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Developing A Risk Assessment Instrument For Immigration Cases Under Federal Supervision

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DEVELOPING A RISK ASSESSMENT INSTRUMENT FOR IMMIGRATION CASES

UNDER FEDERAL SUPERVISION

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Dedication

To my small, but big in heart family.

DEVELOPING A RISK ASSESSMENT INSTRUMENT FOR IMMIGRATION CASES

UNDER FEDERAL SUPERVISION

by

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Introduction

The illegal immigration flow into the United States continues to be one of the most volatile subjects when it comes to border security. The southwest border which has nine sectors: Big Bend, Del Rio, El Centro, El Paso, Laredo, Rio Grande Valley, Tucson, San Diego, and Yuma, has the most registered encounters and apprehensions since the 1970's. Apprehensions in the southwest border have fluctuated throughout the years impacting the U.S. border security and other national security aspects. Since 2017 the number of encounters and apprehensions has rapidly increased, reaching a total of 851,508 apprehensions in 2019 (U.S. Customs and Border Protection, FY 1960-2020) of undocumented individuals attempting to cross into the United States.

In 2020, the number of apprehensions for illegal entry into the United States were dramatically diminished to 458, 088. In March 2020, during the initial stages of the COVID-19 pandemic, in an effort to halt the spread of the virus into the United States, the Trump Administration closed the border indefinitely by implementing Title 42 under the 1944 Public Health Service Act (Chisti, 2022). The U.S. health law Section 256 of the U.S. Code Title 42 allows the Centers for Disease Control and Prevention (CDC) director to "prohibit the introduction into the United States of individuals when there is a serious danger of the introduction of a communicable disease" (American Immigration Council, 2022). Under Title 42, any individual attempting to illegally enter or seeking asylum into the United States was to be removed to their country of origin without further prosecution in order to mitigate the transmission of COVID-19 within the United States. The deployment of this policy mandated Customs and Border Protection (CBP) to "catch and release" those individuals attempting to enter into the U.S., decreasing the number of illegal entry apprehensions.

Conversely, the number of legal admissions into the United States through a refugee program or asylum claims was severely impacted by Title 42. In 2020, President Trump set the refugee ceiling for Fiscal Year 2021 to only 15, 000 applications. In 2021, the number of affirmative asylum filings decreased by 33% compared to the 93,518 applications in 2020, and the 97,270 applications in 2019 (Office of Immigration Statistics, 2021) Affirmative asylum claims are referred to the U.S. Citizenship and Immigration Services (USCIS) and granted by the Department of Homeland Security (DHS). Defensive asylum cases were equally impacted during this period. Only a total of 85, 537 applications were received in 2021 compared to the 214, 490 applications received in 2019 (Office of Immigration Statistics, 2021) Defensive asylum claims are granted by the Department of Justice (DOJ) before an EOIR (Executive Office for Immigration Review) immigration judge.

In January 2021, the Biden Administration took office and issued Executive Order No. 13768 (2021) to postpone removals and deportations from the United States for one hundred days, in order to employ the limited resources to alleviate the impact caused by COVID-19. In his executive order, Biden acknowledged the significant operational challenges confronting the global health crisis and the need to employ resources to secure the border. The order allocated available funds to rebuild effective asylum procedures, and simultaneously prioritized the response to threats to national security, public safety, and border security (U.S. Department of Homeland Security, 2021). In addition to this order, in February 2021, President Biden issued Executive Order No. 14013 which aimed at rebuilding, expanding, and improving the U.S. Refugee Admissions Program (Office of Immigration Statistics, 2021)

Consequently, under these directives, the Department of Homeland Security (DHS) developed a removal/deportation criteria to ensure coverage in three sectors:

> *(1)* National security: Individuals who have engaged in or are suspected of terrorism or espionage, or whose apprehension, arrest and/or custody is otherwise necessary to protect the national security of the U.S.; (2) Border security: Individuals apprehended at the border or ports of entry while attempting to unlawfully enter the U.S. on or after November 1, 2020, or who were not physically present in the U.S. before November 1, 2020; (3) Public safety: Individuals incarcerated within federal, state, and local prisons and of an "aggravated felony" and are determined to pose a threat to public safety (U.S. Department of Homeland Security, 2021).

The DHS prioritized those cases meeting the criteria to be removed/deported from the U.S. by the U.S. Immigration and Customs Enforcement (ICE). Cases not meeting the removal or deportation criteria were screened for asylum eligibility and referred to the USCIS for further review. Moreover, if ICE determined the case not to be a threat to public safety or to be a flight risk, the individual was released on immigration parole into the U.S. while the case was reviewed by USCIS. Subsequently, the USCIS reviewed the referred cases and, if the claim of fear of persecution or torture in the country of origin was found to be credible, then affirmative or defensive asylum (before an EOIR immigration judge) was granted, and the individual was allowed to remain in the United States.

In summary, whereas the implementation of Title 42 and the closure of the border under the Trump Administration may have temporarily mitigated the illegal entry into the United States, Biden's subsequent executive order, intended to promote legal entry into the United States, has created a plethora of issues for federal agencies outside the executive cabinet departments, such as the U.S. Courts and the U.S. Probation Office under the judicial branch.

Non-citizen individuals criminally convicted of immigration-related offenses in a U.S. Court are released within the U.S. under these directives. Whereas non-citizen individuals are allowed to file for asylum claims and released on bond if eligible, they must be supervised and report to an immigration officer while undergoing immigration proceedings. In the same manner, if a non-citizen is not removed or deported from the U.S., they must report to the U.S. Probation Office for supervision. These circumstances create an overlap in two different governmental systems, confusion amongst the non-citizen population, and a significant over-supervision and resource expenditures.

Criminal prosecution of undocumented U.S. citizens

Per the Immigration and Nationality Act (INA; 8 U.S.C. § 1101), federal courts have jurisdiction over criminal immigration offenses (Motivans, 2019). Individuals are subject to criminal prosecution if illegal entry/reentry into the U.S, failing to depart from the U.S. when ordered, overstaying with a temporary permit, bringing in or harboring undocumented non-U.S. citizens occurs.

The U.S. Probation Office manages the United States federal supervision system. Under Title 18 U.S.C. §3601 of the U.S. Federal Criminal Code and Rules, an individual who is criminally prosecuted and sentenced is to be supervised by the U.S. Probation Office. In the federal system there are two types of supervision: probation which is a period of supervision without the imposition of an incarceration term (Cohen et al., 2018), and supervised release which refers to term of supervision after a period of incarceration. Whether receiving probation or supervised release, individuals under supervision must comply with certain conditions imposed by the judge on the sentencing judgment.

The Administrative Office of the United States Courts (2018) states that the conditions of supervision set the parameters of supervision as they define how supervision is to be carried. Immigration-related offenses that are sentenced to a term of probation or supervised release typically have immigration-related special conditions included in the judgment. For example,

> If ordered deported from the United States, the defendant must remain outside the United States. If the defendant re-enters the United States, he or she must report to the nearest probation office within 72 hours of his or her return. If release from confinement or not deported, the defendant must report to the nearest probation office within 72 hours (The Administrative Office of the United States Courts, 2016)

This special condition is most commonly imposed on immigration-related cases for a specific reason. In most immigration-related offenses, an immigration detainer is lodged against the non-citizen undergoing criminal proceedings and it is honored upon completion of the custody sentence imposed. Due to the legal immigration status of these cases, it is expected that the majority are highly likely to be removed or deported from the United States to their country of origin by the Immigration and Customs Enforcement (ICE). Sentencing judgments in immigration-related cases where removal or deportation is the likely outcome are phrased with the "non-reporting" language. The term non-reporting is utilized to address the removal or deportation. If the convicted individual is indeed removed or deported from the United States, then the individual will not have to report to the U.S. Probation Office for the term of probation or supervision imposed. Even though the sentencing judgment includes the "non-reporting" language in immigration-related cases, if the individual is not removed or deported from the United States upon being released from federal custody, the individual must report to the nearest U.S. Probation Office for supervision upon releasing from custody. Individuals are admonished by the court at the time of their sentencing about the special condition in their judgments and sign such condition after the sentence acknowledging the same.

Prior to the COVID-19 pandemic, the U.S. Probation Office placed confirmed, removed, or deported immigration-related cases on an inactive-supervision status. If, subsequent to the removal or deportation, an individual re-entered the U.S., then the individual was prosecuted with a new charge and, if the term of probation or supervised release remained current, the case was to be revoked and processed along with the new charge. However, due to Exec. Order No. 13768 (2021) and other immigration initiatives, removals and deportations were to be halted for one hundred days to devote the available resources to secure the border more effectively. Although securing the borders is definitely a national security priority, the initiatives taken severely impacted the U.S. Probation Office. Following these directives caused ICE to lift all immigration detainers on criminally convicted immigration-related cases that did not meet the priority criteria to be removed or deported. As such, these individuals were to be released on immigration supervision within the U.S, pending a civil immigration disposition.

