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Predictive Utility of the El Paso Pretrial Risk Assessment Instrument - Revised (EPPRA-R)

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PREDICTIVE UTILITY OF THE EL PASO PRETRIAL RISK ASSESSMENT INSTRUMENT – REVISED (EPPRA-R)

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Dedication

I want to dedicate this piece of work to my partner and support system, Stephen. Thank you – for truly everything. I would also like to extend this dedication to my family for continually encouraging all of my pursuits. Lastly, and arguably most important, this research would have simply not been possible without the love and support from my animals: Marilyn, Adam, Ellie, and the memory of our wonderful Jade.

PREDICTIVE UTILITY OF THE EL PASO PRETRIAL RISK ASSESSMENT INSTRUMENT

– REVISED (EPPRA-R)

by

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Abstract

Pretrial risk assessments are used to divert defendants from pretrial detention by estimating risk of pretrial specific outcomes (i.e., failure to appear, rearrest). Ongoing validation of this tool is recommended to assess accuracy and ensure that there is no bias against specific subgroups (e.g., gender, race/ethnicity, or age) of defendants. The present study evaluates the utility of a locally developed instrument in El Paso County – a predominantly Latinx county. Area Under the Curve (AUC) Receiving Operator Condition (ROC) analyses indicate statistically "fair" predictive utility for the tool. Binary logistic regression models suggest no evidence of bias. This study will provide direct and significant outcome information to key stakeholders in the community and inform future validation efforts with diverse populations in pretrial settings.

Table of Contents

List of Tables

List of Figures

Predictive Utility of the El Paso Pretrial Risk Assessment Instrument – Revised

Among those incarcerated in the United States' correctional system, approximately 746,000 are residing in local and federal jails (Prison Policy Initiative, 2020). Of that population, 74% are waiting for trial and not yet convicted of a crime (Milgram et al., 2015; Prison Policy Initiative, 2020). This period of time is defined as pretrial detention.

Consistent with correctional facilities more generally, jail facilities are overpopulated. Large bodies of research have repeatedly reported the harmful effects of pretrial detention on incarcerated people (Heaton et al., 2017; Dobbie et al., 2016); thus, emerging research has aimed to reduce jail populations by diverging defendants away from pretrial detention (Lowder et al., 2020b). One such tactic that has gained empirical interest in the incorporation of risk assessment instruments into the pretrial space. Risk assessments are actuarial tools used to measure one's likelihood of reoffending (Bechtel et al., 2017), and ensuring the general public's safety (Monahan & Skeem, 2016) once a defendant is released from jail or prison. Large-scale attempts have been made to diverge defendants from jail through the implementation of pretrial risk assessments and bail reform legislation (Lowder et al., 2020; Bechtel et al., 2017; Ares, Rankin, & Sturz, 1963).

Bail Reform

Until the 1960's, cash bail was the main form of pretrial release (Van Brunt & Bowman, 2018). Cash bail is a method of pretrial release still used today; a financial amount is assigned to the defendant based on characteristics of their charge, and the defendant can choose to pay said amount for their release. The purpose of financial bail was to ensure the return of defendants to court for their pretrial hearing (Palafox & McLeod, 2019). However, given the financial component, this design has been argued that cash bail favors defendants based on wealth, rather than any other factors that should be considered for release (e.g., guilt, likelihood to appear at court, potential risk; Monaghan et al., 2020; Van Brunt & Bowman, 2018; Leslie & Pope, 2017). Advocates for a reduction in pretrial detention largely argued that the current cash bail system was in place to permit judges to set bail at unaffordable rates without cause under the guise that such defendants were too dangerous to be released into the community (Goldkamp, 1985).

In the 1960's, engineers and businessmen alike engaged in discussion over cocktails about the current pretrial incarceration numbers (Smith, 2018). Their disbelief at the gravity of the situation, and money to contribute to the cause, resulted in the first cultural shift of bail reform by way of The Manhattan Bail Project (Van Brunt & Bowman, 2018). The Manhattan Bail Project, started by the Vera Foundation in New York, introduced release on one's own recognizance (ROR), or personal recognizance (PR), bonds (Friedman, 1976, McElroy, 2011). The goal of such reform was to replace cash bond systems as means of pretrial release (Friedman, 1976). Through the Manhattan Bail Project initiative, those in pretrial detention who could not financially afford their set bail were identified and advocated that they be released on their own recognizance (Wiseman, 2014). This required that the individual was trusted to return to their set court date without having to pay money in order to be released from jail. The method of determination was based on interviews conducted prior to release and discussed defendants' community ties, and whether such ties were strong and reliable protective factors (Friedman, 1976, Smith, 2018).

By way of cultural and legislative changes, bail reform moved to its second wave – advocation for community safety. In the 1970's and around the time of deinstitutionalization – the "tough on crime" era – white flight and urban decay were rampant, and public calls for bail reform escalated (Monoghan et al., 2020; Smith, 2018; Van Brunt & Bowman, 2018). Political rhetoric during this time was largely advocating for the importance of public safety over civil rights of those accused (Monoghan et al., 2020; Goldkamp, 1985).

The Federal Bail Reform Act of 1984

The Federal Bail Reform Act of 1984 was the result of such societal shift. The intent was to reclaim the use of cash bail systems and encourage pretrial detainment when needed if the release of defendants could put community safety in jeopardy (Van Brunt & Bowman, 2018). This movement advocated for preventative detention for pretrial defendants and prioritized community safety (Goldkamp, 1985, Smith, 2018). The Federal Bail Reform Act of 1984 established the first legal permission of pretrial detention in federal cases (Gain, 1988). Legal standards for preventative detention were first set by the District of Columbia Court Reform and Criminal Procedures Act of 1970, permitting considered dangerousness to the community as means for detainment (Scott, 1989). This Act was upheld in following legal proceedings (*United States* v. *Edwards*, 1974; *Schall* v. *Martin*, 1984), providing constitutional precedent to move forward and maintain preventative detention (Scott, 1989). However, this Act did not come without controversy.

The Federal Bail Reform Act of 1984 was argued by legal entities stating that the imposition of bail on citizens was in direct violation of multiple constitutional rights, the strongest of which is the Eighth Amendment. The Eighth Amendment "prohibits the federal government from imposing excessive bail, excessive fines, or cruel and unusual punishment" (U.S. Const. art. VIII). The Eighth Amendment is textually the most relevant portion of the Constitution discussing the imposition of bail on pretrial defendants (Van Brunt & Bowman, 2018; Wiseman, 2009). Regardless of community safety, any preventative detention through the use of excessive bail could not be imposed. The landmark case in which this exact argument was brought forth was *United States* v. *Salerno* (1987).

United States v. Salerno (1987)

The Federal Bail Reform Act of 1984 was famously challenged in court when American Mafia member, Anthony Salerno, claimed that pretrial detention while awaiting trial violated his Eighth Amendment right (*United States* v. *Salerno*, 1987; Jacobs, 2019; Farmer, 1987; Wiseman, 2009). Prior to *United States* v. *Salerno* (1987), the Federal Bail Reform Act of 1984 had only applied to capital cases and had not been considered in lesser Courts (Farmer, 1987). Prosecution claimed that the violent history illustrated by the defendant permitted preventative detention while he awaited trial (*United States* v. *Salerno*, 1987). The Court granted preventative detention and the decision was upheld on appeal to the Second Circuit (*United States* v. *Salerno*, 1987). The primary argument used suggested the language in the Eighth Amendment inherently provides the right to bail, and denying that is strictly unconstitutional (Wiseman, 2009). Moreover, declaring preventative detention for community safety implies ambiguous detention periods, and thus denies a defendant the right to due process under the Fifth Amendment (Farmer, 1987). However, the Court held that the preventative detention imposed in *Salerno* (1987) did not violate such rights above and beyond what release would potentially create for public safety. This landmark case established precedent for the permission of preventative detention in any case that may impose potential threat to community safety. However, many states have independently built their own precedent in managing bail reform on local levels.

Bail Reform in Texas

Texas has commonly implemented a monetary bail schedule for misdemeanor offenses throughout its jurisdictions. This suggests that judges and magistrates could make recommendations for financial bail amounts based on charge-types without any additional factors (e.g., criminal history, employment) playing a role in the release decision. Recent case law in Texas has challenged such a system, claiming the unconstitutional nature of money bail schedules. This is especially salient for indigent populations – those who experience heightened financial disadvantage within society – as they were often subject to monetary bail schedules (Hussmann & Seigel, 2019).

A suit was brought against Harris County, Texas, after defendants were given excessive bail despite their inability to pay (*O'Donnell* v. *Harris County*, 2019). The suit claimed the County set a wealth-based bail that violated due process and equal protection rights provided by the U. S. Constitution. The Court ruled in favor of the plaintiff, affirming that such money bail schedules were unconstitutional. Harris County appealed to the Fifth Circuit Court, but the ruling was held. It was quoted that a wealth-based bail schedule was a "basic injustice" that acted entirely unconstitutionally. This landmark case set important precedent for the Texas, stating that wealth-based bail schedules were unconstitutional and disproportionately targeting those categorized as indigent.

Shortly after *O'Donnell* v. *Harris County* (2018), a suit was brought against Dallas County, Texas for implementing monetary bail schedules predominately for those identified as indigent without judicial discretion permitted in bail decisions (*Daves* v. *Dallas County*, 2020). In partial support of the plaintiff, the Court only recommended that the use of monetary bail schedules be discontinued but required a time frame that must be utilized when making bail decisions for pretrial defendants. By this ruling, pretrial officers must determine the defendants' eligibility to pay bail, and they are required to ensure a hearing with a magistrate no later than 48 hours following arrest. This ruling aimed to decrease unnecessary pretrial detainment, while providing defendants the time necessary to determine their personal financial conditions in preparation for bail decisions.

Case law proceeding these events extended beyond misdemeanor cases for indigent defendants and ensured that monetary bail schedules were not allowed for felony defendants; specifically, those that were unaware of their indigent status (*Booth* v. *Galveston County*, 2019; *Russell* v. *Harris County*, 2020). While *Russell* v. *Harris County* (2020) is ongoing, closing remarks for *Booth* v. *Galveston County* (2019) supported the plaintiff and required counsel at initial bail hearings for defendants. This decision supersedes the felonious aspect to the case, as it prioritized indigent status in need of bail sentencing counsel.

