQ4). As expected, age did not moderate the relationship between the mean LS/CMI total score and rearrest. The findings showed that younger (18-39) compared to older (55+) and middle-aged (40-54) compared to older (55) AICs had the same slope. This means that recidivism rates increase with increasing LS/CMI scores. Importantly, the intercept findings lead to a different story, indicating that age adds significant incremental value to the LS/CMI in predicting rearrest. Alternatively stated the intercept of the relationship between the

LS/CMI total score and rearrest decreases with increasing age. While the direction (i.e., slope) is similar, older AICs recidivate at much lower rates than younger or middle-aged AICs (i.e., intercept). As an example, younger AICs scoring 25-30 points were found to recidivate 65% as compared to older AICs at 36%. To further illustrate, a positive-predictive value (PPV) and negative-predictive value (NPV) analysis was performed. Results indicated that the scale accuracy in predicting recidivists in the older AIC population (PPV) is 23.9% lower than younger AICs and 11.3% lower when compared to middle-aged AICs. The findings confirm that the LS/CMI risk scale might not be applied appropriately for older AICs.

In summary, although only one study was found investigating predictive accuracy in risk instruments considering age, Monahan et al., (2017), it is encouraging that the findings from this study were found to be similar. While modern-day risk instruments do provide more reliable results than subjective assessments of the past, research gaps remain (Taxman, 2017, p.18). As this study suggests, there is much more to unpack when considering age and risk instruments such as the LS/CMI. This study's findings raise the concern that while the LS/CMI may indicate risk trajectories correctly, the application of risk scale cut-points suggests that the LS/CMI may not be age-responsive and may overclassify risk of recidivism for older (55+) AICs.

Limitations

This study only begins to build upon a very limited body of older AIC empirical research. As this study was a first of its kind, a body of research should be established to ensure generalizability. In addition, in Oregon community corrections, the LS/CMI is generally only used for offenders who have medium or high scores on the Public Safety Checklist (PSC), a state-specific risk instrument (Radakrishnan et al., 2019). This means that a portion of the population may be missing in this study (i.e., 14,354 cases removed without an LS/CMI assessment) and may make it harder to assess how well the LS/CMI predicts reoffending based on age. Specifically, the loss of cases in this study's sample reduces the generalizability of this study.

This study dichotomized age, and as such older AICs were treated homogenously. As DLC theories help us to understand, important nuances are associated with the aging process and criminal propensity (Laub & Sampson, 2001; Sampson & Laub, 2005; Hanson, 2006; Wolfe et al., 2016). As an example, as AICs age considerably more health concerns may arise which may lead to further reductions in recidivism not captured in this study. Therefore, future studies should consider age as a continuous variable or break down age into more categories to increase the power of the results. Another point of consideration would be gaps in arrest records before the 1970s. Older offender criminal records that pre-date the 1970s may not be available and are considered a limitation as they may influence LS/CMI results for older AICs.

Prior Oregon LS/CMI research by Radakrishnan et al. (2019) found that the AUC scores for the LS/CMI in Oregon are roughly 0.63, which indicates weak to moderate predictive ability. Radakrishnan et al. (2019) state that the overall LS/CMI predictive accuracy is lower in Oregon as compared to other geographical locations. As risk scores can be impacted by reliability, it is important to understand LS/CMI interrater reliability.

An interrater reliability assessment in Oregon may help to shed light on lower than expected predictive utility, especially in relationship with age.

Overall, matching processes help a researcher balance a sample and control for confounding variables (Osbourne, 2008). The choice of matching method used in this research, case-control matching, followed the research methods of Monahan et al. (2017). Matching processes, such as case-control matching, can help to address issues of selection bias. However, heterogeneity may still exist despite the attempts to eliminate the issue. As such, the use of case-control matching could be considered a limitation of this study.

Several studies have shown that propensity score matching (PSM) may be a more effective analytic method of matching and balancing a sample (Campbell et al., 2022; Stuart, 2010). PSM helps to eliminate issues of "predictors of convenience" (i.e., demographic variables) which may affect performance and deliver poor outcomes (Stuart, 2010). Stuart (2010) states that PSM combined with additional regression models can be considered a "doubly robust" approach as it isolates the effects of other covariates. PSM is considered best at replicating a "mini-randomized experiment" (Osbourne, 2008, p. 160). PSM is also known as the best method of removing selection bias that can exist between groups (Campbell et al., 2022). In this study, a large significant standard deviation was found in the continuous measures of age in the matched samples (SD=53.3 to 53.4, $p < .001$). This indicates that the results may have reduced power as the age range has been restricted by utilizing dichotomized variables for age. PSM allows for a method of matching based on the standard deviation therefore age as a continuous measure could be utilized to increase the power of the results (Stuart, 2010). In summary, future research testing the LS/CMI for predictive accuracy considering age should consider PSM as the best-known method for balancing the sample and to help the researcher elicit noncausal or even causal disparities in findings (Stuart, 2010).