The drop in immigration detainers severely impacted the caseload of supervision officers in many aspects of supervision. Under Exec. Order No. 13768 (2021), ICE could lift immigration detainers at any point up to ten days prior to federal custody release without notice. In some cases, individuals under supervision were released in the middle of the night without any means of transportation or communication (U.S. Probation Office, 2021). Some other individuals were released in a different state without having proper living arrangements. Additionally, ICE could take custody of some cases and later determine bond eligibility. Some cases were known to be released from ICE custody after months of detention (American Civil Liberties Union, 2021)

These circumstances triggered a high rate of individuals not reporting to the U.S. Probation Office for supervision. In March 2021, in an effort to alleviate the impact of Exec. Order No. 13768 (2021), the U.S. Probation Office for the Western District of Texas, established an Immigration Task Force responsible for identifying and locating cases in need of supervision. Locating these individuals became a consuming and challenging task and raised several questions for the U.S. Probation Office. For instance, why are individuals under supervision not reporting as they should? Is there any initiative-taking solution that can be implemented? Can failure to report be predicted? Figure 1 shows the sequence of the post-conviction process and possible release outcomes.

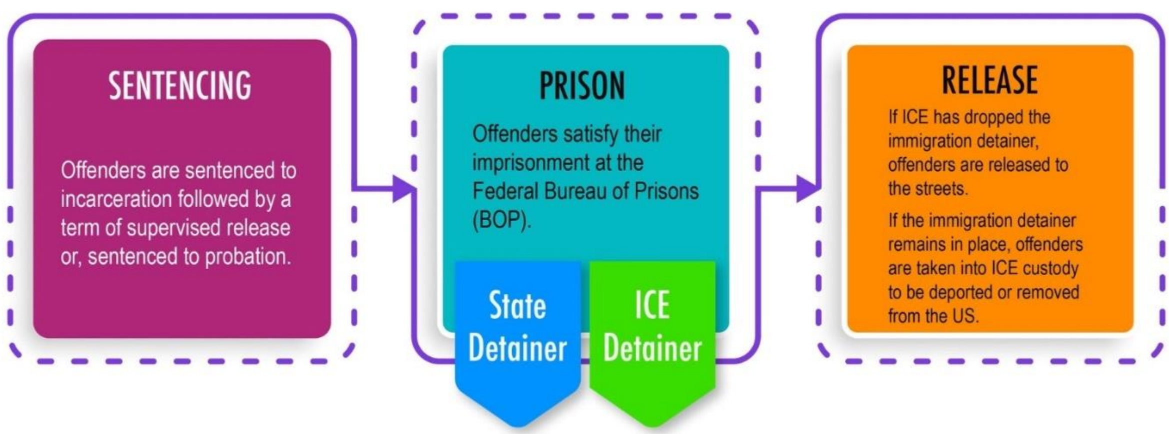

Figure 1: *Post-conviction process and possible release outcomes*

Challenges to supervising the undocumented population

One principle of supervision is the individualized outcome-based plan of action to monitor compliance with the conditions of supervision and intervene as necessary to address any identified risks (Office of Probation and Pretrial Services, 2003). The supervision of individuals involves ongoing investigations, assessments, planning, implementation, and evaluation. Developing individualized supervision plans for immigration-related cases is an extremely complicated task due to the nature of the immigration population. For example, a portion of these individuals do not have any ties in the United States, which could cause the individual under supervision to be displaced, which in turn could translate to failure to report for supervision. If a non-citizen individual under supervision is released from custody and is estranged from family members or friends, this individual may be more interested in finding a place to stay, rather than reporting for supervision.

In order to achieve tailored supervision plans, the federal supervision system uses tools to assist in identifying those individuals who are at risk of non-compliant behavior during supervision. In general, U.S. citizens are assessed upon commencement of supervision. However, because non-citizens individuals under supervision typically face removal or deportation from the U.S., these cases are not assessed, as supervision is likely to not be activated. Moreover, even if non-citizen individuals were to report for supervision, due to the non-legal status of immigration-related cases, the majority of these individuals are not eligible for resources that would generally be available for U.S. citizens, which becomes problematic for probation officers trying to address their criminogenic needs.

Risk assessment instruments

Risk assessment has evolved over time, from clinical judgment to actuarial risk assessment tools (Cohen et al., 2018). Clinical methods are not often used anymore because the decisions are not easily observable and often difficult to replicate (Gottfredson, 2006). Actuarial methods that are based on statistical algorithms consistently outperform models based on clinical judgment, in terms of accuracy (Gottfredson, 2006). Several institutions such as graduate school admissions, insurance companies, the criminal justice system, and hospitals have developed risk assessment instruments that have assisted in the prediction of risk and decision making. Actuarial methods that are based on statistical algorithms consistently outperform models based on clinical judgment in terms of accuracy (Gottfredson, 2006). The following risk assessment instruments have been known to be utilized by federal agencies at different points in the criminal justice process to assess and predict different types of criminal behavior (e.g., recidivism, failure to appear to a court proceeding, flight risk, and public safety).

The ICE Risk Classification Assessment (RCA) is used to assess immigration cases under ICE custody undergoing civil immigration proceedings. The RCA is used to determine bond eligibility and custody classification for ICE detainees. The RCA has two outcome variables: public safety and flight risk. Detainees are assessed based on characteristics such as age, gender, country of origin, country of citizenship, physical illness, mental health illness, disabilities, whether the detainee is a victim of persecution or torture, a victim of sexual abuse, violent crime, or human trafficking, criminal records checks, criminal supervision history, family history, substance abuse history, legal representation, and history of absconding through interviews with the detainees. This information is obtained from background checks and self-report (Nofferi and Koulish, 2014). The RCA then separates detainees into three distinct categories: high, medium, and low risk for public safety and flight risk based on the detainees' scored points. If a detainee is eligible for release, the RCA determines the bond amount and the level of supervision the detainee should be placed on. If the detainee is not eligible for bond, the RCA determines custody classification.

Similarly, the Federal Probation Post-Conviction Risk Assessment (PCRA) is designed to evaluate individuals under supervision regarding criminogenic needs that influence risk behaviors, to assign the individual under supervision to an appropriate level of supervision and to predict recidivism. The evaluation of these criminogenic needs is required to generate tailored case plans (risk-need-responsivity RNR model). The PCRA is administered through the scoring of information obtained from two sources: the probation officer and the individual under supervision self-report. The probation officer scores six domains which measure criminal history, age, education history, employment history, substance abuse history, employment history, marital status, family and peer support, and the individual's attitude towards supervision. Probation officers obtain information through intake interviews, pre-sentence investigation reports, sentencing judgments, and custody discharge summaries (Cohen et al., 2018). Individuals under supervision complete a questionnaire used to identify criminal thinking styles. Although criminal thinking styles do not have an impact on risk level classification, these allow the officers to have a general idea of an individual's criminal thinking patterns (Cohen et al., 2018). Subsequently, the PCRA calculates a risk score and classifies individuals into four risk categories: low (0-5), low/moderate (6-9), moderate (10-12), and high (13 or above). The PCRA aims to reduce recidivism rates by allowing officers to customize supervision to the individuals' risk category (Administrative Office of the United States Courts, 2018).

The Federal Bureau of Prisons (BOP) also uses actuarial risk assessment tools to assign inmates into risk categories. A recent instrument was developed by the Department of Justice (DOJ) as a result of passage of the First Step Act (FSA) of 2018: the Prisoner Assessment Tool Targeting Estimated Risk and Needs (PATTERN) (Garret, 2020). PATTERN classifies current prisoners into four risk categories of future recidivism: high, medium, low, or minimal. (Carson, Mueller, & Lauren, 2021; Garret, 2020). PATTERN not only allows the BOP to predict recidivism, but also helps determine which prisoners should be placed in programs to allow them to earn time credits that increase the eligibility for prerelease custody (e.g., home confinement or a Residential Reentry Center; James, 2019). Nevertheless, current research suggests there is no further analysis as to the type of predictive indicators are being considered in the administration of this assessment and consider that this assessment should not be implemented as the scores derived from the assessment may be unreliable.

