# Race and Algorithmic Risk Assessments

Haley Archambault

American University

## Abstract

Algorithmic risk assessments are being implemented in the criminal justice system to inform decisions made about pretrial detention, sentencing, and supervision. Their use even extends to the juvenile justice system. While technology is often viewed as a mechanism to move away from biases and create more uniformity, risk assessments have been criticized for their inclusion of, and heavy reliance on, factors that could create and perpetuate racial disparities within the criminal justice system. These factors include criminal history and socioeconomic characteristics. This paper examines validation studies that have been completed on various risk assessments used throughout the United States. The findings vary widely but most conclude that risk assessments cause higher rates of false positives for minority populations, including African Americans and Hispanics. Findings also suggest that risk assessments often use factors that are not significantly attributed to predicting risk for minority populations. Both issues could create and perpetuate racial disparities within the criminal justice system depending on their application. However, the use of algorithmic risk assessments should not be abandoned. Instead, universal standards of fairness and validity should be implemented, and all risk assessments should be validated for each racial group that they will be used for. Additionally, race-specific interactions with the factors used within risk assessments should be taken into consideration.


*Keywords:* algorithmic risk assessments, disparity, race, criminal history

# Race and Algorithmic Risk Assessments

The 21st century is demanding innovation and improvement from the criminal justice system. Change is being demanded by politicians, advocates, and everyone in between. Problems of prison overcrowding, mass incarceration, and biased policing and prosecution warrant solutions. As technology pushes its way into every aspect of life, “data-driven” and “evidence-based” solutions are popping up everywhere. A popular proposed solution is the implementation of risk assessment instruments. Simply put, risk assessments are designed to determine a person’s risk of something. Some of the intended improvements associated with the use of risk assessments include diverting low-risk persons from prison to community-based programs, reducing prison overcrowding, and informing a fairer sentencing structure to be applied to all persons in order to reduce sentencing disparities experienced by minority populations.

On the surface, a technological solution to the problems of the criminal justice system sounds promising. People have been quick to point to technology to fix the racial discrimination, disparity, and injustice in the criminal justice system, because technology removes some of the human element from decision making. Advocates of risk assessments often point out the advantage of them removing human biases from a system that disproportionately impacts people of color. However, it is important to remember that technology is created by humans and the data being used to teach algorithms is the result of human actions. In this way, even technology is impacted by human biases. Currently, risk assessments are utilized in 27 states to inform imprisonment and sentencing decisions, supervision decisions, and pretrial detention decisions (Lowder, Morrison, Kroner & Desmarais, 2018).

Many concerns have been raised about the validity of risk assessments. The concerns about risk assessment validity stem from the factors and variables that are inputted into the instruments that may cause higher risk scores for minority populations, which may then lead to harsher consequences. In *Buck v. Davis,* the Supreme Court emphasized the unconstitutionality of determining a defendant to be a future danger based on his or her race. While risk assessments do not explicitly include race as a factor, they do consider other factors that are highly correlated to race (Slobogin, 2018).

Many of the factors have a relationship with race and class such as education, employment, and criminal history (Whiteacre, 2006). The focus of this paper is on race, but due to the close relationship of race and class it is imperative to include the concerns about class related variables. This paper explores the concerns that have been raised about potential overclassification of minority offenders when using risk assessments and the potential disparate outcomes that may stem from their use.

The patterns that emerge from an examination of various validation studies suggest that the concerns about algorithmic risk assessments are valid. However, their use should not be abandoned. Instead, universal validation requirements and fairness standards should be implemented. Algorithmic risk assessments should be validated for each racial group using a consistent concept of fairness before it is used to ensure predictive ability and limited occurrence of false positives. Consideration should also be given to race-specific interaction with factors of offending during the creation of risk assessments. A colorblind instrument is ineffective because it assumes that all races interact with the world in the same way and therefore respond to all risk factors of criminal behavior similarly.