These landmark cases in Texas state law have built stronger consideration into pretrial detainment than it had implemented in the past. On a national scale, more progressive-leaning political agendas have encouraged a return to the initial 1960's bail reform movement by recommending the elimination of cash bail once again (Monaghan et al., 2020). By way of this, years of research have developed more empirically sound methods of encouraging pretrial decarceration, such as integrating risk assessment tools into pretrial settings.

Risk Assessments

Across the United States, correctional agencies and policy makers alike have been working to erode the mass incarceration that overpopulates these facilities. One such method has been to implement risk assessment instruments. Risk assessments have been used in various points throughout the criminal justice system since the 1920's (DeMichele et al., 2019; Singh, 2012) to both decrease re-offending and decarceration efforts (Monahan & Skeem, 2016). They are actuarial tools designed to quantify risk and protective factors – such as criminal history and family ties, respectively – to produce an overall risk (e.g., violence, violating conditions) score

(Desmarais & Lowder, 2019). The goals of these tools are to assist with post-adjudication decision-making for release, treatment mandates, and long-term recidivism outcomes (Cadigan & Lowencamp, 2011; Viljoen et al., 2019). Many risk assessment tools have been developed for various offending populations, yet each ultimately aim to determine the potential risk of criminal behavior once released back into the general community (Kroner et al., 2003).

Risk Assessment Utility

Many risk assessment tools have been developed and validated to best address release decisions, supervision recommendations, treatment mandates, and projected recidivism estimates (Viljoen et al., 2019; Cadigan & Lowenkamp, 2011). Such tools were built to provide structured approaches to post-adjudication decisions, which have resulted in more positive outcomes (i.e., lower recidivism) for justice-involved persons (Desmarais et al., 2016). To ensure tool accuracy, components are statistically assessed. We will review factors that are statistically predictive of risk, and how such items are evaluated to determine instrument accuracy.

Risk Factors. Risk categories are populated by scoring empirically founded risk and protective factors for each individual assessed (Singh, 2012; Andrews et al., 2006). Risk factors are characteristics that, when present, may be indicative of outcome failure (e.g., violence, non-adherence to treatment, etc.; Ullrich & Coid, 2011). Risk factors include static factors, such as criminal history and a history of drug abuse (Andrews & Bonta, 2010); and dynamic factors, such as antisocial personality processes (e.g., anger, impulsivity, sensation-seeking behaviors), antisocial cognitions (e.g., crime supported thoughts and values), and antisocial peers (Andrews & Bonta, 2010; Skeem et al., 2013; Skeem & Monahan, 2020; Walters & DeLisi, 2013; Wooditch et al., 2014). Dynamic risk factors are considered more amenable to change, and changes in them in either direction are associated with changes in criminal behavior (Andrews &

Bonta, 2010; Wooditch et al., 2014). Protective factors are social “buffers” such as prosocial involvement (e.g., helping others) and strong social supports that help deter individuals from crime (Soderstrom et a., 2020; Sharma et al., 2019; Singh, 2012).

Validation Efforts. Quantifying such risk and protective factors provide categorical estimates for one’s risk through varying points of the criminal justice system. To ensure that these tools are empirically sound and unbiased, validation efforts are common. Such efforts assess for predictive validity (i.e., scores assessed at an earlier time are accurately predictive of the outcome; Wei-Ling & Yao 2014) and predictive bias (i.e., mis-predicting outcomes based on grouping characteristic; Yang et al., 2021) (Desmarais et al., 2016; Skeem & Lowenkamp, 2016).

Validation efforts are often conducted to assess risk assessment tools for errors and fairness in risk classification across groups (e.g., race and ethnicity) and general accuracy of the tool (Zottola et al., 2021; Cohen & Lowenkamp, 2019; Berk et al., 2018). Accuracy of the tool is commonly expressed via classification indicators: true-positive, false-positive, true-negative, false-negative. These four classification indicators are collectively indexed by Area Under the Curve (AUC) analyses, which report whether the tool was accurately predictive of recidivism rates pertaining to defendants within risk categories. Moreover, validation efforts ensure calibration of the tool, suggesting that classification errors are not distributed unfairly based on group characteristics, such as race and ethnicity (Cohen & Lowenkamp, 2019). Regardless of the tool, validation efforts are critical for fair implementation among population variation that may be assessed using such a tool.

Risk Assessment Tools. A number of risk assessment tools were developed to target and address such post-adjudication sentencing, treatment, and/or supervision (Cadigan &

Lowenkamp, 2011). The first reported risk assessment tool was developed by Dr. Ernest Burgess in 1928 to assess risk of recidivism for those placed on parole in Illinois (Singh, 2012). As risk assessment research evolved, actuarial tools have been developed in applied settings (e.g., corrections, clinical) to predict varying types of risk (Desmarais et al., 2016; Picard-Fritsche et al., 2017). Specific to risk assessments in correctional settings, numerous tools have been developed to assess potential future recidivism. The Correctional Offender Management Profile for Alternative Sanctions (COMPAS; Brennan et al., 2009) and the Level of Service Inventory – Revised (LSI-R; Andrews & Bonta, 1998) were both developed for all justice-involved persons in the criminal justice system to assess for any recidivism. This refers to any new offense or violation of set conditions (Desmarais et al., 2016). However, the Ohio Risk Assessment – Reentry Tool (Latessa et al., 2009) targets all justice-involved persons for only new offenses (excluding parole violations). Other risk assessments, such as the Salient Factor Score -1981 Version (Hoffman, 1983), are specifically designed to assess risk for people being released to parole.

Pretrial Risk Assessments

Bail reform efforts have encouraged the integration of risk assessment tools to be used in a pretrial setting. In doing so, post-adjudication risk assessment tools have been revised to be more applicable for pretrial defendants. Recall that post-adjudication risk assessment tools are structured to assess risk of recidivism (i.e., new arrests or violation of parole conditions) for populations that have already been sentenced (Desmarais et a., 2016; Skeem & Lowenkamp, 2016). Pretrial risk assessments, while similar in theory, are intended to predict risk of pretrial specific outcomes, such as the likelihood of defendants appearing in court, avoiding rearrest if released to the community, and any potential threat to community safety if one is released to the community prior to their trial (Desmarais et al., 2020; Adler et al., 2019; Cohen & Lowenkamp, 2019). While case law has found that the use of pretrial risk assessment tools alone is not permissible for release decision-making (*Wisconsin* v. *Eric Loomis*, 2016), the implementation of said tools was designed to contribute to the overall determination of pretrial detention or release (Desmarais et al., 2021). Additional goals of introducing risk assessments in pretrial settings were to limit the unpredictable and discriminatory nature of human decision-making in pretrial release decisions (Dalakian, 2018), reduce pretrial detention (Lowder et al., 2020a; Olseson et al., 2016), and aid release decisions to those who may not be able to financially afford bail (Dalakain, 2018; Petee, 1994). At this time, approximately 88% of pretrial departments across the United States use risk assessment tools to guide such decisions (Viljoen et al., 2019). Moreover, each of the 50 states in the United States have implemented some form of pretrial legal reform (Desmarais et al., 2021). The expansive nature of bail reform integrating pretrial risk assessment instruments in decision-making has strengthened the work in developing such tools.

Risk Assessment Tools Implemented in a Pretrial Setting

Similar to post-adjudication tools assessing risk, pretrial risk assessment instruments are structured by quantifying risk and protective factors pertaining to each defendant respectively (Desmarais et al., 2020). The first risk assessment tool implemented in a pretrial setting was the Vera Point Scale; a component of the Manhattan Bail Project in 1961 (Desmarais et al., 2020; Ares et al., 1963). Empirically improved instruments were developed over the following years to implement in pretrial settings across the nation, targeting varying uses for the tool (Desmarais et al., 2020). The Virginia Pretrial Risk Assessment Instrument (VPRAI; VanNostrand, 2003) and the Ohio Risk Assessment System-Pretrial Assessment Tool (ORAS-PAT; Latessa et al., 2009) were two tools developed for individual jurisdictions that were then disseminated and used by others across the country. The Public Safety Assessment (PSA; Lowenkamp et al., 2013) was developed with the intention to be easily integrated into different jurisdictions and publicly available to do so. Additionally, the Pretrial Risk Assessment (PTRA; Lowenkamp & Whetzel, 2009) was developed to target federal pretrial defendants specifically. Each of these tools have undergone validation efforts (Desmarais et al., 2020; Cowen & Lowenkamp, 2016), but concerns remain. For example, initial (Cadigan & Lowenkamp, 2011) and secondary validation (Cohen and Lowenkamp, 2019) efforts conducted on the PTRA suggested that the tool fairly predicted pretrial outcomes across groups. However, secondary data analyses of this tool portray unfair predictions for marginalized racial groups (Desmarais et al., 2021; Lowder & Wilson, 2021; Zottola et al., 2021; Desmarais et al., 2020). Desmarais and colleagues (2021) advocate for additional work with the PTRA, VPRAI, and PSA due to the insufficient empirical evidence for predictive utility and fairness.

Biases within Pretrial Risk Assessment

While the implementation of these tools is expansive, it does not come without controversy. By providing numeric value to defendants' risk, jail facilities and judges making pretrial decisions are doing so with limited potential human bias associated with outcomes (Desmarais et al., 2020). However, utilizing actuarial tools in replacement of, or in tandem with, judges' decision-making has come with strong opposition and contradicting research. Critics of the use of pretrial risk assessments and their use in pretrial decision-making claim that biases are integrated within the tool itself, thus continuing inequity within release decisions (Adler et al., 2019; Berk et al., 2018).