Lastly, the U.S. Pretrial Services Office developed and implemented the Pretrial Services Risk Assessment (PTRA) to control the costs of pretrial detention in the federal system (Cadigan and Lowenkamp, 2018). The PTRA assists officers in the prediction of failure-to-appear (FTA), new criminal arrest (NCA), and technical violations (TV) to provide the court with a recommendation on a defendant's likelihood to appear in court for future hearings. The PTRA is comprised of two domains in which a total of eleven items are scored and a total of nine items are unscored. The unscored items are only rated but not counted in the total overall risk score. (Cadigan and Lowenkamp, 2018). The PTRA then adds all points for each of the scored items to create a total risk score and classifies the defendant into five risk categories: 0-4 (Category I), 5-6 (Category II), 7-8 (Category III), 9-10 (Category IV), eleven and more (Category V) (Cadigan and Lowenkamp, 2018).

In summary, research has shown risk assessment instruments can improve decision-making concerning the risk of future criminal and/or non-compliant behavior (Gottfredson, 2006). As mentioned, federal agencies across the criminal justice system have opted to use risk assessments to predict future criminal behavior such as recidivism, failure to appear, or flight risk and implement proactive measures consistent with the assessment results to achieve better case management.

Indicators found to be predictive of failure to report

The choice of indicator variables for the present study was influenced by prior empirical and theoretical research on existing risk assessment instruments implemented in federal agencies.

The use of risk assessment tools such as the Pretrial Risk Assessment (PTRA), the Immigration and Customs Enforcement Risk Classification Assessment (RCA), the Federal Probation Post-Conviction Risk Assessment (PCRA), and the Federal Bureau Prisoner Assessment Tool Targeting Estimated Risk and Needs (PATTERN) were used as guidance to select the indicators for this study. Prior research has found the following indicators to be useful in the prediction of future criminal behavior.

Citizenship

There are several indicators being utilized in risk assessments to predict future criminal behavior. In immigration-related offenses, citizenship has been found to be indicative of flight risk and failure to appear (FTA) before the court. For instance, the Pretrial Services Risk Assessment (PTRA) utilizes multiple domains such as criminal history, employment, residence, education, substance abuse, and citizenship as indicators to determine if a defendant is eligible to be released on bond or to remain in custody. Lacking legal immigration status and having ties to a foreign country increases flight and FTA risk, which often results in bond being denied (Office of Probation and Pretrial Services, 2013).

Criminal history

Criminal history is perhaps the strongest predictor of future criminal behavior (Office of Probation and Pretrial Services, 2013). Most risk assessment tools utilize criminal history to classify offenders into risk categories and to address behavioral issues linked to past criminal history. For example, ICE'S RCA determines public safety risk category based on prior criminal history. The RCA considers whether the detainee has any outstanding warrants, pending criminal dispositions, history of bond breaches, supervision violations/revocations, or if the detainee has present or prior gang affiliations/associations. The severity of the charges and convictions is used to determine whether a detainee poses a significant threat to the public safety or if the detainee qualifies for release under any type of alternative supervision, such as GPS electronic monitoring (Nofferi, 2014). Extensive criminal history increases the likelihood of future criminal behavior

Type of offense

According to Harer (2001), the type of current offense is predictive of the type of future offense. Moreover, this type of offense is often utilized in risk assessments to identify who is likely to be reconvicted of a similar offense (Craig & Beech, 2010). In immigration-related offenses, the type of offense could include the unauthorized re-entry into the United States after being removed or deported.

Residence history

The Pretrial Services Office and ICE risk assessment instruments include history as a predictor for FTA. The flight risk assessment portion of the RCA collects family history, which includes information regarding the detainee's spouse or children immigration status, any other non-U.S. citizen family member currently residing in the U.S., and if the detainee has any U.S. citizen relative to determine a flight risk category. Correspondingly, the PTRA takes residence history into account as the lack of ties to the area may relate to high risk of FTA (Office of Probation and Pretrial Services, 2003). Additionally, the social domain in the PCRA addresses the presence of family instability as indicative for the offender being at risk of being displaced (Cohen et al., 2018). Residence history could be important in predicting FTA in immigration-related cases, as the lack of/or unstable residence could be one of the main reasons offenders fail to report for supervision.

Employment history

A study conducted by Luallen, Radakrishnan, and Rhodes (2016) found that unemployed offenders tend to be arrested while under supervision. Similarly, the ICE's RCA flight risk assessment portion considers whether the detainee has authorization to work in the United States. Correspondingly, the PCRA assesses the individual under supervision current employment status and work history over the past twelve months. Employment history reflects the ability of an individual to be responsible and reliable, which could increase the likelihood of an offender reporting for supervision. The PTRA emphasizes that employment is vital in risk assessment because it provides individuals with a legitimate means to meet financial needs and obligations (Office of Probation and Pretrial Services, 2013). Luallen et al. (2016) found that employed offenders are less likely to be re-arrested while under supervision.

Age & Sex/Gender

Age and sex/gender are the most common indicators utilized to predict future criminal behavior. Age has been found to be predictive of criminal behavior. Older offenders tend to be less involved in illicit activities (Austin, 2003). Additionally, sex/gender has also been found to be a strong predictive of criminal behavior. Research suggests that females are less likely to recidivate, while males are more prone to re-offending (Austin, 2003).

Sentence length

Austin (2003) found sentence length to have almost no predictive capability for future criminal behavior. However, it could be argued that offenders serving a long sentence could face re-integration issues, such as unemployment, lack of a stable residence, or family support, which could lead to failure to report for supervision. Therefore, it will be used as a predictor in this study.

Existing risk assessments vs proposed assessment

A variety of risk assessment tools are used by agencies and organizations to assist them in making decisions about offenders. According to Helmus (2017), risk assessment is a prognostic task designed to predict the likelihood of an outcome of interest. Kroner, Morrison, and Lowder (2020) additionally argue that deriving meaning from an assessment score or category is at the core of conducting assessments. However, not all risk assessment instruments are calibrated to accurately assess what is intended to be assessed or have been externally validated by researchers.

One of the concerns highlighted by Noefferi and Koulish (2014) in their evaluation of the RCA is the structural differences between immigration enforcement and the criminal justice system. Characteristics of the offender helpful to the criminal context may have little predictive value in the immigration context (Nofferi and Koulish, 2014). In addition to this, immigration law has less moderating procedural checks than the criminal justice system (Nofferi and Koulish, 2014). For instance, mandatory immigration detention laws prevent detainees from being assessed for bond eligibility because a risk score will not override the mandatory detention. If the DHS determines a detainee is subject to mandatory detention, then the RCA is not conducted. Further, validation of the RCA was not transparent and should be tailored towards the immigration population. Nofferi and Koulish (2014) recommended that the RCA be externally validated by criminal researchers.

Unlike the RCA, the PCRA'S predictive ability has been evaluated by external researchers, who have found the instrument to be valid and reliable in classifying offenders into risk categories and predicting recidivism on violent offenses. However, the PCRA is not designed to predict future criminal behavior in immigration offenses. In fact, Luallen, Radakrishnan, and Rhodes (2016) highlight how PCRA provides less utility in predicting uncommon offenses, such as immigration offenses compared to the predictive accuracy the instrument provides on drug offenses, violent offenses, and property offenses. Furthermore, as discussed in previous sections of this paper, the federal supervision system is typically not applied to immigration cases. Individuals convicted of an immigration offense are generally removed or deported from the United States upon their release from federal custody.

Garret and Stevenson (2020) have argued that the DOJ's prisoner assessment (PATTERN) should be openly validated so that independent researchers can assess its validity. Several inconsistencies were found in reviewing the assessment. For instance, there is no available information detailing how the thresholds for risk categories were set. This is problematic because this could potentially classify inmates in the wrong risk level and deny inmates the opportunity to be considered for early release. Garret and Stevenson (2020) emphasized how policy decisions have a tremendous impact when it comes to setting the risk thresholds. Risk thresholds for risk categories should have a clearly defined rationale and should be transparent and supported. Another concern raised by Garret and Stevenson (2020) in their evaluation was the differences in the precision of measurement in the "general recidivism" outcome variable. The latter variable is designed to predict minor offenses (e.g., vandalism) and technical violations (e.g., failure to report for supervision). Whereas, the second outcome variable "violent recidivism" clearly defines violent crimes, offenses for general recidivism could range from jaywalking to a DWI, and yet these would still fall under the same risk category.