Implications and Areas for Future Research

A body of empirical research conveys growing concerns about race and gender demographic characteristics being utilized in risk scales as they may result in unjust/unwarranted disparities (Monahan et al., 2017; Skeem & Lowenkamp, 2016). This study contributes to the growing concerns associated with risk instruments and unjust/unwarranted disparities, by adding age to the discussion. Similar to the large body of criminology research examining risk instruments for gender-responsivity, which aided in the eventual development of the Women's Risk Needs Assessment (WRNA) (Taxman, 2017, p. 227), this study argues that age-responsive risk instruments are an important consideration. The LS/CMI does not integrate critical measures to assess the unique risks and needs of older AICs 55+ such as maturation processes, elder stability, elder economic marginality, mobility needs, age-appropriate housing, age-appropriate health care needs, risk of social isolation, higher likelihood of comorbidities, higher likelihood of suicide ideation, cognitive decline, and increased risk of mortality. It is unclear if a new risk scale that is specifically age-responsive is warranted yet, but future research should examine the possibility.

Policy considerations should include reexamining the application of the LS/CMI risk category cut-points for older (55+) AICs. Age must be considered differently. As evidenced in this study, the overclassification of older AICs' risk of recidivism may result in unjust/unwarranted disparities. Future research studies need to go beyond predictive accuracy (i.e., AUC analyses) when testing risk scales considering age. Older AICs have a significantly lower base rate of recidivism, the LS/CMI cut-points would need to change to produce age-based similar recidivation. As an example, older AICs with a mean score of 37% recidivism were scored as high-risk (20-29). By comparison, middle-aged AICs with a mean score of 37% recidivism were scored as medium risk (11 to 19). Overclassification of one full risk category in the LS/CMI level of risk (i.e., high-risk score versus medium-risk score) has important implications for both sanctions and case planning. The overclassification of older AICs could perhaps be mitigated through LS/CMI professional override processes. Thus, LS/CMI professional override policies could also be more closely examined across criminal justice settings. In addition, professional override processes should be examined in future research considering older AICs. Therefore, future criminal justice system policies and future research should further evaluate the evidence from this study indicating one full risk category of overclassification for older AICs.

Risk instruments such as the LS/CMI should be informed by DLC theories. Therefore, future research could perhaps go beyond the risk-need model entirely. The "Good Lives Model" (GLM) could be examined in future research as it may better address the unique needs of special populations such as older AICs. The GLM model of rehabilitation is a more positive approach to "promoting prosocial and personally more satisfying goals" (Ward & Brown, 2006). For older AICs with a reduced propensity for criminal behavior, and potentially higher needs, GLM may be a more viable option. GLM takes capacity into account when assessing offending behavior (Ward & Brown, 2006). Capacity is particularly relevant to older AICs with declining health and increased age-responsive needs (i.e., age-appropriate housing or health care). Thus, GLM should be further investigated in the context of the unique risks and needs of older AICs.

Consideration should be given to the lower base rate of recidivism for older AICs as found in this study. Overclassification may further marginalize older AICs and may exacerbate an already destitute population. As an example, older AICs with a high-risk LS/CMI total score may require more check-ins with their parole officer (PO). More frequent PO check-ins could be difficult for an older AIC with limited mobility or declining health. POs should consider the declining health of older AICs when assessing both needs and risks during the LS/CMI assessment process. Future studies should examine how POs account for declining health in older AICs during the LS/CMI risk assessment process. In addition, research should explore the unique needs associated with older AICs (i.e., health care, age-appropriate housing) and how they might be evaluated in the LS/CMI process. In summary, the criminal justice system should be cognizant of the higher needs and the reduced risk of recidivism in the older AIC population.

Understanding the implications of the overclassification of the risk of recidivism for older adult offenders may help to generate more questions, research, and inform policies on the wider use of reduced sanctions, compassionate release, and medical parole. Holland et al. (2021) state that less than half of individuals eligible for compassionate release apply for compassionate release. Risk assessment processes must be better understood in conjunction with compassionate release as they may be able to better facilitate compassionate release processes that are highly under-utilized.

As this study demonstrated, age matters. Age is an important factor to consider when assessing risk instruments such as the LS/CMI. Previous research has focused mainly on race, gender, crime types, and general recidivism in risk instruments such as the LS/CMI. As this study was the first of its kind to test the LS/CMI considering age, a larger body of empirical research focused on older AICs is needed. Future research should also further examine age, the LS/CMI, and recidivism, in conjunction with factors such as gender, race, and crime types. In addition, varying geographic locations beyond Oregon should be explored. Lastly, the overclassification of older AICs' risk of recidivism, found in this study's sample, should not only be considered in future LS/CMI research but also in other risk instruments utilized by the criminal justice system.

Conclusion

Risk assessments impact the lives of AICs and have both institutional and societal implications. Skeem et al. (2016) argued that any demographic characteristics that an offender cannot control (i.e., age) should be considered for reduced sanction if a reduced rate of recidivism is evident in research findings. As such, a body of research must be established investigating potential age bias in risk instruments to help inform future policy, reduce unnecessarily stringent sanctions, and eliminate potential age bias in procedures embedded within the criminal justice system.

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