## The Algorithmic Risk Assessment

There are different types of risk assessment instruments including algorithmic (or actuarial) risk assessments, and clinical risk assessments. Algorithmic risk assessments are "data-driven" and rely on statistical algorithms to determine a person's relative risk. Clinical risk assessments, on the other hand, involve professional interviews and human determination of risk (Slobogin, 2018). This paper focuses on algorithmic risk assessments only (herein after called "risk assessments").

There are hundreds of risk assessments in use today and they vary in purpose. Some risk assessments have been created to predict general recidivism, while others focus on the prediction of violence or sexual violence (Slobogin, 2018). Risk assessments also vary in the risk factors taken into consideration. Some include static risk factors, and others include static and variable risk factors (Perrault, Vincent & Guy, 2017). Risk assessments are also being used in multiple ways within the criminal justice system. They are being employed during pretrial, sentencing, and even post-incarceration to inform community-supervision decisions. An instrument so widely used and heavily relied upon deserves careful evaluation and consideration of the potential impacts and harms that may result.

**History of Risk Assessments**

The creation of risk assessments dates back to the 1920s. From their creation until the Civil Rights movement, most risk assessments explicitly used race (either of the person or the parents) as a factor for prediction of future criminal behavior. For example, one of the first assessments used in the parole decision-making process was based on the Burgess method, which consisted of 21 factors, one being the father's race. As the assessments moved away from using race expressly, they simultaneously narrowed in scope and began to, instead, focus on a person's criminal record (Harcourt, 2015). There are now a few cited ways that race interacts with risk assessments despite not explicitly including it: data used to train the assessments may be the result of bias, and classification rules may result in different outcomes between racial groups (Huq, 2019).

The heavy weight today's assessments place on criminal history is a focal point of criticism. Some argue that prior criminal activity has become a proxy for race given the racial disparities that exist in nearly all areas of the criminal justice system: arrests, convictions, and incarceration (Harcourt, 2015). The history of oppression against African Americans through laws and law enforcement has resulted in criminal history correlating with race (Mayson, 2019). Since the African American community experiences large disparities, it is possible that the use of risk assessments that place heavy weight on criminal activity will exacerbate the disparities felt by this population.

The inclusion of socioeconomic characteristics also faces criticism, since these factors are relatively static for African Americans and can put them at a disadvantage when compared to Whites (Lowder et al., 2018). This is also a concern for Hispanics. Relative to Whites, African Americans and Hispanics have less wealth and income and are less likely to own a home (Walker, Spohn & DeLone, 2018). Social and economic inequalities are pervasive in society and largely impact minority communities. These same inequalities are correlated with crime.

When applied to the risk assessment context, the patterns suggest that African Americans are likely to receive higher risk assessment scores than Whites and the disadvantage they already experience will be perpetuated. Higher risk scores can lead to pretrial detention, longer sentences, and stricter supervision upon release from incarceration. All of these outcomes can lead to negative impacts. For example, pretrial detention has been linked to a higher likelihood of being convicted and longer sentences. Criminal convictions then lead to difficulty securing employment, securing public benefits, and impact the family (Walker et al., 2018). For minority populations who already experience disadvantage, criminal justice system involvement exacerbates it.

**Concepts of Fairness**

There are a few major concerns to highlight with the use of risk assessments. The first is that risk assessments utilize factors that may be impacted by a person's race, such as criminal history, socioeconomic status, and education level. Because minority populations, specifically African Americans, experience higher rates of criminal justice system involvement and higher rates of disadvantage when compared to Whites, including these factors is predicted to result in higher risk scores and, ultimately, harsher consequences for African Americans.

The second concern is that algorithmic risk assessments are created to predict, but prediction is a function of using past data to project an outcome. Prediction assumes that history will repeat itself, absent an intervention (Mayson, 2019). Because African Americans experience over policing and are proportionally overrepresented in many criminal justice statistics: arrests, incarceration rates, and interactions with the police, a tool built from this data will predict similar results. Overprediction will disproportionately impact minority communities (Mayson, 2019). This second concern is a result of how the technology is created.