A new instrument is needed to address these limitations in existing risk assessment instruments. Such an instrument is needed for the several reasons. First, the new tool was specifically designed for offenders convicted of immigration-related offenses. Assessment instruments that are not tested and validated on immigration offenders should not be used to predict non-compliant behavior in this population. Second, currently there is not a risk assessment in place that assesses whether an offender will fail to report in the post-conviction phase for immigration-related cases. Whereas it could be argued that the purpose of the PTRA is to predict FTA, this assessment is administered in the pretrial phase of the criminal process and is utilized to determine bond eligibility. Similarly, the RCA assesses flight risk; however, like the PTRA, the RCA is also utilized to determine bond eligibility. In the post-conviction phase, there is no bond to be determined. The proposed tool was exclusively designed to predict failure to report on immigration-related cases as these possess a specific base of FTA, which are officially recorded as convictions (Craig and Beech, 2010). This means that the risk scores of this instrument have validity for the specific population it is validated on. Lastly, the current study had the opportunity to validate this tool on the population for which they are to be used. This tool was validated on convicted immigration-related felony cases that were processed in the southwest border. Although the other tools were or might have been validated on the El Paso population, these were not specifically designed to predict FTA in the post-conviction phase.

Method

Sample

The dataset for this study consisted of four hundred cases processed in the divisional offices in Alpine, Austin, Del Rio, El Paso, Midland/Odessa, Pecos, San Antonio, and Waco of the U.S. Probation Office for the Western District of Texas. It was initially estimated that data on approximately 1,000 cases would be obtained on cases processed in the El Paso division. However, a preliminary eligibility screening of cases yielded too small a sample from the El Paso division. Therefore, the pool of potential cases was expanded across the Western District of Texas.

A total of 3,000 cases district-wide were screened for eligibility. The primary selection criteria were that the offender must not have had legal documentation to remain in the United States, the offender must have been convicted of an immigration-related offense between January 2019 and December 2021, and an immigration detainer on the offender must have been lifted by ICE after they were released from federal custody for the convicted offense. Individuals convicted of an immigration-related offense who were legally in the United States through a family-based visa such as the U.S. Lawful Permanent Resident (LPR) at the time of the offense were included in this study. The resulting dataset included 400 cases.

Indicators

The data for this study was extracted from the internal electronic database known as Pretrial Services Automated Track System (PACTS), and from the presentence investigation reports (PSRs) which are stored in PACTS. Based on prior research, eight indicators were included as predictors of failure to report. Table 1 shows 1) the indicators selected for inclusion in the development of the risk assessment tool, 2) the source of data regarding each indicator and

3) the part of the pre-sentence process during which the indicator is measured. Figure 2 shows an overview of the criminal process from the arrest to sentencing.

Table 1: Indicators included in the development of the risk assessment instrument

Indicator	Source of Information	Part in the process where the indicator is obtained
Sex, age, and citizenship	Probation and Pretrial Automated Track System; Presentence Investigation Report	Arrest
Sentence length	Probation and Pretrial Automated Track System	Sentencing
Type of offense	Probation and Pretrial Automated Track System; Presentence Investigation Report	Arrest and prosecution
Criminal history	Probation and Pretrial Automated Track System; Presentence Investigation Report	Arrest; Pretrial Services; Pre-sentence
Prior residence in the US/Family ties in the US	Probation and Pretrial Automated Track System; Presentence Investigation Report	Arrest; Pre-sentence
Employment history	Probation and Pretrial Automated Track System; Presentence Investigation Report	Pre-sentence

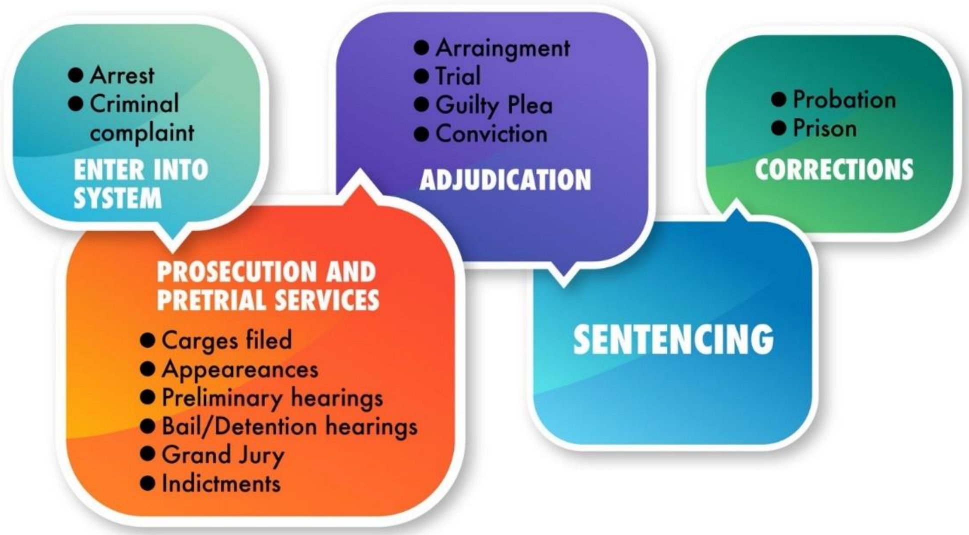

Figure 2: *Overview of the United States criminal process*

The data utilized for this risk assessment instrument is collected from multiple agencies at multiple points in time throughout the criminal process. Demographic characteristics of the offender, such as sex, date of birth, and citizenship are initially collected by the arresting agency at the moment of the arrest. The arrest is then referred to the U.S. Attorney's Office for review and prosecution. If prosecution is not declined, then a charge is filed, the arrest turns into a case and enters the court process. Subsequently, if the defendant decides to plead guilty, a guilty-plea hearing is held, and the defendant is convicted. At this point, a PSR is ordered by the court and a probation officer is assigned to the case. The PSR is prepared by the probation officers to provide the federal courts with a collection of comprehensive information concerning the defendant's life (e.g., demographics, criminal history, mental health history, employment history, substance abuse history, residence and financial history), apply sentencing guidelines, and provide recommendations for sentencing based on the offense and the defendant's history. The information included in the PSR is obtained through interviews with the defendants, criminal records, and other government documents. This information is corroborated through collateral contact and by cross-referencing existent records against other law enforcement databases.

Some of the indicators, residence and employment history are obtained through self-report by the defendants at the time of the presentence interview. Although self-reporting could lead to concealing information relevant to the case and could potentially create validity issues, the defendants are admonished by a U.S. Magistrate or District Judge at the guilty plea hearing about the repercussions of providing dishonest information to the probation officer (e.g., losing a plea agreement, or a penalty increase). By advising the defendants about the potential consequences of concealing information, the likelihood of obtaining accurate information increases. Nonetheless, in some instances, defendants do omit information.

The information obtained for the preparation of PSRs is manually recorded into the Presentence Investigation Form (Prob 1). Upon completion of the interview, this form is uploaded and entered into PACTS. PSR interviews should be conducted by the probation officer within seven days subsequent to the guilty plea and should last between one or two hours, depending on the case (e.g., offender has a lengthy mental health history, or family issues). Although this protocol is standard for conducting pre-sentence interviews, a departure from the standard interviewing procedure occurs when probation officers face restrictions placed by the defense counsel. These restrictions restrain probation officers from obtaining information about a specific subject, for instance, obtaining the offender's signature for medical, employment, or educational waivers, or asking questions about the offense conduct, criminal history, or relevant conduct. Moreover, in some cases, the defense attorney requests to be present during the presentence interview. Additionally, although the questions in the Prob 1 form are standardized, the officers' interviewing style also varies. Inconsistencies across the measurement of the relevant indicators included in this study are addressed in the analysis.

In the present study, demographical data was primarily collected by the arresting agencies and is entered into the PACTS database by the U.S. Pretrial Services Office when prosecution proceeds, and the case enters the court system. The U.S. Probation Office in the Western District of Texas shares the PACTS with the U.S. Pretrial Services Office, as such, the information initially collected and entered into PACTS by the U.S. Pretrial Services Office is cross-referenced with the investigative information obtained by the U.S. Probation Office. The following sections will introduce and describe in depth the indicators selected for the development of this assessment instrument and their unit of measurement.

Sex and age

Sex and age are found in PACTS under the offender's general and demographics tab. Sex and age are obtained at the time of the arrest by the arresting agency (e.g., Customs and Border Protection (CBP) or ICE) through records checks, interviews, and any foreign document the individual possess at the time of the arrest. Sex was coded as male/female (Male = 1, Female = 0). Date of birth was converted into years of age to avoid identifying the offender.