Judicial Decision-Making. Pretrial risk assessment tools are designed to aid judges and magistrates when making pretrial release decisions (Dalakian, 2018; Bybee, 2012). This is in part due to the knowledge that human judgement is inherently influenced by personal beliefs, which can reflect inaccurate stereotypes that contribute to biased and erroneous decision-making (Desmarais et al., 2021; Desmarais & Lowder, 2019; Bybee, 2012). Such influences are often called legal (e.g., criminal history) and extralegal (e.g., age, race, gender) factors that play a role in decision-making (Oleson et al., 2016; Alarid & Montemayor). This is especially salient within pretrial decision-making, as empirical work suggests such bias (e.g., racial and ethnic) is prevalent in this context. For example, Bushway and Piehl (2001) have noted that judicial pretrial decision-making alone results in Black defendants receiving 20% longer sentences than White defendants. However, if legal factors were exclusively considered in this decision, Black defendants would receive only three percent longer sentences than White defendants. Additionally, a compilation of pretrial outcomes based on judicial decisions point to Black and Latino defendants found to be more likely to have bail denied and detained during their pretrial period following a control for legal factors. Moreover, previous research has suggested that mental health, community ties, and a defendant's drug usage and history are also considered in pretrial decisions (Alarid & Montemayor, 2010). Such considerations are outside of the factors pertaining to pretrial risk assessment tools, and thus are unlikely to be properly used in decision-making (Barno et al., 2020).

Although utilizing risk assessment tools are more favorable to judicial discretion exclusively, the limitations present with the use of actuarial tools in such events must be acknowledged. This point is exacerbated given pretrial decisions may have a significant impact on defendants' outcomes later on (Alarid & Montemayor, 2010). Critics of the implementation of pretrial risk assessments point to the potential bias towards subgroups of defendants embedded within such tools, arguing that their use will only exacerbate inequity amongst those incarcerated (Viljoen et al., 2019). As we discuss next, bias in risk assessment tools has been identified pertaining to defendants' racial and ethnic identity, gender, and age.

Racial and Ethnic Bias. Arguably the most salient concern of bias within actuarial tools is the potential variation among racial and ethnic groups' predicted risk scores. Opponents of actuarial tools in legal decision-making claim that even when controlling for legal factors (e.g., criminal history), extralegal factors such as employment and marital status may act as a "proxy" for race and have comparable legal outcomes (Harcourt, 2015; Starr, 2014). However, validation efforts of pretrial and post-adjudication risk assessments tools suggest predictive validity is consistent across groups (Desmarais et al., 2020; Cowen & Lowenkamp, 2016).

While this notion is promising, not all tool validation efforts have taken the role disparate impact may play when determining pretrial outcomes into consideration. Disparate impact posits that larger numbers of ethnic and racial minorities are represented in the justice system at a higher rate than their White counterparts due to systemic differences in resource allocation resulting in a higher rate of incarceration (Clair & Winter, 2016; Skeem & Lowenkamp, 2016b). Such groups are often more likely to experience over-policing of community neighborhoods, social disadvantages, and fewer opportunities for education and employment that could result in higher risk scores (Viljoen et al., 2019). These considerations in turn increase the correlation between race and criminal history as direct (i.e., legal) factors used in algorithmic risk scores (Berk et al., 2018; Desmarais et al., 2021; Clair & Winter, 2016).

Some tools more than others have been under strict criticism for bias within the instruments. For example, the Correctional Offender Management Profiling for Alternative

Sanctions (COMPAS; Northpointe, 2015), used in post-adjudication settings to predict recidivism for all adult justice-involved populations showed on multiple occasions to find Black defendants twice as likely for rearrest, when their White counterparts' outcomes were similar across race (Adler et al., 2019). Moreover, the reverse was found for White defendants, as they were more likely to inaccurately be categorized as low risk in comparison to their Black counterparts (Larson et al., 2016). While biases within a tool depend which tool is being used, the concern that any tool being utilized may increase punitive punishments for racial and ethnic groups is substantial reason enough to continue validation efforts.

Gender Bias. Many validation efforts suggest fair predictive utility across genders (Desmarais et al., 2020; Desmarais et al., 2016). However, feminist literature argues that pathways to offending differ between genders, and as such inherently include biases within actuarial tools (Gehring, 2018; Gehring & Van Voorhis, 2014). Research suggests that women are more likely to engage in criminal behavior due to factors that vary from men, such as employment, substance use, abuse, mental health, and homelessness (Gehring & Van Voorhis, 2014). Average risk assessment tools utilized in pre- and post- adjudication settings do not take specific considerations of the differences in criminal behavior etiologies, resulting in potential inaccuracies for women's calculated risk scores (Huebner et al., 2010). As such, present bias has been empirically shown through poor predictive utility in assessments of the post-adjudication.

Analyses of the Level of Service/Case Management Inventory (LS/CMI; Andrews et al., 2004) posit that post-adjudication risk is accurately predictive of women who are economically advantageous, but that women who experience gendered pathways into crime are predicted as higher risk than other justice-involved women (Reisig et al., 2006). Moreover, the Post-Conviction Risk Assessment (PCRA) shows that while re-arrest rates are equally predictive between men and women during post-adjudication, the PCRA overestimates recidivism (i.e., violation of conditions) for women (Skeem et al., 2016; Van Voorhis et al., 2010; Vose et al., 2009). However, little work has been done in assessing a gender bias present in specifically pretrial tools. At present, research suggests that pretrial risk assessment tools do not utilize gender-responsive needs (e.g., employment, substance use, abuse, mental health, homelessness) to their fullest extent (Gehring & Van Voorhis, 2014; Desmarais et al., 2020). As such, arguments are made that further assessment of pretrial risk assessment instruments must be conducted to advance our understanding of potential gendered bias integrated in these tools.

Age Bias. Additional bias considerations in pre- and post- adjudication risk assessment tools, such as age, are underreported. In general, research suggests that young adults often commit crimes at a higher rate than older adults with justice-involvement, and this may make them seem more culpable in a legal setting (Monahan et al., 2017; Bushway & Piehl, 2007). Older adults are more likely to decrease in offending due to simple maturation. Age in sentencing is a control for exposure time that is useful to make inferences about rates of offending and desistence probabilities (Bushway & Piehl, 2007). However, research has suggested that due to the reliance of criminal history in predicting risk, age overpredicts risk for older defendants (Monahan et al., 2017).

This foundation of bias towards age in decision-making is reflected in empirical assessments of risk. However, information around bias across age groups is largely dependent on the tool being used (Viljoen et al., 2019). For example, the Post-Conviction Risk Assessment (PCRA) was empirically shown to underestimate risk for younger justice-involved persons, and similarly overestimate risk for older justice-involved persons (Monahan et al., 2017). Yet, similar to research on gender bias existing in risk assessment tools, the understanding of age bias is largely lacking in pretrial risk instruments. This, too, encourages additional work to be done to further understand how age may impact predictive risk scores, specifically in a pretrial setting.

The Present Study

Approximately 80% of literature assessing pretrial risk assessments instruments is largely based on legal reviews and policy pieces, and do not utilize formal data (Bechtel et al., 2017). This can hinder empirical progress and continued methodological rigor when discussing effective means of pretrial diversion. In January of 2016, El Paso County implemented a modified version of the Virginia Pretrial Risk Assessment Instrument (VPRAI), the El Paso Pretrial Risk Assessment (EPPRA), to better orient the tool to serve the community demographics. This study looks to add to the needed body of work by empirically assessing the El Paso Pretrial Risk Assessment Instrument – Revised (EPPRA-R).

In April of 2019, data analysts of the El Paso County Criminal Justice Coordination Department assessed the original tool and validated the instrument on El Paso's local population. Recommendations based on empirical findings were made (i.e., two item were removed due to lack of predictive utility towards risk), which has since resulted in the revised tool: El Paso Pretrial Risk Assessment – Revised. The newly revised tool sorts defendants into four categories based on their risk likelihood, which is calculated from eight risk factors predicting both recidivism and failure to appear for court (i.e., FTA). Scores on the EPPRA-R are empirically based and derived from data from past defendants in El Paso. Many of the items are scored based on criminal justice records (e.g., current charges, history of violence), whereas some items are scored based on information obtained from the defendant at the time of the assessment (e.g., employment status, residential stability). This study will serve to assess the validity of the revised tool in the local El Paso population.

In doing so, this study will seek to (1) determine the accuracy of the tool in predicting defendants' likelihood of failure-to-appear for trial and recidivating, and (2) determine whether there are any potential biases towards subgroups of defendants (e.g., women, members of ethnic minority groups) within the tool. It is hypothesized that:

1. The El Paso Pretrial Risk Assessment Instrument – Revised will have stronger predictive utility than the original assessment.
2. The El Paso Pretrial Risk Assessment Instrument – Revised will overpredict re-arrest and FTA ratees for racial and ethnic minorities.
3. The El Paso Pretrial Risk Assessment Instrument – Revised will overpredict negative outcomes for women.
4. The El Paso Pretrial Risk Assessment will provide predictive utility across age groups.
5. The El Paso Pretrial Risk Assessment Instrument – Revised will overpredict negative outcomes for women of ethnic and racial minority groups compared to white women.

Method

Participants

Participants in this study include individuals that were arrested, brought to the El Paso County jail, and administered a pretrial risk assessment from the dates April 02, 2019, to May 2020. April 02, 2019 is the date that El Paso County formally integrated the El Paso Pretrial Risk Assessment – Revised into daily use. Almost every individual who is arrested and booked at the El Paso County jail is eligible to receive a risk assessment interview. Those who do not have a pretrial risk assessment conducted at the time of pretrial booking are those booked on tickets (a court date set for misdemeanors without bringing an individual in to jail for booking), detainers (a rebooking of an inmate currently incarcerated on a new charge), and bench warrants (the issuing of a warrant for one's arrest by a sitting judge). Each defendant included in this study was 17 years of age or older, as Texas remains one of four states that continues to consider adolescents at the age of 17 an adult within the criminal justice system (Texas Criminal Justice Coalition, 2021). In line with previous pretrial risk assessment validation literature, a statistical power analysis to determine sample size was not needed, as previous work can be used to guide sample size (Lowder et al., 2020; Cohen & Lowenkamp, 2019). To ensure that this study met power as an added safeguard, we conducted a post-hoc power analysis of a logistic regression on the binary race variable using G*Power software. Using a two-tailed approach with an indicated α=.05, a power level of 0.99 was detected suggesting our sample was sufficiently powered to detect effects in this sample. Participants (*n*=2,153) were predominantly White (*n*=1,925, 89.4%) males (*n*=1,758, 81.7%) with an average age of 31.6 years. The majority (*n*=1,297, 60.2%) of participants identified as Hispanic or Latino.

