Personal Recognizance Interview &

Needs Screen (PRINS)

Evaluation and Revalidation

Completed on Behalf of the Department of Adult and Juvenile Detention (DAJD)

and The Office of The Executive, Performance Strategy and Budget

King County, Washington

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EXECUTIVE SUMMARY

Recently, the use of cash bail/bond has been critiqued regarding its effectiveness in preventing flight and recidivism, and its equity of use (Scott-Hayward & Fradella, 2022). Simultaneously, greater court adoption of pretrial risk assessments (PRAs) has been observed. PRAs often use a set of criminal history and demographic indicators (e.g., prior arrests, failure to appear [FTA], gender) to identify a defendant's relative risk of failure. Many agencies have adopted PRAs as a method of improving the accuracy of release decisions, reducing the use of cash bail/bond, and improving community safety and court efficiency as a result (Rabuy & Kopf, 2016). Risk assessments have repeatedly demonstrated the ability to assess the likelihood of justice outcomes more accurately and consistently when compared to human actors (VanNostrand & Keebler, 2009). However, due to inherent bias reflected in criminal justice indicators, recent evidence has also demonstrated that risk assessments may contribute to gender and race/ethnicity inequities (Angwin, 2016; Hamilton, 2019; Miller et al., 2021).

In 2017, King County Department of Adult and Juvenile Detention (DAJD) contracted with Washington State University (WSU) to develop the Personal Recognizance Interview & Needs Screen (PRINS). Like other contemporary PRAs, a set of criminal justice and demographic indicators were collected. However, to reduce potential sources of gender and race/ethnicity bias, a semi-structured interview was also completed by DAJD Person Recognizance (PR) investigators. Conducted prior to a defendant's first court appearance, interview items provide a set of need and service indicators thought to improve PRA prediction while also reducing/diluting potential biases of criminal history indicators. Using advanced statistical modeling, the PRINS tool identified and weighted assessment items to predict FTA and a variety of recidivism types. Automating many of the assessment responses and scoring via software, King County implemented the PRINS assessment in 2019. In 2021, King County DAJD contracted with the Nebraska Center for Justice Research (NCJR) to evaluate the performance of the current PRINS (1.0) and provide recommended updates to items weights for version 2.0.

Specifically, NCJR was contracted to complete two sets of analysis deliverables. The first set consisted of research questions evaluating the tool's validity and its equity of prediction across race/ethnicity and gender. A second set of analyses was then completed to create an optimized version of the PRINS – version 2.0 – reshaping the tool's response weights with an updated sample collected following PRINS 1.0 implementation. Using ridge regression analyses updated assessment models and weights were computed and both versions 1.0 and 2.0 were evaluated for predictive performance and bias. Further, as a point of reference, the PRINS was compared to two contemporary pretrial assessments – the Virginia Pretrial Risk Assessment Instrument (VPRAI) and the Public Safety Assessment (PSA). The current report provides NCJR's findings.

Using a large sample (N=28,147) of defendants, study findings assess the PRINS 1.0 and 2.0 calculated scores and risk level categories (RLCs) accuracy in predicting FTAs and recidivism following pretrial release. Further, the PRINS assessments were evaluated for gender and race/ethnicity bias across several predictive performance metrics. As no current policy requires the use of PRINS for court release decisions, a natural experiment (of sorts) was created to evaluate the estimated improvement in release decision accuracy, allowing the comparison of King County pretrial release decisions and PRINS assessment on pretrial outcomes. Key study findings include:

- PRINS 1.0 identified moderate-to-strong prediction of FTAs and recidivism that is comparable to, or better than, other contemporary PRAs.

- Using data collected since implementation to recalibrate the tool, the PRINS 2.0 prediction of FTAs and recidivism indicates 'exceptional' performance.

    - The PRINS 2.0 is designed to effectively eliminate gender overclassification, and biases observed across race/ethnicity sub-groups are negligible indicating prediction parity rarely observed via a pretrial assessment.

    - When compared to commonly used assessments – the VPRAI and PSA – the PRINS provides improved predictive performance across all outcomes and reduced.

- Further, while there is substantial overlap between release decisions, FTA, and recidivism risk, the PRINS assessment categories – Low-, Moderate-, and High-Risk – provided a substantially more accurate prediction of pretrial outcomes than King County Court release decisions.

    - While bail/bond releases intended for use with high flight/recidivism risk defendants, only 13% of these releases were identified as High-Risk, and similar rates of FTA and recidivism are observed for this release type, suggesting both ineffective and overuse of cash bail/bond.

    - Despite expanded application in 2019, roughly half of eligible defendants were assessed via the PRINS, suggesting resource limitations restricted its provision.

Recommendations are provided, highlighting the continued use of the PRINS by King County and the DAJD.

> *First*, given the strong and positive results demonstrated, *policy regarding the use of PRINS to help guide release decisions should be developed*. Specifically, if defendants are assessed to be Low-Risk are released by PR investigators, Moderate-Risk provided conditional court release, and High-Risk individuals are detained and/or provided bail/bond release, fewer FTA and recidivism events will be observed.
>
> *Second*, *alternatives to release conditions (e.g., electronic monitoring, home confinement) should be developed/expanded* to decrease the ineffective use of cash bail/bond. Using cash bail/bond puts an unnecessary burden and ineffective deterrent on those struggling with poverty, who are disproportionately female and people of color.

> *Third*, PR *investigative resources should be expanded* to increase the number of defendants assessed and released earlier. While notably better for the defendant's well-being to await pretrial in the community, more frequent and quicker releases will reduce court costs that will likely outweigh the additional resources provided for PR investigators.

Collectively, these recommendations have the potential to reduce justice processing times and detentions, create net savings, reduce gender and race/ethnicity inequities, and improve defendants' lives and community safety.

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INTRODUCTION

For individuals charged with a criminal offense, a common path of justice system entry is arrest, followed by booking, and a first court appearance, where commonly a judge determines if an individual can be released on their own recognizance, set a bail/bond amount, or detain the individual until trial. However, recent concerns of the bail/bond system's impact on those in poverty, and predominantly those of minority status, have led some courts to eliminate the bail/bond system entirely (Rabuy & Kopf, 2016). For those court systems looking for alternative solutions, pretrial risk assessments (PRAs) have been developed to assist court release decisions.

The need for standardized assessment to guide pretrial release decisions dates back several decades. The Pretrial Services Act of 1982 and the Bail Reform Act of 1984 were passed as efforts to balance public safety and defendants' rights, requiring agencies to make pretrial detention and bail decisions based on objective measures of the risk defendants pose to the community (Desmarais & Singh, 2013). These acts led to the creation of the Federal Pretrial Risk Assessment Instrument (Lowenkamp & Whetzel, 2009). Fast-forward 20 years, PRAs are now commonly used to help guide pretrial adjudication decisions (VanNostrand & Rose, 2009).

Specifically, these tools are used to classify defendants into risk categories based on their likelihood of failing to appear (FTA) in court, and the danger defendants pose to the community while awaiting trial (Summers & Willis, 2010). A chief reason for the development of risk assessments is to provide standardization where multiple judges and decision makers may view the same case differently. Risk assessments quantify an individual's likelihood to appear in court and/or recidivate while on pretrial supervision, standardizing the assessment of an individual's risk in an effort to help judges make more consistent and accurate release decisions. An additional goal of PRAs is to reduce racial and gender differences in pretrial detention decisions (Scott-Hayward et al., 2022). Like traditional risk assessments, PRAs do not exist in a vacuum, where locally developed tools can incorporate contextual elements of the courts, and the people they serve, to provide greater predictive accuracy with assessment items and outcomes that are guided by agency needs and the population they serve (VanNostrand & Rose, 2009).

The use of cash bail/bonds has been increasingly scrutinized by scholars and justice advocates (Coffman, 2018; Louis, 2022). Contemporary research suggests that the use of cash bail adds to the cumulative disadvantage the justice system levies on racial and ethnic minorities (Louis, 2022; Menefee, 2018). For example, prior research has found that White defendants are more likely to have the resources needed to post bail, allowing them to receive pretrial release (Becker, 2022). Further, individuals who are unable to post bail, and subsequently detained pretrial, have been shown to receive more severe sentencing outcomes than those not detained pretrial (Louis, 2022). These issues have prompted some states to abolish the use of the cash bail/bond system (Scott-Hayward et al., 2022). Notably, Washington D.C. eliminated the use of cash bail in 1992, and adopted a PRA that assisted in the release of 94% of pretrial defendants (Block, 2018).

Since then, many states have passed legislation that utilize PRAs to help guide release decisions and limit the use of cash bail and its negative effects. Some common strategies that states have employed to address cash bail issues include capping amounts based on crime types. For example, Vermont passed legislation in 2018 that sets a cap for most misdemeanors at $200 (Baughman et al., 2021). Additionally, New York passed legislation in 2019 that precluded bail being imposed for most nonviolent offenses, drastically reducing the number of individuals being held in pretrial detention.

Proponents of the cash bail system contend that releasing individuals pretrial increases the opportunity of committing additional crimes while awaiting trial (Stevenson et al., 2017; Weldon, 2018). Conversely, research on pretrial release suggests that the cash bail system does not mitigate pretrial rearrest rates. For example, a nationwide study found that in 2009, 16% of individuals released pretrial were rearrested prior to their court dates. Additionally, 17% failed to appear at their hearings (Stevenson et al., 2017). During the same time, rearrest rates in Washington D.C., where bail/bond had been eliminated, were 12% and failure to appear rates were 13% (Pretrial Services Agency for the District of Columbia, 2016). These findings highlight a growing trend of courts restricting the use of bail/ bond, due to its reduced utility impacting failure to appear or recidivism and emphasizing the importance of using PRAs to guide pretrial detention decisions.

In 2019, Washington State University (WSU) was contracted by the King County Department of Adult and Juvenile Detention (DAJD) to develop a PRA for King County, creating the Personal Recognizance Interview Needs Screen and Reentry (PRINS). Seeking to evaluate the performance of the PRINS, DAJD contracted with the Nebraska Center for Justice Research (NCJR) to validate PRA for King County. The current report provides the findings from NCJR's evaluation.

BACKGROUND

Prior to describing the current study design and methods, it is important to briefly describe the function and history of contemporary justice risk-need assessments (RNAs). Most justice assessments are created to help classify individuals based on criminal history records and a structured interview to quantify both static (non-changeable) and dynamic (changeable) risks of recidivating. These tools are commonly developed with an initial data collection from a population that is similar to the one in which the assessment will be implemented. Each response is provided with a raw score to aid in prediction. For example, an item may ask how many prior felony convictions a person has committed – zero (0), one (1), two or more (2). In early development phases, some items are jettisoned for a variety of reasons (e.g., ethical viability, lack of prediction, scoring feasibility), reducing the final assessment tool to a vetted set of predictors. Through a summative calculation of assessment item response values, an individual is provided a risk score that ranks their likelihood of failure while on supervision, as compared to other similarly assessed individuals. Development samples commonly use thousands of individuals' calculated risk, spanning a large scoring range, where risk level categories (RLCs) (i.e., Low-, Moderate-, High-Risk) are calculated to guide supervision decisions (i.e., release, supervise, detain).

