Five-County Validation of the Indiana Risk Assessment System – Pretrial Assessment Tool (IRAS-PAT) Using a Local Validation Approach

Evan M. Lowder[a]*, S. G. Lawson[b], E. Grommon[c], and B. R. Ray[d]

[a]*Department of Criminology, Law and Society, George Mason University, Fairfax, VA, USA;* [b]*School of Criminal Justice, Michigan State University, East Lansing, MI, USA;* [c]*Paul H. O'Neill School of Public and Environmental Affairs, IUPUI, Indianapolis, IN, USA;* [d]*School of Social Work, Wayne State University, Detroit, MI, USA*

*corresponding author:
Evan M. Lowder
Enterprise Hall, Room 354
4400 University Drive, 4F4
Fairfax, VA 22030
elowder@gmu.edu | 703-993-9714

Evan M. Lowder

E. M. Lowder is an assistant professor in the Department of Criminology, Law and Society at George Mason University. Her research interests include strategies to reduce offending and improve behavioral health outcomes among justice-involved adults, with special focus on risk assessment and diversion programs. Her research has been published in outlets including *Law and Human Behavior*, *Criminal Justice and Behavior*, *Psychiatric Services*, and the *American Journal of Public Health*.

Spencer G. Lawson

S. G. Lawson is a doctoral student in the School of Criminal Justice at Michigan State University. His community-based research focuses broadly on justice-involved behavioral health populations and police safety and wellness, with other interests spanning topics such as organizational justice and pretrial risk assessments. His recent work has appeared in *Criminology*, *Police Quarterly*, C*orrections: Policy, Practice and Research*, and the *Journal for Advancing Justice*.

This is the author's manuscript of the article published in final edited form as:

Lowder, E. M., Lawson, S. G., Grommon, E., & Ray, B. R. (2020). Five-County Validation of the Indiana Risk Assessment System – Pretrial Assessment Tool (IRAS-PAT) using a Local Validation Approach. Justice Quarterly, 37(7), 1241–1260. https://doi.org/10.1080/07418825.2020.1829006

Eric Grommon

E. Grommon is an associate professor in the Paul H. O'Neill School of Public and Environmental Affairs at IUPUI. His research interests include corrections, offender reentry, and the rigorous evaluation of justice system programs, policies, and operations. His research has been published in outlets including *Journal of Experimental Criminolo*gy, *Journal of Quantitative Criminology*, *Justice Quarterly*, and *Criminology & Public Policy*.

Brad R. Ray

B. R. Ray is an associate professor at the Wayne State University School of Social Work and Director of the Center for Behavioral Health and Justice. He is a community-engaged researcher whose work focuses on persons with mental health and substance use disorders, particularly where these populations intersect with the criminal legal systems. His work has been published in outlets including *Addiction*, *Criminal Justice and Behavior*, *Behavioral Sciences & the Law*, and the *American Journal of Public Health*.

Funding and Disclosure Statement

This work was funded by the Indiana Office of Court Services. All study authors received funding to complete this work. The findings and conclusions expressed herein are solely those of the authors and do not necessarily represent the views or opinions of the Indiana Office of Court Services or the State of Indiana.

Five-County Validation of the Indiana Risk Assessment System – Pretrial Assessment Tool (IRAS-PAT) Using a Local Validation Approach

Local jurisdictions are increasingly using pretrial risk assessment instruments to assess risk of pretrial misconduct and inform release decisions. We adopted a local validation approach to examine the predictive validity of Indiana Risk Assessment System – Pretrial Assessment Tool (IRAS-PAT) assessments in 3,739 unique pretrial defendants across five Indiana counties. Jail, court, and pretrial risk assessment records were matched within each jurisdiction to examine pretrial misconduct outcomes (i.e., any arrest, any new arrest, and any failure to appear) during the case processing period. Area Under the Curve (AUC) estimates showed good-to-excellent levels of predictive accuracy for total scores for all outcomes (AUC Range: 0.67-0.72). Multivariable models showed defendants assessed at High (OR Range: 5.42-8.62) and Moderate (OR Range: 2.56-3.08) risk had higher rates of pretrial misconduct relative to those assessed at Low risk. Findings provide strong evidence for the predictive accuracy of IRAS-PAT assessments overall, though some item-level considerations are noted.

Keywords: pretrial risk assessment; predictive validity; local validation; pretrial misconduct

Introduction

There are more than 10 million unique admissions into U.S. jails per year (Zeng, 2020). At any given time, individuals in pretrial detention represent roughly two-thirds of local jail populations, resulting in a pretrial detention rate of 148 per 100,000 residents (World Prison Brief, 2018). The pretrial population comprises individuals who have no formal charge filing or are awaiting legal disposition on formally filed charges. Incarceration during the pretrial period has been linked to adverse effects on case processing, including increased likelihood of a guilty plea and harsher sentencing (Heaton et al., 2017; Scott-Hayward & Fradella, 2019) as well as negative effects on employment, family relationships, and future justice system contact following reentry (Gupta et al., 2016; Scott-Hayward & Fradella, 2019).

Increased attention on the adverse effects of pretrial detention has prompted debates on how to reform pretrial operations to maximize personal liberty, increase court appearances, and improve public safety (Stevenson & Mayson, 2017). Pretrial risk assessment tools have emerged as a key component of pretrial reform efforts. Results from these actuarial tools are designed to guide the judiciary's release decision by providing information on a defendant's likelihood of pretrial misconduct (e.g., failure to appear for a court hearing or new criminal activity during the pretrial period). This information is based on items that measure static and dynamic risk factors, typically collected through interviews and followed by case file or criminal history record review. Responses are scored to create risk categories based on pre-determined cutoff values that communicate probability of misconduct (Desmarais & Lowder, 2019). In many jurisdictions, pretrial staff summarize scoring results and provide a written recommendation at the initial hearing. The judicial officer assesses the information within a policy environment bound by state statute, local rules, and local resources to render a non-monetary release decision, set monetary bail, detain, or impose other supervision conditions to mitigate the risk of pretrial misconduct.

There is growing, but limited, research on the predictive accuracy of pretrial risk assessments. Despite the importance of local validation, few studies have undertaken this approach (Desmarais & Lowder, 2019; Picard-Fritsche et al., 2017). Because local record management systems often do not communicate with one another, data accessibility remains a barrier to local validation. The inaccessibility of comprehensive county- and state-level data has been described as one of the biggest barriers to developing data-driven solutions for criminal justice populations (Latessa et al., 2013; Sloan et al., 2018). This study reports on a long-term, multifaceted, academic-practitioner partnership resulting in the first validation of Indiana Risk Assessment System – Pretrial Assessment Tool (IRAS-PAT) assessments across five Indiana counties. Each county implemented the tool with different populations and at different points in the booking process; thus, validation efforts required that researchers collaborate with county practitioners to detail system processes, collect new data, facilitate record linkage, conduct the validation, and disseminate results to local and state-level stakeholders.