Materials

This study utilized data accessed via El Paso County permissions. Pretrial risk assessments were made available to researchers, which were used to complete initial individual searches on the County's criminal database, Odyssey, a secure network as agreed upon between El Paso County and The University of Texas at El Paso.

Measure of Risk

The El Paso Pretrial Risk Assessment Instrument – Revised (Appendix A) was used to measure defendants' risk for this study. The first rendition of this tool (El Paso Pretrial Risk Assessment Instrument; EPPRA; Appendix B) was influenced by the validated Virginia Pretrial Risk Assessment Instrument (VPRAI; VanNostrand, 2003) and implemented in El Paso County prior to 2017. See Appendix C for the original VPRAI tool. The EPPRA tool was designed by county personnel to reflect items utilized by the VPRAI but was altered to better suit the resident demographic of El Paso County more accurately. The initial tool was assessed for face validity in early 2019 and determined to be sufficiently predictive with minor modifications. Such modifications included the removal of two risk items ("Current charge felony or violent misdemeanor?" and "Any outstanding warrants in other jurisdictions?"), and the addition of one item ("Age 18.5 or under at the time of booking") based on results of the analyses and resulted in the EPPRA-R. This risk assessment tool includes six items directly assessing risk (e.g., "Does the defendant have any prior charges?"), general demographic information (age, gender, race), general criminal history details (felonies and misdemeanors), and other bond considerations specific to a defendant (e.g., "Are you a veteran or active in the U.S. military?" and "Length at Current Address?"). Item responses related to criminal history are auto populated using the

Texas Department of Public Safety criminal history database. Extralegal items on the assessment are verbally asked of the defendant at the time of booking.

Criminal Outcomes

Odyssey is an online, central repository for all data utilized by the Texas criminal justice system. This database provides information relevant to defendants' pretrial outcomes, such as a failure to appear to their hearing, or failure to comply with parole conditions. Odyssey contains highly confidential information and researchers require additional authorization by El Paso County for access. Such information includes arrest records, bond decisions, and court documents relevant to the specific case. All this information will be used to determine pretrial outcomes during data collection.

Following the initial data pull, researchers will collect additional outcome data provided by the Texas Department of Public Safety through a criminal history request[1]. This is intended to match individuals with any possible re-offenses throughout the state of Texas, as Odyssey provides criminal history limited to El Paso County. For further outcome data, we want to ensure that any crime committed outside of El Paso County is accounted for to the best of our abilities.

Outcome Variables

This study assessed defendants' pretrial outcomes, such as failure to appear (FTA) and recidivism after pretrial release. While both events are separate in their own right, the instrument being used creates a composite score: Pretrial Success (Yes; No). For example, if a defendant followed all necessary conditions to their release, but failed to appear to their scheduled court date, then they would be categorized as failing during their pretrial period. These outcome

[1] Data provided by Texas Department of Public Safety has not yet occurred. Obtaining these data require the research to be federally funded. Necessary funding is currently pending approval. Once funding has been approved, this portion of the procedure will continue.

variables were then assessed for any biases evident across groups (race, ethnic identity, gender, age).

Failure to Appear. A failure to appear (FTA) signifies that a defendant has missed their scheduled court date. This is a binary outcome (Yes; No) in data collection.

Failure to Comply. A failure to comply outcome is synonymous with any form of recidivism by a defendant. In this context, recidivism refers to a defendant committing a new crime while released during their pretrial period, or a violation of their probation conditions (e.g., failing to meet with their probation officer once a month). A new arrest is delineated by a violent or non-violent arrest pending trial; both items are answered on a binary (Yes; No) scale. Regardless of how a defendant has recidivated (arrested on a new charge or brought in for failure to comply), it is collapsed into a binary (Yes; No) outcome of failure. A violent arrest was assessed in separation to general outcomes.

Procedure

Researchers associated with this study were required to become an intern with El Paso County, as this was necessary for access to the required information. Upon completing all documentation necessary to become properly associated with the County, researchers were sufficiently trained on the database used to hold criminal records within El Paso County. By having access to this information, researchers were able to identify defendants that were arrested in El Paso County and had a pretrial risk assessment conducted at the time of booking. This is limited to those that were assessed between April 02, 2019, to present. This date is specific to an additional modification of the risk assessment tool as previously noted. The identifying information (first name, last name, date of birth) of each defendant that had been assessed was used to search Odyssey to determine whether they failed to appear at their assigned court date and/or a failure to comply with their pretrial supervision conditions in El Paso County. Given the highly confidential nature of this data, security measures were put in place to ensure that confidentiality was maintained. Per The University of Texas at El Paso's Internal Review Board (IRB) protocols, researchers only used software that was directly connected to a secure university server rather than a public connection. In addition, each researcher conducted this work in a secure and private setting. While the IRB deemed this a program evaluation and not a direct research project, the research team adhered to strict confidential guidelines and security measures given the delicate nature of the information on hand. Each member of the research team signed a confidentiality agreement agreeing to such protocols. At the completion of data collection[2], researchers will have their internship time terminated by El Paso County so as to not have further and unnecessary access to confidential information.

Analytic Plan

Prior to formal analyses being conducted, descriptive statistics and correlations were obtained to illustrate the sampled participants and assess for potential collinearity. Consistent with previous validation efforts of risk assessment measures (Lowder et al., 2020b; Desmarais & Singh, 2013), we conducted Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) statistical analyses to assess for predictive accuracy of the pretrial risk assessment instrument. AUC of ROC is commonly used in applied settings, as it sets a threshold for classification indicators (i.e., true-positive, false-positive, true-negative, false-negative) around a base rate of 50% predictive accuracy pertaining to model performance. AUC of ROC analyses are the suggested effect size analyses over Cohen's *d*, as Cohen's *d* was designed for two continuous, and normally distributed scores (Harris & Rice, 2005). These conditions are not

[2] Data collection is ongoing for the purposes of a formal report requested by El Paso County. Data collection for this report is estimated to be complete by May 2023.

often found in applied settings such as the criminal justice system. As such, AUC of ROC effect sizes are more appropriate because it does not allow influence of varying base rates of offending across groups in its measures of predictive accuracy (Skeem & Lowenkamp, 2016). AUC values range from 0.5 to 1.0 – 0.5 indicates chance value, and 1.0 suggests perfect predictive accuracy of the tool (Lowder et al., 2020). Literature reports that AUC values between a 0.00 to 0.54 are considered poor, scores between a 0.55 and 0.63 are fair, 0.64 to 0.70 are good, and scores ranging from 0.71 to 1.00 are ideal for predictive utility of a tool (Desmarais & Singh, 2013).

To assess for biases within the pretrial risk assessment tool, we conducted binary logistic regressions. For each of the following models, the binary outcome variable was pretrial success (Yes; No). The first model included the initial predictor variables on their own: race (White, Black, Asian or Pacific Islander, Native American or Alaskan Native, Other), ethnicity (non-Hispanic, Hispanic), gender (Male, Female), and age. We continued to include interactions to our model to determine whether the interactions were predictive of pretrial success above and beyond the initial predictor variables on their own. Binary logistic regressions were more appropriate to use in comparison to linear regression models due to the dichotomous nature of our outcome variable (Alexopoulos, 2010; Brunner & Giannini, 2011). Such statistical results (i.e., regression slopes and intercepts) can help determine bias across groups (i.e., race, ethnicity, gender, age) given the predicted risk scores and outcome occurrences (Skeem & Lowenkamp, 2016) in the El Paso population.

Results

Descriptives

Participants' risk categories were reasonably distributed across categories; with the most participants scoring in Level 2 (*n*= 620, 28.8%), followed by Level 1 (*n*=582, 27.0%), Level 3 (*n*=519, 24.1%), and Level 4 (*n*=431, 20.0%). In consideration of the two components of pretrial success, approximately 87.7% of participants (*n*=1,889) appeared to their court hearing and 84.4% of participants (*n*=1,817) complied with their set conditions during their pretrial hearings. Of those who were arrested prior to their hearing (*n*=264), over half (*n*=213, 80.6%) were arrested for non-violent charges. Overall, most participants (*n*=1,557, 72.3%) were categorized as completing their pretrial period successfully.

Table 1: Demographic Information of Participants

Variable	*M*	*SD*	*Mdn.*
Age in years (17-82)	31.60	11.23	
Monthly Income	$790.07	$1,405.79	$0.00

	n	% of *P*s
Gender		
Male	1,758	81.7
Female	384	17.8
Other	10	0.5
Race (Pretrial Risk Assessment)[a]		
White	1,925	94.1
Black or African American	102	4.7
Asian or Pacific Islander	5	0.2
American Indian or Alaska Native	5	0.2
Other	9	0.4
Did Not Answer	102	4.7
Race (Database)		
White	1,913	88.9
Black or African American	155	7.2

Asian or Pacific Islander	5	0.2
Other	55	2.6
Did Not Answer	25	1.2
Ethnicity (Pretrial Risk Assessment)[b]		
Hispanic or Latino	1,297	60.7
Not Hispanic or Latino	840	39.2
Ethnicity (Database)		
Hispanic or Latino	1,834	85.4
Not Hispanic or Latino	314	14.6
Currently Homeless		
Yes	153	7.1
No	1,900	88.2
Not Applicable	4	0.2
Length of employment[c]		
Disabled	62	2.9
Full Time Student	38	1.8
Housewife/Primary Caretaker > 2 Years	8	0.4
Less Than 6 Months	333	15.5
Longer Than 6 Months	1,013	47.1
Retired	2	0.1
Unemployed	697	32.4
Veteran or Active US Military		
Yes	129	6
No	1,916	89
Not Applicable	15	0.7
Mental health flag[d]		
Yes	658	30.6
No	1,495	69.4

Note. N =2,153. % of Ps = Participants.
[a]Defendant race differed between what was reported on the pretrial risk assessment and what was entered in the County database.
[b]Defendant ethnicity differed between what was reported on the pretrial risk assessment and what was entered in the County database.