Beginning with large state agencies, justice assessments have been used for decades to assess a multitude of correctional outcomes. Utilized routinely in nearly every justice setting, it is relatively uncommon for an individual to have contact with the correctional system and not receive an assessment (Hamilton et al., 2016). Although risk assessments are most often used by correctional agencies, they have utility in judicial settings, as well. In the next section, we provide a brief overview of current RNAs and PRAs.

Risk Assessment

One of the major advancements in the correctional field was the establishment of the Risk-Need-Responsivity (RNR) model (Andrews & Bonta, 1990). The model outlines the importance of using actuarial assessments to measure individuals' likelihood of recidivating. This portion of the model is referred to as the *Risk Principle* and emphasizes using the resulting scores of assessment tools to determine the level of supervision and prioritize programming for higher risk individuals. The *Need Principle* outlines that, among a tool's items, dynamic (or changeable) measures can be used to establish areas to target via programming and services (e.g., substance abuse treatment, vocational training, housing). It is through the provision of interventions that an agency seeks to reduce risk of recidivism and other negative outcomes. Finally, the *Responsivity Principle* refers to the matching and sequencing of individuals to the appropriate correctional intervention (Andrews & Bonta, 2010). For example, an individual suffering from a severe mental illness or is transient, may not be suitable for a traditional outpatient substance abuse treatment program prior to stabilizing their other needs.

Decades of research have identified the positive impact of the RNR model and the use of Risk-Need Assessments (RNAs), identifying the improvement of RNA tools' decision making over human actors (Andrews & Bonta, 2010; Lipsey & Cullen, 2007). A primary issue addressed via RNA tools is standardization, reducing error and naturally occurring ideocracies resulting from multiple decisions makers. Using similar items available to human decision makers, RNAs provide a quantification of criminal history and other indicators to standardize risk ratings and guide decision making. Further, these tools have improved over their decades of use and development, notably transitioning through four generations (Andrews et al., 2006). Where first generation tools relied mostly on clinical judgement and expertise, second generation tools incorporated many of the criminal history indicators commonly reviewed in an individual's record to score both the quantity and severity of prior offenses. The biggest improvement in both quantity of items and prediction was the development of third and fourth generation tools in the early 2000s, which added dynamic needs and responsivity items (Andrews et al., 2006).

A notable change in the delivery of RNAs was the discovery of overlapping content used to predict differing outcomes. Specifically, correctional departments began to assess the ability of RNAs to not only predict recidivism, but other outcomes important to system management, such as prison infraction behavior and technical violations while on community supervision. More recently, PRAs were developed and applied to pretrial populations, attempting to identify those most likely appear for their court date and/or stay offense free while awaiting court processing in the community. Outlined in the next section, pretrial assessments have emerged, with research demonstrating their positive use in judicial decision making (Ahlin et al., 2022; Scott-Hayward & Fradella, 2020).

Pretrial Risk Assessments

Risk assessments can be seen as measuring individuals' risk of 'failure.' Traditional risk assessments use instances of recidivisms as indicators of 'failure,' while pretrial risk assessments measure individuals' risk of failure to appear (FTA), or the likelihood that an individual will not attend their court date if they are released into the community (Demarais & Singh, 2013). Additionally, most PRAs measure the likelihood of individuals committing a new crime if they are not detained pretrial. Contemporary PRAs still measure common risk factors, like criminal history, as well as common criminogenic need measurements, like substance abuse and employment status (VanNostrand & Keebler, 2009). Pretrial risk assessments demonstrate responsivity by recommending options of pretrial release or detention based on the individuals' risk scores. Examples of recommendations include release on one's own recognizance, reduced bond, supervised release with bond, or no bond (VanNostrand & Rose, 2009).

Within the landscape of PRAs, variation exists. Some generalized RNAs, like the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) have pretrial risk scales incorporated into the tool (Scott-Hayward & Fradella, 2020). A noted limitation of these tools is a lack of specification of local courtroom practice, including methods and types of release and pretrial outcomes. Conversely, specialized PRAs have been developed and commonly predict both failure-to-appear and recidivism while awaiting trial (Lowenkamp & Whetzel, 2009). For example, the Federal Pretrial Risk Assessment predicts risk of general failure to appear, the probability of the individual getting a new charge while on pretrial release, and the likelihood that the individual will have their bond revoked due to a technical violation (Lowenkamp & Whetzel, 2009). Further, the Ohio Risk Assessment System-Pretrial Assessment Tool (ORAS-PAT) and the Virginia Pretrial Risk Assessment Instrument-Revised (VPRAI-R) were developed to predict similar outcomes (Demarais & Singh, 2013; VanNostrand & Rose, 2009). Finally, sponsored by Arnold Ventures, the Public

Safety Assessment (PSA) is the newest tool (2020), utilizing nine items to assess FTA, and both general and violent recidivism.

Notably, each tool is created with a development sample collected within a distinct location (i.e., Virginia, Ohio, Kentucky) with varying sample sizes. These tools, with their pre-established item set and scoring, are then adopted and applied to new courts systems and defendant populations with potentially varying characteristics (e.g., gender, race, age, income) and variation in prior offense histories. Further, most PRA items are based on criminal history, or administrative records. For example, the ORAS-PAT and the VPRAI use the information systems to measure a small number of salient risk factors (Demarais & Singh, 2013). Notably, these tools do not include need-based items when creating a risk score. Instead, the ORAS-PAT provides a list of need-based items (e.g., mental health issues) that when confirmed, indicate that further assessment may be warranted (Latessa, 2016). Similarly, the VPRAI includes an additional comment section, where the assessor can write substantive comments that may be deemed useful for the judicial officer when making bail decisions (VanNostrand & Rose, 2009). The advantage of a records-based tool is that they are quicker to complete, requiring less labor to score. Despite this advantage, research suggests that reliance on records-based items when assessing risk can increase gender and racial/ethnic disparities (Desmarais et al., 2022).

Prediction & Bias

Like correctional RNAs, the two primary concerns of PRAs are predictive accuracy and reducing bias. Specifically, developers seek to maximize a tool's accuracy, such that those scoring as High-Risk commit more FTAs and recidivism than those scoring as Low-Risk. In addition to achieving overall accuracy, the tool should also score and predict similarly across sub-populations. In 2016, Angwin identified issues of 'overclassification' and bias in a popular RNA, providing evidence that Black individuals were more often identified as High-Risk, yet recidivated at a lower rate than their White counterparts. In 2010, Van Voorhis and colleagues identified a similar issue by gender, where rates of reoffending were lower for females than for similarly scored males. These issues of overclassification are common to all RNAs and PRAs but causes and impact are known to vary. Specifically, recent research has identified that the use of static, criminal history indicators may be the source of overclassification and bias (Campbell et al., 2018), where a greater inclusion of dynamic, needs indicators has been shown to reduce overclassification (Butler et al., 2022; Hamilton et al., 2019, 2020; Miller, 2021).

Like traditional risk assessments, PRAs have the greater predictive validity when developed using samples from the population that they are intended to serve (Hamilton et al., 2021). Demarais and Singh (2013) conducted a meta-analysis and found that the ORAS-PAT showed excellent predictive validity when used in the jurisdiction in which the development sample was drawn. Yet, when used to assess individuals outside the development sample jurisdiction, predictive accuracy of the tool was greatly reduced (Latessa et al., 2009). This has led some to argue that jurisdiction-specific assessments be considered a best practice in the development and application of PRAs (Butler et al., 2022; Duwe, 2014; Duwe & Rocque, 2021; Hamilton et al., 2021).

In 2007, Van Nostrand created the Pretrial Service Legal and Evidence-Based Practices (LEBP). LEBP best practice indicates routine tool validation to ensure accurate prediction for the communities in which it is to be applied (VanNostrand & Rose, 2009). For example, the VPRAI was implemented in Santa Barbara, California in 2016. After collecting jurisdiction-specific data using the VPRAI, the items and weights were statistically analyzed and adjusted to optimize the tool for the local population. This optimization process notably increased the assessment's predictive performance and demonstrated reduced variance across race and gender (Lovins & Lovins, 2016). This optimization study relates to the second LEBP guideline - that instruments should equitably classify defendants regardless of race and gender (VanNostrand, 2007). Meaning the tool should predict similarly for all individuals, and those classified at High-, Moderate-, or Low-Risk commit FTA and recidivism outcomes at the same rate regardless of race/ethnicity and gender. This is consistent with the growing emphasis placed on developing tools locally, in order to increase predictive performance (Butler et al., 2022; Campbell, 2018; Hamilton et al., 2019; 2020; Miller et al., 2021).

Development of the PRINS

In 2010, the King County Council adopted legislation (ordinance #16953) that required the county to develop a validated PRA that would provide the court with an effective and fair assessment of the defendants' risk to public safety or failure to appear. In 2012, King County established the Recidivism Reduction and Reentry Policy Work Team. This cross-disciplined work group was tasked with developing and implementing a county-wide strategic plan of action that addresses recidivism reduction and sustained reentry. They defined and agreed to several concepts relative to the application of the developed tool, which included but were not limited to, identifying those to whom to provide criminal justice services, divert from jail booking or refer from the jail before first appearance, and retool and update the appearance and usefulness of the current first appearance report prepared by PR Screeners. In 2015, the King County Council authorized and funded the DAJD to procure an IT solution that would allow it to track and evaluate individuals leaving secure detention to improve program outcomes and develop new alternatives that reduce recidivism.

In 2017, DAJD contracted with Washington State University (WSU) to develop a PRA for King County. In an effort to incorporate dynamic, needs based items for the tool, a pilot study was conducted with an item test pool. Under the oversite of Dr. Robert Barnoski, pilot data was collected from 2011 through 2012. These 44 test items were administered using a semi-structured interview format and collected via DAJD's PR investigators. In total, 9,104 individuals were assessed by PR investigators. This data was linked with individuals' court records and criminal history indicators to create a development sample to be used for PRA creation. At the direction of DAJD stakeholders, several risk models were developed. Specifically, separate models were developed to predict FTA and 'Any' recidivism. Models predicting more specified types of recidivism were developed to predict Felony, Violent, Property, Drug, and Domestic Violence (DV) recidivism. To reduce the potential for female overclassification, each model was developed separately for males and females. RLCs were also produced based on stakeholder specifications in the development of a three categorical scale (Low, Moderate, High-Risk). One set of RLC categories was created for FTA and a second for recidivism risk, where the 'Any' risk model provided Low-, Moderate-, and High-Risk categories. Additionally, if an individual was identified to be High-Risk in any of the specified recidivism models, they were categorized as High-Risk in the Any RLCs. Initial validation estimates identified the tool to possess moderate-to-strong predictive accuracy and relatively equivalent prediction across race/ethnicity and gender categories. DAJD named the tool the Personal Recognizance and Needs Screen (PRINS).

