Justice involvement prediction as individuals age: An age-graded evaluation of the Public Safety Assessment

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Abstract

Background: Scholars have recently critiqued pretrial assessments for potentially offering biased predictions of future legal system outcomes for racial and ethnic minorities. While these critiques have limited empirical support, the scholarship has yet to examine the predictive validity and differential prediction of pretrial assessments across another protected class – age. Following the guidance of the life-course literature, the current study serves as the first age-graded evaluation of a pretrial assessment – the Public Safety Assessment –, focused on assessing if the predictive validity and scoring predictions of the tool varies across the life-course.

Methods: The current study relied on pretrial information collected from 31,527 individuals during the Advancing Pretrial Policy and Research (APPR) project. Six logistic regression models were estimated to evaluate the differential prediction of the PSA for individuals from 18-68 years of age. The results of bivariate models were used to produce AUC estimates at each age.

Results: In contrast with the literature on post-conviction assessments, the results of the current study provided limited evidence that the PSA differential predicted pretrial outcomes for individuals from 18-68 years of age.

Conclusions: The results suggest that the PSA is a valid predictor of pretrial outcomes independent of a defendant's age.

200 words

Keywords:

1. Introduction

The implementation of actuarial risk assessments designed to predict future legal outcomes has a longstanding history in the criminal legal system (Bonta & Andrews, 2016; Simon, 2005). Initially established as a means to improve predictive accuracy and over reliance on professional judgement or gut feelings (Andrews, Bonta, & Wormith, 2006), actuarial assessments are used across the legal system to predict the likelihood of a group of individuals experiencing a wide-range of system related outcomes (e.g., rearrest, failure to appear for court, new violent criminal arrest, sex offense recidivism; Simon, 2005). These assessments are typically designed to inform decisions at specific stages of the criminal legal system. For instance, pretrial assessments often seek to estimate likelihoods of failing to appear in court or committing new criminal activities and are used to inform pretrial release decisions, including determining what conditions to impose during the period of pretrial. Institutional assessments are designed to predict measures of rule compliance in custodial settings, such as misconduct or escape potential, and are used to determine security custody levels and housing decisions. Additionally, post-conviction assessments are designed to estimate the likelihood of various recidivism measures (e.g., general recidivism, domestic violence recidivism, sexual recidivism) and are used to inform community supervision decisions, such as reporting requirements and program decisions (Kemshall, 2003; Simon, 2005).

Although the empirical literature supports the predictive accuracy of these tools (Desmarais et al., 2021; Fazel et al., 2022; Singh et al., 2011), there are some critiques about the use of assessments to gauge the risk of future justice involvement (e.g., Eckhouse et al., 2019; Feeley & Simon, 1992; Simon 2005). These concerns are focused on the potential for assessments to overclassify people based on race and ethnic background as well as sex.

Overclassification would result in incorrectly labeling individuals into higher categories of risk of recidivism, thus increasing their likelihood of being exposed to more severe punishments or unwarranted treatment. In response to these concerns, there is a large body of research suggesting that assessments are valid predictors of future justice involvement and do not result in differential prediction across racial/ethnic groups and sex (i.e., the assessments provide equal probabilities of the outcome across groups; Desmarais et al., 2021; Desmarais et al., 2022; Vincent & Viljoen, 2020).[1]

However, there is some support for these concerns, given that there is evidence of disparate impact based on race and ethnicity, such that measures like criminal history can lead to higher scores reflecting the biases present in the criminal legal system (e.g., over-enforcement; Hamilton, 2019; Skeem & Lowenkamp, 2016). Relatedly, with age, the reliance on criminal history could result in higher scores for older individuals who have had more years to accumulate arrests and convictions. Thus, while the tool may make equal predictions across age groups, those who are older may be penalized by having a longer time-period to accumulate exposure to the legal system resulting in disparate impacts on older individuals.

Despite the development and implementation of pretrial assessments in the criminal legal system, the empirical research considering how the predictive validity of these tools varies by the age of an assessed individual is relatively limited with much of the research focusing on post-conviction assessments (e.g., Monahan, Skeem, and Lowenkamp, 2017). These assessment types are different in that pretrial assessments are administered when the person is presumed innocent and are awaiting trial, and they are used to make different behavioral predictions that inform supervision. Research on the predictive validity and disparate impact of pretrial assessments

[1] In the current context unbiased refers to similar predictive validity across race and sex groups.

often only focus on bias by race, ethnicity, and/or sex (DeMichele & Baumgartner, 2021; Skeem & Lowenkamp, 2016; Skeem, Monahan, & Lowenkamp, 2016). There is, however, a large body of literature in criminology pointing to developmental changes throughout the life-course that could impact the predictive validity of key measures of these assessments (Giordano et al., 2002; Sampson & Laub, 2017). For example, the predictive strength of criminal history on future involvement in the justice system could be lower for older individuals when compared to younger individuals. Alternatively, the lack of criminal history could lead to assessments performing worse for younger individuals.

Considering the limited focus on pretrial assessments and age, the current study draws upon key life-course literature and previous research to develop an understanding of how the predictive validity of actuarial assessments could vary by age. Correspondingly, we developed an age-graded examination of the predictive validity and potential disparate impact of one such pretrial assessment: the Public Safety Assessment (PSA).[2] The PSA is an actuarial assessment that relies on criminal history factors to predict failure to appear, new criminal arrest, and new violent criminal arrest for pretrial populations (DeMichele & Baumgartner, 2021).[3] In addition to being the first comprehensive age-graded evaluation of the PSA, the current study serves to understand how the predictive validity of pretrial assessments can vary across the life-course. Although a longitudinal design would allow for a test of whether prediction of the tool varies across an individual's life course, due to data limitations we look at whether the validity of the PSA varies by age.

2. Predicting Involvement in the Justice System and Bias

[2] The authors are currently engaged in a number of research projects on the PSA as part of their partnership with Arnold Ventures, but they are not personally invested in the PSA.
[3] Importantly, while our age-graded evaluation of the PSA was guided by the life-course literature, we are not directly testing life-course theories against one another.