[c]This table reflects how the item was noted on the pretrial risk assessment with corresponding item response options.
[d]A mental health flag was indicated if the defendant had any form of mental health record. No further information is known or provided for the purposes of the assessment.

Accuracy of the Pretrial Risk Assessment Instrument

It was hypothesized that the results AUC of ROC analyses would suggest that the modified version of the pretrial risk assessment tool currently implemented in El Paso County would be more accurately predictive of risk than the original version of the tool. Results using data collected from this instrument were considered "fair" in performance, with an AUC=0.609. Validation efforts of the original tool (Debora & Meils, 2019) reported an AUC=0.602, suggesting that the modifications made to the initial version of the tool provided only marginal improvement. Recall that literature reports values between a 0.00 to 0.54 to be considered poor, 0.55 and 0.63 are fair, 0.64 to 0.70 are good, and 0.71 to 1.00 are excellent predictive scores by the tool (Desmarais & Singh, 2013).

Additional research questions pertaining to this study asked whether the tool overpredicted risk scores for subgroups of participants (e.g., racial and ethnic minority groups, women, age groups). These research questions will be further addressed below using additional analyses. However, we did conduct further Receiving Operating Characteristic (ROC) analyses on subgroups of participants for further illustration of the tool's utility. Due to the nature of these additional analyses, it was required that subgroup variables were dichotomized. When assessing race, the tool suggested more accurate predictive utility for White defendants (AUC=0.61) than non-White defendants (AUC=0.59). Following a similar trend, the predictive utility was stronger for non-Hispanic or Latino defendants (AUC=0.62) than Hispanic or Latino defendants (AUC=0.60). With regard to gender, male defendants (AUC=0.61) appeared to have less predictive utility by the tool than women (AUC=0.612) who were assessed. Lastly, a cutoff value was included to create two groupings of age; the cutoff value was the average age (31.6 years). The tool had weaker predictive utility for defendants under 31.6 years of age (AUC=0.60) than defendants over the age of 41 (AUC=0.61). No difference in AUC scores were significantly different.

Table 2: Predictive Utility for Defendant Subgroup

Group	AUC	Sig	Cutoff	95% CI	Sensitivity	Specificity
White	0.61	0.00	1.5	[0.58, 0.64]	0.62	0.57
Non-White	0.59	0.10	2.5	[0.48, 0.69]	0.70	0.42
Race Difference	*0.02*	*0.72*		*[-0.09, 0.13]*		
Hispanic or Latino	0.62	0.00	1.5	[0.58, 0.66]	0.61	0.56
Not Hispanic or Latino	0.60	0.00	1.5	[0.57, 0.64]	0.61	0.59
Ethnicity Difference	*0.02*	*0.54*		*[-0.04, 0.7]*		
Male	0.61	0.00	1.5	[0.58, 0.64]	0.60	0.59
Female	0.62	0.00	1.5	[0.55, 0.68]	0.67	0.54
Gender Difference	*-0.01*	*0.76*		*[-0.08, 0.06]*		
Age: < 31.6	0.61	0.00	1.5	[0.58, 0.65]	0.59	0.59
Age: ≥ 31.6	0.60	0.00	1.5	[0.56, 0.64]	0.54	0.64
Age Difference	*-0.03*	*0.36*		*[-0.10, 0.04]*		
Total	0.61	0.00	1.5	[0.58, 0.64]	0.61	0.58

Note. This table demonstrates Area Under the Curve (AUC) of the Receiving Operating Characteristic (ROC) results.

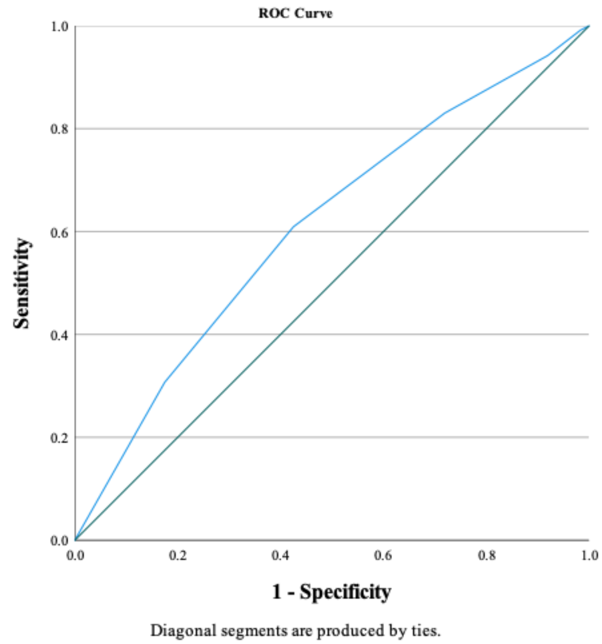

Figure 1: Accuracy of Predicted Risk Scores on Pretrial Outcomes

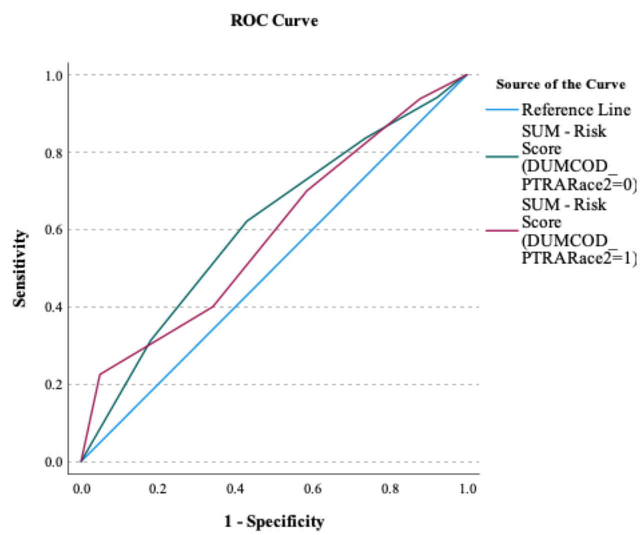

Figure 2: Accuracy of Predicted Risk Scores on Pretrial Outcomes by Race

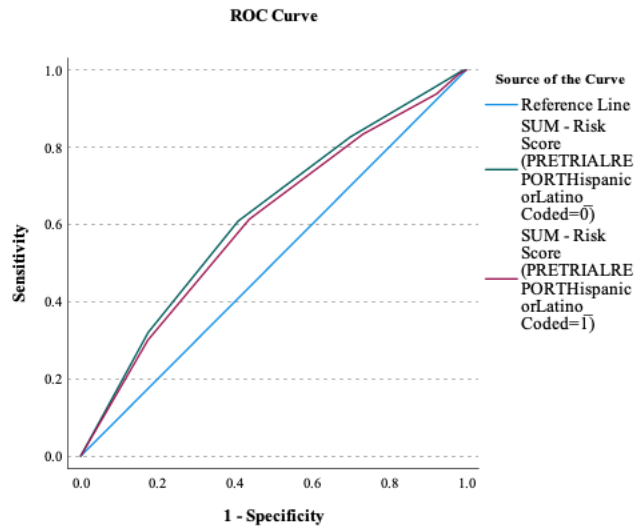

Figure 3: Accuracy of Predicted Risk Scores on Pretrial Outcomes by Ethnicity

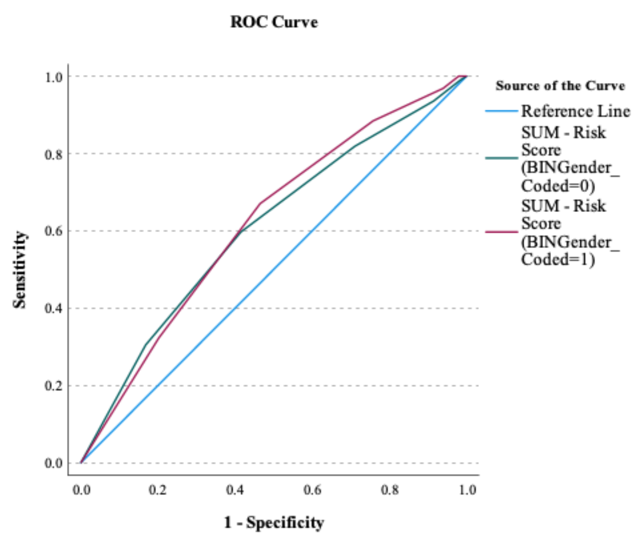

Figure 4: Accuracy of Predicted Risk Scores on Pretrial Outcomes by Gender

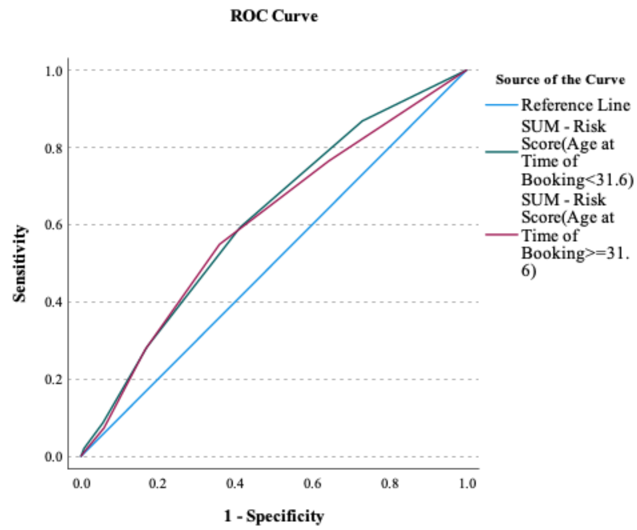

Figure 5: Accuracy of Predicted Risk Scores on Pretrial Outcomes by Age

Binary Models

Binary logistic regression models were conducted to determine whether there were predictive biases present in predicted risk towards subgroups of participants (i.e., racial and ethnic groups, gender, age). Binary logistic regression models were the deemed best approach for these analyses due to the dichotomous nature of the outcome variable (Tabachnick & Fidell, 2013). We hypothesized that the modified instrument, while an improvement from the original version, would still overpredict risk for racial and ethnic minority groups of defendants, and women who were assessed using the EPPRA-R. The first model (Model 1) included only the main predictor (predicted risk scores) on pretrial success. Results suggest that risk scores populated by the tool do significantly predict pretrial success (OR= 0.74, 95% CI: [0.69, 0.80], *p*< .001). This suggests that for every increase of one in risk score, the odds of success are 0.74 times as high. To assess our hypotheses pertaining to fairness of the tool, binary predictor variables (Race: White, non-White; Ethnicity: non-Hispanic or Latino, Hispanic or Latino;

Gender: Male, Female) and age (continuous predictor variable) were included in Model 2. Contrary to our hypotheses, defendants of racial and ethnic minority groups and women who were assessed did not receive statistically significant overpredictions of risk (Table 3). We also sought to explore the effects of age bias on predicted risk in Model 2. Results suggested that age had no significant effect on predicted risk and pretrial success (OR=0.86, 95% CI: [0.99, 1.01], p=0.86). To further determine potential bias present within the tool, we interacted predicted risk with defendant characteristics (Model 3). Results suggested that no evidence of biases were present when interacting with predicted risk on pretrial outcomes (Table 3). Lastly, we hypothesized that women of racial and ethnic minority groups would receive higher risk scores in comparison to White women (Model 4). Our results did not support this hypothesis, as the interaction between gender and race (OR=0.97, 95% CI: [0.30, 3.20], p=0.97) or ethnicity (OR=1.09, 95% CI: [0.62, 1.89], p=0.77) did not significantly predict risk scores and pretrial outcomes. These results were similar when including predicted risk as a third interacting variable in Model 4 (Table 3).