Citizenship

Country of origin is found in the PSR in PACTS under the identifying data section. Citizenship is obtained at the time of the arrest by the arresting agency (e.g., CBP or ICE) through records checks, interviews, and any foreign document the individual possesses at the time of the arrest. Due to the variety in citizenships, citizenship was coded into three categories: Mexico =1, Central/South American, and Caribbean = 2, Other = 3.

Type of offense

Type of offense is found in PACTS in the PSR under the offender's original sentence summary tab. The U.S. Federal Criminal Code and Rules determines the type of offense and the imprisonment range. The imprisonment range is utilized to determine the felony classification assigned to each particular offense. Felony immigration-related offenses under Title 18, Chapter 75: Passports and Visas and Title 8, Chapter 12: Aliens and Nationality were utilized in this study. Table 2 shows the U.S. criminal code title and the offense pertaining to the title.

Table 2: United States Federal Criminal Code title and offense pertaining to the title

U.S.C. Title	***Offense***
18 U.S.C. §1542	False Statement in Application and Use of Passport
18 U.S.C. §1543	Forgery or False Use of Passport
18 U.S.C. §1544	Misuse of Passport
18 U.S.C. §1546(a)	Fraud and Misuse of Visas, Permits, and Other Documents
18 U.S.C. §1001(a)(2)	False Statement
8 U.S.C. §1323	Unlawful Bringing Aliens into the United States
8 U.S.C. §1324	Bringing in and Harboring Certain Aliens
8 U.S.C. §1326 (a) and (b)(1)	Illegal Re-Entry

Cases under 8 U.S.C. § 1323: Unlawful Bringing Aliens into the United States and 8 U.S.C. § 1324: Bringing and Harboring Certain Aliens, were only considered for the analysis if the offender committed the offense while legally in the United States under a U.S. Lawful Permanent Resident (LPR) visa (Green-Card Holder) and faced removal or deportation proceedings subsequent to the conviction. For this study, only the instant (most recent) offense is considered. The attributes of this indicator are ordinal. Offense type was categorized and coded as follows in alignment with the imprisonment ranges dictated by the U.S. Federal Criminal

Code and rules, from more severe felony classification to less severe felony classification: Class B = 1, Class C = 2, Class D = 3, and Class E = 4. Felony classifications are found in the PSR under the offense section. No Class A felonies were found in the sample. Penalty enhancements are commonly awarded to repeated offenders. When these are applied, the felony classifications result in the increase of the felony class which also increases the penalty range for the offense. For example, Class D felonies may turn into Class C felonies after the enhancement. Table 3 reflects the felony classification and the imprisonment range pertaining to the classification.

Table 3: Felony classification and imprisonment range

Felony Classification	***Imprisonment range***
Class A	Life imprisonment or death penalty
Class B	25 years or more
Class C	Less than 25 years imprisonment but more than 10 years imprisonment
Class D	Less than 10 years imprisonment but more than 5 years imprisonment
Class E	Less than 5 years imprisonment but more than 1 year imprisonment

Sentence length

Sentence length is found in PACTS under the offender's original sentence summary tab. Sentence length is imposed at the time of the sentencing by the judge. A judgement document is produced and uploaded into PACTS by the courts. Sentence length is divided into two categories: custody time imposed, and term of supervised release or probation imposed. These are recorded by the number of days an offender is sentenced to custody and the number of months an offender is imposed a term of supervised release or probation (e.g., 120 days custody, followed by 36 months of supervised release or probation).

Criminal history

Criminal history is derived from data sources outside of PACTS (Luallen et al., 2016). Criminal history is obtained from the National Crime Information Center (NCIC), where a criminal records check, commonly known as a rap sheet, is extracted by a probation officer/assistant from the Access to Law Enforcement System (ATLAS) computerized database which operates under shared management between the Federal Bureau of Investigation (FBI) and other state and federal criminal justice agencies. Once the NCIC is retrieved, the cycles (arrests and convictions) on the rap sheet are reviewed and records requests are submitted to the pertaining arresting agencies/courts regarding the offense/arrest/conviction to obtain supporting documentation. This information is then utilized by the probation officers to determine the criminal history category. Criminal history category is determined by the number of criminal history points scored for each prior offense. Probation officers calculate criminal history through a point system in which points are added to the offenders' prior convictions. In other words, the more criminal convictions the higher criminal history points will be. Criminal history is found in the PSR under Part B: the defendant's criminal history section. The total criminal history points were utilized in this analysis to measure an offender's criminal history. The attributes of this indicator are numerical. Criminal history scores varied from 1 to 14.

Residence history

Residence history is obtained by the probation officer at the time of the pre-sentence investigation interview with the defendant and is found in the PSR under Part. C: offender characteristics; personal and family data. Residence history was coded into Yes/No categories. If the offender had a history of residing in the U.S. prior to his/her conviction for which he/she is serving a sentence, this was coded as 1; if the offender is a first-time offender, or if the offender did not previously reside in the U.S., this was coded as 0.

Employment history

Employment history is found in the PSR in PACTS under the employment history section and is obtained by the probation officer at the time of the pre-sentence interview. The attributes of this indicator are ordinal. Employment was categorized by the type of job the offender reported. Employment was coded as follows: 1 = unemployed, 2 = manual labor job, 3 = technician job, 4 = professional job, 5 = retail job. A second coding layer was added to record whether the offender sustained employment before the arrest and coded as Y/N; Y = 1, N = 0.

Failure to report

A special condition is imposed on the sentencing judgment for immigration cases. Offenders are instructed to report to the nearest U.S. Probation Office within the first 72 hours of their release from custody should they not be removed or deported from the United States. Failure to report was measured by whether the offender reported within the 72-hour period after being released from custody or did not report. Failure to report was coded as follows: 0 = the offender reported to the U.S. Probation Office for supervised release/probation within the 72-hour period or 1 = the offender did not report to the nearest U.S. Probation Officer for supervised release/probation within the 72-hour period.

Procedures

Data Access Request

In March 2022, a research proposal memorandum requesting access and permission to utilize data from the U.S. Probation Office in the Western District of Texas, was submitted via email to the El Paso Division Assistant Deputy Chief U.S. Probation Officer (ADCUSPO). The memorandum provided a synopsis of the purpose, background, and significance of the research proposal. The memorandum additionally described the eight indicators known to be predictors of failure to report and the type of data that was needed for the development of this instrument. The memorandum was reviewed by the El Paso Division ADCUSPO and was forwarded to the Deputy Chief U.S. Probation Officer (DCUSPO) and the Chief U.S. Probation Officer (CUSPO) for the Western District of Texas, in San Antonio, TX, for further review. In March 2022, the data access request was approved, and a written approval letter was provided to the primary researcher. In October 2022, an additional data request was submitted to the El Paso Division ADCUSPO requesting access and permission to expand the sample pool district-wide to include immigration-related cases from the Alpine, Austin, Del Rio, El Paso, Midland/Odessa, Pecos, San Antonio, and Waco divisions. In November 2022, the request was granted.

Data Extraction

Six (sex, age, type of offense, sentence length, criminal history score, and felony classification) out of the eight indicators selected for this study were identified to meet the criteria for automatic retrieval from PACTS. These indicators were retrieved directly from PACTS by the PACTS administrator into an Excel spreadsheet. The rest of the indicators (employment and residence history) were extracted from the PSRs on a case-by-case basis; data on these indicators were added to the data spreadsheet. To preserve the confidentiality of the offenders' identity, the PACTS numbers utilized to track the cases during data collection were removed upon completion of the data collection. PACTS numbers were replaced by participant numbers ranging from one to four hundred.

Confidentiality of the data

During the data collection period, the Excel spreadsheet was stored on the primary researcher's computer at the U.S. Probation Office. Upon data collection completion, the spreadsheet was submitted to the El Paso Division ADCUSPO for final review and extraction approval. A copy of the password protected spreadsheet was transferred onto an encrypted external USB drive approved by the IT personnel. In order to maintain confidentiality, no personal identifiers (e.g., names, dates of birth, PACTS numbers) were included. Because no identifying information was included in the data set, the data remained anonymous throughout the study. The approved password protected data spreadsheet was transported to the university on an encrypted USB drive where it remained secured throughout the completion of the study. The drive will be returned to the U.S. Probation Office upon after the study has been completed. The U.S. Probation Office expects a report about the study to be shared with them and a copy of the entire thesis will be provided to them by the researchers.