Pretrial Risk Assessments

As of 2019, roughly two-thirds of counties have adopted a risk assessment tool to guide pretrial decision-making, nearly half within the last five years (Pretrial Justice Institute, 2019). Most jurisdictions have adopted instruments originally developed for a different jurisdiction (Myburgh et al., 2015; Pretrial Justice Institute, 2019). Locally developed pretrial assessment tools have been criticized for being non-standardized and lacking independent validations (Bechtel et al., 2017; Myburgh et al., 2015). Conversely, use of tools developed for other jurisdictions has been criticized due to lack of local validation (Bechtel et al., 2017). A recent meta-analytic review on the predictive accuracy of pretrial risk assessment tools identified 10 tools commonly used across jurisdictions (Desmarais et al., 2020), yet only a handful have been validated.

While research is still accumulating, evidence on the predictive accuracy of pretrial risk assessments has been generally positive (Bechtel et al., 2017; Desmarais et al., 2020). The present study focuses on a 7-item tool that—despite being used as the statewide tool in five states and adopted in at least 48 counties (Media Mobilizing Project, 2020)—has yet to be independently validated in the academic literature: the Ohio Risk Assessment System – Pretrial Tool (Latessa et al., 2009). In 2010, the Indiana Supreme Court adopted a suite of tools from the ORAS to form the Indiana Risk Assessment System (IRAS), including the IRAS-PAT. Despite its adoption, however, the IRAS-PAT was never validated for use in Indiana.

To date, we are aware of only three publicly accessible documents validating assessments produced by the ORAS-PAT. An initial validation by its developers in a sample of 452 defendants from seven Ohio counties suggested fair performance of ORAS-PAT assessments (Latessa et al., 2009). No cross-validation, however, was performed as part of this initial validation (i.e., the development and validation sample were the same) which is a critical component of test development to separate sampling error from model estimates (Schumacher et al., 1997; Wollert, 2002). Additionally, although the authors reported correlations and proportions of defendants with any pretrial misconduct, the authors did not assess outcomes individually, control for county-level differences, or report on other risk assessment performance indicators. A subsequent ORAS-PAT validation study in a sample of defendants from three Hawaiian counties found risk classifications were positively associated with pretrial misconduct (Davidson, 2014). More recently a report from Travis County, Texas noted positive correlations between ORAS-PAT scores and bond forfeiture (a proxy for FTA) and new criminal activity (Carmichael et al., 2017). Methodological details and results of statistical tests were omitted, which begs questions about the findings and associated conclusions. Incomplete reporting practices have been noted as a troublesome pattern in the current body of knowledge on pretrial risk assessments (Bechtel et al., 2017; Desmarais et al., 2020).

More broadly, pretrial risk assessment validity research is limited in several respects. First, few validation studies have been subject to the peer-review process, limiting rigorous evaluation of the performance of these tools. Indeed, a recent review of the literature found only three validation studies published in peer-reviewed outlets (Desmarais et al., 2020). A statewide validation of PSA assessments conducted in Kentucky was recently published (DeMichele et al., 2020), but there are no independent validations of the ORAS-PAT published in peer-reviewed outlets. Second, despite large sample sizes, studies from statewide pretrial risk assessment validations suffer from methodological limitations. These include use of a case-level unit of analysis, which does not account for correlated observations from repeated assessments conducted on the same individuals (Sainani, 2010). Additionally, the pretrial processing period is inherently different across individuals, varying the length of exposure period during which an individual could commit pretrial misconduct. Few studies account for variable follow-up length in multivariable modeling. Third, despite the importance of local validation (Desmarais & Lowder, 2019; Picard-Fritsche et al., 2017), few validations have undertaken this approach. Most rely on statewide samples and records, which may limit data availability and precision of measurement (Mamalian, 2011). A local validation approach can improve issues in measurement consistency across counties by addressing variation in county-level practices and record-keeping.

The Present Study

In 2014, the Indiana Supreme Court ordered the development and study of an evidence-based pretrial program in Indiana. This directive aimed to increase the use of release on own recognizance, while reducing monetary conditions of release and exploring use of a pretrial risk assessment system to guide pretrial release decisions. In 2015, with technical assistance from the National Institute of Corrections' Evidence-Based Decision-Making Initiative, stakeholder partnerships were formed between state policymakers, local practitioners, and researchers. Several counties agreed to participate in a pretrial pilot project that required using the IRAS-PAT to screen for pretrial release; providing differential supervision based on the results; and agreeing to data collection for validation purposes. However, counties had flexibility in the populations they assessed and when the tool was administered during the booking process.

The unique implementation strategies, along with the need for cross-system county data, required a multifaced academic-practitioner partnership with county jails, community correctional agencies, and policymakers. A research coordinator maintained contact with county practitioners (e.g., sheriff, pretrial services, probation, community corrections, and courts) over the duration of the evaluation to detail implementation strategies and secure local jail data while lead researchers worked with the state court administrator's office to obtain court and risk assessment information. Through an iterative process of data review and analysis, researchers worked to understand county workflow process around the risk assessment administration to inform the temporal ordering for the record linking and case inclusion criteria.

From these efforts, and in a broader attempt to advance research on the predictive accuracy of pretrial risk assessments, we report on the predictive accuracy of IRAS-PAT assessments in a multi-jurisdictional sample of 3,739 unique criminal defendants in Indiana. The objectives of this study were three-fold: 1) to conduct a rigorous test of the predictive accuracy of IRAS-PAT assessments across five Indiana counties; 2) to demonstrate the utility of a local validation approach to account for differences in county practices; and 3) to provide an approach to local validation of pretrial risk assessments that could be replicated in other jurisdictions.

Methods

Local Context

Table 1 presents a comparison of the geographic, sociodemographic, and pilot program characteristics for each jurisdiction. As shown, local use of the IRAS-PAT, both in terms of the target populations and administration of assessments, was similar across jurisdictions. Jurisdictions varied in their sociodemographic composition as well as which correctional agency was responsible for administering assessments. All counties began using the IRAS-PAT in 2016, which marked the start of the 1-year study period for each jurisdiction.

Data Sources

For each validation, data sources included jail, court, and risk assessment records, primarily drawn from separate data management systems. The specific data source varied based on data availability in each county. First, for each county, we received county-level jail data on all admissions, associated release dates, and booking charge(s). Jail data were used to establish the start of the pretrial period (i.e., release date), to assess initial charges against the defendant, and to indicate re-arrest during the pretrial period. Statewide arrest records were not available. For four of five counties, court data were drawn from Indiana's statewide court case management system, Odyssey. For the fifth county, court records were drawn from a local records management system. For both sources, court data contained information on all criminal cases and case-related information (e.g., hearings, case disposition, warrants, and FTAs) processed in each county. Finally, we received risk assessment records from the Indiana Court Information Technology Extranet (INcite) system, which included assessment date, total score, and item-level data. When necessary, we triangulated risk assessment records with internal county records. All data sources included basic individual identifying information (i.e., first name, last name, date or year of birth, sex, and race), but few unique identifiers to facilitate cross-system data integration.