A variety of pretrial and post-conviction assessments have been developed to estimate the rate at which groups of individuals will experience future justice system outcomes (Desmarais & Singh, 2013). For example, pretrial assessments include the PSA and the Federal Pretrial Risk Assessment, while post-conviction assessments include the Ohio Risk Assessment System and the Level of Service Inventory (Desmarais & Singh, 2013). Actuarial assessments designed to predict future justice system outcomes rely on a series of scored factors to classify individuals into groups with distinct probabilities of future justice system outcomes (Andrews et al., 2006; Vincent & Viljoen, 2020). Second generation assessments, such as the PSA, use static, evidence-based factors to provide quantitative scores that indicate lower or higher likelihoods of future justice-related outcomes, while third and fourth generation assessments incorporate dynamic factors and systematic interventions, respectively (BJA, n.d.; Public Safety Canada, 2022). Furthermore, post-conviction assessments, such as the Post-Conviction Risk Assessment (PCRA), are used to inform decisions on supervision and treatment as well as the criminogenic needs to address during reentry. While pretrial assessments, like the PSA, are used during the pretrial period to inform release and/or supervision decisions based on the likelihood of returning to court or being arrested for a new crime.

Research has supported the use of pretrial assessments to inform the decision-making process for pretrial supervision (Desmarais et al., 2018; Desmarais & Singh, 2013). Prior evaluations have shown that a number of factors, such as criminal history, are highly predictive of future justice system contact and, in turn, can be used to accurately classify individuals into groups with distinct likelihoods of key outcomes during pretrial (Desmarais et al., 2021; Fazel et al., 2022). After classification, agencies are encouraged to provide interventions, services, or treatments that decrease the probability of future contact with the justice system and maintain public safety (Desmarais et al., 2021; Bonta & Andrews, 2017).

While the literature has provided a robust pattern of findings illustrating the predictive validity of these assessments, calls remain for further exploration of disparate impact across gender, race, and ethnicity (see Desmarais et al., 2021; Fazel et al., 2022). Although the results vary by tool, limited evidence exists to suggest that pretrial assessments provide biased predictions based on race, ethnicity, and/or sex (Desmarais et al., 2021; Fazel et al., 2022). Nonetheless, pretrial assessments could differentially predict outcomes for individuals by age and, importantly, be more or less predictive of pretrial outcomes for older individuals compared to younger individuals. Moreover, age is a factor that has received relatively less attention in the pretrial assessment literature compared to race, ethnicity, and sex. That is, we are aware of no scholarship to date that has examined the predictive bias and disparate impact of pretrial assessments by the age of an individual.

3. Age and the Predictors of Criminalized Behavior

One of the most robust findings within criminological research is the age-crime curve (Farrington, 1986). The age-crime curve refers to the relationship found between involvement in criminalized behavior and age, where involvement begins to increase in early adolescence, peak in the late teens/early twenties, and then decline throughout adulthood. This developmental pattern of behavior gave rise to life-course criminology, where scholars have long debated the mechanisms causing this observation (see Farrington, 2003; Laub & Sampson, 2020). While a variety of theoretical postulations have been developed, a major contribution of the life-course perspective to the broader criminological literature was the establishment of an empirical focus on how age influences the predictors of future criminal behavior. These perspectives include, but are not limited to, Sampson and Laub's (1990) Age Graded Theory of Informal Social Control, Moffitt's (1993) Developmental Taxonomy, and Giordano and colleagues' (2002, 2007) Cognitive Transformations and Hooks for Change. To examine the validity of these perspectives, life-course criminologists have relied on a variety of analytical approaches including age-graded evaluations of involvement in the justice system.

Although these theoretical perspectives provide different arguments by which engagement in criminalized behavior changes throughout the life-course, they incorporate an underlying assumption that there is the possibility for change as people age (Farrington, 2003; Laub & Sampson, 2020). The possibility of change across age groups suggests that the predictive validity of static risk assessments, such as the PSA, could differ by age groups. Several life-course perspectives can be used to develop postulations surrounding the predictive accuracy of pretrial risk assessments (Moffitt 1993; Sampson and Laub, 1990). To provide an example, the ensnarement hypothesis would argue that a long criminal history for justice involved adults is indicative of limited access to prosocial opportunities, which overtime has ensnared them in a persistent pattern of antisocial and criminalized behavior (Moffitt 1993). Ensnarement in this pattern, however, is not expected to occur during early adulthood due to the ability to recover some or all prosocial opportunities. Similarly, the social bonds an individual forms during adulthood (e.g., work, family, and marriage) directly contribute to a reduction in the likelihood of being involved in the justice system (Sampson and Laub, 1990). Nevertheless, bonds to age-graded institutions in adolescence and early adulthood may not yet mitigate engagement in antisocial activity to the same extent as those bonds in adulthood (Laub, Sampson, and Sweeten, 2006).

In the context of life-course criminology, an age-graded evaluation is an examination of the predictors of criminal behavior and effects of contact with the justice system at distinct stages of the life-course (e.g., McLean et al., 2019). Regarding actuarial assessments, evaluating the predictive validity of these tools using an age-graded approach is beneficial for a variety of reasons. At the forefront of these benefits is the ability to examine the similarities and differences in the predictive validity of an actuarial assessment at distinct developmental stages and across the life-course to test the validity of the theoretical postulations developed by life-course criminology (Loeber & Le Blanc, 1990). Prior research has evaluated the predictive validity and disparate impact of post-sentencing assessments at distinct developmental stages, producing findings that these tools might differentially predict recidivism for some age groups when compared to other age groups (Monahan et al., 2017; Vincent, Perrault, Guy, & Gershenson, 2012; Vincent, Drawbridge, & Davis, 2019). Notably, however, these prior examinations of the literature did not draw on the theoretical perspectives and empirical approaches common within the broader life-course literature.

3.1 Age and the Predictive Validity of Post-Sentencing Assessments.

As stated above, the existing literature to date has only evaluated the effects of age on post-sentencing assessments. Monahan et al. (2017) were among the first to empirically examine the predictive bias and disparate impact of a post-conviction assessment by the age of individuals. Specifically, Monahan et al. (2017) evaluated the predictive validity of the PCRA across several age groups, 25 years and younger, 26-40, and 41 years and older. They found that while the association between PCRA scores and future arrests were similar across groups that the tool underestimated rates of recidivism for younger individuals and overestimated rates of recidivism for older individuals. The age categories used in this study were drawn from the

PCRA and were rather large in range. The authors propose that "expanding the number of age categories on a risk assessment instrument…or interpreting categorical risk estimate in an age-specific fashion, all might enhance the predictive validity…[and] such actions could go far in attenuating the overestimation of risk among older offenders" (Monahan et al., 2017, pg. 27).