Results

The mean age of the offenders was 36.21(SD= 10.681), the mean days in custody was 242.86 (SD= 265.845), and the mean months in TSR/Probation was M = 26.36 (SD =12.557). The descriptive statistics of the remaining variables are presented in Table 5. In preparation for the analysis, dummy variables were created for three categorical variables (citizenship, felony class, and employment history). For citizenship, two dummy variables were created: Mexican offenders and Central/South American/Caribbean offenders. For the felony class, three dummies were created: B, C, and D. Three dummy variables were created for employment: manual labor, professional, and unemployed. All continuous variables were grand-mean-centered. Missing data were estimated through a single imputation approach. One percent of the data was missing. Missing data were on the following variables: citizenship (n = 1), prior failure to report (n = 1), employment history (n = 27), and employment before arrest (n = 23). Some data were missing for 7% of the offenders in the sample. All analyses were conducted in R; the code can be found in the appendix.

Bootstrapping procedures were utilized in the development of this risk assessment. One hundred samples, each with 400 cases, were randomly selected with replacement. This resulted in some offenders being included in the sample more than once and some others not being selected. Next, a stepwise logistic regression analysis was conducted, with all of the indicators entered as predictors, to determine which variables were the most useful in the risk model. The criterion for variables to be retained in the step-wise regression model was improvement in the Akaike Information Criterion (AIC) of the model. Table 6 provides the mean and standard deviation of the regression coefficients for each predictor across the 100 analyses. Those variables that were retained in 51% or more of the step-wise regression models were included in the risk model. The following variables were included: age, TSR, citizenship (Mexican), Class B felony, and Class C felony met the selection criteria. The coefficients were all negative, indicating that offenders who were older, had spent more time under supervision, were Mexican, and who had a Class B or Class C felony, were less likely to fail to report for supervision than those who were younger, had spent less time under supervision, had an "Other" citizenship (i.e., not Central/South American/Caribbean or Mexican), or who had a Class E felony. Table 7 lists the percentage of step-wise regression models in which each predictor was included.

For each bootstrapped sample, there was a corresponding out-of-the-boot (OOB) sample, resulting in 100 OOB samples. The average sample size was 147.43 (*SD* = 5.914). Because the OOB samples were not used in the development of the risk models, they were utilized to validate the models. Those offenders included in the OOB samples did not appear more than once.

To validate the final risk model, risk scores were calculated. Prior to doing this, the two continuous variables that were retained in the risk model, age and TSR, were transformed into z-scores. Because the coefficients were negative, the z-scores were multiplied by -1 so that a higher risk score indicates greater risk.

As described earlier, two versions of the final risk model were tested. The failure to report regressed on the unweighted risk score comprised the unweighted risk model. The unweighted risk score was calculated as follows:

unweighted risk score=Rev_z_Age+Rev_z_TSR custody-Felony Class B-Felony Class C-Mexican,

wherein the values of the predictors were summed over each case. Unweighted risk scores ranged from -0.531 to -2.57 (*M* = -2.05, *SD* = 1.80).

The weighted model was the regression of failure to report on weighted risk score. The weighted risk score was calculated as follows:

$$\textit{weighted risk score} = (0.0068 \cdot Rev\_z\_Age) + (.0062 \cdot Rev\_z\_TRS\ custody) + (1.7311 \cdot Felony\ Class\ B) + (-0.9426 \cdot Felony\ Class\ C) + (-1.5392 \cdot Mexican),$$

wherein the values of the predictors were weighted by the average regression coefficients across samples from the stepwise regression analysis. Weighted risk scores ranged from -3.29 to -0.017 (M = -1.57, SD = 1.03). As mentioned, these risk scores were calculated so that higher scores indicate a greater risk of failing to report. However, many offenders had risk scores below zero because those variables that mitigated risk (Felony Class B, Felony Class C, and Mexican citizenship) were subtracted from the reverse-scored z-scores of age and TSR custody.

The unweighted and weighted models were tested with logistic regression analyses performed on each of the OOB samples. Table 8 shows the mean and standard deviation of the regression coefficients from the unweighted model. Table 9 shows the mean and standard deviation of the regression coefficients from the weighted model.

The utility of the risk model was evaluated in two ways. First, to assess if the models could discriminate between those offenders who are at high risk of reporting and those who are at a low risk of reporting, the area under the curve (AUC) was calculated for each sample using each risk score as the test variable. A perfectly accurate measure would result in an AUC of 1.0 and a measure that has chance-level accuracy would result in an AUC of .50. The AUC in this context can be interpreted as the probability that a randomly selected offender who fails to report would have a higher risk score than a randomly selected offender who reports. AUC's of .56, .64, and .71 represent small, moderate, and large effects, respectively (Rice & Harris, 2005). AUC scores developed with the unweighted risk score ranged from 0.44 to 0.63, with a mean corresponding to 0.529 (*SD* = 0.038), suggesting a small effect. AUC scores developed with the weighted risk score ranged from 0.56 to 0.78 with a mean of 0.682 (*SD* = 0.041), suggesting a moderate effect.

Another indicator utilized to assess the models' discrimination was the slope of the risk score in the regression of failure to report on risk score. As indicated in Table 9, the mean slope of the unweighted risk score was -0.037, indicating a very small decrease in risk for every unit increase in risk score. The test of the slope of the unweighted risk score produced p-values that were at or below .05 in only 4% of the samples, which suggests that the model was not useful to predict FTA. On the other hand, as indicated in Table 10, the mean slope of the weighted risk score was 0.560, representing an increase in risk for every unit increase in risk score. In 85% of the samples the test of the slope produced a p-value that was less than .05, suggesting that the weighted model was useful in predicting FTA. As noted earlier, a risk score of zero did not correspond with zero risk. An unweighted risk score of 0.0367 and a weighted risk score of -0.278 corresponded to zero risk of reporting, which is a log odds of one. In the sample of offenders, 306 offenders (77%) had an unweighted risk score below 0.0367, whereas 327 offenders (82%) had a weighted risk score less than -0.278. Approximately 74% of the offenders actually failed to report. In summary, the unweighted model was not adequately able to discriminate between offenders at low versus high risk of failing to report, whereas the discrimination of the weighted model was adequate.

Both models were also assessed for calibration, which is how well the risk score classifies offenders regarding their predicted failure to report rates. A Hosmer-Lemeshow goodness-of-fit test was conducted for each logistic regression to examine how well the observed frequencies of offenders in the two groups, those who failed to report and and those who reported, fit the expected frequencies derived from each model. The null hypothesis for this test is that the expected frequencies are a good fit with the observed frequencies. Therefore, if calibration is acceptable, the null hypothesis will be accepted. The chi-square statistics for the Hosemer-Lemshow tests corresponding to the regression of failure to report on the unweighted risk score ranged from 1.63 to 16.96 (M = 7.89, SD = 3.23). Ninety-eight percent of the associated p-values were > .05 which suggests that, in the majority of samples, the unweighted model is useful to correctly classify the offenders according to their failure to report. The chi-square statistics for the tests that corresponded to the regression of failure to report on weighted risk score ranged from 3.63 to 26.2 (M = 12.53, SD = 4.28). Twenty-one percent of the associated p-values were > .05, and ranged from .00 to .89, which indicates that the weighted model was generally useful for correctly classifying offenders. Table 11 shows the means and standard deviations for the Hosmer-Lemeshow test corresponding to the regression analyses with the weighted and unweighted models. In summary, the weighted model demonstrated adequate discrimination and calibration, whereas the unweighted model demonstrated inadequate discrimination but adequate calibration.