Local Validation Approach

We developed a local validation approach to balance several competing needs. These included the need to: 1) account for local practices in linking data sources and developing reliable and valid measures of pretrial misconduct; 2) adhere to best practices for examination of predictive accuracy of risk assessments (Douglas et al., 2011); and 3) minimize sources of between-county heterogeneity consistent with standards for integrative data analysis (Curran & Hussong, 2009). To achieve these objectives, we established strict, a priori inclusion criteria to guide selection of participants in each jurisdiction to model pretrial risk assessments as they are designed to be used in typical case processing. Second, we adopted uniform operationalization of variables across jurisdictions to reduce measurement-related heterogeneity. Third, we conducted multivariable models to adjust for fixed effects of county and time at risk in the community.

Individuals were included in each county-level validation if they met the following criteria: 1) had an IRAS-PAT conducted during the first 12 months of the pretrial pilot period; 2) the IRAS-PAT assessment could be connected to a jail booking to establish the start of an at-risk period in the community; 3) the booking could be linked to a new court case filing; 4) the court case disposition occurred after an individual's release date; and 5) the individual had not received an IRAS-PAT assessment previously during the study period. Thus, the final sample included unique individuals who received an IRAS-PAT assessment during an index episode of incarceration and had time at risk in the community prior to a court case disposition. We applied inclusion criteria within each county to link records across jail, court, and pretrial services record systems. This approach was important because not all counties used data systems equivalently.

Due to the absence of global identifiers across records systems, we used a combination of the first three letters of a defendant's first name, the first three letters of a defendant's last name, and year of birth to link assessments to jail and court records within each county. Prior studies have shown that exact name matching can result in data loss and lower statistical power (Tahamont et al., 2020). We have found that local records often contain slight name misspellings, and this shortened identifier can detect the same individuals with good accuracy in a given jurisdiction.

Assessments had to be conducted during the index episode of incarceration, but most commonly within three days of a booking date. The linkage of court data to jail data varied slightly across counties based on consultation with county officials and county-level practices. In three counties, court cases were linked based on an initial hearing occurring up to three days following a jail booking or a case filing date occurring within three days (on either side) of a jail booking. In a fourth county, the case filing date was extended up to five days following an index booking after consulting with county officials and after initial application of matching strategies yielded a low match rate. In the fifth county, court data was integrated into local jail data due to use of a separate court data management system. Following matching, repeated assessments by the same defendants were removed from the dataset, as were assessments linked to court cases without a disposition date or where defendants had no time at risk in the community.

Across counties, IRAS-PAT assessments were conducted on a large portion of individuals who did not meet inclusion criteria (i.e., were not pretrial defendants, did not have time at risk in the community, or did not have an assessment conducted during an episode of pretrial detention). As a result, following application of inclusion criteria, not all administered IRAS-PAT assessment were included in the validation. Across the five counties, roughly half of all conducted IRAS-PAT assessments met study inclusion criteria (N = 3,739 of 8,019 assessments). See Appendix A in online supplement for inclusion flow chart by county.

Participants

Table 2 presents demographic and case characteristics of participants overall and by county. The final sample included 3,739 unique pretrial defendants who received an IRAS-PAT assessment between January 2016 and December 2017. Participants had an average of 172.67 days of follow-up time (SD = 141.28, Range: 1 to 1,005). The sample was primarily male (71.4%) and an average age of 32.59 (SD = 11.67). The majority of participants were White (76.5%) with smaller proportions identifying as Black (18.5%) or other racial identities (5.0%). Most participants were booked on misdemeanor- (57.2%) versus felony-level (42.8%) charges.

Variables

IRAS-PAT assessments

The IRAS-PAT is a 7-item instrument designed to assess risk of any arrest, any new arrest, and any FTA in pretrial defendants (see Appendix B in online supplement). The IRAS-PAT was adopted in Indiana based on the more widely known ORAS-PAT (Latessa et al., 2009). Items broadly assess four criminogenic risk domains: criminal history (3 items), employment (1 item) residential stability (1 item), and substance use (2 items). Five items are scored on a 0 to 1 rating scale, with two items scored on a 0 to 2 scale, resulting in a total possible score ranging from 0 to 9. Total scores create three risk levels: Low (0-2), Moderate (3-5), and High (6-9). Variables used included *total scores* (continuous) and *risk levels* (Low; Moderate; High).

Pretrial misconduct outcomes

Outcomes included *any FTA* (yes; no), *any arrest* (yes; no), and *any new arrest* (yes; no) occurring during the pretrial processing period (i.e., following initial release from jail but prior to court case disposition). FTA was operationalized as an official court record of a warrant issued for an FTA. For two counties, FTAs were inconsistently recorded in administrative court datasets, and we relied on jail booking records for an FTA warrant that could be linked to administrative court warrant records using a warrant served date. In turn, court warrant records provided an issued date and were linked to a specific court case. Any arrest was measured by any return to the local county jail custody (i.e., for a new offense or any other reason) prior to case disposition. Any new arrest was measured by a return to jail custody for at least one new offense and excluded instances where a defendant was returned to custody for other reasons (e.g., warrant-based arrests for technical violations, community supervision holds, or warrants originating from other jurisdictions). For descriptive purposes only, we additionally reported two measures of *any pretrial misconduct*, which were defined as an arrest or FTA during the pretrial period. This outcome was operationalized separately using any arrest or any new arrest.

Covariates

Covariates included *county* (dummy coded, with County 1 as the reference group) and *time at risk*, which measured the total number of days from the date of pretrial release to the date of court case disposition, minus any time incarcerated in the local jail. *Survival time* was used in survival models to indicate time to event or time to case disposition from date of pretrial release.

Analytic Strategy

We first conducted descriptive statistics on all variables overall and by county. Subsequent analyses were conducted using pooled data across counties. Second, we conducted bivariable comparisons between IRAS-PAT total scores, risk levels, and pretrial misconduct outcomes. For categorical comparisons, Cramer's V values of .10, .30, and .50 indicated small, medium, and large effect sizes, respectively (Cohen, 1988). For point-biserial correlations, values below .10 were considered poor, .10-.23 fair, .24-.36 good, and .37-1.00 excellent (Cohen, 1988; Desmarais

& Singh, 2013). Third, consistent with metrics commonly reported in risk assessment research in correctional settings (Desmarais & Singh, 2013), we examined Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) statistics for total scores. AUC values range from .50 to 1, with .50 indicating predictive accuracy at chance levels and 1 indicating perfect prediction. AUC values below .54 are considered poor, values .55 to .63 fair, values .64 to .70 good, and values above .70 excellent (Desmarais & Singh, 2013; Rice & Harris, 2005). Fourth, we conducted multivariable analyses to model outcomes while adjusting for time at risk. Each model was conducted separately for total scores and risk levels and by outcome. We additionally conducted Cox proportional hazards models to examine event rates as a function of survival time at risk in the community, controlling for county (see Appendix C in online supplement). Fifth, we examined the item-level functioning of IRAS-PAT assessments using multivariable logistic regression. All logistic regression models adjusted for time at risk in the community and county.

Results

Descriptives

Descriptive statistics are presented in Table 2. IRAS-PAT total scores averaged 3.06 (*SD* = 1.86), corresponding to a Moderate risk level. The majority of defendants were classified at Moderate risk level (*n* = 1,664, 44.5%), followed by Low (*n* = 1,641, 43.9%) and High (*n* = 438, 11.6%) risk levels. Roughly one in three pretrial defendants had any pretrial misconduct (*n* = 1,189, 31.8%), defined as any arrest or FTA during the pretrial period. The rate of pretrial misconduct was lower when defined with any new arrest (*n* = 879, 23.5%). Roughly 10% of defendants had an FTA during the pretrial period (*n* = 393, 10.5%). Less than one-fifth of defendants had a new arrest (*n* = 606, 16.2%), but twice as many had any arrest (*n* = 1,122, 30.0%).