DAJD contracted with the Vant4ge organization to develop software, automate data collection and scoring, and train PR investigators to administer the tool. Pilot testing was conducted in 2017, and feedback on the tool's functionality was solicited from DAJD PR investigators. Responses to feedback, minor modifications made by PRINS developers to response weights and item language were made to accommodate recommended adjustments. In 2019, the PRINS was implemented. In 2020, DAJD contracted with the Nebraska Center for Justice Research (NCJR) to evaluate and revalidate PRINS. Further, researchers were tasked with optimizing the PRINS response weights, creating a second version of the tool (2.0) using data collected since implementation. This report provides the findings of this research and an updated and optimized version of the PRINS outlined for future implementation.

METHODS

In this section, we describe the methods used to complete the PRINS study. First, the contract deliverables are outlined. Then, study measures are described. Next, sample descriptive statistics are provided. Finally, the analysis plan is outlined.

Deliverables

NCJR was contracted to complete two sets of analysis deliverables. First, we were tasked with evaluating the predictive validity of the PRINS. In addition to overall accuracy, we also examined equity of prediction across race/ethnicity and gender sub-populations. A second set of analyses was then completed to create an optimized version of the PRINS – version 2.0 – reshaping the tool's response weights with an updated sample collected following PRINS 1.0 implementation.

First, we were tasked to compute predictive metrics, assessing the predictive performance of the PRINS. Predictive performance is assessed in multiple ways and is intended to identify if individuals that score higher on an assessment are more likely to commit pretrial outcomes (e.g., FTAs or recidivism) than those that score lower. Tools that more accurately score those that commit pretrial outcomes higher (and vice vera for lower) are identified to have greater predictive performance. We completed this assessment for the tool overall and further examined potential areas of racial/ethnic inequities. To complete this analysis, we investigated the predictive metrics of the PRINS FTA and Recidivism risk scores using common industry statistics (to be described). Related, we examined the concurrence between the RLC risk rating and pretrial outcomes. Each of these analyses were then computed for the total sample and for five race/ethnicity subgroups – White, Black, Hispanic, Asian, Native American/Pacific Islander.

King County judges and PRs were free to use PRINS assessment results but were not directed by policy or required by statue to consider its findings when issuing release decisions. This created a natural experiment, of sorts, allowing NCJR to assess the accuracy of the PRINS prediction as compared to judicial release decisions. Like correctional assessments, overrides of tool predictions are often evaluated to identify if there is concordance between the results of the tool and human decision makers. Thus, we examined if release and detention decisions corresponded to PRINS RLCs.

The DAJD were also interested in examining their population's pretrial outcomes. We thus examined the proportion of assessed defendants that recidivated. Related, we examined the relationship between pretrial and release outcomes for defendants released by Personal Recognizance (PR) Investigators compared to conditional release and detention/bail/bond release types. Further, the RLC differences between those released by PRs and those released after their first court appearance. Also, we sought to examine the differences in RLC and pretrial outcomes between those who post bail/bond vs. those conditionally released by the court.

Next, we completed a second set of deliverables, optimizing the PRINS scores with data collected since implementation. Through this optimization process, we developed new item weights for each of the PRINS models and RLC thresholds. These findings present an updated and more accurate version – the PRINS 2.0 – calibrated to the population assessed following implementation.

Data

In conjunction with DAJD, several sources of data were obtained and merged to create our analyzable data set. First, Vant4ge provided assessment data on 28,147 subjects for all 22 PRINS predictor items. In addition, seven risk scores (i.e., FTA, Any, Felony, Violent, Property, Drug, DV) were provided, as well as RLCs for FTA and Any risk. The Washington State Center for Court Research (WSCCR) provided criminal history information for all subjects, including dates and offense types used to measure recidivism following subjects' release to the community. Court records were compiled by DAJD, which provided FTA, charge booking, and release dates, as well as demographic information (e.g., age, race/ethnicity, sex) and subject identifiers used to link assessment and criminal history information.

Measures

All PRINS measures and responses were provided via Vant4ge. We note that four additional measures were added to further explore improvements to the PRINS. Specifically, we categorized prior FTAs as two ordinal measures, those that had occurred in the two years just prior to their PRINS assessment and those that occurred over two years prior to said assessment. We also added system involvement indicators, one to assess if an individual was currently on community corrections supervision and another to assess if the individual had previously been incarcerated in prison.

Next, study outcomes were computed. As described, one of the primary issues of prior PRA assessments is the operationalization of the outcome. Specifically, pretrial release outcomes differ from correctional RNAs in that a fixed follow-up period is not feasibly observed. For example, an individual charged with a minor misdemeanor may be released and asked to attend their next court hearing in three weeks, only to have their case disposed at said appearance. In this case, a judge weighs the likelihood of an individual committing an FTA or recidivism within a short exposure window. However, an individual that is charged with a gross misdemeanor may not be asked to appear before the court for several months, this extended exposure in the community allows for greater opportunity to recidivate, and thus, result in multiple court dates that incur a greater potential for FTA. Therefore, exposure times differ per defendant, requiring adjustment to account for said variations.

The recidivism outcomes tracked consisted of both charges and convictions, using a 12-month follow-up duration, broken down by any offense, violent, property, drug, domestic violence, and FTA outcomes. To prevent a reduction in sample size via elimination of cases with insufficient follow up, an offset capturing an offender's true exposure time was used. Three different events could result in early termination of an individual's follow-up, which included being detained in a correctional facility due to committing a technical violation, receiving disposition on the current court case prior to the 12-month period ending, or committing an FTA or recidivism outcome. The subsequent exposure time was thus used as an offset in all recidivism prediction models. Offset measures specify exposure time, accounting for the number of days between PR, Court, or Bail/Bond release to the community and either FTA, recidivism, or case disposition. By including an offset measure model estimates were adjusted to account for the greater opportunity to commit an FTA or recidivism event, the longer a defendant remains on pretrial release.

An indicator representing whether an individual was detained pending trial, or released, was also constructed. The criteria for determining whether the individual was released, rather than detained, consisted of defendants whose duration between their booking date and booking release date was less than or equal to three days and was paired with any of the following booking release codes for conditional court and personal recognizance release. If the defendant did not match the above criteria, that subject was considered 'detained' pending their court case.

Sample

Following the assembly of our analyzable data set, descriptive statistics were computed for the sample. In total, 28,147 defendants were assessed via the PRINS for pretrial release outcomes. Sample descriptives are provided in Table 1, broken down by gender and race/ethnicity.

Table 1. Sample Descriptives (N=28,147)

Demographics	**Total %**	**Male %**	**Female %**	**White %**	**Black %**	**Asian %**	**Hispanic %**	**Nat. Am./ Pac. %**
Age at Assessment								
50-59	10	10	8	10	9	9	4	5
40-49	17	18	16	19	16	21	14	15
30-39	33	34	33	35	34	33	32	33
20-29	33	33	37	31	37	33	44	41
<19	4	4	4	3	4	4	6	6
Marital Status								
Married/Domestic Partnership	12	12	13	12	8	20	20	11
Cohabitating	8	8	8	9	7	6	9	10
Single	80	80	80	79	85	74	72	79
Residence/Area stability								
Duration in Current Residence								
5+ Years	15	15	15	16	14	20	15	11
4 Years	3	3	3	3	3	4	4	5
3 Years	4	4	4	4	4	5	6	6
6 Months - 1 Year	11	11	13	12	11	10	13	13
Less than 6 Months	16	16	18	16	15	16	21	18
Homeless	16	17	14	17	14	17	18	18
No Current Residence or Refused to Answer	19	20	18	19	22	15	14	15
Missing	14	14	16	14	17	14	9	15
Rent/Own/Financially Contributes to Residence	46	46	44	46	42	50	60	51
Current Living Situation								
Lives With Friends/Family or Lives Alone	62	61	66	62	59	71	76	69
Transient/Unstable Housing	4	3	4	4	4	2	2	3
Homeless	18	19	16	19	18	14	12	17
Unknown	16	16	14	15	18	13	10	11
Number of Moves in Last 6 Months								
1-2 or Unknown/Refused to Answer	92	92	92	92	93	94	96	94
3-5	2	2	2	2	2	2	2	2
6+	6	5	6	6	6	5	2	5
Family in Area	67	66	70	67	65	70	70	68
Friends in Area	66	66	68	68	61	30	71	68
Has a Reference for Release	49	48	53	50	49	47	49	53
Employment/Education								
Employ Status								
Full-time Employment/Full-time Student	30	31	26	29	26	37	47	43
Part-time Employment/Part-time Student	5	5	7	5	7	6	6	5
Sporadic Employment/Day Labor/Other	8	9	5	7	8	6	12	6
Unemployed and able to Work	27	29	33	31	31	20	13	17

Not in the Labor Force or Unknown	30	26	29	27	29	30	22	30
Length Employment								
2 Years or More	13	14	11	14	9	18	22	22
6 Months to 2 Years	12	12	12	11	12	13	15	15
Less than 6 Months	23	20	25	20	24	19	19	17
Unemployed	53	53	52	54	54	49	43	46
Refused to Answer	1	1	1	1	1	1	1	1
Length Unemployment								
Employed	36	37	34	34	34	44	54	48
Less than 6 Months	11	12	9	11	24	17	13	16
6 Months to 2 Years	14	14	16	15	11	10	12	14
More than 2 Years	18	17	21	19	14	13	11	12
Unknown or Refused to Answer	20	21	20	20	17	16	10	10
School Achievement								
Technical/Vocational School or AA/AS	6	6	9	7	4	6	3	6
Completed BA Degree or Greater	7	7	10	9	6	12	12	13
Less Than HS Diploma or GED	20	20	18	18	21	19	3	18
Some College/Technical/Vocational School	20	19	23	20	17	22	40	44
Unknown	47	49	41	46	52	42	43	44
Substance Use								
Time Since Last Weekly Alcohol/Drugs Use								
1 Year or Longer	8	8	7	8	7	6	7	7
2 to 11 Months Ago	6	6	5	6	5	4	6	7
Past Month	45	46	45	48	46	50	46	39
Unknown	41	41	42	37	42	40	41	47
Last Use of Marijuana								
1 Year or Longer	14	13	15	16	10	13	13	12
2 to 11 Months Ago	7	7	7	8	6	6	8	2
Past Month	34	35	31	33	40	56	27	6
Unknown	45	44	48	43	44	26	53	80
Last Use of Stimulants								
1 Year or Longer	7	7	7	9	10	5	4	2
2 to 11 Months Ago	4	4	4	5	6	3	2	2
Past Month	20	20	22	24	15	17	7	8
Unknown	68	68	67	62	77	76	87	88
Last Use of Alcohol								
1 Year or Longer	17	17	18	20	13	14	12	13
2 to 11 Months Ago	9	9	8	9	9	9	10	10
Past Month	40	41	40	39	39	34	52	42
Unknown	33	33	34	31	39	43	26	34
Last Use of Opioids								