Addressing both concerns requires examination of the types of fairness. Validation studies are critical, but accuracy and fairness can take many forms. There are four common viewpoints of fairness: the false positive rate of high-risk for each racial group; the false positive rate of low-risk for each racial group; fairness in the classification rule being utilized to designate risk category across racial groups; and equal proportion of each racial group being labeled with similar risk scores (Huq, 2019).

Many validation studies focus on evaluating the instruments for misclassification errors, which are the first two viewpoints of fairness. Overclassification errors, or false positives, occur when a person is predicted to be high risk but then does not recidivate. Underclassification errors, or false negatives, occur when a person is predicted to be low risk, but then does recidivate (Whiteacre, 2006). A margin of error is always expected since instruments cannot be 100% accurate, but the importance in the context of racial fairness is that error rates are consistent among different racial groups. If they differ, this is indicative that the risk assessment is unfair. For example, if a risk assessment produces 10% error for Whites but then produces 20% error for African Americans and Hispanics, the tool is unfair and will disproportionately impact African Americans and Hispanics.

A balance must also be found between the occurrence of false positives and false negatives. Favoring the decrease of false negatives may increase the occurrence of false positives and favoring the decrease of false positives may increase the occurrence of false negatives. When viewing the issue from a public safety standpoint, there may be a preference to limit false negatives. When viewing the issue from a social justice standpoint, there may be a preference to limit false positives. As data-driven criminal justice reform continues and evolves, the question to this balancing test must be answered.

A controversial validation study conducted on the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) exemplifies why the selected viewpoint of fairness matters. ProPublica concluded that COMPAS was not a valid tool for Black offenders because the ratio of false positives in comparison to White offenders was much higher. White offenders were overclassified 23% of the time whereas Black offenders were overclassified 45% of the time. The company that created COMPAS, Northpointe, fought back against this conclusion. Their response focused on the relationship between assigned classification and risk score. In their viewpoint, COMPAS was a valid risk assessment instrument because both Black and White offenders were assigned the same risk score based on the factors (Huq, 2019). The issue demonstrated by this scenario is that Northpointe and ProPublica are using different viewpoints of fairness to assess the validity of the same tool. ProPublica was concerned with the rate of false positives for each racial group whereas Northpointe was concerned with fairness in the classification rule across racial groups. Without a universal definition of fairness, validation studies will continue to yield conflicting results about the same instruments.

## The Empirical Research and Evidence

As risk assessments become more heavily implemented within the criminal justice system, and sometimes viewed as a step toward fairness and social justice, the call to action for empirical research and validation studies is pressing. Though validation studies have been completed, minorities are often underrepresented in the test sample. There is also a relatively small number of validation studies completed for minority populations specifically (Hamilton, 2019).

Not all risk assessments are created equal. There is no standard mandating which factors a risk assessment must take into consideration or how many factors a risk assessment must include in their algorithm. Some risk assessments are designed to be widely implemented, while others, such as the risk assessment currently utilized in Virginia, are designed specifically for a certain population. The assessment in Virginia was developed based on the felon population in Virginia to be used with persons convicted of felonies (Ostrom & Kauder, 2013). Many other geographic areas use their own risk assessments, some of which are incorporated in the analysis below.

## Post-Conviction Risk Assessment

The Post-Conviction Risk Assessment (PCRA) is utilized in the federal criminal justice system. This assessment includes 15 variable risk factors housed under one of five categories: employment and education, criminal history, substance abuse, social networks, and attitudes. The PCRA is used after an offender has been convicted, and does not play a role in sentencing determinations, but release decisions (Skeem & Lowenkamp, 2016).

Skeem and Lowenkamp (2016) examined the relationship between race and PCRA outcomes. Their study was limited to two races: Black and White. Their sample population of White and Black offenders was matched by offense type, age, and sex to isolate the potential effects of race. Their study resulted in three main findings. First, the PCRA is a strong predictor of arrest for both White and Black offenders. This means that a score indicates the same probability of recidivism for both racial groups; a given score has the same meaning across the groups. Second, there is a higher average score among Black offenders than White offenders. This conclusion does not mean that Black offenders will experience disparate outcomes, but instead suggests that the application of the risk assessment score could cause disparate outcomes. Lastly, the difference in risk score between Black and White offenders is mainly attributed to criminal history. Skeem and Lowenkamp found that 66% of the racial difference in risk score was tied to the criminal history factor (Skeem & Lowenkamp, 2016). Because the PCRA is developed for the federal criminal justice system, the results of this study may not be generalizable to other populations.