Bivariable Comparisons

Point-biserial correlations showed IRAS-PAT total scores were positively associated with any arrest (r[3,737] = .35), any new arrest (r[3,737] = .22), and any FTA (r[3,737] = .23), ps < .001. Crosstabulations of risk levels and pretrial misconduct outcomes are presented in Table 3. High risk participants experienced higher rates of all outcomes relative to Moderate and Low risk participants. Cramer's V estimates ranged from .21-.32 (i.e., small-moderate effect sizes).

AUC of the ROC

AUC estimates for total scores overall and by county are presented in Table 2. As shown, AUC values corresponded to good levels of predictive accuracy for any new arrest and excellent levels for any FTA or any arrest.

Multivariable Models

Results of multivariable logistic regression models adjusting for time at risk in the community and county are presented in Table 4. In Model 1, each 1-point increase in IRAS-PAT total score was associated with a 1.49, 1.41, and 1.56 times increase in the rate of any FTA, any new arrest, and any arrest, respectively, ps < .001. In Model 2, IRAS-PAT assessments showed similar ability to discriminate between participants assessed at Low and Moderate risk levels (OR range: 2.56-3.08, ps <.001). Larger effect sizes were found for the prediction of any FTA (OR = 7.18) and any arrest (OR = 8.62), ps < .001 between defendants classified as High and Low risk.

Table 5 presents results of multivariable logistic regression models examining the unique predictive accuracy of IRAS-PAT items on pretrial misconduct outcomes. For any FTA, age at first arrest (Item 1; OR = 2.30) and unemployment relative to full-time employment status (Item 4; OR = 2.29) were the strongest unique predictors, ps $\leq$ .004. More than two FTAs in the past 24 months (Item 2), part-time employment (Item 4), and illegal drug use in the past six months (Item 6) were not significantly associated with any FTA, ps $\geq$ .071. IRAS-PAT items were weaker predictors of any new arrest overall, but three or more prior incarcerations (Item 3; OR = 1.69) and residential instability (Item 5; OR = 1.63) were the strongest item-level predictors of a new arrest, *p*s < .001. Age at first arrest (Item 1) and any number of FTAs in the past 24 months (Item 2) did not uniquely predict any new arrest, *p*s $\geq$ .061. In contrast, all items uniquely predicted any arrest, although three or more prior incarcerations (Item 3; OR = 2.32), two or more FTAs in the past 24 months (Item 2; OR = 2.03), and unemployment relative to full-time employment status (Item 4; OR = 2.03) were the strongest unique predictors, *p*s $\leq$ .001. Illegal drug use in the past six months (Item 6; OR = 1.23) was the weakest unique predictor, *p* = .025.

Four items uniquely contributed to the prediction of all three outcomes: three or more prior incarcerations (Item 3; OR range: 1.69-2.32), unemployment relative to full-time employment (Item 4; OR range: 2.58-2.29), residential instability (Item 5; OR range: 1.39-1.63), and a severe drug use problem (Item 7; OR range: 1.58-1.69), *p*s $\leq$ .001.

Discussion

Pretrial risk assessments are used increasingly across the United States to inform pretrial release and supervision decisions. However, research on pretrial risk assessments is limited by data accessibility issues and incomplete reporting practices, which have decreased the quality of evidence on their predictive validity (Desmarais et al., 2020). Moreover, despite the importance of local validation (Desmarais & Lowder, 2019; Picard-Fritsche et al., 2017), many jurisdictions that use these tools do so without rigorous local validation, often relying instead on the promise that findings from another jurisdiction will transfer and produce similar results (Mamalian, 2011). We collaborated with local practitioners to conduct a rigorous test of the predictive accuracy of IRAS-PAT assessments. Through this process, we established a county-level validation approach that accounted for differences in local practices while establishing measurement consistency across jurisdictions. Our findings demonstrate that IRAS-PAT assessments can predict pretrial misconduct outcomes and place individuals into appropriate risk classifications based on likelihood of pretrial misconduct. The results provide evidence that ORAS-PAT initial validation findings largely transferred to five Indiana counties.

Overall, IRAS-PAT predictive accuracy estimates met or exceeded standards for the performance of risk assessments in criminal justice settings (Desmarais & Singh, 2013). Both total scores and risk levels showed good-to-excellent performance across measures. Risk levels showed differential and increasing rates of pretrial misconduct across risk classifications. AUC performance has been considered a key indicator in actuarial risk assessment for the past several decades (Mossman, 1994; Singh et al., 2013). AUC estimates (ranging from .67-.72) showed IRAS-PAT assessments slightly outperformed assessments produced by other instruments. For example, in a meta-analytic review of pretrial risk assessment validation studies, Desmarais and colleagues (2020) found AUC values of .66 for new criminal activity and .65 for FTA across studies. Similarly, a recent statewide validation of the Public Safety Assessment (PSA) in Kentucky found AUC values of .65 for new criminal activity and FTA (DeMichele et al., 2020). Moreover, in multivariable models, we found strong evidence for the ability of IRAS-PAT assessments to discriminate between risk classifications. Estimated odds ratios were larger than those reported in prior studies based on proportional odds models (Desmarais et al., 2020).

Similar to the results found in Hawaii's ORAS-PAT validation (Davidson, 2014), we found smaller effect sizes for IRAS-PAT assessments in the prediction of new arrest in relation to other forms of pretrial misconduct. This was true across all models and is potentially problematic. Beyond concerns about risk assessment generally, legal scholars have argued that in keeping with Supreme Court precedent, risk assessments should be used only to identify individuals who pose public safety risks to the public (Gouldin, 2016; Koepke & Robinson, 2018), underscoring the importance of a tool's ability to predict new criminal activity.

At the IRAS-PAT item-level, we identified four consistent predictors of pretrial misconduct outcomes. These included three or more prior incarcerations (Item 3), employment status (Item 4), residential instability (Item 5), and a severe drug use problem (Item 7). Across pretrial tools, length of residence and history of drug or alcohol use are among the commonly assessed risk factors (Desmarais et al., 2020), with the exception of the PSA. More broadly, these four items are closely tied to the central eight criminogenic risk domains (Andrews et al., 1990), and findings suggests their predictive utility extends to the pretrial processing period as well.

We found illegal drug use in the past six months (Item 6) predicted any new arrest. However, this item did not predict FTA and had a weak relationship with any arrest relative to other items. This domain is measured in qualitatively distinct ways across pretrial risk assessment instruments. Similar to IRAS-PAT Item 7, most tools measure substance abuse or substance use problems, rather than illegal drug use. This includes history of drug abuse (Virginia Pretrial Risk Assessment Instrument [VPRAI]; Virginia Department of Criminal Justice Services, 2018), past or current problems with alcohol (Colorado Pretrial Assessment Tool [CPAT]; Colorado Association of Pretrial Services, 2015), and current drug problems and current alcohol problems (Federal Pretrial Risk Assessment [PTRA]; U.S. Office of Probation and Pretrial Services, 2010). We are not aware of any other pretrial risk assessment tool measuring illegal drug use, specifically, raising questions about the predictive utility of this item.