1 Year or Longer	6	6	6	8	4	3	4	4
2 to 11 Months Ago	3	3	3	4	2	2	6	4
Past Month	15	14	18	19	10	10	16	12
Unknown	76	77	73	69	84	85	74	81
Substance Abuse Treatment								
Currently in Treatment	4	3	4	4	3	2	3	2
History of Treatment	29	29	28	33	24	18	21	16
No Treatment, but Recommended	5	5	5	5	5	5	6	6
Treatment not Recommended	63	63	63	57	68	75	71	77
Prescribed Medications								
No Prescribed Medication	15	14	18	16	16	11	10	12
Not Taking Prescribed Medication	4	4	6	4	5	2	2	2
Taking Prescribed Medication	10	8	14	11	9	6	4	6
No Known Problems	71	74	62	69	70	80	84	80
Current Charges								
Current Felony	69	71	63	68	75	66	59	61
Current Misd. and Felony	8	8	8	8	9	5	6	5
Current Violent	41	42	36	37	49	35	36	40
Current DV	18	18	18	17	19	19	18	20
Current Property	64	36	37	38	37	33	24	32
Current Drug	17	16	17	17	16	19	17	13
Criminal History								
Prior Juvenile Adjudications for Violent Crimes								
None	92	92	93	93	89	95	95	95
One	6	6	4	5	8	4	4	4
Two	2	3	2	2	4	1	1	2
Out of State Convictions	23	25	15	24	27	12	18	16
Age at First Violent Conviction								
<15	3	3	3	3	5	9	1	3
15-16	5	5	4	4	7	14	3	3
17-23	20	22	13	18	28	13	14	10
24 or Older	23	23	18	23	24	26	14	17
No Prior Convictions	49	46	62	53	36	38	68	67
Time Since Last Conviction								
Less than 6 Months	11	11	9	11	12	9	7	7
6 to 17 Months	17	18	15	17	20	14	11	13
18 to 36 Months	17	18	14	16	19	13	15	15
More than 36 Months	31	31	29	32	31	26	28	24
No Prior Convictions	24	22	33	24	18	38	39	42
Total Adult Convictions								
None	25	23	34	24	20	39	40	43

One	9	9	11	10	7	10	15	13
Two	6	7	7	7	6	6	10	6
Three	5	5	6	5	5	5	4	6
Four	5	5	5	5	5	4	4	5
Five	4	4	4	4	4	4	4	3
Six	4	4	4	4	3	4	4	5
Seven or More	42	44	31	41	50	28	20	20
Prior Felony								
None	45	43	57	48	34	57	67	66
One	13	12	14	13	12	11	10	12
Two	9	9	9	9	10	8	7	8
Three	6	7	5	7	8	4	5	5
Four	5	5	4	5	6	3	3	2
Five	4	4	3	3	6	3	2	2
Six	3	3	2	3	4	2	2	1
Seven or More	15	16	7	12	21	11	5	5
Prior Violent								
None	42	40	55	46	29	57	60	55
One	14	14	15	15	13	13	15	15
Two	9	10	7	9	10	8	7	9
Three or More	35	3	23	29	49	21	18	21
Prior DV Assault								
None	66	65	74	69	58	78	76	75
One	13	13	12	13	15	8	11	10
Two	7	7	5	7	8	4	6	8
Three or More	13	14	9	12	19	40	8	6
Prior Property								
None	38	38	44	39	51	51	64	61
One	12	12	13	12	15	12	11	9
Two or More	50	51	43	49	34	37	24	31
Prior Drug								
None	56	54	65	55	51	38	71	75
One	15	15	14	16	15	12	13	11
Two or More	30	31	21	29	34	20	15	13
Prior Weapon								
None	81	78	92	83	73	88	86	91
One	12	13	6	10	16	7	9	6
Two or More	8	2	9	6	11	5	5	3
Prior Failure to Appear								
None	32	31	38	33	24	44	47	51
One	7	7	7	7	7	8	11	9

Two	5	5	5	5	5	4	7	6
Three	4	4	4	4	4	4	4	4
Four or More	52	53	46	51	60	40	32	31
Prior Protection Orders								
None	55	56	64	59	49	69	70	69
One to Two	16	16	16	16	18	14	14	16
Three to Five	12	12	10	12	13	8	9	9
Six or More	15	16	10	14	20	8	7	7
FTA <2 Years								
None	74	73	76	73	72	78	79	81
One to Two	15	16	15	15	17	14	14	12
Three or more	11	12	10	12	12	9	8	7
FTA 2+ Years								
None	59	57	63	58	52	66	71	72
One to Two	13	13	13	13	15	12	13	12
Three to Five	11	12	10	11	13	10	7	8
Six to Ten	9	9	8	9	11	7	6	4
Eleven or more	8	9	6	9	9	5	4	4
Community Supervision	2	2	2	2	3	2	1	2
Prior Prison Incarceration	10	11	4	9	14	6	4	5

Analysis Plan

To complete the outlined deliverables, an array of analyses was completed. When examining pretrial outcomes by RLCs, cross-tabulations were completed for each model and effect sizes were assessed via odds ratios (ORs), where OR values above 1.5 were considered ‘small,’ 2.5 ‘moderate,’ and 4.3 ‘strong.’ When examining predictive performance, several metrics were utilized. Predictive discrimination was measured via the psychometric industry standard area under the curve (AUC) (Singh et al., 2013). The AUC also represents an effect size, where values above: 0.55 indicate a small effect, 0.63 a moderate effect, and 0.70 a large effect (Rice & Harris, 2005). Next, as a combined measure of discrimination, accuracy, and calibration, the Squared error, Accuracy, and Receiver operating characteristic (SAR) score was computed (Caruana & Niculescu-Mizil, 2006). These predictive performance analysis findings were further calculated by race/ethnicity and gender sub-groups. Using the sample's FTA (23%) and recidivism (12.8%) base rate as a reference, False Positive Rates (FPRs) identify the rate higher risk subjects[1] do not recidivate, while the positive predictive values (PPVs) assess the proportion of higher risk persons that reoffended (Singh, 2013).

To create the PRINS 2.0, we used ridge regression[2] to select and weight items, optimized for their given sample (male or female) and outcome type (FTA, Any (felony or misdemeanor), Felony, Violent, Property, Drug, or DV). We use the burgeoning industry standard, k-fold validation procedure to validate predictive metrics (Steyerberg et al., 2003). Regression coefficient (or logit) values were then used to create item weights, in which model values are multiplied by 100 to create discrete, whole number. Weights were then multiplied by items' raw values and summed for everyone in the sample, where each individual is provided a composite risk score for each model in which they were assessed. Thresholds, or cut points, were then set for each model to create risk level categories (RLCs), where a score along the continuum of defendants' composite risk scores is selected and used to separate High- from Nonhigh-Risk and Moderate- from Low-Risk When selecting cut points, we attempted to match the proportion of subjects in the RLC based on the initial PRINS (1.0) development models. Again, ORs were used to assess the predictive impact of newly developed RLCs, where the odds of committing a pretrial outcome in the High-Risk group is compared to the odds of said outcomes in a lower risk category.

Finally, as a point of reference, we provide the scores of the PSA and the VPRAI. These two well-known and contemporary pretrial tools calculate an assessment score for FTA, Any, and Violent recidivism using only criminal history and court indicators. Fortunately, the PSA and VPRAI use indicators that were available within the data gathered for the current study. We computed scores for each tool and compared the results to the PRINS 2.0 predictive performance. Further

[1] Or those with a predicted probability of pretrial outcomes that exceed the identified base rate of a given model.
[2] Ridge regression represents a form of 'penalized' model that reduces the likelihood that a model coefficient/weight is overestimated.

comparisons were provided to assess race/ethnicity and gender bias of the PSA and VPRAI. For an operational definition of each tool's items and responses we direct readers to the original works (see Arnold & Arnold, 2014; Danner et al., 2016). Descriptive statistics of each item response in the current sample are provided in Appendix A.

RESULTS

In this section, we describe the study findings. We first provide findings for deliverables focused on the evaluation and revalidation of the PRINS 1.0. As the initial PRINS was developed with retrospective data, this first set of analyses describes how well the implemented assessment lives up to previously estimated expectations. Next, using data collected since implementation, the PRINS 2.0's findings are presented to describe modifications and updates that are anticipated to increase tool performance and equity.

PRINS 1.0 Predictive Performance

As indicated, PRAs are developed to provide standardization and improve predictive performance. It is though standardization and the use of non-criminal history, needs-based items that we anticipated reduced bias will be observed when examining the tool's performance across race/ethnicity groups. To assess predictive strength, we computed AUCs for each of the developed models and their outcomes. Then, we compared model performance by race/ethnicity for FTA and recidivism.

AUC performance for each PRINS model is provided in Table 2, with breakdowns by gender and race/ethnicity. Overall, the PRINS demonstrates moderate-to-strong predictive validity across all models with an average AUC of 0.68 (0.65-0.73). Notably the tool's assessment of Property and DV offending are strongest (AUC = 0.72, 0.73, respectively). When comparing across gender, the AUC is, on average, 1% greater for females and 1% to 4% greater for FTA, Any, and Violent prediction. When comparing models by race/ethnicity, for individuals identifying as Asian and Hispanic the average AUC is 2% to 5% larger than that of White defendants; for individuals who identify as Black and Native American the average AUC is 4% lower. As indicated in prior research (Hamilton et al., 2020), AUC differences that exceed 6.5% are considered substantial. Therefore, while the observed variations are notable, they are less than substantial, and should be characterized as minor deviations in equity by gender and race/ethnicity.

Table 2. AUC by Gender and Race/Ethnicity.

Model	Total	Male	Female	White	Black	Asian	Hispanic	Native Am./Pacific
FTA	0.65	0.64	0.68	0.64	0.64	0.73	0.70	0.62
Any	0.68	0.68	0.69	0.68	0.65	0.75	0.71	0.67
Felony	0.67	0.67	0.66	0.66	0.64	0.75	0.69	0.66
Property	0.72	0.72	0.71	0.73	0.66	0.76	0.72	0.71
Drug	0.67	0.67	0.67	0.67	0.62	0.73	0.67	0.62
Violent	0.67	0.65	0.68	0.65	0.62	0.72	0.70	0.61
DV	0.73	0.73	0.73	0.71	0.61	0.70	0.68	0.58
Average	**0.68**	**0.68**	**0.69**	**0.68**	**0.64**	**0.73**	**0.70**	**0.64**

While some variation in the AUC was observed between race/ethnicity groups, we sought to further describe potential distinctions. Specifically, while the AUC is a summary measure of predictive accuracy, it is a composite scale, with the potential to overlook issues of bias. The SAR is a metric that compiles the AUC plus two additional metrics – accuracy and calibration – known to identify issues of model misfit. The False Positive Rate (FPR) is another metric used to measure bias. A sub-component of the AUC, the FPR is used to identify the proportion of individuals recognized as having higher risk who do not recidivate. By contrast, the Positive Predictive Value (PPV) identifies the proportion of higher risk individuals who do recidivate. The FPR and PPV are key measures of overclassification in which lower values for FPR and higher values of PPV are preferred. For our purposes, it is ideal if race/ethnicity categories possess similar SAR, FPR, and PPV values.