## Level of Service Inventory - Revised

The Level of Service Inventory – Revised (LSI-R) is a risk assessment designed to predict the risk of general offending by measuring both dynamic and static risk factors. The LSI-

R is widely used throughout the United States by over 900 correctional agencies. This risk assessment focuses on 10 risk categories, including criminal history, financial, and education and employment, and includes a total of 54 items (Lowder et al., 2018). Given its wide use, the LSI-R has also been widely studied. One area of concern for the LSI-R is that it was created based on a sample of mostly White male offenders (Chenane, Brennan, Steiner & Ellison, 2014).

In one study, the LSI-R was found to correctly predict high risk offenders for 87% of Whites, 78.9% of African Americans, and 86.7% of Hispanics. In terms of overclassification and underclassification, African Americans had the highest rates of both. African Americans were overclassified 12.2% of the time and underclassified 9% of the time. Whites and Hispanics were overclassified and underclassified at similar rates: 9% and 7.9% for overclassification respectively and 4% and 5.3% of underclassification respectively (Whiteacre, 2006). The higher rates of overclassification and underclassification experienced by African Americans respective to other racial groups found in this study indicates the LSI-R is not as accurate in predicting risk for African American offenders. As mentioned, in order to be accurate, a risk assessment should have similar rates of false positives and false negatives for each racial group to be deemed fair (Whiteacre, 2006).

Fass, Heilburn, Dematteo, and Fretz (2008) examined recidivism rates for 1,000 male offenders assessed by the LSI-R and found substantial differences in predictive error for White, Hispanic, and Black offenders. Whites and Hispanics had similar prediction error at 20% and 18%, whereas Blacks had an error rate of 57%. A significantly larger portion of Black offenders were overclassified by the LSI-R compared to the White offenders and Hispanic offenders. Over half (52%) of Black offenders were overclassified compared to the 8% and 0% of White and Hispanic offenders (Fass, Heilbrun, Dematteo & Fretz, 2008). This high rate of overclassification for Black offenders could be detrimental to their life and liberty and has far reaching consequences. Assessments that produce this much error could perpetuate the racial disparities in the criminal justice system (Lowder et al., 2018).

Other validation studies have focused on evaluating the LSI-R in the sentencing and corrections context, including. In this context, the concern is that higher risk scores may result in longer sentences for minority populations (Lowder et al., 2018). One such study of 11,792 Kansas probationers examined the associations between race and LSI-R score, risk classification, and sentence length. Overall, the average LSI-R score was higher for Black probationers, but there were no differences in the average sentence length received. In this context, the application of the risk assessment score did not result in disparate effects. However, known legal and extralegal factors that have been found to be highly correlated with sentencing decisions were not controlled for (Lowder et al., 2018). This study suggests the possibility that racial disparities could occur from the use of risk assessments, given the higher average scores for Black probationers, though this study found little evidence of this actually occurring within their considered population.

Another comprehensive evaluation of the LSI-R was conducted by Chenane, Brennan, Steiner, and Ellison. Their sample population was pulled from inmates in a Midwestern prison during 2009 and the purpose of their study was to evaluate the LSI-R's predictive validity for White, Hispanic, and Black offenders. The total sample of 2,778 males overwhelmingly consisted of White inmates: 1,910 compared to 196 Hispanic and 672 Black inmates. Overall, Chenane et al.'s analysis found the LSI-R to have high predictive validity for the occurrence of misconduct (nonviolent and violent), but did not accurately predict the frequency (Chenane et al., 2014).