We found mixed support for ordinal scoring on Item 2 (i.e., 2+ FTAs in the prior 24 months) and Item 4 (i.e., part-time employment). Effect sizes were smaller for these items and two or more FTAs (Item 2), in particular, only predicted any arrest. Beyond limited predictive utility, there may be other concerns about these weightings. Scholars and advocates have voiced concerns regarding the potential for racial bias in risk assessments. Specifically, items measured in risk assessment tools may bias minority defendants toward higher risk classifications without an increase in misconduct rates (Harcourt, 2015; Pretrial Justice Institute, 2020; Starr, 2014). Prior studies have found that Black defendants are at higher risk of FTA, often due to barriers to making court appearances, and are more likely to have a past history of FTA (Reaves & Cohen, 2007; Siddiqi et al., 2002; Zettler & Morris, 2015). Additionally, Black individuals are less likely to be in the labor force overall, and Black men, in particular, are more likely to be employed in a part-time capacity relative to White men (U.S. Bureau of Labor Statistics, 2020). Overall, these trends suggest ordinal scoring (in lieu of assessment of other criminogenic domains) may do little to improve the predictive accuracy of assessments for defendants overall and for Black defendants, in particular. There is very real and growing concern about the potential for racial bias in the predictive accuracy and application of risk assessments in correctional decision-making. Investigation into these issues is critically important to ensure risk assessments do not contribute to racial disparities in criminal processing. Investigation into the predictive accuracy of IRAS-PAT assessments by race is underway and will be reported in a subsequent study.

Limitations

Results should be interpreted with some limitations in mind. First, as noted in prior reports (Mamalian, 2011), FTAs were infrequently recorded in court records for two jurisdictions. This necessitated creative triangulation of jail booking, warrant, and court case records to develop a consistent measure of FTA across counties. Second, jail bookings from local jail records served as proxy measures of arrests. We were unable to receive statewide arrest records for this purpose and arrests occurring in other jurisdictions were unobserved. Although

Indiana continues to improve the accuracy and completeness of records in its criminal history repository (Indiana Criminal Justice Institute, 2018), statewide arrest records remain inaccessible for research purposes. Despite this limitation, our use of local jail records enabled us to observe the start of the pretrial period and adjust for time at risk in the community Though, we note that there is limited research comparing use of local and statewide records in pretrial validation. Third, we validated assessments as implemented in routine practice. Importantly, during the pretrial pilot period, counties used assessments in different ways. As a result, we adopted strict inclusion criteria for assessments to be included in the validation to provide consistency across jurisdictions and to generalize validation findings to prototypical case processing. However, because assessments were implemented in practice, it is possible that their predictive accuracy may be attenuated due to detention of high-risk defendants and use of risk assessment-informed supervision. Fourth, one challenge to any pretrial risk assessment validation is the variable length of case processing time, which means assessments predict pretrial misconduct outcomes over a variable period. Although we adjusted for time in the community in multivariable models, data collection protocols did not allow sufficient follow-up time for every case to reach disposition. As a result, individuals with longer case processing times were excluded from the sample.

Despite limitations, our investigation improves on prior research in several respects. First, we adopted a local validation strategy, which resulted in more relevant information for local agencies and allowed us to balance the need for standardized measurement with allowances for local practice. Through prior implementation work (Grommon et al., 2017), it was clear that understanding variation in local practices would be key to successful validation. For example, across counties, assessments were not always administered on individuals formally charged with a crime, on individuals who would receive pretrial release, or even at the same stage of criminal processing. These deviations required protocols to balance county-level practices with inclusion criteria to model routine criminal processing. Second, we reduced within-person correlation by excluding repeated assessments conducted on the same individuals. Third, we adjusted for time at risk in the community. Finally, we used a large and multi-jurisdictional sample (N = 3,739) considerably larger than previous ORAS-PAT validation studies (Ns = 395-452).

Our findings point to the need to refine and reach consensus on the core components of the next generation of locally conducted pretrial risk assessment validation studies. Pretrial justice research demands the development and use of innovative research designs to manage methodological challenges in this context (Mamalian, 2011). The local validation approach herein was based on best practices in risk assessment validation research (Douglas et al., 2011). As a result, our approach emphasized validating assessments as they are designed to be used in practice and with consistent measurement of pretrial outcomes to allow for meaningful comparisons across jurisdictions. Other approaches to local validation may prioritize more fully capturing the wide variation in how risk assessments are used in local practice. Both approaches come with trade-offs between the quality of validation evidence, the ability to draw conclusions across jurisdictions, and the extent to which validation evidence reflects local practice.

Conclusion

Our findings overall show strong predictive accuracy of IRAS-PAT assessments but raise questions about the unique contributions of some items and weighting procedures. These findings demonstrate the strength of a local approach to validation of pretrial risk assessments. Beyond issues of predictive validity, as jurisdictions increasingly implement pretrial risk assessment tools, there will be a growing need for rigorous evaluation of how these tools are used in practice to inform pretrial release and supervision decisions.

References

Andrews, D. A., Bonta, J., & Hoge, R. D. (1990). Classification for effective rehabilitation: Rediscovering psychology. *Criminal Justice and Behavior*, *17*(1), 19–52. https://doi.org/10.1177/0093854890017001004

Bechtel, K., Holsinger, A. M., Lowenkamp, C. T., & Warren, M. J. (2017). A meta-analytic review of pretrial research: Risk assessment, bond type, and interventions. *American Journal of Criminal Justice*, *42*(2), 443–467. https://doi.org/10.1007/s12103-016-9367-1

Carmichael, D., Naufal, G., Wood, S., Caspers, H., & Marchbanks III, M. P. (2017). *Liberty and justice: Pretrial practices in Texas*. Texas A&M, Public Policy Research Institute.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Routledge.

Colorado Association of Pretrial Services. (2015). *The Colorado Pretrial Assessment Tool (CPAT): Administration, scoring, and reporting manual version 2*. https://university.pretrial.org/HigherLogic/System/DownloadDocumentFile.ashx?DocumentFileKey=47e978bb-3945-9591-7a4f-77755959c5f5

Curran, P. J., & Hussong, A. M. (2009). Integrative data analysis: The simultaneous analysis of multiple data sets. *Psychological Methods*, *14*(2), 81–100. https://doi.org/10.1037/a0015914

Davidson, J. T. (2014). *Validation of the Ohio Risk Assessment System Pretrial Assessment Tool on a Hawaii pretrial population*. Hawaii Department of Public Safety.