Table 4. *Descriptive Statistics*

Variable	*Mean*	*SD*
Age	36.21	10.681
Custody days	242.86	265.845
TSR/Probation	26.36	12.557

Note: N= 400

Table 5. *Frequencies and percentages of each selected variable (n=400)*

Variable		*Frequency*	*Percentage*
Sex			
	Female	74	
	Male	326	81.5%
Citizenship			
	Mexico	226	56.5%
	Central/South American and Caribbean	169	42.3%
	Other	5	1.3%
Residence history/ family ties in the U.S.			
	Yes	323	80.8%
	No	77	19.3%
Employment history			
	Unemployed	82	20.5%
	Manual labor	169	49.%
	Technician	35	8.8%
	Professional	52	13%
	Retail	35	8.8%
Employment before arrest			
	Yes	324	81%
	No	76	19%
Felony class			
	Class B	27	6.8%
	Class C	249	62.3%
	Class D	28	7%
	Class E	96	24%
Criminal history score			
	0	214	53.5%
	1	46	11.5%
	2	29	7.2%
	3	41	10.3%
	4	22	5.5%
	5	15	3.8%
	6	14	3.5%
	7	5	1.3%
	8	5	1.3%
	9	4	1.0%
	10	3	.8%
	12	1	.3%
	14	1	.3%
Failure to report for supervision			
	No	105	73.8%
	Yes	295	26.3%

Table 6. *Means and Standard Deviations of the partial slopes for all predictors and intercept (n =100)*

Variable	*N*	*Mean*	*SD*
Intercept	100	2.43	4.19
Criminal history score	17	0.01	0.12
Citizenship Central	41	-0.86	6.53
Citizenship Mexican	60	-1.54	5.28
Employment Manual	29	0.94	0.56
Employment Professional	44	0.77	0.67
Employment Unemployed	50	0.62	0.32
Employment before Arrest	31	0.76	0.40
Felony B	96	-1.73	0.58
Felony C	61	-0.94	0.31
Felony D	34	0.35	4.13
Age	99	-0.07	0.30
Custody	13	0.00	0.00
TSR	60	-0.08	0.36
Prior FTA	7	0.42	0.86
Sex	46	-0.82	0.35

Table 7. *Percentage of step-wise regression models which included the initial selected variables (n=100)*

Variable	*N*	*Frequency*
Sex	100	46
Age*	100	99
Custody days*	100	14
TSR*	100	59
Citizenship Mexican*	100	60
Felony B*	100	96
Felony C*	100	61
Felony D	100	33
Residence History	100	22
Employment Unemployed	100	48
Employment Professional	100	42
Criminal history score	100	17
Prior FTA	100	7
Employment Manual	100	28
Citizenship Central	100	41
Employment before Arrest	100	31

**Represents retained variables for final model*

Table 8. *Regression coefficients mean and standard deviation for unweighted model*

	N	*Minimum*	*Maximum*	*Mean*	*SD*
Intercept	100	0.678	1.492	1.007	0.196
Unweighted risk score	100	-0.258	0.139	-0.037	0.086

Table 9. *Regression coefficients mean and standard deviation for weighted model*

	N	*Minimum*	*Maximum*	*Mean*	*SD*
Intercept	100	1.142	2.882	2.014	0.352
Weighted Risk Score	100	0.102	1.008	0.560	0.174

Table 10. *Unweighted and weighted model AUC's means and standard deviations*

	N	*Minimum*	*Maximum*	*Mean*	*SD*
Unweighted	100	0.447	0.631	0.529	0.038
Weighted	100	0.565	0.783	0.682	0.041

Table 11. *Hosmer-Lemeshow Mean and Standard Deviation for weighted and unweighted model*

	N	*Range*	*Minimum*	*Maximum*	*Mean*	*SD*
Weighted	100	22.57	3.630	26.203	12.53	4.28
Unweighted	100	15.33	1.63	16.96	7.88	3.37

Discussion

The purpose of this study was to develop a risk assessment instrument to assist the U.S. Probation Office for the Western District of Texas to identify non-citizen offenders convicted of an immigration-related offense who are at risk of failure to report for supervision after being released from federal custody.

The analyses conducted in this study resulted in the creation of two risk models which were composed of indicators that were found to be predictive of failure to report. Both risk models were evaluated for calibration and discrimination to find a risk model that was adequate in the identification of non-citizen offenders who are at risk of failure to report.

Indicators predicting risk of failure to report

Five indicators were found to be useful in the prediction of FTA: age, Mexican citizenship, time in supervision (TSR), class B and class C felony. Age is one of the most common indicators predicting future criminal activity in the research. The results from this study concur with Austin (2003), suggesting that younger immigration-related offenders are more likely to fail to report for supervision upon release from custody. In 2017, the U.S. Sentencing Commission report on the "Effects of Aging on Recidivism Among Federal Offenders" found that older offenders are at less risk of reoffending. These findings can also be applied to failure to report as older offenders will likely display compliant behavior and report for supervision as instructed.

Offenders' felony classification was another predictor of FTA. Results showed that offenders with a class B felony; statutorily punishable by 25 years or more imprisonment and not more than 5 years of TSR, offenders with a class C felony; statutorily punishable by less than 25 years imprisonment but more than 10 years imprisonment and not more than 3 years of TSR, are less likely to fail to report for supervision. A plausible explanation for non-citizen offenders in these felony classifications (B and C) are repeated offenders and they have familiarized with the supervision system, whereas non-citizen offenders with less severe felony classification such as class D or E felonies are associated with shorter terms of imprisonment might be first time offenders. Further, it is common for immigration related offenses, especially for illegal re-entry cases to receive a penalty enhancement which translates to moving up to the next felony class. For example, an offender being originally charged with a class D felony on an illegal re-entry case is highly likely to receive a penalty enhancement for being a repeated offender and move up to a class C felony. Offenders without a penalty enhancement will likely phase a less severe penalty which can lead to higher possibilities of failure to report.

Time in supervision was also found to be predictive of failure to report. Offenders who have a shorter term of supervision (TSR) are more likely to fail to report than offenders who are imposed a longer term of supervision. In the federal probation system, the term of supervision is considered an extension of the sentence. The TSR for offenders convicted of a class D or E felony ranges from not more than three years to not more than one year, respectively. This would suggest that offenders who get less TSR, also have a less severe felony classification. This could imply that offenders who receive less TSR might not take the sentence too seriously as it is only a short period of supervision.

Previous risk assessment instruments have linked citizenship with future criminal behavior such as failure to appear in court, recidivism, or flight risk. For instance, ICE's RCA utilizes citizenship of origin to determine the detainees' flight risk level. Nevertheless, the majority of the extant risk assessment tools fail to differentiate how certain citizenships are at higher risk of failure to report than others. In other words, the country of origin does not make any difference in other risk assessments. For example, an offender could be from Mexico or Guatemala and that would not make any difference. This study found that non-citizen offenders from Mexico appear to be at less risk of failure to report than offenders with other citizenships. This trend could be attributed to two factors: First, Rosenbloom (2022) highlights how Mexican nationals account for the largest group of unauthorized immigrants. Secondly, Chisti (2022) explains how Mexican nationals are motivated and likely to repeat their attempts to cross the border. In sum, Mexican nationals appear to be more familiar with how the criminal justice system work as they may not be first time offenders.

Risk assessment instruments are designed to facilitate classification processes and to make better-informed decisions (Gottfredson, 2006). Craig and Beech (2017) explain how actuarial instruments transform factors predictive of risk to risk scores, which are associated with risk categories, which are used to classify offenders (Craig and Beech, 2017). In this study, the risk models were evaluated according to how well risk scores could discriminate between offenders who are at a higher risk of failure to report and offenders who are at a lower risk of failure to report. The risk models were also evaluated according to how well they could correctly classify offenders according to their predicted failure to report rates. The unweighted risk score was not adequately capable of discriminating between offenders who failed to report and those who did not, but the weighted risk score showed adequate discrimination. Both models were adequately calibrated. Helmus and Babchishin, 2017, explain how measuring the accuracy of both discrimination and calibration is necessary to obtain a more complete understanding of the utility of a risk scale. Accuracy in risk assessment instruments is crucial as criminal justice agencies will make decisions based on these predictions. Wrongly classifying offenders could be problematic, not only for the offender but also for the agency. For example, if a low-risk offender classified as having a high risk of failure to report really may be over supervised, whereas one who is classified as low risk who is really high risk may become lost in the system. Therefore, the weighted risk model is useful in predicting failure to report for supervision among individuals completing prison terms served for immigration-related offenses.

Limitations

In this study, data was limited to only offenders from the U.S. Probation Office in the Western District of Texas, so the results are only generalizable to offenders from this district. However, it could be argued that these results could generalize to the offender population in the Southern District of Texas, as its demographics and border characteristics may are very similar to the sample used in this study.

Additionally, the offense type determines the felony classification and the statutory penalty range which includes custody time and TSR. In addition to statutory penalty ranges, TSR can be imposed based on sentencing guidelines calculations and/or judicial discretion. These two indicators were retained in the final model and are dependent on each other, which suggests that there exists the possibility of these indicators not providing independent predictive risk information. Future research could focus on examining only one of these indicators and comparing the results with the results produced by this study to observe if there is a difference in predicting failure to report or if results are similar.

Further, the development of this risk assessment instrument utilized two demographic indicators: sex and age. Whereas, age was retained in the final model, sex was included in the initial model. Hannah-Moffat (2009) highlights how gender in risk assessments should be “gender-specific” and recommends that if utilizing demographic characteristics such as sex/

gender, these should be carefully adjusted when it comes to assigning a value for each category. In other words, a male offender should not be considered at higher risk than a female offender and vice versa.