Additional tests of performance/bias are provided in Table 3. For easier readability, we only provide findings on the two main outcomes (i.e., FTA & Any recidivism). As with the prior findings, we focus on key considerations of bias, comparing those identifying as White to the four other race/ethnicity categories. Notably, White subjects represent over 51% of the population and thus, their values on all three metrics match that for the Total, while the Native American/Pacific Islander group is less stably predicted, representing less than 3% of the total sample. Black defendants possess a 4% larger FPR, compared to White defendants, but similar rates of PPV. When examining Asian and Hispanic defendants, all metrics demonstrate greater PRINS predictive strength with SAR, FPR, and PPV, with improvements ranging from 2% to 16%. However, the PRINS for the Native American/Pacific Islander population demonstrated reduced performance of 2% to 10% by comparison to White defendants.

These findings indicate that the PRINS has the potential to overclassify Black defendants, albeit to a small-to-negligible degree (4%). There is also a larger potential for overclassification for the Native American/Pacific Islander population based on these findings. However, again, one should be cautioned, as the stability of this effect may change with greater data collection. Yet, comparisons of the continuous risk score only describe the building blocks of the risk levels used as recommendations/release guidelines provided by the PRINS, where bias in the assessment application is better observed via risk level categories (RLCs).

Table 3. SAR, FPR, & PPV for FTA & Any Recidivism by Race/Ethnicity

Model	Total	White	Black	Asian	Hispanic	Nat. Am./Pacific
FTA						
SAR	0.64	0.64	0.62	0.70	0.66	0.62
FPR	0.40	0.40	0.44	0.29	0.24	0.50
PPV	0.32	0.32	0.31	0.36	0.34	0.35
Any						
SAR	0.69	0.69	0.67	0.74	0.72	0.64
FPR	0.40	0.40	0.44	0.25	0.19	0.50
PPV	0.39	0.39	0.39	0.44	0.37	0.37

Next, we compared RLCs by gender and race/ethnicity. Again, equity is investigated across a variety of metrics, including population percentages in each RLC, as well as each category's rate of FTA, recidivism, and odds of Moderate- and High-Risk categories recidivating as compared to Low-Risk defendants. RLC findings are provided in Table 4.

It is important to note that the RLC cut points for the PRINS category thresholds were set in cooperation with King County DAJD. Of particular importance was to ensure that the Low-Risk population possessed a distinctly low rate of FTAs and recidivism. Ideally, Low-Risk defendants would possess a low enough threshold for pretrial outcomes that they could reasonably be released by PR investigators.

When examining the RLCs, a breakdown of 18% (Low-Risk), 56% (Moderate-Risk), and 26% (High-Risk) was observed for the Total population. Comparing males and females, we see a higher proportion of males in the High-Risk category (30%) and more females in the Low-Risk category (39%). When comparing White to Black defendants, an 8% greater rate of White defendants is observed in the Low-Risk category (19%) and a 5% and 3% greater rate of Black defendants is observed in the Moderate- and High-Risk categories, respectively. Both Asian and Hispanic populations identify greater proportions of Low-Risk defendants, and the Native American/Pacific Islander population is roughly similar to the Total. Yet, it should be noted that disproportionate population totals by gender or race/ethnicity do not necessarily mean bias within a PRA's RLCs. It is therefore important to also observe the pretrial outcomes.

When examining pretrial outcomes by RLC, the Total sample indicates a very small rate of both FTAs and recidivism for Low-Risk defendants (6%, 2%, respectively). This stark difference is also observed in the ORs, where Moderate-and High-Risk defendants possess 6 and 10 times the odds of committing FTAs and recidivism respectively, when compared to Low-Risk defendants.

When comparing genders, females in the High-risk group have an FTA rate that is 2% lower, yet Moderate-and Low-Risk females recidivate at a 2% and 3% greater rate than males, suggesting minimal-to-negligible bias. However, when examining recidivism, High-Risk females recidivate at 4% lower rate than males, an indication of overclassification that should be eliminated via a cut point adjustment for females. Further, ORs are greater for males (8 & 13, respectively) when compared to females (4 & 5, respectively) indicating greater predictive discrimination for male RLCs.

When comparing defendants' RLCs by race/ethnicity, fewer distinctions are observed. Regarding FTA and recidivism of Black and Hispanic to White, categories differ by 0% to 2% and ORs are relatively similar. For Asian defendants, greater discrimination is observed by RLC, where High-Risk categories are observed to commit more FTAs and recidivism, as compared to White defendants, and the reverse is true for Low-Risk Asian defendants. For Native American and Pacific Islander defendants, relatively similar recidivism rates and ORs are observed. However, higher rates of FTAs are observed for all three RLC categories of this population. Again, when considering the lower proportion of Native American and Pacific Islander defendants (<3%), caution should be used when interpreting and further investigation should be completed to clarify these reported inconsistencies.

Table 4. RLC Population, Recidivism & OR by Gender & Race/Ethnicity

RLC	**Total**	**Male**	**Female**	**White**	**Black**	**Asian**	**Hispanic**	**Nat. Am./ Pacific**
Pop. %								
Low	18	12	39	19	11	27	25	22
Mod.	56	58	47	54	59	51	57	53
High	26	30	14	27	30	22	18	25
FTA%								
Low	6	5	8	6	7	3	6	11
Mod.	25	24	26	25	25	25	25	27
High	31	31	29	31	30	35	32	32
Recidivism%								
Low	2	2	3	3	3	1	1	2
Mod.	13	13	10	14	14	11	11	12
High	19	20	16	20	19	18	15	17

OR								
Low	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Mod.	6	8	4	6	5	5	5	5
High	10	13	5	9	9	10	7	7

However, with all RLC findings reviewed, we observe notable and expected differences by gender, where females are more often Low-Risk and recidivate at lower levels than males. Given these discrepancies by gender, RLC cut point adjustments are recommended to remedy remaining inconsistencies. Finally, when comparing race/ethnicity variations, few are observed, suggesting near parity of prediction when examining White, Black, and Hispanic defendants, while the PRINS predictive discrimination is best for Asian defendants and least effective for Native Americans/Pacific Islanders. All told, the collection of PRINS 1.0 findings suggests *greater equity than bias*, with some areas to examine further and potentially adjust going forward.

Potential PRINS Impact

One of the intentions of the PRINS is to inform case management and release decisions. As mentioned, the tool was designed to guide recommendations by 1) PR investigators, 2) released at first appearance, or via 3) bail/bond/detained would correspond to 1) Low, 2) Moderate, and 3) High-Risk categories, respectively. We thus conducted a set of analyses to examine the concurrence of release decisions and PRINS scores. In Table 5, we provide a side-by-side comparison of RLCs and release types. Notably, 18% of defendants were rated as Low-Risk, while only 3% of defendants were released by PRs. Cross-walking RLCs with release type, if all Low-Risk defendants were released by PR investigators, 15% more defendants would be released by PRs. While this would have resulted in 3% more FTAs, the same rate of recidivism was observed (2%). Advancing these concepts, roughly 17% more Moderate-Risk defendants were forced to wait until their first appearance to be provided Conditional Court Release, many of which could have been safely released by PR investigators following assessment. However, the rate of FTAs for conditional releases was the same as that of Moderate-Risk (25%), yet there was a 2% greater rate of recidivism for Conditional Court Releases. This suggests if the PRINS were used to guide release decisions, more accurate release decisions would have been provided for the King County Court and slight improvements to community safety would have been observed for conditional court releases.

Finally, when cross-walking bail/bond to High-Risk defendants, a 2% greater rate of recidivism is observed for High-Risk defendants; yet the High-Risk categorization identified an 11% increased rate of FTA and twice the rate of recidivism when compared to bail/bond. This finding suggests that if the PRINS RLC had been outlined to guide release decisions, a greater proportion of recidivists and those committing FTAs would have been detained or made to post bail/bond. However, the PRINS was found to classify Moderate and Low-Risk defendants more appropriately, increasing the proportion released earlier in the court process with limited impact on community safety.

Table 5. Population, FTA, Recidivism by RLC & Release Type

	Pop. %	FTA%	Recidivism %
PRINS RLC			
Low	18	4	2
Moderate	56	25	13
High	26	31	19
Court Release Type			
PR	3	3	2
Conditional Court Release	73	25	15
Bail/Bond	24	*20*	*8*

Next, we examined detention release decisions, where those released by PRs or by the court were compared to those detained and/or those released on bail/bond. This comparison was completed to identify if court decision making would have been aided via PRINS results. For these analyses, we assessed both recidivism and FTA and findings. Said findings are provided in Table 6.

Considering the data provided by DAJD, we note that 52% of the sample was detained[3]. When examining the rate of failure, we find that for those Low-Risk defendants that were detained by the court committed FTAs at the same rate (6%) and recidivated at a slightly lower rate (1% vs. 3%). For Moderate-Risk individuals, a higher rate of FTAs was observed (6%), however, a lower rate of recidivism was observed (2%). Finally, for High-Risk individuals, a higher rate of FTAs (6%) and a lower rate of recidivism is observed (3%).

Overall, findings suggest that detaining Low-Risk defendants provides no benefit to the court or community. Further, the court's decision to detain a portion of the Moderate-and High-Risk defendants provides a 6% reduction in FTAs and the rate of recidivism for those detained was lower by comparison (3%). While it is difficult to estimate the deterrence impact of bail/bond with the current analyses, these findings indicate that detention decisions may not be having the desired impact, preventing only modest portions of pretrial release outcomes, where greater consideration to one's PRINS risk level and release alternatives (e.g., electronic home confinement) may be more effective.

Table 6. Rates of FTA and Recidivism by PRINS RLC & Detentions Status

FTA	**Low %**	**Moderate %**	**High %**
Not Detained	6	21	27
Detained	6	27	33
Recidivism	**Low %**	**Moderate %**	**High %**
Not Detained	3	14	21
Detained	1	12	18

However, not all of those booked were assessed via the PRINS. PR investigator resources were limited and only a portion of those booked are eligible for PRINS assessment[4]. In Table 7, we provide the number of cases that were booked, those eligible for an assessment, and those assessed.

[3] We note that defendants eligible for this analysis were booked and released within 72 hours of their booking date.
[4] Readers should note that eligibility requirements restricted the analysis to only those defendants with a King County booking and those not charged with a DV offense.

As shown, there was a substantial portion of subjects that are booked, but not eligible to be assessed via the PRINS (15%). Yet, of those eligible (85%), roughly half were PRINS assessed (43%). This finding suggests that, if the PRINS is to be given greater weight in release decisions, greater resources will be needed to ensure that PR investigators have the bandwidth to assess all eligible subjects.

Table 7. Booked, Eligible, & PRINS Assessed

Booking Type	**n**	**%**
Booked	61,532	100
Eligible	51,063	85
Assessed	28,093	43

As mentioned, future policy may incorporate the PRINS' RLCs as a guide for release type, where Low-Risk are released by PR investigators, Moderate-Risk provided conditionally released by the court, and High-Risk are detained or released via bail/bond. To examine the current concordance, we cross-tabulated PRINS RLCs with court release decision. Results from these analyses are provided in Table 8.