In addition to evaluating the predictive validity of post-sentencing assessments, specific instruments have been developed and tested for youth and individuals at distinct developmental stages (see Viljoen et al., 2008; Vincent et al., 2012). A recent study by Vincent et al. (2019) compared the predictive validity and disparate impact of assessments developed for individuals at distinct developmental stages. This study focused on juvenile and adult post-conviction assessments including, but not limited to the Structured Assessment of Violent Risk (SAVRY), the Youth Level of Service Case Management Inventory (YLS/CMI) and the Violence Risk Appraisal Guide (VRAG). Similar to Monahan et al. (2017), this study had an adult age group ranging from 25 to 40 years old, in addition to an adolescent group (12 to 15) and transition-age youth (16 to 24) group. Their primary goal was to assess the performance of adult- and youth-specific tools for those in the transition-age group – which are thought to be more mature than adolescents but less mature than adults –, to understand whether a developmentally informed assessment might predict outcomes better for this group (Grisso, 2019). Although they did find significant mean age-related differences in scores for one adult actuarial assessment, they concluded that overall, well-validated instruments, whether developed for adolescents or adults, could be used for transition-age youth. While there is some debate about whether there is a need for more developmentally informed post-sentencing assessments, such as those focused on transition-age youth, there are age-based post-sentencing assessments currently in use.

3.2 Age and Pretrial Assessments (The Current Study)

Age is typically, if not always, factored into pretrial assessments. For example, the PSA accounts for age when creating the Failure to Appear (FTA), New Criminal Activity (NCA), and New Violent Criminal Activity (NVCA) scores: 1) age at current arrest and 2) current violent offense and 20 years old or younger. Despite age being incorporated into the scoring of pretrial assessments, there is no empirical evidence examining the predictive validity or disparate impact based on age. Specifically, it can be expected – as discussed in the broader life-course literature – that the age of an individual could impact the predictive validity of an individual (Farrington, 2003). However, despite this knowledge, a substantive gap in our understanding of the predictive validity and differential prediction of pretrial assessments persists with regards to age. Specifically, it is currently unknown if the predictive validity of an assessment used during the pretrial period, including the PSA, is conditional upon the age of an individual being evaluated. Furthermore, the inconsistent employment of age-categories could influence the existing evaluations of post-sentencing assessments, resulting in a pattern of findings suggesting that age might or might not influence the predictive validity of pretrial assessments. An age-graded evaluation assessing the predictive validity and differential prediction of an assessment at each age across the life-course could not only inform our understanding of whether developmentally specific assessments are needed, but also outline potential future age categorizations that appear significant, particularly during the pretrial period.

The current study presents an age-graded evaluation of the PSA. The PSA is a research-based pretrial assessment tool that uses administrative records to complete a criminal history review to provide judges with information about the likelihood that a defendant will return to court and/or commit a new crime. The PSA was developed by a research team that analyzed 750,000 cases from more than 300 jurisdictions to discern factors that were the most predictive of new criminal activity, failure to appear, and violence, and it does not take into account race, gender, employment status, level of education, or history of substance use (Arnold Ventures, 2017). After 5 years of testing, the PSA was made publicly available in 2018. Further information on the PSA tool can be found online.[4]

Following the guidance of life-course perspectives and Monahan et al. (2017), we hypothesize that the predictive validity of the PSA will differ by the age of the defendant and that the PSA differentially predicts the probability of future justice outcomes at distinct developmental stages (Farrington, 2003; Monahan et al., 2017). In particular, we expect for the PSA to underpredict for younger individuals and overpredict for older individuals corresponding with the postulations of Moffitt (1993) and Sampson and Laub (1990). The current study relies on a sample of 31,527 unique individuals ranging in age between 18 and 68 permitting an evaluation of the predictive validity and differential prediction of the PSA across 50 years. However, in contrast with Monahan et al., (2017), the current evaluation does not group individuals by age, but rather evaluates if the predictive validity of the PSA differs by age from 18 to 68 years.

5. Methods

5.1. Sample

The data for the current study were derived from the APPR project (https://advancingpretrial.org/appr/appr-research/). The APPR data provide the unique opportunity to evaluate the differential prediction and predictive validity of the PSA for individuals 18 to 68 years of age. The complete APPR dataset contains 44,831 pretrial detention bookings into jail between January 2017 and December 2018 in three counties (2 counties from a

[4] What Is the PSA? | Advancing Pretrial Policy & Research (APPR)

northwestern state and 1 county from a southeastern state).[5] Of these bookings, 34,651 resulted in a release from pretrial detention at some point prior to the disposition of booking charges. Furthermore, the sample was limited to unique individuals by isolating the first pretrial jail booking per defendant. As such, the analytical sample for the current study is 31,527 individuals. The information required to score the PSA, data corresponding to key pretrial outcomes, and data associated with key covariates were captured for all the individuals included in the analytical sample using official data sources from various criminal justice agencies (e.g., court dockets, jail bookings, race, sex, and pretrial supervision information).

5.2. Measures

5.2.1. Public Safety Assessment Scores

Nine criminal history items were used to calculate the FTA, NCA, and NVCA scores for the PSA (scores calculated using the psa2013 R package developed by Tueller et al., 2022). These nine items include: (1) older than 23 at the time of the current arrest,[6] (2) current violent offense, (3) pending charge at the time of arrest, (4) prior misdemeanor conviction, (5) prior felony conviction, (6) prior violent conviction, (7) prior failure to appear in the past two-years, (8) prior failure to appear older than two-years, and (9) prior sentence to incarceration (misdemeanor or felony; DeMichele & Baumgartner, 2021; DeMichele et al., 2020). The FTA score was calculated using four items (Items 2, 6, 7, and 8), the NCA score was calculated using seven items (Items 1, 3, 4, 5, 6, 7, 9)[7], and the NVCA score was calculated using five items (Items 2, 3, 4, 5, 6; https://advancingpretrial.org/psa/factors/). The FTA, NCA, and NVCA scores

[5] Individuals were excluded if their jail admission was associated with post-trial sentences, probation/parole violations, appeals, transfers, immigration detainers, warrants from other counties, or juvenile arrests/adjudications.
[6] Being older than 23 at the time of the current arrest is only used to calculate the NCA score, suggesting that it should have limited influence on evaluating the age-graded predictive validity of the PSA.

range between 1 and 6, where lower values are designed to correspond with a lower probability of experiencing the corresponding outcome and higher values correspond with a higher probability of experiencing the corresponding outcome (DeMichele & Baumgartner, 2021). Unlike other actuarial pretrial assessments that collapse these probabilities into low, moderate, or high likelihood of an outcome, the PSA classifies defendants into an overall composite score associated with distinct likelihoods of failure to appear, new criminal arrest, and new violent criminal arrest (DeMichele et al., 2020; Buskey & Woods, 2018).