DeMichele, M., Baumgartner, P., Wenger, M., Barrick, K., & Comfort, M. (2020). Public Safety Assessment: Predictive utility and differential prediction by race in Kentucky. *Criminology & Public Policy*. https://doi.org/10.1111/1745-9133.12481

Desmarais, S. L., & Lowder, E. M. (2019). *Pretrial risk assessment tools: A primer for judges, prosecutors, and defense attorneys*. Safety and Justice Challenge, John D. and Catherine T. MacArthur Foundation. http://www.safetyandjusticechallenge.org/wp-content/uploads/2019/02/Pretrial-Risk-Assessment-Primer-February-2019.pdf

Desmarais, S. L., & Singh, J. P. (2013). *Risk assessment instruments validated and implemented in correctional settings in the United States*. Council of State Governments Justice Center.

Desmarais, S. L., Zottola, S. A., Duhart Clarke, S. E., & Lowder, E. M. (2020). Predictive validity of pretrial risk assessments: A systematic review of the literature. *Criminal*

Justice and Behavior, 0093854820932959. https://doi.org/10.1177/0093854820932959

Douglas, K. S., Skeem, J. L., & Nicholson, E. (2011). Research methods in violence risk assessment. In *Research methods in forensic psychology* (pp. 325–346). John Wiley & Sons, Inc.

Gouldin, L. P. (2016). Disentangling flight risk from dangerousness. *Brigham Young University Law Review*, *2016*(3), 837–898.

Grommon, E., Ray, R., Sapp, D., & Thelin, R. (2017). *Process evaluation of the IRAS-PAT pilot program implementation*. Center for Criminal Justice Research, Public Policy Institute, Indiana University.

Gupta, A., Hansman, C., & Frenchman, E. (2016). The heavy costs of high bail: Evidence from judge randomization. *The Journal of Legal Studies*, *45*(2), 471–505. https://doi.org/10.1086/688907

Harcourt, B. E. (2015). Risk as a proxy for race: The dangers of risk assessment. *Federal Sentencing Reporter*, *27*(4), 237–243. https://doi.org/10.1525/fsr.2015.27.4.237

Heaton, P., Mayson, S., & Stevenson, M. (2017). The downstream consequences of misdemeanor pretrial detention. *Stanford Law Review; Stanford*, *69*(3), 711–794.

Indiana Criminal Justice Institute. (2018). *State fiscal year 2018 annual report*. Indiana Criminal Justice Institute.

Koepke, J. L., & Robinson, D. G. (2018). Danger ahead: Risk assessment and the future of bail reform. *Washington Law Review*, *93*(4), 1725–1808.

Latessa, E. J., Lovins, B. K., & Makarios, M. (2013). *Validation of the Indiana Risk Assessment System: Final report*. University of Cincinnati, Center for Criminal Justice Research.

Latessa, E. J., Smith, P., Lemke, R., Makarios, M., & Lowenkamp, C. T. (2009). *Creation and validation of the Ohio risk assessment system: Final report*. University of Cincinnati, Center for Criminal Justice Research.

Mamalian, C. A. (2011). *State of the science of pretrial risk assessment*. US Department of Justice, Bureau of Justice Assistance.

Mossman, D. (1994). Assessing predictions of violence: Being accurate about accuracy. *Journal of Consulting and Clinical Psychology*, *62*(4), 783–792. https://doi.org/10.1037//0022-006x.62.4.783

Myburgh, J. E., Camman, C., & Wormith, J. S. (2015). *Review of pretrial risk assessment and* *factors predicting pretrial release failure*. University of Saskatchewan, Centre for Forensic Behavioural Science and Justice Studies.

Picard-Fritsche, S., Rempel, M., Tallon, J. A., Adler, J., & Reyes, N. (2017). *Demystifying risk assessment*. Center for Court Innovation. https://nicic.gov/demystifying-risk-assessment-key-principles-and-controversies-2017

Pretrial Justice Institute. (2019). *Scan of pretrial practices* (No. 2019-10-02KN). https://university.pretrial.org/viewdocument/scan-of-pretrial-practices-pji-20

Pretrial Justice Institute. (2020). *Updated position on pretrial risk assessment tools*. https://www.pretrial.org/wp-content/uploads/Risk-Statement-PJI-2020.pdf

Reaves, B. A., & Cohen, T. H. (2007). *Pretrial release of felony defendants in state courts*. Bureau of Justice Statistics, Office of Justice Programs, U.S. Department of Justice.

Rice, M. E., & Harris, G. T. (2005). Comparing effect sizes in follow-up studies: ROC Area, Cohen's d, and r. *Law and Human Behavior*, *29*(5), 615–620. https://doi.org/10.1007/s10979-005-6832-7

Sainani, K. (2010). The importance of accounting for correlated observations. *PM & R: The Journal of Injury, Function, and Rehabilitation*, *2*(9), 858–861. https://doi.org/10.1016/j.pmrj.2010.07.482

Schumacher, M., Holländer, N., & Sauerbrei, W. (1997). Resampling and cross-validation techniques: A tool to reduce bias caused by model building? *Statistics in Medicine*, *16*(24), 2813–2827. https://doi.org/10.1002/(SICI)1097-0258(19971230)16:24<2813::AID-SIM701>3.0.CO;2-Z

Scott-Hayward, C. S., & Fradella, H. F. (2019). *Punishing poverty: How bail and pretrial detention fuel inequalities in the criminal justice system*. University of California Press.

Siddiqi, Q., Kim, T., Walton, E., Caligiure, R., Nehwadowich, W., & Linen-Reed, B. (2002). *Prediction of pretrial failure to appear and alternative pretrial release risk-classification scheme in New York City: A reassessment study*. New York City Criminal Justice Agency.

Singh, J. P., Desmarais, S. L., & Van Dorn, R. A. (2013). Measurement of predictive validity in violence risk assessment studies: A second-order systematic review. *Behavioral Sciences & the Law*, *31*(1), 55–73. https://doi.org/10.1002/bsl.2053

Sloan, C. W., Naufal, G., & Caspers, H. (2018). *The effect of risk assessment scores on judicial* *behavior and defendant outcomes*. Social Science Research Network. https://papers.ssrn.com/abstract=3301699

Starr, S. B. (2014). Evidence-based sentencing and the scientific rationalization of discrimination. *Stanford Law Review*, *66*, 803.

Stevenson, M. T., & Mayson, S. G. (2017). *Bail reform: New directions for pretrial detention and release*. Social Science Research Network. https://papers.ssrn.com/abstract=2939273

Tahamont, S., Jelveh, Z., Chalfin, A., Yan, S., & Hansen, B. (2020). Dude, where's my treatment effect? Errors in administrative data linking and the destruction of statistical power in randomized experiments. *Journal of Quantitative Criminology*. https://doi.org/10.1007/s10940-020-09461-x

U.S. Bureau of Labor Statistics. (2020). *Current population survey: Table 8. Employed and unemployed full- and part-time workers by age, sex, race, and Hispanic or Latino ethnicity*. U.S. Department of Labor. https://www.bls.gov/cps/cpsaat08.pdf

U.S. Office of Probation and Pretrial Services. (2010). *Federal Pretrial Risk Assessment: User's manual and scoring guide*. http://edwinwall.com/PTRA/PTRA%20user%20guide.pdf

VanNostrand, M., & Lowenkamp, C. T. (2013). *Assessing pretrial risk without a defendant interview.pdf*. https://nicic.gov/assessing-pretrial-risk-without-defendant-interview