Another important aspect of this evaluation was the examination of the subcomponents of the LSI-R in relation to the different races. Only two of the subcomponents of the LSI-R were not statistically significant in predicting a White inmate's risk of nonviolent misconduct: alcohol/drug problems and emotional/personal. However, only one subcomponent was significant in predicting nonviolent misconduct for Black inmates: emotional/personal. None of the subcomponents of the LSI-R were found significant in predicting nonviolent misconduct for Hispanic inmates. In terms of subcomponents associated with prediction for violent misconduct, the LSI-R again fared well for White inmates. All but one subcomponent, alcohol/drug use, predicted violent misconduct. Black and Hispanic inmates both had five subcomponents significant in predicting violent misconduct, with four of the subcomponents being the same: accommodation, companions, emotional/personal, and education/employment. Criminal history was the fifth subcomponent for Hispanic inmates and financial was the fifth subcomponent for Black inmates (Chenane et al., 2014).

**Correctional Offender Management Profiling for Alternative Sanctions**

The COMPAS assessment is used to inform bail and parole decisions all over the country. COMPAS consists of 137 questions (Huq, 2019) and uses an algorithm to produce three different risk results: pretrial risk, general recidivism risk, and violent recidivism risk (Wisser, 2019). Information collected to determine general recidivism risk includes criminal history, including age of first arrest and age at intake, educational and vocational information and problems, and drug problems. Information collected to determine violent recidivism expands on the base information by collecting details related to a person's history of violent behavior and non-compliance (Hamilton, 2019). Race is not a factor considered by COMPAS (Wisser, 2019).

One of the main validation studies on COMPAS was conducted by ProPublica. Their results concluded that the algorithm falsely labeled black defendants as high-risk twice as much as white defendants (Huq, 2019). This finding suggests that COMPAS may be more accurate in predicting the recidivism risk of whites versus other racial groups. As previously mentioned, this study was met with critique from COMPAS's developer, Northpointe. From their viewpoint, COMPAS was an accurate predictor of risk since similar classifications were made for each assigned risk score despite the offender's race (Huq, 2019).

Hamilton (2019) conducted a validation study on COMPAS using data from Broward County, Florida. The focus of her study was to determine if COMPAS accurately measured recidivism risk for Hispanics. Gender, age, and prior counts were controlled for, and recidivism was measured for a two-year follow-up period. Hamilton's study found COMPAS to become less accurate in predicting recidivism as the COMPAS risk score increased. There was a high false positive rate for recidivism prediction, meaning many persons labeled as high risk did not recidivate (Hamilton, 2019). The results highlight one of the major concerns of algorithmic risk assessments. If racial and ethnic minorities are incorrectly labeled as high risk at a high rate, they will be more likely to experience pretrial detention, face longer sentences, and be less likely to receive parole, or face higher restrictions when they do get released. In this way, algorithmic risk assessments could perpetuate racial inequalities within the criminal justice system.

**Juvenile Risk Assessments**

Risk assessments are also used in the juvenile justice system. Similar to the criminal justice system, there is a wide variety of the assessments in use. Validation of juvenile risk assessments is just as important, especially since African American youth is an overrepresented population in every stage of the Juvenile Justice system (Perrault, Vincent & Guy, 2017). The

Youth Level of Service/ Case Management Inventory (YLS/CMI) and the Structured Assessment of Violence Risk in Youth (SAVRY) are two commonly used juvenile risk assessment tools. In one study, Perrault, Vincent, and Guy conducted an evaluation of both assessments. The SAVRY evaluation used a sample of 383 juveniles who were mostly African American males. The YLS/CMI evaluation used a sample of 359 juveniles who were mostly White males. Both assessments were found to significantly predict general recidivism, regardless of race. There was no evidence that race affected the prediction of reoffending. This study also examined racial differences in scores for each of the factors included in the YLS/CMI and SAVRY. Black youth scored significantly higher than White youth for criminal history and living in a disorganized neighborhood (Perrault et al., 2017). Both of these are factors that are highly controversial due to their relationship with race.