5.2.2. Age at the Time of Arrest

The age of the defendant at the time of arrest was calculated as years between their date of birth and their arrest date for the current charge. The individuals in our sample ranged in age from 18 to 68 years old, with a mean age of 34.

5.2.3. Outcomes: Failure to Appear, New Criminal Arrest, and New Violent Criminal Arrest

Three outcome measures were captured to evaluate the age-graded predictive validity of the FTA, NCA, and NVCA scores (DeMichele et al., 2020). First, failure to appear was operationalized as a dichotomous construct capturing if a defendant failed to appear for court ("0" = No; "1" = Yes). Second, new criminal arrest was created to identify if an individual experienced an arrest for a new crime ("0" = No; "1" = Yes). Finally, new violent criminal arrest identified if a defendant was arrested for a new violent crime ("0" = No; "1" = Yes). Violent crimes were defined by the state or county's revised code of criminal offenses. Each of these outcomes were tracked until the defendant's disposition on the current charge or through December 2019, if the defendant did not experience a disposition.

5.2.4. Covariates of Interest

Eleven covariates were included in the model to adjust for the potential biasing effects of these constructs when examining the association between the PSA and future involvement in the justice system (Desmarais et al., 2022; Desmarais et al., 2021; Van Eijk, 2020). The importance of adjusting for these covariates was identified by developing a theoretically and empirically informed Directed Acyclic Graph (DAG; Silver et al., 2022) These covariates included: 1) current offense misdemeanor ("1" = yes; "0" = felony offense), 2) current offense violent offense ("1" = yes; "0" = no; reference category = drug offense), 3) current offense property offense ("1" = yes; "0" = no; reference category = drug offense), 4) current offense public order offense ("1" = yes; "0" = no; reference category = drug offense), 5) current offense other offense ("1" = yes; "0" = no; reference category = drug offense), 6) time at risk (number of days between release and disposition or December 31st 2019), 7) total number of charges for the current arrest (higher values indicative of more charges), 8) white ("1" = yes; "0" = non-white), 9) sex female ("1" = yes; "0" = male), 10) county 2 ("1" = yes; "0" = no), and 11) county 3 ("1" = yes; "0" = no). Time at risk was included as a covariate in our multivariate models to adjust for the inconsistent follow-up period for the respondents.

5.3. Analytical Strategy

A five-step analytical strategy was developed to answer the identified research questions. First, descriptive statistics for the analytical sample were produced. Second, histograms were created to evaluate the bivariate association between the age of the defendant and failure to appear, new criminal arrest, and new violent criminal arrest. Third, three fixed-effects binary logistic regression models were estimated regressing failure to appear, new criminal arrest, and new violent criminal arrest on the corresponding PSA score (i.e., FTA, NCA, and NVCA), the age of the defendant, the identified covariates, and the county identifiers (Aguinis et al., 2010;

Chouldechova et al., 2017 Desmarais et al., 2021; Skeem & Lowenkamp, 2016). A fixed-effect model was employed to adjust for the unobserved differences between County 1, County 2, and County 3. Fourth, the fixed-effects binary logistic regression models were replicated except for the inclusion of an interaction term between the PSA score and the age of the defendant (e.g., Desmarais et al., 2021).

Finally, the results three bivariate models were used to produce Area Under the Curve (AUCs) for the FTA, NCA, and NVCA for individuals 18 to 68 years of age (Desmarais et al., 2018). These bivariate models regressed failure to appear on the FTA score, new criminal arrest on the NCA score, and new violent criminal arrest on the NVCA score. Briefly, the AUCs for the FTA, NCA, and NVCA scores were calculated by predicting if a case would fail to appear, experience a new criminal arrest, or experience a new violent criminal arrest and comparing those predicted outcomes to the observed outcomes for the individuals in the analytical sample.[8] Correspondingly, AUC is used to calculate how accurate of a prediction a measure provides, with values ranging from 0 to 1.0 with .5 referring to no better than a random prediction and 1.0 referring to perfect prediction. For example, if the FTA score predicts the likelihood of an individual failing to appear better than random chance, the AUC will be larger than .5.

The AUCs for the FTA, NCA, and NVCA were plotted at each age and a trendline across the age groups was calculated using a linear regression line (Hastie & Tibshirani, 1995). The plotted AUCs provide the ability to evaluate similarities and differences in the predictive validity of the PSA at each age from 18 to 68. The AUCs at each age were evaluated using the standard outlined by Desmarais and colleagues (2018), where AUC values of .54 or less are indicative of *poor* predictive validity, .55 to .63 are defined as *fair* predictive validity, .64 to .70 suggest *good*

[8] An individuals scores for each of the PSA items were used to generate the predicted values.

predictive validity, and values higher than .71 suggest *excellent* predictive validity for the FTA, NCA, and NVCA.

6. Results

Table 1 provides the descriptive statistics for the sample and demarcates the descriptive statistics by county, providing an understanding of the similarities and differences. The average age was 34 years old, with individuals who ranged from 18 and 68 years old. To further detail, approximately 26% of the sample was between 18 and 25 years of age, 36% of the sample was between 26 and 35 years of age, 20% of the sample was between 36 and 45 years of age, 12% of the sample was between 46 and 55 years of age, and 6% of the sample was between 56 and 68 years of age. On average individuals scored 2.70 on the FTA, 2.68 on the NCA, and 1.82 on the NVCA. Approximately 21% of individuals experienced a failure to appear, while 23% and 7% experienced a new criminal arrest and new violent criminal arrest (respectively).

***** Insert Table 1 About Here *****

6.1 Failure to Appear, New Criminal Arrest, and New Violent Criminal Arrest by Age

Figure 1 provides the rate of failure to appear (Panel A), new criminal arrest (Panel B), and new violent criminal arrest (Panel C) at each age from 18-68. As evidenced in the figure, individuals below the age of 56 had a higher rate of failure to appear when compared to individuals over the age of 56 (Panels A). A noticeable decline in new criminal arrest was observed as age increased, where 18 year-old defendants had the highest rate of new criminal arrest and 68 year-old defendants had the lowest rate of new criminal arrest (Panel B). Consistent with the other associations, Panel C illustrates that younger individuals have the highest rate of new violent criminal arrests, the rate of which appears to decline with age.