Virginia Department of Criminal Justice Services. (2018). *Virginia Pretrial Risk Assessment Instrument (VPRAI): Instruction manual—Version 4.3*. https://www.dcjs.virginia.gov/sites/dcjs.virginia.gov/files/publications/corrections/virginia-pretrial-risk-assessment-instrument-vprai_0.pdf

Wollert, R. (2002). The importance of cross-validation in actuarial test construction. *Journal of Threat Assessment*, *2*(1), 87–102. https://doi.org/10.1300/J177v02n01_06

World Prison Brief. (2018). *Highest to lowest—Prison Population Rate*. https://www.prisonstudies.org/highest-to-lowest/prison_population_rate

Zeng, Z. (2020). *Jail inmates in 2018*. US Department of Justice, Bureau of Justice Statistics. https://www.bjs.gov/content/pub/pdf/ji18.pdf

Zettler, H. R., & Morris, R. G. (2015). An exploratory assessment of race and gender-specific predictors of failure to appear in court among defendants released via a pretrial services agency. *Criminal Justice Review*, *40*(4), 417–430. https://doi.org/10.1177/0734016815583350

Table 1: County Geographic, Sociodemographic, and Pilot Program Characteristics

	Geographic Characteristics	Sociodemographic Characteristics				Pilot Program Characteristics					
	Location	Population Size	Less Than Age 18	Racial Composition	Below Poverty Line	Start Date	Target Population	Assessment Administration	Typical Administration	Administered By	Administered In
County 1	Northeast region of Indiana	Large[a]	26%	79% White; 11% Black	14%	March 2016	Pretrial defendants prior to release on supervision	After jail intake but prior to initial court appearance	Within 24 hours of arrest	Pretrial services officers	County jail
County 2	Central Indiana	Large[a]	28%	87% White; 4% Black	5%	June 2016	All new arrestees	At/after jail intake but prior to initial court appearance	Within 8 hours of arrest	Probation officers, jail personnel, or community correction staff	County jail
County 3	Central Indiana	Medium[b]	26%	88% White; 7% Black	5%	January 2016	All arrestees	After jail intake but prior to initial court appearance	Within 24 hours of arrest	Probation officers	County jail
County 4	Southeastern portion of Indiana	Small[c]	21%	95% White; 2% Black	15%	October 2016	All pretrial defendants	After jail intake but prior to initial court appearance	Within 24 hours of arrest during the week and within 72 hours of arrest on weekends	Community corrections staff	County jail
County 5	Central Indiana	Medium[b]	16%	86% White; 3% Black	24%	October 2016	Misdemeanor and felony new arrestees	After jail intake but prior to initial court appearance	Within 24 hours of arrest, excluding weekends and holidays	Probation officers	County jail for defendants who are unable to pay bond; Probation office for defendants who pay bond

Note. All sociodemographic estimates drawn from 2018 American Community Survey 5-year estimates. [a] Population over 300,000 residents. [b] Population between 100,000 and 200,000 residents [c] Population under 50,000 residents.

Table 2. Descriptive Statistics Overall and by County

Variable	Overall *N* = 3,739	County 1 *n* = 834	County 2 *n* = 852	County 3 *n* = 625	County 4 *n* = 398	County 5 *n* = 1,030
	M (SD)	***M (SD)***	***M (SD)***	***M (SD)***	***M (SD)***	***M (SD)***
Age	32.59 (11.67)	33.92 (11.98)	32.76 (11.69)	32.04 (11.05)	32.40 (10.20)	31.79 (12.22)
IRAS-PAT total score	3.06 (1.86)	2.66 (1.62)	2.94 (1.92)	3.70 (1.78)	3.62 (1.96)	2.86 (1.85)
Time at risk	163.54 (138.04)	114.51 (95.98)	174.24 (115.71)	165.34 (157.54)	172.13 (141.73)	189.96 (158.49)
	%	**%**	**%**	**%**	**%**	**%**
Gender						
Female	28.6	28.4	29.9	29.6	30.7	26.3
Male	71.4	71.6	70.1	70.4	69.3	73.7
Race						
White	76.5	57.7	81.7	81.2	92.0	78.6
Black	18.5	34.4	18.1	17.1	4.3	12.4
Other	5.0	8.0	0.2	1.8	3.8	9.1
Charge level						
Felony	42.8	44.2	37.3	56.5	54.3	33.6
Misdemeanor	57.2	55.8	62.7	43.5	45.7	66.4
IRAS-PAT risk level						
Low	43.9	51.8	45.9	25.4	33.7	51.1
Moderate	44.5	42.3	42.8	58.1	45.7	39.0
High	11.6	5.9	11.3	16.5	20.6	9.9
Pretrial misconduct outcomes						
Any FTA	10.5	5.5	8.5	9.6	16.8	14.3
Any new arrest	16.2	21.6	10.2	10.7	30.4	14.5
Any arrest	30.0	28.2	32.4	30.2	38.4	26.1
Any pretrial misconduct (any new arrest)	23.5	23.9	17.3	18.7	41.0	24.6
Any pretrial misconduct (any arrest)	31.8	29.4	32.4	30.4	42.5	29.9
AUC Estimates	**AUC (SE)**	**AUC (SE)**	**AUC (SE)**	**AUC (SE)**	**AUC (SE)**	**AUC (SE)**
Any FTA	.71 (0.01)	.65 (0.04)	.72 (0.03)	.72 (0.03)	.66 (0.03)	.73 (0.02)
Any New Arrest	.67 (0.01)	.66 (0.02)	.73 (0.03)	.60 (0.03)	.68 (0.03)	.70 (0.02)
Any Arrest	.72 (0.01)	.69 (0.02)	.71 (0.02)	.70 (0.02)	.68 (0.03)	.76 (0.02)

Table 3. Crosstabulations of Risk Level and Pretrial Misconduct Outcomes

Case Outcomes	**Risk Level**						**Comparison**	
	Low		Moderate		High			
	n	%	*n*	%	*n*	%	X^2 (df)	Cramer's V
Any FTA	71	4.3	214	12.9	107	24.8	170.21*** (2)	.21
Any new arrest	145	8.8	321	19.3	138	31.9	156.55*** (2)	.21
Any arrest	252	15.3	611	36.7	259	60.0	387.95*** (2)	.32
Any pretrial misconduct (with any new arrest)	194	11.9	473	28.4	211	48.8	299.98*** (2)	.28
Any pretrial misconduct (with any arrest)	274	16.7	646	38.8	268	62.0	392.83*** (2)	.32

Note. ***$p < .001$, $N = 3{,}739$

Table 4. Logistic Regression Models of IRAS-PAT Total Scores and Risk Levels Predicting Pretrial Misconduct Outcomes