In a study focused on the Ohio Youth Assessment System-Disposition Instrument (OYAS-DIS), McCafferty (2018) found little evidence to support the existence of racial disparities in the assessments' predictions between a total of 2,600 White and Black youth. Overall recidivism (all measures of recidivism being combined and analyzed as a whole) was predicted consistently across the two groups. Black youth were found to be overclassified 4.26% of the time versus 3.15% of the time for White youth. However, because the difference is small, McCafferty (2018) acknowledges it may be due to methodological factors implemented within the study. Potential disparate effects for Hispanic youth could not be tested for due to their small population within the Ohio juvenile justice system (McCafferty, 2018).

Another validation study sought to determine predictive validity of the Los Angeles County Needs Assessment Instrument (LAC) by isolating the sample population to include only Hispanic and African American male juveniles on probation. With a final sample size of 480, researchers found the LAC produced accurate predictions for 64% of Hispanic juveniles and 57% of African American juveniles. Both groups experienced the same rate of overclassification: 19%, which means they were incorrectly identified as high risk of probation failure and experienced unwarranted limitations on their freedom. Researchers also found underclassification errors for the two racial groups: 17% of Hispanic juveniles and 24% of African American juveniles were underclassified (Rembert, Henderson, & Pirtle, 2013).

In addition to evaluating predictive ability, this study also examined the association between each factor included in the assessment and recidivism. For Hispanic juveniles, five out of the nine factors were found to have a strong association with recidivism: community service, gang association, restitution, school performance, and home and community adjustment. For African American juveniles, there was no strong association between any of the factors and recidivism (Rembert et al., 2013). This finding raises the importance of conducting validation studies for each racial and ethnic group and supports the suggestion for race-specific factors to be taken into consideration.

## Considerations

It is important to view these findings through a lens of the specific methodology employed and the sample population that was used. Methodology and sample population used within the study can impact the findings. Recent research suggests that the proportion of White participants within a sample affects the findings of predictability. As the proportion increases, the risk assessment's predictability also increases (Rembert et al., 2013). In application, this means that validation studies may produce results indicating the risk assignment has a high rate of predictability, but the finding could be less accurate depending on the racial group. In other words, the result needs to be understood in context of how many white participants the sample includes. If there is a large proportion of White participants, it’s possible the results were skewed because of this. One possible example of this is the YLS/CMI evaluation. The sample of 359 youth was almost 75% White (Perrault et al., 2017). So even though the study showed high rates of predictive ability for Black youth, the results could be skewed.

These validation studies focused on overall assessment predictability across different racial groups as well as the rate of false positives and false negatives. Only a few of the validation studies took their research a step further to evaluate the resulting sentences and other potential impacts that were a direct result of the risk scores produced. Though the study that examined sentence length did not find a difference in sentence length for the African American offenders who had higher risk scores, this does not mean that all applications of risk assessment results are free from harsh application. Further research on the potential disparate racial impact of algorithmic risk assessments is warranted. This requires more than simply evaluating the assessments results. It requires an evaluation of the decisions made based on risk assessment scores.

## Recommendations

Given the hundreds of risk assessments in existence, it is impossible for this paper to be exhaustive. Therefore, the following analysis and recommendations are generalizations based on the studies included. Since the validation studies were limited in scope and used specific population groups such as federal felony offenders, prison inmates, and juveniles on probation (to name a few), there is the risk of overgeneralization. Therefore, the following conclusions and recommendations are based on the patterns that emerge about risk assessments from the examination of the included validation studies.

The first recommendation is for universal validation requirements and fairness standards to be implemented for risk assessment instruments. The competing viewpoints of fairness result in validation studies that focus on different measures. This gets confusing because competing claims arise about the same risk assessment instruments. This is the essence of the issue between ProPublica and Northpointe. The requirement should include low rates of false positives that are consistent between racial groups.

Currently, the numerous validation studies indicate that Hispanics and African Americans experience higher rates of false positives than Whites. Some of this can be attributed to the higher risk scores that result from certain factors, specifically criminal history. Two of the studies indicated that Black and Hispanic offenders scored much higher than their White counterparts on the criminal history sections of the assessment (Skeem & Lowenkamp, 2016; Perrault et al., 2017). This is an extremely important finding, because it confirms that certain factors interact differently with race.