***** Insert Figure 1 About Here *****

6.2. FTA score, NCA score, and NVCA score by Age

Figure 2 provides the rate of FTA score (Panel A), NCA score (Panel B), and NVCA score (Panel C) at each age from 18-68. Focusing on Panel A, the average FTA score for each age group appeared to increase until the age of 30 and then decline nominally from 31 to 68. Alternatively, the average NCA score for each age group appeared to peak from 18 to 23 and then steadily increase from 24 to 50 until declining from 51 to 68 (Panel B). The peak NCA score being below the age of 23 is not surprising as the NCA score penalizing individuals for being under the age of 23. Coinciding with this penalization, it appears that younger individuals score higher on the NCA than older individuals on average. Regarding Panel C, A spike in the average NVCA score was observed for individuals 18 to 20 (corresponding to a penalization for being younger) before declining and increasing until the age of 60. Notably, despite penalizing younger individuals, individuals aged 65 to 68 appeared to have the highest average NVCA score.

***** Insert Figure 2 About Here *****

6.3. Evaluating Differential Prediction by Age[9]

To evaluate if the PSA predicts the pretrial outcomes differently by age, a series of regression models were estimated (Table 2). Model 1 provides the corresponding pretrial outcome regressed on the appropriate PSA score, the age at arrest, and the identified covariates using a fixed effects binary logistic regression model. Model 2 provides the corresponding pretrial outcome regressed on the appropriate PSA score, the age of the individual at arrest, an

[9] The regression models were replicated for each county individual. The results for County 1 and County 2 were identical to the results presented in the primary text. The findings for County 3, however, suggested that the age of an individual did not predict the likelihood of them failing to appear, experiencing a new criminal arrest, or a new violent criminal arrest. The complete results of these models can be provided upon request.

interaction between the PSA score and age, and the identified covariates using a fixed effects binary logistic regression model.

Focusing on failure to appear, Model 1 suggests that both the age at arrest (*OR* = .995, $p < .001$) and the FTA score (*OR* = 1.261, $p < .001$) predict the likelihood of failing to appear for court. The odds ratios indicate that a 1-year increase in age is associated with a .5 percent decrease in the odds of failing to appear for court. Moreover, a 1-point increase in the FTA score was associated with a 26 percent increase in the odds of failing to appear for court. Regarding the interaction model (Model 2), the findings suggest that the odds of failing to appear for court across the FTA scores does not differ by the age of an individual (*OR* = 1.002, $p = .086$). In particular, a 1-year increase in age resulted in a .2 percent increase in the *predicted odds* of each FTA score. Given the baseline association (*OR* = 1.261, $p < .001$), the .2 percent increase in the predicted odds of each FTA score is nominal.

A similar pattern of results was observed for new criminal arrest, where being older (OR = .985, $p < .001$) was associated with a lower odds of new criminal arrest, and having a higher NCA score (*OR* = 1.383, $p < .001$) was associated with an increased odds of new criminal arrest (Model 1). Specifically, a 1-year increase in age was associated with a .15 percent decrease in the odds of new criminal arrest, while a 1-point increase on the NCA score was associated with a 38 percent increase in the odds of new criminal arrest. The results further suggest that the odds of experiencing a new criminal arrest by NCA score did not differ by age (*OR* = 1.002, $p = .087$). Similar to the FTA score, a 1-year increase in age resulted in a .2 percent increase in the *predicted odds* of each NCA score. The .2 percent increase in the predicted odds of each NCA score is relatively small when compared to the baseline predictive ability of the NCA score.

Regarding new violent criminal arrests, the results of the models appeared to suggest that older individuals have a lower odds of experiencing a new criminal arrest (OR = .983, p < .001) and having a higher NVCA score was associated with a higher odds of new violent criminal arrest (OR = 1.485, p < .001). Specifically, a 1-year increase in age was associated with a .17 percent decrease in the odds of experiencing a new violent criminal arrest, while a 1-point increase in the NVCA score was associated with a 49 percent increase in the odds of experiencing a new violent criminal arrest. However, similar to the previous findings, the results suggested that the age of an individual did not improve the predictive validity of the NVCA score (OR = 1.003, p = .106). In particular, a 1-year increase in age was associated with a .3 percent increase in the predicted odds of each NVCA score. When compared to the baseline predictive ability of the NVCA score, this represents a relatively small increase in the predicted odds from ages 18 to 68.

***** Insert Table 2 About Here *****

6.4. Evaluating The Predictive Validity by Age

To evaluate the predictive validity of the FTA, the AUC for the FTA was plotted at each age between 18 and 68 years old (Figure 2). The red line provides the linear relationship between the AUC of the FTA (Panel A), NCA (Panel B), or NVCA (Panel C) and age. The gray area represents the standard error surrounding the linear trendline. Evident by the figures, the predictive validity of the FTA, NCA, and NVCA remains and appears to increase slightly as individuals age. For instance, the AUC for the FTA score appeared to increase from .62 to .65, which shows that modest improvements do occur across the age groups. Similarly, the AUC for the NCA score appeared to increase from .63 to .68. This increase represents a .05 increase in the predictive validity of the NCA suggesting that some slight improvements do occur across the age groups. The AUC for the NVCA score increases from approximately .62 to .67, highlighting that only modest increases in the AUC occur across the age groups. Overall, these results suggest that the PSA does improve across the age groups of individuals on pretrial supervision, but only modestly.

***** Insert Figure 3 About Here *****

6.5. Sensitivity Analysis: Time Until FTA, NCA, and NVCA

While the PSA was developed to predict if a defendant failed to appear, had a new criminal arrest, and/or had a new violent criminal arrest and not the time until each event, supplemental parametric survival models were estimated predicting time until failure to appear, new criminal arrest, and new violent criminal arrest using the FTA, NCA, and NVCA (respectively) and the interaction term with age.[10] Corresponding with the primary results, the results of the sensitivity analysis suggested that being older was associated with longer periods of time until experiencing a failure to appear (HR = 1.009, $p = .001$), while higher scores on the FTA were associated with shorter periods of time until experiencing a failure to appear (HR = .784, $p < .001$). Notably, the age of the respondent did not moderate the association between the FTA score and time until failure to appear (HR = .999, $p = .169$). A similar pattern of findings was observed when predicting time until new criminal arrest and time until new violent criminal arrest. Specifically, while the age of the defendant and the NCA/NVCA score predicted time until new criminal arrest and time until new violent criminal arrest, the age of the defendant did not appear to increase or decrease the ability of the NCA or NVCA to predict time until new criminal arrest and time until new violent criminal arrest. Overall, these findings support the

[10] The survival model was estimated using a lognormal distribution after comparing the AIC values across all potential distributional specifications for the survival model. The complete model results can be provided upon request.

primary models, suggesting that the FTA, NCA, and NVCA might not differentially predict failure to appear, new criminal arrest, and new violent criminal arrest by age.