Findings reveal a strong concordance between PR release and Low-Risk defendants (85%) and only 1% of PR releases were identified as High-Risk. Yet, there are an additional 15% of court releases and 29% of Low-Risk defendants that were required to post bail/bond. Given Low-Risk defendants commit FTAs and recidivism at a lower rate (6% and 2%, respectively), there appears to be a missed opportunity to utilize the PRINS and divert more defendants via PRs earlier in the justice process. Regarding Moderate-Risk, roughly the same proportion were conditionally released by the court and required to post bail/bond (58%). To remind readers, as displayed in Table 5, Moderate-Risk defendants commit FTAs and recidivism at roughly the same rate as those provided conditional release by the King County Court. In Table 8 we find that, despite the similarities in pretrial outcomes, if the PRINS were used to guide the decisions, an additional 58% of individuals required to post bail/bond may have been safely released conditional court conditions (and without the monetary requirements of bail/bond). As a result of the reduced use of conditional release, we find that only 13% of those released via bail/bond were high risk to commit a pretrial outcome. Further, 27% that were released conditionally by the court were High-Risk, indicating a misalignment of resources and inaccurate release decisions.

Table 8. RLC by Release Type

RLC	PR	Court Release	Bail/Bond
Low	*85*	15	29
Moderate	14	*58*	58
High	1	27	*13*

When making release decisions, the likelihood of recidivism is not the only concern. The severity and type of offense are also critical. For example, those charged with a Violent or Felony offense may be more likely to recidivate with similar severity. Thus, we examined the PRINS RLCs by recidivism type. Results are provided in Table 9.

Risk assessment developers often refer to the 'stairstep effect' when presenting RLC results. This effect refers to predictive discrimination at each level, where Moderate-Risk individuals have a greater rate of recidivism than Low-Risk, and High-Risk a greater rate than Moderate-Risk. Even though base rates decrease for more specified crimes, this stairstep effect is observed for each of the recidivism types. Further, in the 'Total' row, the base rate, or average rate of each recidivism type, is provided. Notably, the 'Moderate-Risk' rate is roughly the same as the base rate for each crime type. This is an appealing property of the PRINS, as it provides an underlying rationale for interpreting RLCs, where Moderate-Risk defendants possess an average rate of offending for all crime types. These findings should give court decision makers greater confidence in utilizing the PRINS for all offenders and in estimating all future offense types.

Table 9. RLC by population %, FTA, & Recidivism type

RLC	Pop. %	FTA	Any	Felony	Violent	Property	Drug	DV

Low	18	6	2	1	2	1	1	1
Mod.	56	24	13	5	6	8	2	2
High	26	31	19	8	8	14	3	3
Total	100	23	13	5	6	8	2	2

Finally, we examined the concordance of PRINS RLCs and release types by pretrial outcome. These findings are presented in Table 10. Again, the stairstep effect is observed for all release types. However, the stairstep effect is more pronounced for PR pretrial outcomes, where PR Low-Risk rates are 0% to 1% and Moderate-Risk rates were lowest for all PR release outcomes (1 to 14%). For High-Risk defendants, PR rates are typically the highest (except for DV & Drug) but were like that of conditional releases.

One additional interesting finding is that bail/bond releases tend to have the greatest FTA rates for High-Risk subjects, *a pretrial outcome that bail/bond is specifically outlined to prevent.* However, any recidivism for bail/bond release is lower than that of the other two types, indicating a rate like a Moderate-Risk conditional release defendant and may suggest that many of these offenders could have been conditionally released with no additional risk to the community.

Table 10. RLC by Release & Pretrial Outcome

Release type	**Low%**	**Mod.%**	**High%**
FTA			
Bail/Bond	6	23	37
Cond. Release	7	26	32
PR	1	14	33
Any			
Bail/Bond	2	9	15
Cond. Release	3	15	21
PR	1	6	22
Felony			
Bail/Bond	2	5	8
Cond. Release	2	6	8
PR	1	1	11
Property			
Bail/Bond	1	4	9
Cond. Release	2	9	15
PR	1	4	11

Drug			
Bail/Bond	0	1	2
Cond. Release	1	2	2
PR	0	1	1
DV			
Bail/Bond	1	3	3
Cond. Release	1	2	2
PR	0	1	1

PRINS 1.0 Summary

Overall, findings identify that the PRINS is an efficient mechanism for predicting pretrial outcomes. The tool possesses minimal issues regarding overclassification for females and minority defendants. Furthermore, if policy were adopted that reflected RLC results, where PR investigators release all Low-Risk, conditional court releases were provided for Moderate-Risk, and bail/bond set for most High-Risk defendants, the court would observe greater accuracy, consistency, and equity resulting from said policy change.

PRINS 2.0

In our next set of analyses, we sought to update and recalibrate the PRINS using data collected following implementation. As described, best practice for risk assessment development is revalidation, and the need to adjust the tool based on findings following implementation to better calibrate the items and weights to the current population (Andrews & Bonta, 2010). We computed 14 models, selecting items and weights using a pool of 39 items. Not all items were selected for all models. The greatest number of items selected for a single model was 37 (Any Recidivism) and the least was 24 (Drug Recidivism). These findings present an updated and more accurate version of the

PRINS, calibrated to the population assessed following implementation. Model items and weights are presented in Appendix A[5].

We then assessed the predictive validity of each model. Specifically, AUC values were computed using k-fold validation. AUC findings are provided in Table 11. All model AUCs are rated as 'strong,' ranging from 0.73 to 0.81. Compared to other PRAs, this AUC range is 'exceptional'. When comparing performance by race/ethnicity, on average, Black defendants possessed AUCS that were roughly 2% lower that White defendants and Asian, Hispanic, and Native American/Pacific Islanders possessed larger AUCs, on average. Generally, these findings are both strong and positive, while the PRINS 2.0 is slightly less predictive for Black defendants, the reduction is minimal (2%), the observed variation is less than the PRINS 1.0 (4%), and the tool is more predictive for all other race/ethnicity categories.

Table 11. PRINS 2.0 AUC by Race/Ethnicity

Model	Total	White	Black	Asian	Hispanic	Native/Pacific
FTA	.73	.74	.70	.78	.76	.76
Any	.73	.72	.71	.77	.74	.82
Felony	.73	.73	.71	.77	.75	.83
Violent	.73	.73	.69	.75	.75	.84
Property	.75	.74	.74	.79	.76	.82
Drug	.75	.74	.74	.81	.81	.81
DV	.81	.82	.77	.84	.85	.92
Average	*.75*	*.74*	*.72*	*.78*	*.76*	*.82*

Findings for model SAR values are provided in Table 12. On average, SAR values range from .63 to .68. When comparing performance by race/ethnicity, on average, Black defendants have 1% lower SAR values than White defendants. While all other race/ethnicity categories of defendants have 3% and 5% larger SAR values than White individuals, on average. Similar to the AUC findings, the SAR results are positive, where PRINS 2.0 results indicate similar levels of accuracy, calibration,

[5] Readers should note that each weight is multiplied by the raw item score for each response, where items that do not score are indicated by an empty cell.

and predictive discrimination for Black and White defendants, with larger values observed for all other race/ethnicity categories.

Table 12. PRINS 2.0 SAR by Race/Ethnicity

Model	Total	White	Black	Asian	Hispanic	Native/Pacific
FTA	.71	.72	.70	.73	.75	.72
Any	.64	.63	.64	.66	.62	.70
Felony	.60	.60	.60	.64	.66	.65
Violent	.66	.61	.61	.67	.68	.74
Property	.64	.63	.62	.66	.64	.70
Drug	.60	.60	.58	.64	.67	.60
DV	.68	.68	.63	.67	.72	.74
Average	*.65*	*.63*	*.62*	*.66*	*.67*	*.68*

Findings for model FPR values are provided in Table 13. On average, FPR values range from .25 to .40. When comparing performance by race/ethnicity, on average, Black defendants possess 3% larger FPR values than White defendants, while all other race/ethnicity categories of defendants have 7% to 12% lower FPR values than White individuals. As a key indicator of overclassification and bias, the FPR results are encouraging, where PRINS 2.0 results indicate only a 3% greater rate for Black compared to White defendants, with smaller rates observed for all other race/ethnicity categories.

Table 13. PRINS 2.0 FPR by Race/Ethnicity

Model	Total	White	Black	Asian	Hispanic	Native/Pacific
FTA	.37	.38	.40	.39	.32	.28
Any	.40	.44	.41	.39	.50	.37
Felony	.21	.19	.19	.05	.15	.06
Violent	.30	.45	.37	.26	.23	.29
Property	.41	.44	.43	.36	.36	.33
Drug	.44	.57	.45	.35	.33	.24
DV	.29	.36	.31	.33	.20	.15
Average	*.35*	*.37*	*.40*	*.30*	*.30*	*.25*

Finally, findings for model PPV values are provided in Table 14. On average, PPV values range from 12% to 17%. When comparing performance by race/ethnicity, on average, Black defendants have a 1% greater PPV, than White individuals, while Asian, and Hispanic defendants possess lower PPV values (1% & 2%, respectively), while Native American/Pacific Islander defendants possess a 3% greater PPV by comparison to White defendants. Another measure of overclassification and bias, the PPV suggest the PRINS predict pretrial outcomes better for Black and Native American/Pacific Islander defendants. Yet, all categories are within 5%, indicating near parity of prediction.

Table 14. PRINS 2.0 PPV by Race/Ethnicity

Model	Total	White	Black	Asian	Hispanic	Nat. Am/Pacific
FTA	.37	.37	.36	.36	.39	.38
Any	.22	.21	.23	.20	.15	.24
Felony	.09	.10	.09	.07	.07	.10
Violent	.11	.09	.12	.08	.08	.14
Property	.15	.15	.15	.14	.10	.22
Drug	.03	.02	.03	.03	.02	.06
DV	.06	.06	.05	.04	.06	.08
Average	*.15*	*.14*	*.15*	*.13*	*.12*	*.17*

PRINS 1.0 Summary

Overall, PRINS 2.0 models demonstrate improved predictive performance by comparison to 1.0 models. Specifically, AUC findings all indicate industry standard 'strong' performance, typically not seen in PRA tools. This noted strength is due to the more exhaustive list of risk and needs items collected via PR Investigators, and the optimization of items and response weights was completed with data collected post-implementation. With that said, performance is not equal by race/ethnicity, where White defendants perform at-or-near the Total sample average, while the PRINS 2.0 presented improved performance Hispanic and Asian defendants. Further, Black defendants demonstrated slightly reduced performance on most predictive metrics. Overall differences between race/ethnicity categories are negligible, suggesting near equality of predictive accuracy.

Contemporary Assessment Comparison

In our final set of analyses, we compared the PRINS 2.0 to estimated effects of the VPRAI and the PSA. We note that the VPRAI produces a single composite score to predict FTA and recidivism risk. The PSA also produces a composite score for FTA, Any recidivism, and Violent recidivism. Thus, for the PSA we used the tool's non-violent recidivism model to predict Any, Felony, Property, and Drug recidivism, and the violence risk score to predict Violent and DV recidivism. Comparative predictive performance findings are provided in Table 15.