Table 3: Summary of Binary Logistic Regression Analysis for Pretrial Outcomes

	B (S.E.)	O.R.	95% CI	Wald	df	Sig
Step 1 - EPPRA-R Predictability						
Risk Score	-0.30 (.04)	0.74	[0.69, 0.80]	55.06	1	<.001
Constant	1.42 (0.08)	4.15	[3.54, 4.84]	313.75	1	<.001
Step 2 - Defendant Characteristics						
Risk Score	-0.30 (.04)	0.74	[0.69, 0.81]	52.97	1	<.001
Race	-0.15 (.21)	0.86	[0.60, 1.30]	0.52	1	0.47
Ethnicity	0.09 (.11)	1.09	[0.88, 1.35]	0.62	1	0.43
Gender	0.04 (.13)	1.04	[0.80, 1.35]	0.08	1	0.77
Age	0.00 (.01)	0.86	[0.99, 1.01]	0.03	1	0.86
Constant	1.37 (.11)	3.94	[3.17, 4.89]	151.91	1	<.001
Step 3 - Interactions of Risk Score with Defendant Characteristics						
Risk Score	-0.32 (.08)	0.73	[0.63, 0.84]	18.13	1	<.001
Race	-0.24 (0.39)	0.79	[0.37, 1.68]	0.36	1	0.55

Ethnicity	-0.02 (0.18)	0.98	[0.69, 1.39]	0.01	1	0.91
Gender	0.24 (0.22)	1.27	[0.82, 1.97]	1.13	1	0.29
Age	0.00 (0.01)	1.00	[0.99, 1.02]	0.06	1	0.82
Race x Ethnicity	1.10 (0.71)	3.00	[0.75, 12.07]	2.41	1	0.12
Race x Gender	-0.35 (0.66)	0.71	[0.20, 2.55]	0.28	1	0.60
Race x Age	0.01 (0.02)	1.01	[0.97, 1.05]	0.27	1	0.60
Ethnicity x Gender	0.08 (0.30)	1.08	[0.61, 1.93]	0.76	1	0.78
Ethnicity x Age	-0.02 (0.01)	0.99	[0.97, 1.00]	3.13	1	0.08
Gender x Age	-0.01 (0.01)	1.00	[0.97, 1.02]	0.41	1	0.52
Risk Score x Race	0.05 (0.17)	1.05	[0.75, 1.47]	0.07	1	0.79
Risk Score x Ethnicity	0.06 (0.09)	1.06	[0.90, 1.26]	0.50	1	0.48
Risk Score x Gender	-0.13 (0.12)	0.88	[0.70, 1.10]	1.23	1	0.27
Risk Score x Age	0.00 (0.00)	1.00	[0.99, 1.01]	0.02	1	0.89
Constant	1.41 (0.15)	4.11	[3.06, 5.51]	80.07	1	<.001
Step 4 - Interactions of Risk Score and Gender with Race and Ethnicity						
Risk Score	-0.33 (0.08)	0.72	[0.62, 0.84]	17.966	1	<.001
Race	-0.24 (0.40)	0.79	[0.36, 1.73]	0.346	1	0.56
Ethnicity	-0.02 (0.18)	0.98	[0.58, 1.16]	0.012	1	0.91
Gender	0.24 (0.22)	1.27	[0.82, 1.96]	1.148	1	0.28
Age	0.00 (0.01)	1.00	[0.99, 1.02]	0.053	1	0.82
Risk Score x Race	0.05 (0.17)	1.06	[0.75, 1.48]	0.098	1	0.75
Risk Score x Ethnicity	0.07 (0.09)	1.07	[0.90, 1.28]	0.599	1	0.44
Risk Score x Gender	-0.10 (.15)	0.91	[0.68, 1.21]	0.414	1	0.52
Risk Score x Age	0.00 (0.00)	1.00	[0.99, 1.01]	0.014	1	0.90
Risk Score x Gender x Race	-0.05 (0.31)	0.95	[0.52, 1.74]	0.028	1	0.87
Risk Score x Gender x Ethnicity	-0.05 (0.15)	0.95	[0.72, 1.27]	0.114	1	0.74
Constant	1.41 (0.15)	4.10	[3.06, 5.51]	89.074	1	<.001

Note. Step 1: Goodness of Fit χ^2 (1) = 55.69, $p < .001$; -2 Log Likelihood = 2327.92; Cox & Snell R^2 = 0.03; Nagelkerke R^2 = 0.04. *Step 2:* Goodness of Fit χ^2 (4) = 1.708, p = 0.79; -2 Log Likelihood = 2326.22; Cox & Snell R^2 = 0.03; Nagelkerke R^2 = 0.04. *Step 3:* Goodness of Fit χ^2 (4) = 1.77, p = 0.78; -2 Log Likelihood = 2324.44; Cox & Snell R^2 = 0.03; Nagelkerke R^2 = 0.04. *Step 3:* Goodness of Fit χ^2 (2) = 0.13, p = 0.94; -2 Log Likelihood = 2324.31; Cox & Snell R^2 = 0.03; Nagelkerke R^2 = 0.04.

Discussion

The validation efforts of the El Paso Pretrial Risk Assessment Instrument – Revised were two-fold. First, we wanted to assess whether the revised tool was more accurately predictive of pretrial outcomes than the original tool validated in 2019. Second, we sought to determine whether there were biases towards subgroups of defendants within the tool's predictive utility. To address the first research question, analyses resulted in statistically "fair" predictive performance for pretrial outcomes. While the revised tool increased in predictive utility in comparison to the original, it was only marginally so. To address the following research questions, results suggested that no subgroup of defendant population (i.e., racial minority groups, Hispanic and Latino defendants, women, age groups) were more prone to an overprediction of risk. These results have rather contradicting implications that we will further discuss.

Accuracy in Predictive Utility

When implemented properly, pretrial risk assessment tools are intended to offer strong predictive utility – the information provided at an earlier time and included within the tool may more accurately predict outcomes for defendants (Wei-Ling & Yao, 2014). To do so, validation efforts must be conducted to assess accuracy of the tool (Zottola et al., 2021; Cohen & Lowenkamp, 2019; Berk et al., 2018). The results of this study suggest that while this tool is statistically "fair" in its predictive utility, it remains lower in its predictive ability than other tools that are used in similar correctional settings. For example, Cohen and Lowenkamp (2019) revalidated the PTRA tool on sample of federal pretrial defendants and found a range of "good" to "excellent" predictive results, as AUC statistics ranged between 0.65 to 0.73. Similarly, a validation of the Indiana Risk Assessment System – Pretrial Assessment Tool (IRAS-PAT) was validated across five Indiana counties and posited “good” to “excellent” results; AUC statistics followed similar suit and ranged between 0.67-0.72 (Lowder et al., 2020). As such, there is room for improvement for El Paso’s local instrument.

While the tool was statistically “fair” in its predictive utility, it only just reached the threshold of “fair.” This is a warrant for concern, as the validation efforts from the initial El Paso pretrial risk assessment tool (prior to the revisions made to the tool currently being assessed) had shockingly similar results. While we are unable to statistically discern the difference between the two AUC results (overall score from the 2019 validation and overall score from current validation), such a small change in predictive utility following modifications intended to improve the tool should be further assessed. It is then assumed that the revisions made had very little impact on the overall utility of the tool and begs the question of what is needed to improve its predictive accuracy.

Fairness in Predictive Utility

In addition to ensuring that a pretrial risk assessment tool is accurate, it is essential that tools are assessed for disparity within predicted risk scores amongst population subgroups, such as defendant race and ethnic identity, gender, and age (Cohen & Lowenkamp, 2019; Desmarais et al., 2016; Skeem & Lowenkamp, 2016). Past literature suggests that those of racial and ethnic minority groups are subject to increased encounters with law enforcement, as they are more likely to experience over-policing of neighborhoods, social and resource disadvantages, and fewer opportunities for employment and advancement (Clair & Winter, 2016; Skeem & Lowenkamp, 2016b; Viljoen et al., 2019). Additionally, feminist literature has advocated for further investigation into predicted risk for women involved with the justice system, as empirical evidence suggests women are more likely to engage in criminal behavior due to factors that differ from their male counterparts (e.g., employment, substance use, abuse, mental health, homelessness; Gehring, 2018; Gehring & Van Voorhis, 2014). As such, it is suggested that women are prone to an overprediction of risk given that actuarial tools do not account for such differences in justice-involvement (Huebner et al., 2010). Lastly, while it is less reported, there is a small consensus that older defendants are prone to overprediction of risk due to tools' reliance on criminal history (Monahan et al., 2017). When assessing these factors for risk disparity within the revised tool in this study, no subgroup of defendants was shown to have an overprediction of risk in relation to their pretrial outcome. Interestingly, we should consider that the homogeneity of the Hispanic and Latino ethnic makeup of El Paso County may alter the bias present in these results; as experiences of ethnic bias may not be as prevalent for local residents in comparison to a non-border city (Curry & Zavala, 2022). While it may differ in other geographic locations, the tool appears to be accurately reflective of risk for the current population. This, on the surface, appears to be a promising result.