7. Discussion

Research on actuarial assessments has consistently supported their use across the justice system, with practitioners using them to classify individuals into groups with distinct probabilities of future justice outcomes (Desmarias et al., 2020; 2022). Prior research, moreover, suggests that the predictive validity of many actuarial assessments, including pretrial assessments, is consistent across race and ethnicity, as well as sex (Lowder et al., 2019). Despite numerous robust evaluations, little is known about the efficacy of pretrial assessments across ages. This oversight in the contemporary scholarship is largely related to the focus on post-sentencing assessments, the approach used to evaluate the predictive validity of actuarial assessments, and the grouping of individuals within age brackets (Desmarias et al., 2020; Monahan et al., 2017). To address this gap in our knowledge, the current study conducted an age-graded evaluation of the PSA to observe if the predictive validity of the PSA varied by age and if the PSA differentially predicted pretrial outcomes by age. Three findings pertaining to the PSA should be highlighted.

First, the findings suggest that younger individuals possess a higher likelihood of failing to appear, experiencing a new criminal arrest, and experiencing a new violent criminal arrest than older individuals. This finding was partially observed in Figure 1 and then supported by the regression models. While the mechanisms contributing to this association are open for debate (e.g., Farrington, 1986), this finding is consistent with the broader criminological literature suggesting that younger individuals are more involved in criminalized activities than older individuals. In this sense, it appears that younger individuals on pretrial supervision are more likely to engage in, or at least to be arrested for, undesired activities during pretrial supervision than older individuals.

Second, the results demonstrate that the PSA was predictive of failure to appear, new criminal arrest, and new violent criminal arrest after accounting for the age of the individual and the covariates included in the model. Specifically, higher scores on the FTA, NCA, and NVCA appeared to be associated with a higher likelihood of failure to appear, new criminal arrest, and new violent criminal arrest (respectively). This finding supports the existing evidence, suggesting that the PSA is predictive of pretrial outcomes across multiple sites (e.g., DeMichele et al., 2020).

Finally, the findings here indicate that the PSA did differentially, although modestly, predict failure to appear, new criminal arrest, and new violent criminal arrest by the age of an individual, suggesting that to some extent it does have disparate impact based on one's age. Moreover, the results demonstrated that the AUC of the FTA, NCA, and NVCA score did slightly increase as individuals aged. These findings suggest that the PSA does have the potential to overpredict or underpredict pretrial outcomes for individuals at different stages of the life course. It is believed that this observation could have occurred for three reasons: 1) the antisocial tendencies of individuals tend to decline with age – as observed in the life-course literature – making it easier to predict (Farrington, 2003), 2) the PSA relies on criminal history items measuring involvement in criminal activity at any time during the life-course (lifetime criminal history measures), and 3) grouping individuals into age categories – e.g., 26-40 – could produce results that exacerbate the differences between age groups. Independent of the causes of the differences, these findings suggest that the behavioral tendencies and lifestyles of older individuals compared to younger individuals could contribute to slight differences in the predictive validity of pretrial risk assessments.

Concerning the age categories employed in the prior literature (Monahan et al., 2017), a supplemental analysis was conducted to observe if using the same three age categories (25 years and younger, 26-40, and 41 years and older) produced estimates distinct from the estimates observed in Table 2. The results of this supplemental model show that the FTA, NCA, and NVCA scores did differentially predict failure to appear, new criminal arrest, and new violent criminal arrest across these age groupings (25 years and younger, 26-40, and 41 years and older). The differences between the primary results and the supplemental results suggest that the employment of an age-graded analytical strategy provides a more robust examination of age-related biases in pretrial assessments when compared to examining age biases using relatively large age groupings. These supplemental findings support the suggestion of Monahan and colleagues (2017) to expand age categories for enhanced predictive validity. With these reasons in mind, it is suspected that pretrial assessments that rely heavily on criminal history are predictive of pretrial outcomes, but slight differences could exist in the predictive validity of the tool depending upon an individual's age.

The current study is not without limitations, three of which should be highlighted. First, the results of the current study pertain only to the PSA, which is scored using a series of static items measuring the legal system history of a defendant. As such, it remains unknown if the predictive validity of dynamic risk factors varies across the life-course. Future research should conduct age-graded evaluations of risk-need assessments that integrate both static and dynamic factors when calculating the likelihood of future legal system outcomes. Second, due to data restrictions, we were unable to evaluate the predictive validity of the PSA for individuals under the age of 18. Future research should assess the predictive validity of the PSA for young people with justice system involvement, as well as evaluate if the AUC for the PSA scores varies substantively when comparing young people to adults. This is of particular importance when applying life-course theories to age-graded evaluations considering the significance of the adolescent and late teenage years. Finally, due to data limitations, we were unable to evaluate how the predictive validity of the PSA varied within an individual over the life-course. Future research should study if the predictive validity of the PSA varies as individuals become older.

7.1. Conclusion

The findings here produced some evidence supporting the postulation that the PSA would be more predictive for older individuals when compared to younger individuals. The current study also provides a framework for evaluating if the predictive validity of an assessment is biased by the age of a defendant. Currently, the literature evaluating the predictive validity of actuarial assessments has largely focused on race, ethnicity, and sex biases. This focus, in turn, has created a substantive gap in our knowledge, producing a situation where it remains largely unknown if the predictive validity of actuarial assessments differs by age. Coinciding with this gap, a substantive number of untested hypotheses remain in the assessment literature. Of particular importance are the hypotheses suggesting that the predictive efficacy of the items used to score justice system assessments should vary across the life-course (Monahan et al., 2017).

Through reliance on age-graded evaluations, the literature can further examine the validity of pretrial assessments for all individuals that encounter the legal system, as well as examine if the items used to score actuarial assessments are biased by the race, sex, and age of an individual. For example, one question that remains unaddressed in the broader literature is whether the predictive validity of assessments may differ for young Black men, a group overrepresented in the criminal legal system, when compared to other pretrial populations. With this, we call on scholars to consider age when evaluating the predictive bias in assessments. Only with more research, can we begin to understand the functionality of these assessments across the life-course and, more importantly, make appropriate changes to limit any biases associated with age.