Regarding the FTA scores, the PRINS 2.0 demonstrates a 3% improvement over the PSA and 5% improvement over the VPRAI. Regarding Any Recidivism, the PRINS 2.0 presents a 6% improvement over the PSA and 5% predictive improvement over the VPRAI. Further, the PRINS 2.0 also provides improved predictive improvement on the more specified recidivism models. Overall, *the PRINS 2.0 demonstrates an 8% improvement over the PSA and 9% predictive improvement over the VPRAI*, on average.

Table 15. PRINS 2.0 AUC by PTA

Model	PRINS 2.0	PSA	VPRAI
FTA	.73	.70	.67
Any	.73	.67	.68
Felony	.73	.68	.70
Violent	.73	.69	.69
Property	.75	.65	.68
Drug	.75	.65	.63
DV	.81	.74	.63
Average	*.75*	*.67*	*.66*

PRINS 2.0 RLC Performance

To assess the potential for PRINS 2.0 overclassification, RLC findings were investigated to further examine model performance, broken down by race/ethnicity. Like the initial version, we created two RLCs, one for predicting FTAs and another for recidivism. While the FTA RLCs were based on a single model, the recidivism RLC uses all recidivism models to determine High-Risk, where a High-Risk categorization in any of the recidivism models categorizes the individual as High-Risk, and, if not High-Risk, the Any model is used to classify defendants as Moderate- or Low-Risk.

PRINS 2.0 RLC findings for FTA models are presented in Table 16. Notably, the moderate risk category is set to the base rate, or the FTA rate for the full sample (23%). With the rate of FTA for the Moderate-Risk group set, we find the *High-Risk group commits FTA at nearly twice the base rate (43%) and the Low-Risk group is nearly one-quarter of the base rate*. Finally, the Odds Ratios (ORs) indicate that the Moderate-Risk group possess *six-times the odds, and the High-Risk fifteen-times* the odds of committing an FTA, when compared to the Low-Risk group.

Comparing population percentages by gender, we observe few High-Risk (21%) and more Low-Risk (34%) females, as compared to males (27% & 20%, respectively). Regarding outcomes, male FTAs rates mirror those of the Total sample. This 'mirroring' of base rates is completed by design, where RLC cut points for male and female models were set to fit the Total RLC and, as a result, produces a risk tool that possess gender parity.

Regarding race/ethnicity, the greatest proportion of High-Risk was observed for Black defendants (24%). Interestingly, despite a slightly larger proportion of High-Risk, Black defendants were observed to possess a 10% greater proportion of Moderate-Risk and 13% reduced proportion of Low-Risk. Yet, when examining the proportion that commit FTAs, only 1% to 2% difference was observed between White and Black defendants. These findings suggest that despite the RLC population variations, particularly in Moderate-and Low-Risk groups, the *predictive performance for the PRINS 2.0 tool is relatively equivalent for White and Black defendants*. For the remaining three groups, all demonstrate similar findings to that of lower proportions classified as High-Risk and greater proportions were classified as Low-Risk, as compared to both White and Black defendants. Both Asian and Hispanic High-Risk defendants identify increased rates of FTA (45% & 50%, respectively), while Native American/Pacific Islander defendants indicate slightly reduced rates (40%). However, the PRINS 2.0 indicates lower FTA risk for both groups when observing RLC proportions. Further, the rates of FTA and ORs by RLC indicate greater predictive performance and greater separation of ORs between High and Moderate-Risk groups for Asian, White, and Hispanic groups, as compared to Black and Native American/Pacific Islander defendants. Yet, despite these variations, the PRINS 2.0 RLCs was better at predicting who will commit FTAs as compared to the original, 1.0 version.

Table 16. PRINS 2.0 FTA RLCs by Gender and Race/Ethnicity

RLC	Total	Male	Female	White	Black	Asian	Hispanic	Nat. Am./Pacific
Pop. %								
High	25	27	21	24	26	20	14	15
Mod.	52	53	46	49	59	43	53	48
Low	23	20	34	27	14	37	33	38
FTA%								
High	43	43	43	43	41	45	50	40
Mod.	23	23	23	22	21	25	24	24
Low	5	5	5	4	6	4	6	6
OR								
High	15	14	16	17	10	23	16	10
Mod.	6	5	7	6	4	9	5	5
Low	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.

Next, we examined the recidivism RLCs developed, where findings are provided in Table 16 for the Total sample and broken down by gender and race/ethnicity. Notably, 37% are High-Risk and 20% Low-Risk, with the majority (43%) identified as Moderate-Risk. We again set the Moderate-Risk group to have a recidivism proportion roughly equal to the base rate (23%), where the High-Risk group possesses 44%, and Low-Risk group has a 8% recidivism rate. ORs indicate that Moderates have four times and High-Risk defendants have 9 times the odds of recidivating, representing 'strong' predictive effects.

Comparing population percentages by gender, we again observe fewer High (24%) and more Low-Risk (26%) females, as compared to males (40% & 19%, respectively). Regarding outcomes, male and females' recidivism rates are similar for Moderate and Low-Risk groups. Female High-Risk defendants' recidivism proportions are lower (42%) than that of males (45%), indicating only a small proportion of potential bias/overclassification indicated at the higher end of the PRINS 2.0 scale.

When examining variations by race/ethnicity, a 4% greater rate of Black High- and a 5% greater proportion of Moderate-Risk individuals was observed by comparison to White defendants; however, the rates of recidivism are roughly equivalent, with only 1% variations observed when comparing the recidivism rates for the High and Low-Risk group. For the remaining three race/ethnicity groups, defendants were observed to have lower proportions of High-Risk defendants, yet higher proportions of Low-Risk defendants are observed. Slight variations in recidivism rates are observed as well, where High-Risk Hispanic and Native American/Pacific Islander possess a lower (40%) and Asian High-Risk defendants a slightly higher recidivism rate (45%). Further, defendants present similar ORs, indicating that the PRINS 2.0 predicts well for all race/ethnicity sub-groups.

Table 16. PRINS 2.0 Recidivism RLCs by Gender and Race/Ethnicity

RLC	Total	Male	Female	White	Black	Asian	Hispanic	Native Am./Pacific
Pop. %								
High	37	40	24	34	38	25	19	21
Mod.	43	41	50	38	43	32	37	37
Low	20	19	26	28	18	43	43	42
Recid. %								
High	44	45	42	44	45	45	40	40
Mod.	27	27	27	27	27	30	26	37
Low	8	8	8	8	9	7	7	4
OR								
High	9	9	8	9	8	11	9	8
Mod.	4	4	5	4	4	6	5	6
Low	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.

To summarize, PRINS 2.0 was developed to optimize items and weights of data collected following implementation. Findings indicate *exceptional prediction strength* for all outcomes and by comparison to other PRA. Further, notable improvements regarding race/ethnicity and gender parity, where relatively small-to-negligible variations are observed across sub-groups.

CONCLUSION

The extended use of cash bail/bond has been critiqued and argued to create foundational and interconnected issues of justice system involvement, poverty, gender, and race/ethnicity. As a result, some courts have moved away from cash bail/bond, incorporating alternate methods of pretrial release. Typically, these methods of release incorporate an actuarial assessment of risk for pretrial outcomes (Loweder & Foudray, 2021). Derived from the RNR model, predicting outcomes such as FTA and recidivism to help guide release decisions and pretrial supervision is becoming commonplace. Yet contemporary tools, such as the PSA and VPRAI, are often generated using existing court records, and in the case of the PSA, only consider criminal history indicators. However, recent research has identified the potential for overclassification and bias for both females and minorities when only static, criminal history indicators are utilized (Miller et al., 2022). In addition, without an interview, the needs of the individual may go unassessed. Further, these tools are found to be more predictive of pretrial outcomes if calibrated to the local populations (Desmarais et al., 2021).

In 2017, the DAJD of King County sought to develop a homegrown assessment. Using court records and several thousand semi-structured interviews, they contracted with WSU to develop the PRINS. In 2019, the tool was implemented. Not dictated by policy or statute, the PRINS was not used as a guideline for release decisions, where PR investigators and judges were precluded from using the assessment findings in their release decisions. Following implementation, the PRINS results, release decisions, and pretrial outcomes were tracked for future evaluation and revalidation. The current report provides the details of the evaluation and revalidation of the PRINS, with a directed focus on gender and race/ethnicity equity of the created tool.

Following years of implementation and data gathering, a large sample (N=28,147) was created and analyzed. Study analyses were completed in two sections. The first set of analyses examined the performance of the implemented PRINS 1.0. The second set provided an updated and optimized version – PRINS 2.0 – for potential use by the DAJD.

PRINS 1.0

Overall, PRINS findings demonstrated moderate-to-strong predictive effects, exceeding those of common PRAs used today. The predictive performance of the tool was slightly better for females than males and for Asians and Hispanics when compared to White defendants. However, some evidence of overclassification was identified for Blacks and Native Americans/Pacific Islanders compared to White defendants. However, these variations by gender and race/ethnicity were less-than-substantial and dissipated when defendants were classified by risk level. Therefore, while some evidence of overclassification is present in the PRINS score, biases are relatively small-to-negligible and reflect a relatively equitable classification.

To further assess potential policy implications, we next examined PRINS performance by prerelease type, including detention/bail/bond, conditional court release, and PR. As described, PRAs such as the PRINS are often used to guide release decisions. As designed, the DAJD could adopt policy to allow PRINS' Low-Risk defendants to be released by PR investigators, Moderate-Risk to be released with conditions at first appearance, and High-Risk to either be detained or provided an alternative method of release (e.g., home confinement). If adopted, the evaluation results consistently demonstrated more accurate prediction of FTA and recidivism risk via the PRINS, as compared to current court release decisions. Specifically, the PRINS was better able to identify those least likely to commit FTAs and recidivate, and High-Risk recommendations for detention may have prevented a greater proportion of recidivism to the King County community. The reverse was also found to be true, where a substantial portion of detained defendants could have been safely released by PR investigators prior to first appearance.

When examining the concordance between RLC and release type, findings also demonstrate an overuse of bail/bond. Specifically, 87% of those released via bail/bond were not High-Risk for recidivism. Further, 15% of Low-Risk defendants were required to wait until their first appearance to be released, and another 29% of bail/bond releases were identified as Low-Risk. Collectively, these findings suggest bail/bond is not being reserved for the highest risk cases and greater PR releases could be utilized without additional risk to the community or jeopardizing court processes.

With this said, while releasing a greater number of defendants via PR following a Low-Risk PRINS assessment result is advisable, current feasibility may be difficult. Specifically, evaluation results indicated that only half of those eligible for a PRINS assessment receive one. Therefore, if a policy (and DAJD commitment) to increase PR releases is created, greater investment is likely needed to extend PR investigator resources. However, releasing more defendants earlier is also likely to provide cost savings that could be redistributed to PR resource needs.