While equity in predictive utility across defendant groups (based on personal characteristics) is a positive outcome, we should be cautiously optimistic in this context. It seems premature to feel confident in these group results for two reasons. First, given the fairly low rate of predictive utility, we are unsure if the tool truly works for any defendant that is assessed at the El Paso County jail, much less across group characteristics. Second, approximately 82.9% of El Paso County identifies as Hispanic or Latino (U.S. Census Bureau, 2021). As such, we may be witnessing skewed findings as a result of the ethnic makeup of the county. While we did see matched racial group representation within our data (base rate of Black residents within El Paso County is 4.2%; U.S. Census Bureau, 2021), our data did not reflect a matched gender representation of the county (50.2% women in El Paso County; U.S. Census Bureau, 2021).

Though these data reflect typical trends for most of those that are justice-involved – Black individuals are more likely to have criminal justice involvement than their White counterparts (Desmarais et al., 2021; Zottola et al., 2021) and men make up the majority of the justice-system population (Federal Bureau of Prisons, 2022a) – the ethnic makeup of the county drastically differs from typical correctional trends (Federal Bureau of Prisons, 2022b). Overall, tt has been discussed that El Paso County's revised tool is statistically "fair" in its predictive utility and does not appear to overpredict risk for any subgroup of defendants that are assessed. However, this statement out of context may be misleading for the continued implementation of the El Paso Pretrial Risk Assessment Instrument – Revised as it currently stands.

Limitations

The shortcomings of this study must be considered when discussing its findings. First, the data collected was obtained from county databases that were subject to human error; both by county officials inputting information, as well as researchers creating the dataset. In efforts to get as much information as possible, researchers collected defendant demographic information from both the pretrial risk assessment itself, and from the database that it was then entered into by county personnel. To use defendant ethnicity as an example, our data shows that 60.7% (*n*=1,297) of our sample directly from the assessment identifies as Hispanic or Latino, but 85.4% (*n*=1,835) of the sample is noted as Hispanic or Latino in the database used by the county. This discrepancy is considerable. It must be noted that the characteristics listed on the pretrial risk assessment tool was provided by observation of the staff member conducting the assessment rather than how the defendant identified themselves. Best practices for reporting race and ethnicity endorse self-report (Flanagin et al., 2021). Moreover, the administrative and procedural processes to transfer information from the assessment sheet to the database is unknown.

Therefore, we cannot speak to how the discrepancy between reporting occurs. For the purposes of this study, we used the information indicated on the pretrial risk assessment, as that is what is made available to judges and magistrates when determining pretrial release decisions. However, it causes concern in our analyses given that we are unable to fully discern accurate rates of defendant characteristics with these data.

Second, there is always room for concern of outcome accuracy given the method in which outcome data were collected. Researchers were trained to identify and understand information available to them on the database used by the county for defendant information. However, all information and documentation uploaded to the database is subject to varying titles and documentation types. We understand that this method of data collection may have lent itself to inaccuracies within pretrial outcome information pertaining to defendants. However, given the level of training and oversight throughout the data collection process, it is unlikely that the inaccuracies were detrimental to our analyses. Additionally, precedent had to be considered when coding outcome data. At this time, defendants that were detained pretrial, and remained detained throughout the duration of their pretrial period, was considered successful. This is due to their inability to fail to appear to court and comply with supervision conditions. It is concerning, as it is unknown at this time whether these cases conflated success rates in our results. Future analyses will look to exclude defendants that are detained for the duration of their pretrial period to discern pretrial outcomes more accurately.

Third, our pretrial outcomes were limited to El Paso County. Researchers attempted to obtain criminal history data from the Texas Department of Public Safety but were unable to. Currently, The Department of Public Safety is only permitting research with federal funding access to such datasets. Given we do not have such funding at the moment, we were unable to match defendants with criminal history records outside of El Paso County. Efforts are underway to obtain federal funding while continuing data collection; future analyses hope to incorporate matched defendant outcomes to allow for more robust findings.

Lastly, the statistical design used to determine predictive utility across defendant groups (i.e., race, ethnicity, gender, and age) was dependent on dichotomous data and aggregating the race predictor within our data. Opposition to forcing dichotomies has been an emerging discussion amongst pretrial reform scholars (see Zottola et al., 2021 for review). Additionally, calls for disaggregating race data specifically is a growing movement. The criminal justice literature historically dichotomizes race categories into White and non-White groups; suggesting that White groups are the de facto comparison group. This should not continue to be the standard given the varying levels of racial and ethnic makeup of any given community; El Paso County is an excellent example of such a point. Future work will look to engage in weighted effects coding to more accurately assess group comparisons and engage in best practices.

Implications

This study leads to many opportunities for further work outside of the scope of predicted risk. First and foremost, the immediate next step is to assess which risk items inform predicted outcomes above and beyond others that do not. This may help to inform how the tool may be improved for predictive utility, or whether there is a more appropriate tool to use on El Paso County's specific and unique population. While this study is sufficiently powered, the inequity between racial groups cannot be ignored. While data collected was reflective of the community rates by White and Black defendants, additional racial groups (i.e., Asian and Pacific Islander, American and Alaskan Native) fell far below the community base rate. As previously mentioned, data collection is ongoing, and researchers anticipate improved group comparisons. Most importantly, this tool has the capability of providing rich information necessary for pretrial decision-making and additional pretrial release options.

In addition to predicted risk, this tool acts as a decision aide for judges and magistrates to determine pretrial supervision levels. Previous research suggests that the use of results from methodologically sound pretrial risk assessment tools in making supervision decisions by judges and magistrates increase rates of pretrial release and the use of pretrial supervision (Desmarais et al., 2021). More specifically, empirical work is starting to discern whether supervision standards are “over” supervising defendants, causing more negative pretrial outcomes (Lowder & Foudray, 2021). Pretrial supervision is a largely emerging area of pretrial reform research, and these data may be instrumental to such development.

In consideration of large implications, these results can contribute to bail reform discussions. The state of Texas is involved in nationwide debates over the use of cash bail. These findings may inform the discussion concerning cash bail systems and their role in the pretrial space. By assessing such individual-level information regarding pretrial outcomes, this may assist in illustrating the effects of releasing defendants on their own recognizance. Pretrial reform is a rich and ever-growing discussion that can greatly benefit from empirical support.

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Appendix A: El Paso Pretrial Risk Assessment Instrument – Revised (EPPRA-R)

El Paso Pretrial Services Report V3

Defendant Name:				AKA's:	
Date:		DOB:		Arrest Date/Time:	
Gender:		AGE:		**Client has no known holds**	
Indigent?	**Unknown**	START TIME:			

CURRENT CHARGE (S)

Most serious current/new charge first with (warrant/case number);

EL PASO PRETRIAL RESEARCH ASSESSMENT - REVISED (EPPRA-R)

The following research provides the latest empirical outcomes of pretrial defendants in El Paso who are most closely associated with this defendant. This research is intended to provide empirical information to supplement a judge's statutory obligation to consider public safety and flight risks. The EPPRA-R empirically categorized defendants into four pretrial categories of research outcomes based on El Paso's local population, as follows:

PRETRIAL RISK LEVEL	**Level 2**

Level 1: 81% Overall Success   Level 2: 70% Overall Success   Level 3: 60% Overall Success   Level 4: 51% Overall Success

"Overall Success" definition: No warrants during the pretrial period for failure to appear in court, no new criminal charges during the pretrial period, and no warrants for failure to comply with bond conditions. This defendant's responses and history result in the following outcomes from the most recent available research:

*SUCCESSFUL COURT APPEARANCE RATE	**91%**	†NO NEW VIOLENT CHARGE RATE	**90%**	‡NO NEW NON-VIOLENT CHARGE RATE	**77%**

EPPRA-R FACTORS & SCORING

Is the defendant currently under supervision?†	No	**0**
Have two or more prior violent or felony convictions?†‡	No	**0**
Does the Defendant have any pending charges?‡	No	**0**
Age 18.5 or under at the time of booking?†‡	Yes	**1**
ASK: Has the defendant been at this location for LESS than 1 year?*‡	No	**0**
ASK: Length of Current Employment	Longer than 6 Months	**0**
Level 1: 0 points Level 2: 1 point Level 3: 2 points Level 4: 3 to 6 points	TOTAL SCORE:	**1**

CRIMINAL HISTORY DETAILS (Convictions only except for DWI):
(Summary does not include Federal Convictions but does show on RAP Sheet)

Felony	N/A				0
Misdemeanor	N/A				0
DWI History (includes arrests)	N/A	Non-convictions Count	0	Convictions Count	0
Deferred Adjudications	N/A				
Juvenile Felony	N/A				
Juv. Misdemeanor	N/A				
Pending Cases:	N/A				

RECOMMENDATION FROM SMART PRAXIS GUIDELINES:	

ADDITIONAL RECOMMENDED BOND CONDITIONS:	
Condition #1:	
Notes:	

Are you a veteran or actively in the United States military?	
Are you currently homeless?	
Have you been homeless in the past year?	
Notes:	

LOCAL TIES & RESIDENCE HISTORY:	**Information Verified?**	**No**		
Current Address:				
Phone Number:	**Email:**		**Alt.#**	
Length at Current Address:				
Amount of Time in Local Area:				
Others living at this address:			**Count:**	**0**
Number of Dependents:				
Notes:				
WHERE WILL THE DEFENDANT RESIDE?	**Information Verified?**	**No**		
Address:	SAME AS ABOVE			
Phone Number:	**Email:**		**Alt.#**	
Defendant will reside with:	**N/A**			

EMPLOYMENT (self-reported, not verified):	**No**
Current Employer:	
Length of Employment:	
How much money can you and your family raise within 24 hours to post a bond?	