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Tables and Figures

Table 1.
Descriptive Statistics for the Analytical Sample.

	Full Sample		County 1	County 2	County 3
	Mean (%)	SD	Mean (%)	Mean (%)	Mean (%)
Age (18-68)	34.01	11.23	34.30	33.71	34.68
Age: 18-25	26%		24%	28%	23%
Age: 26-35	36%		37%	36%	37%
Age: 36-45	20%		21%	19%	23%
Age: 46-55	12%		12%	12%	12%
Age: 56-68	6%		5%	6%	5%
PSA Scores					
FTA (1-6)	2.70	1.54	2.97	2.39	3.43
NCA (1-6)	2.68	1.44	2.90	2.43	3.33
NVCA (1-6)	1.82	0.98	1.72	1.86	1.93
Outcomes					
Failure to Appear	21%		26%	17%	24%
New Criminal Arrest	23%		23%	25%	16%
New Violent Criminal Arrest	7%		7%	8%	4%
Covariates					
Days at Risk (1-1510)	202.87	221.26	114.95	263.57	182.97
Offense Level					
Misdemeanor	49%		49%	49%	45%
Felony	51%		51%	51%	55%
Offense Type					
Other Offenses	6%		>1%	11%	>1%
Property Offenses	28%		29%	28%	28%
Public Order Offenses	18%		30%	9%	29%
Violent Offenses	33%		31%	35%	31%
Drug Offenses	15%		10%	18%	13%
Charge Count (1-79)	2.23	1.90	2.09	2.33	2.24
County of Commitment					
County 1	36%		--	--	--
County 2	55%		--	--	--
County 3	10%		--	--	--
Race					
White	40%		67%	16%	74%
Non-White	60%		33%	84%	26%
Sex					
Male	72%		72%	73%	71%
Female	28%		28%	27%	29%
N	31,527		11,248	17,277	3,002

Table 2.

Full model results predicting failure to appear, new criminal arrest, and new violent criminal arrest with the FTA, NCA, and NVCA scores (respectively) and Age at Arrest.

	Failure to Appear				New Criminal Arrest				New Violent Criminal Arrest			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
	OR	*p*	OR	*p*	OR	*p*	OR	*p*	OR	*p*	OR	*p*
Key Predictors												
Age at Arrest	**0.995**	**.000**	**0.991**	**.001**	**0.985**	**.000**	**0.980**	**.000**	**0.983**	**.000**	**0.976**	**.000**
FTA score	**1.261**	**.000**	**1.200**	**.000**	--	--	--	--	--	--	--	--
NCA score	--	--	--	--	**1.383**	**.000**	**1.311**	**.000**	--	--	--	--
NVCA score	--	--	--	--	--	--	--	--	**1.485**	**.000**	**1.351**	**.000**
Interaction Terms												
Age at Arrest*FTA score	--	--	1.002	.086	--	--	--	--	--	--	--	--
Age at Arrest*NCA score	--	--	--	--	--	--	1.002	.087	--	--	--	--
Age at Arrest*NVCA score	--	--	--	--	--	--	--	--	--	--	1.003	.106
Covariates												
Misdemeanor	**0.679**	**.000**	**0.679**	**.000**	0.995	.889	0.996	.901	1.112	.044	1.110	.047
Other Offenses	**0.397**	**.000**	**0.396**	**.000**	**0.520**	**.000**	**0.522**	**.000**	0.846	.270	0.850	.286
Property Offenses	**1.227**	**.000**	**1.227**	**.000**	**1.424**	**.000**	**1.425**	**.000**	**1.724**	**.000**	**1.720**	**.000**
Public Order Offenses	**0.661**	**.000**	**0.661**	**.000**	**0.772**	**.000**	**0.773**	**.000**	1.194	.096	1.195	.094
Violent Offenses	**0.792**	**.000**	**0.794**	**.000**	1.098	.044	1.100	.040	**1.784**	**.000**	**1.787**	**.000**
Time at Risk	**0.999**	**.000**	**0.999**	**.000**	**0.998**	**.000**	**0.998**	**.000**	**0.998**	**.000**	**0.998**	**.000**
Charge Count	1.009	.259	1.009	.255	1.006	.417	1.006	.390	0.988	.345	0.989	.369
County 2	**0.778**	**.000**	**0.777**	**.000**	**1.798**	**.000**	**1.794**	**.000**	**1.256**	**.000**	**1.254**	**.000**
County 3	0.868	.005	0.867	.005	**0.621**	**.000**	**0.621**	**.000**	**0.608**	**.000**	**0.608**	**.000**
White	0.962	.264	0.963	.283	1.000	.995	1.002	.945	0.827	.001	0.829	.001
Female	0.976	.463	0.977	.477	**0.846**	**.000**	**0.846**	**.000**	**0.767**	**.000**	**0.769**	**.000**
N	31,527				31,527				31,527			

Notes: Bolded estimates indicate that $p < .001$. Full model estimates can be provided upon request.