Predictor	Outcomes														
	Any FTA					Any new arrest					Any arrest				
	Estimate	*SE*	z	OR	95% CI	Estimate	*SE*	z	OR	95% CI	Estimate	*SE*	z	OR	95% CI
Model 1															
Total score	0.40	0.03	12.52***	1.49	[1.40, 1.58]	0.34	0.03	13.20***	1.41	[1.34, 1.48]	0.44	0.02	19.47***	1.56	[1.49, 1.62]
Time at risk	<0.01	<0.01	13.03***	1.00	[1.00, 1.01]	<0.01	<0.01	7.27***	1.00	[1.00, 1.00]	<0.01	<0.01	11.84***	1.00	[1.00, 1.00]
County (1)															
County 2	-0.01	0.20	-0.07	0.99	[0.66, 1.47]	-1.23	0.15	-8.26***	0.29	[0.22, 0.39]	-0.14	0.12	-1.23	0.87	[0.69, 1.09]
County 3	-0.16	0.22	-0.71	0.86	[0.56, 1.32]	-1.40	0.17	-8.46***	0.25	[0.18, 0.34]	-0.55	0.13	-4.27***	0.58	[0.45, 0.74]
County 4	0.62	0.21	2.91**	1.86	[1.23, 2.83]	0.01	0.15	0.05	1.01	[0.76, 1.34]	-0.13	0.14	-0.90	0.88	[0.67, 1.16]
County 5	0.52	0.19	2.79**	1.69	[1.17, 2.44]	-0.84	0.13	-6.30***	0.43	[0.33, 0.56]	-0.54	0.12	-4.62***	0.58	[0.46, 0.73]
Model 2															
Risk level (Low)															
Moderate	1.11	0.15	7.53***	3.03	[2.27, 4.04]	0.94	0.11	8.51***	2.56	[2.06, 3.17]	1.13	0.09	12.78***	3.08	[2.59, 3.66]
High	1.97	0.17	11.29***	7.18	[5.10, 10.11]	1.69	0.14	11.84***	5.42	[4.09, 7.17]	2.15	0.13	17.22***	8.62	[6.75, 11.01]
Time at Risk	<0.01	<0.01	12.80***	1.00	[1.00, 1.01]	<0.01	<0.01	7.17***	1.00	[1.00, 1.00]	<0.01	<0.01	11.76***	1.00	[1.00, 1.00]
County (1)															
County 2	0.03	0.20	0.14	1.03	[0.69, 1.53]	-1.20	0.15	-8.09***	0.30	[0.23, 0.40]	-0.13	0.12	-1.12	0.88	[0.70, 1.10]
County 3	-0.11	0.22	-0.48	0.90	[0.59, 1.38]	-1.35	0.16	-8.22***	0.26	[0.19, 0.36]	-0.49	0.13	-3.83***	0.61	[0.48, 0.79]
County 4	0.69	0.21	3.25**	2.00	[1.32, 3.04]	0.06	0.15	0.44	1.07	[0.80, 1.42]	-0.05	0.14	-0.37	0.95	[0.72, 1.25]
County 5	0.59	0.19	3.14**	1.80	[1.25, 2.60]	-0.78	0.13	-5.94***	0.46	[0.35, 0.59]	-0.49	0.12	-4.19***	0.61	[0.49, 0.77]

Note. For categorical variables, reference group indicated in parentheses. CI = confidence interval for odds ratio.
$^{**}p < .01$. $^{***}p < .001$. $N = 3{,}739$.

Table 5. Logistic Regression Models of IRAS-PAT Items Predicting Pretrial Misconduct Outcomes

Predictor	**Outcomes**														
	Any FTA					Any new arrest					Any arrest				
	Estimate	*SE*	*z*	OR	95% CI	Estimate	*SE*	*z*	OR	95% CI	Estimate	*SE*	*z*	OR	95% CI
1. Age at first arrest[a]	0.83	0.29	2.86**	2.30	[1.30, 4.06]	0.27	0.19	1.37	1.30	[0.89, 1.90]	0.55	0.15	3.58***	1.74	[1.28, 2.35]
2. Number of FTAs[b]															
1	0.70	0.17	4.22***	2.01	[1.45, 2.78]	0.29	0.15	1.88	1.33	[0.99, 1.80]	0.60	0.13	4.61***	1.82	[1.41, 2.34]
2 or more	0.47	0.26	1.80	1.60	[0.96, 2.65]	0.37	0.24	1.54	1.44	[0.91, 2.31]	0.71	0.21	3.31**	2.03	[1.35, 3.09]
3. 3+ prior incarcerations[c]	0.62	0.12	5.10***	1.85	[1.46, 2.35]	0.53	0.10	5.23***	1.69	[1.39, 2.06]	0.84	0.08	9.96***	2.32	[1.96, 2.73]
4. Employed[d]															
Part-time	0.23	0.19	1.23	1.26	[0.87, 1.82]	0.35	0.14	2.45*	1.42	[1.07, 1.89]	0.41	0.12	3.43**	1.50	[1.19, 1.89]
Not employed	0.83	0.13	6.29***	2.29	[1.77, 2.97]	0.45	0.11	4.24***	1.58	[1.28, 1.94]	0.71	0.09	7.89***	2.03	[1.70, 2.42]
5. Residential instability[e]	0.33	0.12	2.70**	1.39	[1.10, 1.77]	0.49	0.10	4.92***	1.63	[1.34, 1.98]	0.47	0.08	5.62***	1.61	[1.36, 1.89]
6. Illegal drug use 6 mo[f]	<0.01	0.14	0.03	1.00	[0.76, 1.32]	0.36	0.11	3.33**	1.44	[1.16, 1.78]	0.20	0.09	2.25*	1.23	[1.03, 1.46]
7. Severe drug use[g]	0.53	0.16	3.38**	1.69	[1.25, 2.30]	0.45	0.13	3.55***	1.58	[1.23, 2.03]	0.52	0.11	4.74***	1.68	[1.36, 2.08]
Time at risk	<0.01	<0.01	12.78***	1.00	[1.00, 1.01]	<0.01	<0.01	7.26***	1.00	[1.00, 1.00]	<0.01	<0.01	11.68***	1.00	[1.00, 1.00]
County[h]															
County 2	-0.02	0.21	-0.07	0.98	[0.65, 1.50]	-1.29	0.16	-8.22***	0.28	[0.20, 0.38]	-0.17	0.12	-1.42	0.84	[0.66, 1.07]
County 3	-0.18	0.22	-0.80	0.84	[0.54, 1.29]	-1.40	0.17	-8.37***	0.25	[0.18, 0.34]	-0.58	0.13	-4.43***	0.56	[0.43, 0.72]
County 4	0.57	0.22	2.58*	1.76	[1.15, 2.72]	-0.06	0.15	-0.37	0.94	[0.70, 1.28]	-0.21	0.15	-1.46	0.81	[0.61, 1.08]
County 5	0.53	0.19	2.78**	1.69	[1.17, 2.45]	-0.82	0.13	-6.14***	0.44	[0.34, 0.57]	-0.55	0.12	-4.60***	0.58	[0.46, 0.73]

Note.CI = confidence interval for odds ratio. *$p < .05$. **$p < .01$. ***$p < .001$. N = 3,735.
[a]Item 1 reference: 33 or older
[b]Item 2 reference: No FTA warrants past 24 months
[c]Item 3 reference: Two or less prior jail incarcerations
[d]Item 4 reference: Yes, Full-time employment at time of arrest
[e]Item 5 reference: Lived at current residence past 6 months
[f]Item 6 reference: No illegal drug use during past 6 months
[g]Item 7 reference: No severe drug use problem
[h]Reference: County 1