COMMUNITY CONTACTS #1:				
Contact Name:			**Contact Phone #:**	
Relation to client:			**Willing to Co-sign?**	**Unknown**
Spoke with Contact (Yes or No)?		**No**		
COMMUNITY CONTACTS #2:				
Contact Name:			**Contact Phone #:**	
Relation to client:			**Willing to Co-sign?**	**Unknown**
Spoke with Contact (Yes or No)?		**No**		

OTHER INFORMATION/NOTES (IF APPLICABLE):		
	Preparer:	**Time:**
END TIME:	**Reviewer:**	**Time:**

REPORT COMPLETED BY:

This information was compiled under stringent timelines from relevant sources for convenience of review by applicable Judicial Officials. Pretrial Services makes no representations or warrantees regarding the completeness or accuracy of this information.

Appendix B: El Paso Pretrial Risk Assessment Instrument (EPPRA)

Risk Assessment

Name: ______________________ DOB: ______________ Gender: M/F Race:__________
Case/Warrant #: __________________ SO #:________________ Booking Date: ___________
Current Address:__________________________________ Length at Address: ___________

Score

Current Offense (Most Serious):_____________________________________
Additional Charge(s):____

Score

Is Defendant Currently Under Supervision: ____________________________
Case No(s)/Charge: ____

Score

Number of Prior FTA's:____
Case No(s)/Charge:____

Score

Number of Prior Violent Offenses:____________________________________
Case No(s)/Charge:____

Score

Does defendant have any Pending Charges: _____________________________
CaseNo(s)/Charge/Court:____
Attorney of Record (Appt'ed/Retained):________________________________

Score

Does defendant have Outstanding Warrants from other Jurisdictions: __________
Case No(s)/Charge:____

Score

Current Employer/Primary Child Caregiver: _____________________________
Length of Time: ____

Score

Notes:

Total Points: ______________

Risk Level: ______________

Appendix C: Virginia Pretrial Risk Assessment Instrument (VPRAI)

Risk Factor	Criteria	Assigned Point(s)
Charge Type	If the most serious charge for the current arrest was a felony	1 point
Pending Charge(s)	If the defendant had one or more charge(s) pending in court at the time of the arrest	1 point
Outstanding Warrant(s)	If the defendant had one or more warrant(s) outstanding in another locality for charges unrelated to the current arrest	1 point
Criminal History	If the defendant had one or more misdemeanor or felony convictions	1 point
Two or more Failure to Appear Convictions	If the defendant had two or more failure to appear convictions	2 points
Two or more Violent Convictions	If the defendant had two or more violent convictions	1 point
Length at Current Residence	If the defendant had lived at their current residence for less than one year prior to arrest	1 point
Employed/ Primary Child Caregiver	If the defendant had not been employed continuously for the past two years and was not the primary caregiver for a child at the time of arrest	1 point
History of Drug Abuse	If the defendant had a history of drug abuse	1 point

Appendix D: Coding Book

- Cause/Warrant Number
  - String variable
- Last Name, First Name
  - String variable
- Disposed/Dismissed
  - No (0)
  - Yes (1)
- Date of Birth
  - Format: MM/DD/YYYY
- Gender
  - Male (0)
  - Female (1)
- Booking Date
  - Format: MM/DD/YYYY
- Offense
  - String variable
    - Current Offense: Most Serious
    - Additional Charge 1 (if applicable)
    - Additional Charge 2 (if applicable)
    - Additional Charge 3 (if applicable)
    - Additional Charge 4 (if applicable)
    - More than 4 Additional Charges (if applicable)
- Under Supervision
  - No (0)
  - Yes (1)
  - Any other response (SYSMIS: "System Missing")
- 2 or More Prior Violent or Felony Convictions
  - No (0)
  - Yes (1)
  - Any other response (SYSMIS: "System Missing")
- Any Pending Charges
  - No (0)
  - Yes (1)
  - Any other response (SYSMIS: "System Missing")
- Been at This Location Less than One Year
  - No (0)
  - Yes (1)
  - Any other response (SYSMIS: "System Missing")
- Length of Current Employment
  - Unemployment (1)
  - Longer than 6 Months (2)
  - Housewife/Primary Caretaker > 2 Years (3)

- Full Time Student (4)
- Disabled (5)
- Less than 6 Months (6)
- Retired (7)
- Any other response (SYSMIS: “System Missing”)

- Score: Length of Current Employment
  - 0, 1
- Months Worked for Pay within Last 12 Months
  - String variable
- First Arrest
  - No (0)
  - Yes (1)
  - Any other response (SYSMIS: “System Missing”)
- Ever Been to Jail
  - No (0)
  - Yes (1)
  - Any other response (SYSMIS: “System Missing”)
    - Continue to Question 25 “Have you Ever Spent More than a Week in Jail?”
      - No (0)
      - Yes (1)
      - Any other response (SYSMIS: “System Missing”)
    - If “No” then skip to Question 27
- Hispanic or Latino
  - Pretrial report
    - No (0)
    - Yes (1)
    - Any other response (SYSMIS: “System Missing”)
  - Odyssey
    - No (0)
    - Yes (1)
    - Any other response (SYSMIS: “System Missing”)
- Race
  - Pretrial report (disaggregated)
    - White (0)
    - Black or African American (1)
    - American Indian or Alaska Native (2)
    - Asian or Pacific Islander (3)
    - Other (4)
    - Any other response (SYSMIS: “System Missing”)
  - Pretrial report (dummy coded)
    - White (0)
    - Non-White (1)
  - Odyssey (disaggregated)
    - White (0)
    - Black or African American (1)

        - American Indian or Alaska Native (2)
        - Asian or Pacific Islander (3)
        - Any other response (SYSMIS: "System Missing")
    - Odyssey (dummy coded)
        - White (0)
        - Black or African American (1)
        - American Indian or Alaska Native (2)
        - Asian or Pacific Islander (3)
        - Any other response (SYSMIS: "System Missing")
- Typical Monthly Income
    - String variable
    - Format: ####.00
    - This will be coded using the following scale:
        - Under $29,999 (0)
        - $30,000-$49,999 (1)
        - $50,000-$74,999 (2)
        - $75,000-$99,999 (3)
        - $100,000-$149,999 (4)
        - $150,000 or More (5)
- Number of Prior FTA in Court Resulting in a Warrant
    - String variables
    - Whole numbers only
- Number of Prior Misdemeanor Convictions
    - String variables
    - Whole numbers only
- Number of Prior Felony Convictions
    - String variables
    - Whole numbers only
- Number of Prior DWI Arrests
    - String variables
    - Whole numbers only
- Number of Prior DWI Convictions
    - String variables
    - Whole numbers only
- How Many People Living with Defendant
    - String variables
    - Whole numbers only
- Recommendation from SMART PRAXIS Guidelines
    - Administrative (0)
    - Standard (1)
    - Enhanced (2)
    - Intensive (3)
    - DWI (4)
- Veteran or Active Military
    - No (0)
    - Yes (1)

        - Any other response (SYSMIS: “System Missing”)
- Homeless
    - Currently Homeless
        - No (0)
        - Yes (1)
        - Any other response (SYSMIS: “System Missing”)
    - Homeless in the Past Year
        - No (0)
        - Yes (1)
        - Any other response (SYSMIS: “System Missing”)
- Length at Current Address
    - String variable
    - In years
    - If less than one year, divide by 12
- Length in the Area (El Paso)
    - String variable
    - In years
    - If less than one year, divide by 12
- Number of Dependents
    - String variable
    - Whole numbers only
- How Much Money Can Be Raised in 24 Hours
    - Format: ####.00
- Posted Bond
    - Posted Cash
        - No (0)
        - Yes (1)
        - Any other response (SYSMIS: “System Missing”)
    - Posted Surety
        - No (0)
        - Yes (1)
        - Any other response (SYSMIS: “System Missing”)
    - Posted PR
        - No (0)
        - Yes (1)
        - Any other response (SYSMIS: “System Missing”)
    - Posted Split (i.e., PR/Surety)
        - No (0)
        - Yes (1)
        - Any other response (SYSMIS: “System Missing”)
    - Cash/Surety Amount
        - String variable
        - Format: ####.00
    - PR Amount
        - String variable
        - Format: ####.00

        - Most Serious Financial Bond
            - PR (0)
            - Cash/Surety (1)
- Did the magistrate judge follow recommended PRAXIS guidelines?
        - No (0)
        - Yes (1)
        - Any other response (SYSMIS: "System Missing")
- Supervision Conditions Placed on Defendant
    - Only answered if defendant has PR or split bond
    - Copy/pasted from bond order
    - Separate each condition with semi-colon (;)
- Mental Health Flag
    - No (0)
    - Yes (1)
    - Any other response (SYSMIS: "System Missing")
- Release Date
    - Format: MM/DD/YYYY
- Case Outcome***
    - Failure to Appear (FTA)
        - No (0)
        - Yes (1)
        - Any other response (SYSMIS: "System Missing")
    - Failure to Comply (FTC)
        - No (0)
        - Yes (1)
        - Any other response (SYSMIS: "System Missing")
- New Arrest Pending Trial***
    - Non-violent
        - No (0)
        - Yes (1)
        - Any other response (SYSMIS: "System Missing")
    - Violent
        - No (0)
        - Yes (1)
        - Any other response (SYSMIS: "System Missing")
- Date of Recidivism (if any)
    - String variable
    - MM/DD/YYYY
- Pretrial Success***
    - No (0)
    - Yes (1)
    - Any other response (SYSMIS: "System Missing")
- Statistical Closure Date (as indicated by Odyssey)
    - String variable
    - MM/DD/YYYY

Vita

Chelsea Queen is a Legal Psychology doctoral student at The University of Texas at El Paso. She earned her Bachelor of Science from University of Oregon in Eugene, Oregon in 2017. Her primary research interests include understanding and assessing pretrial decision-making, pretrial policy reform, and the social stigma surrounding correctional policy. Ms. Queen has previously worked with Cascadia Behavioral Healthcare in Portland, Oregon as a Treatment Specialist II for individuals with Traumatic Brain Injuries (TBI) and co-occurring substance-abuse and/or mental health issues under the Psychiatric Security Review Board. Additionally, Ms. Queen has worked with Mental Health Association of San Mateo County in Redwood City, California as a Housing Case Manager for individuals engaged in County subsidized housing.

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