Therefore, the effective use of the PRINS in release decisions is now difficult to ignore. As described, PRAs were created to provide consistency to decision making. With multiple decision makers (i.e., PR investigators and judges), idiosyncrasies in release decisions are likely to occur, as court decision makers bring their own perceptions of FTA risk and seriousness of future offending. Yet, the predictive effects of the PRINS were not only demonstrated for FTAs and Any recidivism but provided consistent prediction for more specified types of Felony, Violent, Property, Drug and DV. Notably, PRINS RLCs demonstrated an improved ability to identify High-, Moderate-, and Low- risk defendants, regardless of recidivism type.

Further, we find each RLC has a relatively similar rate across all prerelease outcomes, regardless of court release type. Specifically, PRINS RLCs demonstrated an accurate prediction, where High-Risk defendants released by PR, Conditional, or Bail/Bond possessed a greater rate of FTAs across all recidivism types, when compared to Moderate or Low-Risk defendants with similar release types. This final analysis drives home the point that, if the PRINS were used to guide release decisions, fewer errors would occur, and greater community safety and improved court processing would result.

PRINS 2.0

Next, we examined data collected since implementation to further optimize the PRINS and create version 2.0. Using similar processes to create the initial version, we selected and weighted item responses for each model and set RLC cut points reflecting similar proportions of the initial design. While all but one of the initial PRINS items was identified to be predictive in the updated models, reorganizing, adding, and reweighting items demonstrated to improve prediction. Specifically, results demonstrated exceptionally strong performance for all PRINS 2.0 models. Further, performance by race/ethnicity and gender show only minor variations, which were negated when RLCs are assessed by gender and race/ethnicity for each model. In addition, when compared to the PSA and VPRAI, the PRINS 2.0 demonstrated superior performance. However, we note that the PRINS 2.0 was developed to optimize tool performance and could be considered a 'draft'. Stakeholders may view the need to adjust item content or RLC thresholds to improve gender or race/ethnicity equity. With all this said, we are confident that PRINS 2.0 updates will improve prediction and performance of the tool's application for future defendants assessed by DAJD.

Limitations

While there are common limitations for any assessment development effort, we focus here on a single aspect of the study design. Specifically, we compared the PRINS RLCs to judicial and PR investigator release decisions. We mentioned that this provided a natural experiment (of sorts) as these court room actors did not factor in the PRINS score when making said release decisions. Where feasible, we compared distinctions between court release decisions and pretrial release outcomes, where findings indicated that the PRINS demonstrated improved predictive accuracy by comparison to human actors.

However, it may be argued that the decision to detain an individual provides an additional level of security that 'prevents' the opportunity for FTAs and recidivism. Unfortunately, our sample can only assess the decisions of those released to the community pretrial. For those individuals that were detained for their entire pretrial term, we are unable to offer a suitable comparison. This creates an unknown quantity, or 'dark figure', that cannot be assessed with the current study, and barring the ability to randomly assign defendants to detention or release, this quantity of the PRINS prediction will remain unknown.

RECOMMENDATIONS

The driving force for the creation of the PRINS was to increase information to stakeholders responsible for pretrial release decisions. The design of the PRINS focused on including common PR interview items and a homegrown development to increase the predictive accuracy of the tool and reduce potential sources of bias. The evaluation results presented indicate these goals were met and PRINS predictions will provide a substantial improvement to prerelease decisions.

However, while the PRINS was provided and could be reviewed prior to a release decision, no policy directive was provided describing how and when to consider assessment results. Based on the positive findings provided here, we strongly advocate for policy creation around the use of the

PRINS RLCs. As described, the current categories of Low-, Moderate-, and High-Risk, should guide and be tracked in conjunction with the three common court release types – PR, Conditional Court, and Bail/Bond release. If the DAJD were to advocate for PR release of all Low-Risk, Conditional Court release for all Moderate-Risk, and detention/bail/bond release for High-Risk defendants, substantial improvements to community safety and reductions in FTA and recidivism would result.

Related, our findings suggest that judges us of bail/bond recommendations are being overused and not providing the intended effects for King County defendants. Given the recent changes observed nationally around cash bail, we recommend similar considerations for the DAJD. Specifically, for higher risk defendants' release alternatives, such as electronic monitoring and/or home confinement, provide less restrictive options that are also likely to reduce costs for the court and defendants. To account for a variety of less/more restrictive release conditions, additional PRINS categories could be created to identify those higher risk defendants that are ideal for alternative release types.

Next, a contracted project deliverable was the development of an updated version – PRINS 2.0. This is an important contribution, as many RNA and PRA revalidations neglect, or are restricted from, providing recommended updates. While many agencies use tools 'off the shelf', with no adjustment, the RNR model advocates for consistent revalidation and versioning of tools as populations served are known to change over time (Andrews & Bonta, 2010). Creating updates and modified versions based on new data is not only important, helping to calibrate the tool to the population, but this process is especially important following the initial adoption of a tool, as some aspects of the assessment may not meet expectations. Given the advancement of the tool's predictive strength, we recommend the DAJD adopt the PRINS 2.0, or a similarly modified version, in the near future. We further advocate for additional revalidations and updates every two-to-three years, to ensure prediction strength remains strong, gender and racial/ethnicity equity is retained, and adjustments for population changes and stakeholder needs are incorporated.

Finally, the impact and contribution to the pretrial release processes of PR investigators is substantial, providing a quality of service that is important for decision making and notably humane. Yet, our findings suggest that roughly half of all eligible defendants receive an assessment. To fully utilize the PRINS and improve pretrial outcomes, greater PR resources are needed. While it is beyond the scope of this evaluation to quantify the PR investigator resource needs, we recommend a cost-benefit analysis be completed to assess dollars saved through increased PR investigations and greater usage of PRINS. Our findings suggest that there will be substantial cost recovery from reduced use of detention.

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Appendix A. PSA and VPRAI-R Items & Weights

PSA Items	FTA	NCA	NCVA
Pending Charge at the Time of Arrest	1		1
Prior Conviction (Misdemeanor or Felony)	1		
One Prior FTA in the Past Two Years	2	1	
Two or More FTAs in the Past Two Years	4	2	
Prior FTA Older Than Two Years	1		
Twenty-Two Years Old or Younger at Current Arrest		2	
Prior Misdemeanor Conviction		1	
Prior Felony Conviction		1	
One or Two Prior Violent Convictions		1	1
Three or More Prior Violent Convictions		2	2
Prior Sentence to Incarceration		2	
Current Violent Offense			2
Current Violent Offense and Twenty Years Old or Younger			1

VPRAI-R Items	FTA/NCA/TV
Active Community Criminal Justice Supervision	2
Charge is Felony Drug, Felony Theft, or Felony Fraud	3
Pending Charge at the Time of Arrest	2
Prior Misdemeanor or Felony Conviction	2
Two or More FTAs	1
Two or More Violent Convictions	1
Unemployed at Time of Arrest	1
History of Drug Abuse	2

Appendix B. PRINS 2.0 Items & Weights

Items	Male FTA	Female FTA	Male Any	Female Any	Male Felony	Female Felony	Male Violent	Female Violent	Male Property	Female Property	Male Drug	Female Drug	Male DV	Female DV
FTA <2 years	30	30	22	16	30	29	1	18	20	13	20	17	11	13
FTA 2 years+	24	23	1	9	1	4	1	3	4	10	10	13	5	5
Prior Prison Incarceration			1	1	11	33			10	20				
Current Community Supervision	15	20	10	9			10	20	3	4			17	10
Age At Assessment	26	27	29	15	20	13	20	1	20	16	11	20	20	16
Prior Juv. Adjud. for Violent Crimes			1	1			11	1			2	1	20	6
Out of State Convictions			7	1	13	1								
Age At First Violent Conviction					6		4	1					3	
Time Since Last Conviction	16	22	20	20	16	16	22	20	20	20	15	20	20	13
Total Adult Convictions			1	1					2	1	3	3		
Prior Felony	2	2			5	3	1	1						
Prior Violent			8	1	4	2	16	15					10	10
Prior Property	30	35	27	23	21	16	6	7	20	20	18	4		5
Prior Drug	7	16	1	4	1	10			3	1	20	20		5
Prior Weapon			1	6	1	1	1	17						
Prior DV Assault			7	9	3	3	3	12	2	4			20	20
Prior Protection Orders	5	6	5	14	3	2	14	20	1	5			20	20
Current Felony	20	20	20	7	20	20	1	0	10	15	20	20	1	1
Current Misd & Felony	29	20	1	10	1	1	1	20	1	9			4	4
Current Violent			1	1	1	1	20	20					20	20
Current DV			23	1	20	1	20	20					20	20
Current Property	20	20	20	20			13	6	8	10	5	15		
Current Drug	9	1	1	1	1	20	1	3			20	20		
Employ Status	1	6	5	4	1	31	3	1	5	1	2	7	1	1
Length Employment	6	5	2	2	5	1	3	3	4	3	3	8	3	3
Length Unemployment	4	2	1	4	1	5	1	4	1	5	3	3	1	7
School Achievement	10	7	7	1	11	1	1	1	9	1	6	1		
Has a Reference for Release	1	1	7	1	4	1	9	1	7	5			9	1

Current Living Situation			7	3	3	1	4	3	9	5			1	3
Rents, Owns, or Fin. Cont. to Res.	1	5	19	20	3	20	13	20	20	20	12	6	2	20
Duration in Current Residence	1	3	1	1	1	1	1	1	1					
Number of Moves in last 6 months	11	1	5	1	9	1			7	5	9	1		
Marital Status	1	10	7	4	6	2	1	7	16	14	2	1	1	8
Family In Area							1	12						
Friends In Area			1	5	3		16	10	5	17			9	
Prescribed Medications					4	4	11	1			1	1	12	8
Last Weekly Use of Alcohol/Drugs			2	1	3	1	3	2	1	1	5	2	1	2
Last Use of Alcohol							1	2					2	11
Last Use of Opioids	15	4	5	9	9	1			6	17	11	18		
Last Use of Marijuana	0	0	2	5	3	7	9	8	1	4	1	3	6	7
Last Use of Stimulants	15	15	13	8	13	8	2	1	19	14	17	6	2	2
Substance Abuse Treatment			2	1	4	1	6	1	3	1	5	5	5	16
Model AUC	**0.73**	**0.76**	**0.72**	**0.74**	**0.72**	**0.74**	**0.72**	**0.76**	**0.75**	**0.76**	**0.75**	**0.78**	**0.81**	**0.81**

Appendix C. PRINS 2.0 Predictive Scale Metrics

Items	Male FTA	Female FTA	Male Any	Female Any	Male Fel.	Female Fel.	Male Vio.	Female Vio.	Male Prop	Female Prop	Male Drug	Female Drug	Male DV	Female DV
High	241	358	310	290	272	250	219	238	290	235	225	225	260	250
Low	38	109	125	19										
Base rate	23	23	14	14	5.2	5.2	5.7	5.7	8.1	8.1	1.6	1.6	2.3	2.3
High failure	42.6	40.8	30.1	22.8	11.6	6.2	16.3	15.6	20.9	13.6	4.3	3.7	8.4	5.3
High %	11.9	3.6	7.5	5.5	16.6	5.4	12.7	3	14.7	11.9	13.4	11.7	13.2	6.4