Another constraint in this study was the smaller sample size than intended. It should be noted that the sample size utilized in this study was smaller than sample sizes used in other risk assessment instruments. There is the possibility that some of the indicators not retained in the final model might have been retained in a larger sample size. Lastly, it should be highly emphasized that the risk assessment instrument developed in this study is at its preliminary stage and should not be implemented without further validation with a larger sample.

Implications for policy

In addition to the indicators that were useful in predicting failure to report, there are other criminogenic needs that the U.S. Probation Office considers when supervising an offender. Resources to supervise non-citizen offenders are very limited. For example, if a non-citizen offender is displaced and does not have any family or friends with whom they can live, the chances of placing the non-citizen offender into a half-way house or a shelter are small. Employment for non-citizen offenders is also very limited because of their non-legal status in the United States. Another unavailable resource for non-citizens is early termination. The court has the authority to terminate the term of supervised release if the probation officer determines an offender has successfully reintegrated to the community. (U.S. Sentencing Commission, 2012). However, early termination is not an option for non-citizen offenders because of their illegal status More importantly, the majority of these non-citizen offenders go through civil immigration proceedings to file for asylum, which means that they will be assigned to double supervision, as they have to report to an immigration officer throughout their entire immigration proceedings while also reporting to the U.S. Probation for supervision. This creates a double burden for the offenders and for the officers supervising these cases, which begs the question; should the U.S. Probation Office supervise non-citizen offenders at all?

Assessing these non-citizen offenders in the post-conviction phase after sentencing for risk of failing to report using the risk model developed in this study would be beneficial in three ways. First, proactive measures can be implemented by the U.S. Probation Office. An example of a proactive measure could be identifying those offenders who are at higher risk of not reporting for supervision while they are in custody. Because it is uncertain whether ICE will lift the immigration detainer on an offender, identification while in custody could be crucial as this would decrease the office's liability for offenders who get "lost" after they are released from custody. In the same manner, once assessed, if the ICE detainer is not lifted at the completion of their federal custody sentence and non-citizen offenders are taken into ICE custody, the office could confirm with ICE if the offender will be released under immigration parole. At this point, the office could ask the court to rescind the term of supervision imposed on the offender as they will be under supervision with immigration. Lastly, risk assessing non-citizen offenders while in custody could significantly reduce the number of warrants issued for failure to report.

This study identified a validated risk model to predict failure to report. However, the weighted risk score must be associated with thresholds to assign offenders as low-, medium-, or high-risk of failing to report. Garret (2020) explains how risk thresholds are typically determined by the agency's administrators and how important it is for thresholds to be well-supported and justified. The U.S. Probation Office should consider the findings and limitations produced by the present study to assign risk thresholds separating different groups of non-citizen offenders accordingly to their respective risk score. Once risk thresholds have been determined and the offender has been assessed and classified, then a proper supervision plan can be tailored to address the offender's needs. Prior to assigning risk thresholds, the weighted risk score should be rescaled so that zero corresponds to no risk of failing to report; this would make it easier for decision-makers to interpret risk scores.

In summary, non-citizen offenders who are more likely to fail to report share the following characteristics: they are younger, have been convicted of a less severe felony, have been imposed a shorter term of TSR, and are not Mexican nationals. The risk assessment instrument developed in this study is intended to effectively assist the U.S. Probation Office in identifying non-citizens offenders who are at risk of failure to report and reduce the liability of lost offenders as well as decreasing resources expenditures caused by having to locate these individuals after they release from custody.

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Glossary

Defendant: An individual undergoing criminal proceedings

Detainee: An individual in ICE custody

FTA: Failure to appear in court

FTR: Failure to report for supervision

Non-citizen: Citizen of a foreign country

Offender: An individual convicted of a crime

TSR: Term of supervised release

Appendix

```
#Read data file
df = read.csv("Imputed Data.csv")
#Load packages
library(MASS)
library(caret)
library(pROC)
library(qpcR)
library(broom)
#Create vector s with list of 100 numbers
s <- c(1:100)
#Create a loop.  Repeat 100 times.  Create a bootstrapped sample with
#replacement of n=400 and associate that sample with variables in
#dataframe, df.
for(i in s) {iboot <-sample(1:nrow(df), replace=TRUE)
bootdata <-df[iboot,]
#Create a vector of participant numbers from original data
partoriginal <- df$Participant
#Create a vector of participant numbers from boostrapped sample
part <- bootdata$Participant
#Create a vector of out of the bag participant numbers
#These are the ones not included int the bootstrapped sample
oob <- setdiff(partoriginal,part)
#Create a .csv file with vector of oob participant numbers
ooball = paste("oob", i, ".csv")
write.csv(oob,file=ooball,row.names=F)
#Create a logistic regression model
model <- glm(bootdata$FTRforSup ~ bootdata$Sex+bootdata$Mean_Centered_Age+
              bootdata$Mean_Centered_Custody+bootdata$Mean_Centered_TSR+
              bootdata$Cit_Mex+bootdata$Cit_Central+
             +bootdata$CHScore+bootdata$PriorFTA+bootdata$ResHistory

+bootdata$Emp_Unemployed+bootdata$Emp_Manual+bootdata$Emp_Prof+

bootdata$Emp_Tech+bootdata$EmpbeforeArrest+bootdata$Felony_B+
              bootdata$Felony_C+bootdata$Felony_D,
             data = bootdata, family = binomial)
#Define stepwise regression
step <- stepAIC(model,direction = "both",trace=FALSE)
#Save regression coefficients
stepi=paste("step", i, ".csv")
write.csv(tidy(step), file=stepi)
#Create a dataframe with the participant numbers in each bootstrapped
sample
  sample[i] <- data.frame(part)
}
#Write the dataframe to .csv file
write.csv(sample,file="samples.csv",row.names=F)
```

Note: *Script for conducting step-wise regression analyses on bootstrapped samples*

```
#Read data file
df = read.csv("Imputed Data.csv")
#Load packages
library(MASS)
library(caret)
library(pROC)
library(qpcR)
library(broom)
library(glmtoolbox)
#Create an empty vector
z <- vector()
y <- vector()
a <- vector()
b <- vector()
s <- c(1:100)
#Create a loop.  Repeat 100 times.  Read each OOB sample file.
#Delete items from the dataset not included in the oob sample.
for(i in s) {
  ooball = paste("oob", i, ".csv")
  sample = read.csv(file=ooball)
  bootdata <- df[is.element(df$Participant, sample$x),]
#Test model with unweighted risk score
model <- glm(bootdata$FTRforSup ~ bootdata$Unweighted_Risk_Score,
             data = bootdata, family = binomial)
#Test model with weighted risk score
#model <- glm(bootdata$FTRforSup ~ bootdata$Unweighted_Risk_Score,
             #data = bootdata, family = binomial)
#Save regression coefficients
modeli=paste("model", i, ".csv")
write.csv(tidy(model), file=modeli)
#Create indicator of Hosmer-Lemeshow goodness-of-fit test
hl <- hltest(model, verbose=FALSE)
#Save the HL chi-square, df, and p-value
hlchi[i] <- hl$statistic
hldf[i] <- hl$df
hlp[i] <- hl$p.value
#Calculate area under the curve with unweighted risk score
auc[i] <- auc(bootdata$FTRforSup, bootdata$Unweighted_Risk_Score)
#Calculate area under the curve with weighted risk score
#auc[i] <- auc(bootdata$FTRforSup, bootdata$Weighted_Risk_Score)
#Create a vector with auc from all samples
z[i] <- c(auc[i])
y[i] <-c(hlchi[i])
a[i] <-c(hldf[i])
b[i] <-c(hlp[i])
}
#Write the vectors to .csv file
write.csv(z,file="auc.csv",row.names=T)
write.csv(y,file="hlchi.csv",row.names=T)
write.csv(a,file="hldf.csv",row.names=T)
write.csv(b,file="hlp.csv",row.names=T)
```

Note: *Script for validating the risk models using OOB samples.*

Vita

Mayra Pacheco was born in El Paso, Texas. First-generation college graduate. She graduated from the University of Texas at El Paso in 2019 with her bachelor's degree in Criminal Justice. In 2019, she was appointed U.S. Probation Officer Assistant for the Western District of Texas, El Paso Division, where she supervises a high-volume caseload of low-risk felony-convicted offenders and conducts criminal history investigations. Mayra participates in the mentorship program for UTEP students at the U.S. Probation Office and is a member of the Immigration Taskforce which locates lost offenders in need of supervision. She entered the master's program in Intelligence and National Security Studies at the University of Texas at El Paso in 2020. In 2022, she served as the President for the Students in Intelligence and National Security student organization.

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