Given how a person's race interacts with many of the factors taken into consideration by the various algorithmic risk assessments, validation of the instruments needs to occur for each racial group that assessment is being used upon. A high proportion of white offenders compared to Black and Hispanic offenders can skew results and increase appeared accuracy. To avoid skewed results, validation studies need to balance the sample population.

Two validation studies examined the relationship between the factors and predictive ability. Both found that most factors were not associated with risk prediction for African American and Hispanic offenders (Rembert et al., 2013; Chenane et al., 2014). In fact, one of the validation studies conducted on the LSI-R found that there was no association between the factor of criminal history and prediction of risk for Black offenders (Chenane et al., 2014). The consequences of this could be vast, since criminal history is the factor that often results in a higher risk score. An instrument that uses factors with little association to risk should not be used for risk prediction even if, by coincidence, the validation study indicates reliable predictability.

Risk assessments cannot be a "one size fits all" solution and removing factors that may serve as a proxy for race is not the solution. Taking a colorblind approach to algorithmic risk assessments could also yield disparate effects among racial groups. The criminal justice field needs to begin acknowledging and addressing that there may be certain race-specific interactions with factors associated with criminal activity.

For example, proponents of a Black criminology argue that African Americans have unique experiences based on their race and tied to their racial history that may produce criminal behavior. Black Criminology rejects racial invariance thesis, which states that factors causing crime do not vary across races (Unnever & Owusu-Bempah, 2019). Far from arguing that race causes crime, a Black criminology highlights the importance of fully understanding the reasons a person may engage in criminal behavior. This includes broadening understanding of how different races see and interact with the world to form a more complete view of factors that may contribute to criminal behavior.

The importance of acknowledging and including racial differences within risk assessments has also been suggested by other researchers. Hamilton (2019) suggests that risk assessments may be less valid for minority populations if they do not incorporate unique behavioral practices, beliefs, and social and environment experiences (Hamilton, 2019). Each racial group has a unique history and background, especially with the criminal justice system and its actors, and this must be taken into consideration by risk assessment instruments in order to improve predictive ability.

## Conclusion

The validation studies included in this paper's analysis of risk assessments confirm that some of the risk assessments being used in the criminal justice system are unfair to minority populations. Many of the studies found the risk assessments to produce higher rates of false positives for Black or Hispanic offenders. Hamilton found that COMPAS produces a high rate of false positives for Hispanic offenders (Hamilton, 2019). ProPublica found that COMPAS produces a high rate of false positives for African American offenders in comparison to other offenders (Huq, 2019), as do numerous validation studies on the LSI-R (Whiteacre, 2006; Fass et al., 2008).

It is important not to overgeneralize these findings. A high rate of false positives indicates that an offender was assigned a high-risk score, indicating a high likelihood of recidivism, but then did not recidivate. High rates of false positives do not tell us the resulting actions that were taken against the offenders who were misclassified, and therefore do not tell us if a disparate impact was created. One of the studies included examined the sentence lengths of offenders but their findings did not indicate disparate treatment (Lowder et al., 2018). More studies in this area are warranted.

As the criminal justice system continues to navigate reform and works to achieve fairness, special attention must be paid to risk assessments. They have popped up in all stages of the criminal justice system: pretrial detention, incarceration and sentencing, and post-release decisions. Two steps must be taken to decrease the possibility of disparate effects stemming from risk assessment use. First, a universal standard of fairness and accuracy needs to be determined and then validation studies need to be completed for each race the assessment will be used for. Validating an instrument using a large proportion of White offenders is not sufficient because this can skew predictability results. Second, adjustments need to be made to existing risk assessments that produce high rates of false positives and false negatives to account for the racial differences among offenders. Remaining colorblind is not the solution. Acknowledging that racial groups have unique histories that play a role in criminal behavior does not implicate race as a cause for criminal behavior. Instead, it allows criminal justice actors to get an improved understanding of the factors that may be tied to recidivism risk for each race. This could lead to fine-tuned risk assessments that more accurately predict an offender’s future risk.

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