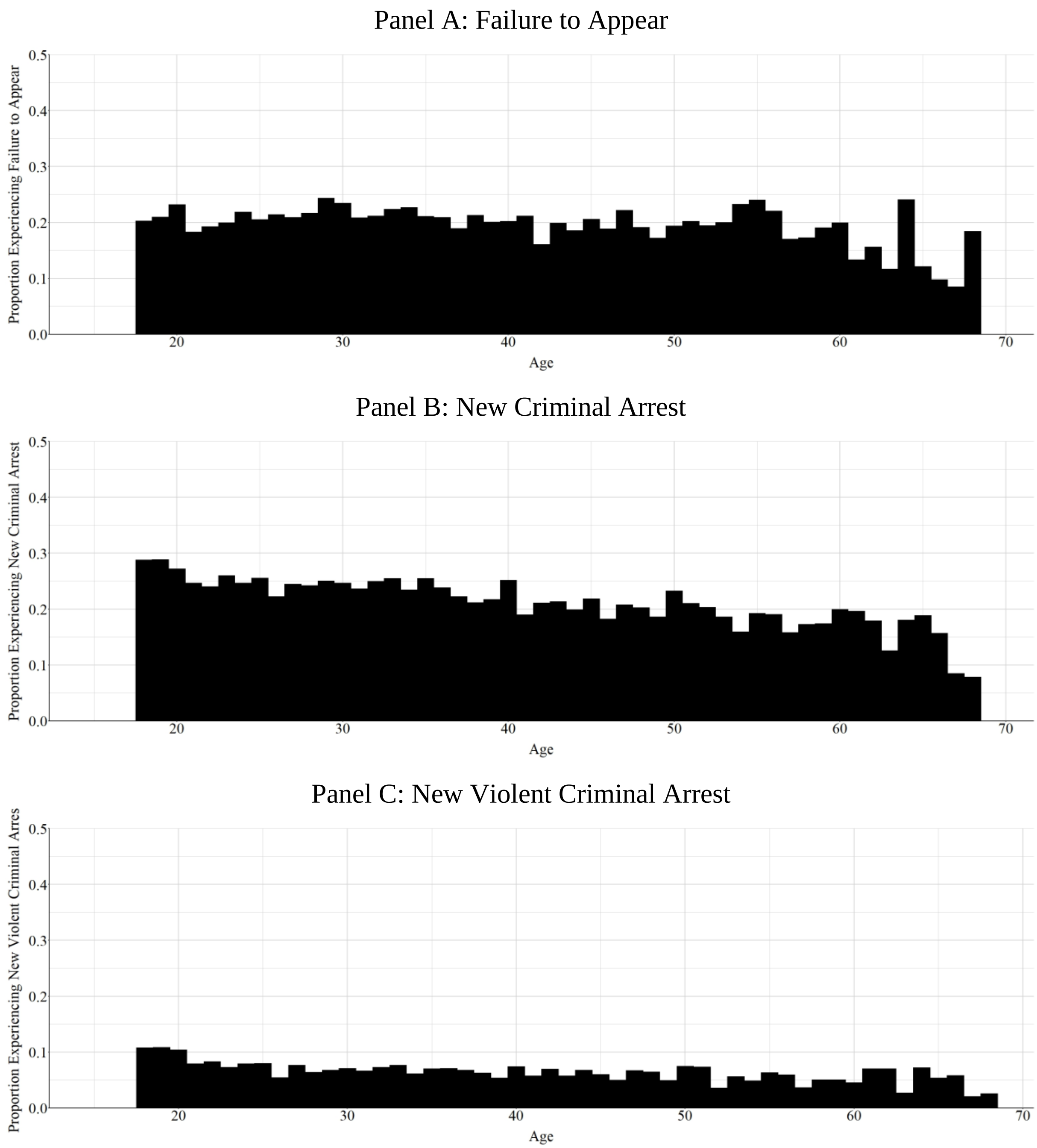

Figure 1.
Proportion of Individuals Experiencing Each Outcome by Age (N = 31,527)
Notes: Gray bars in the proportion of respondents at each age experiencing the corresponding outcome during pretrial.

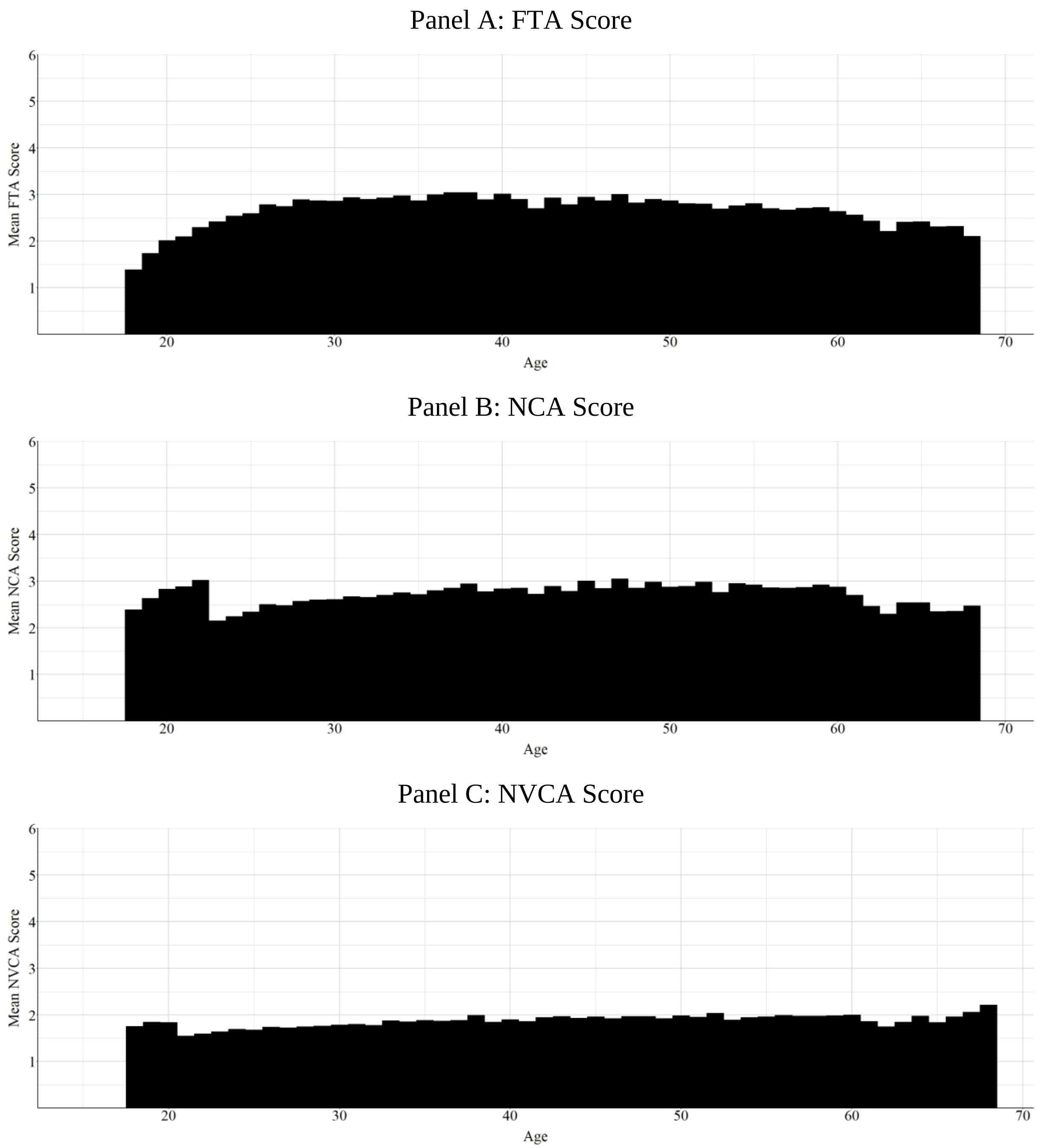

Figure 2.
Average Score on the PSA by Age (N = 31,527)

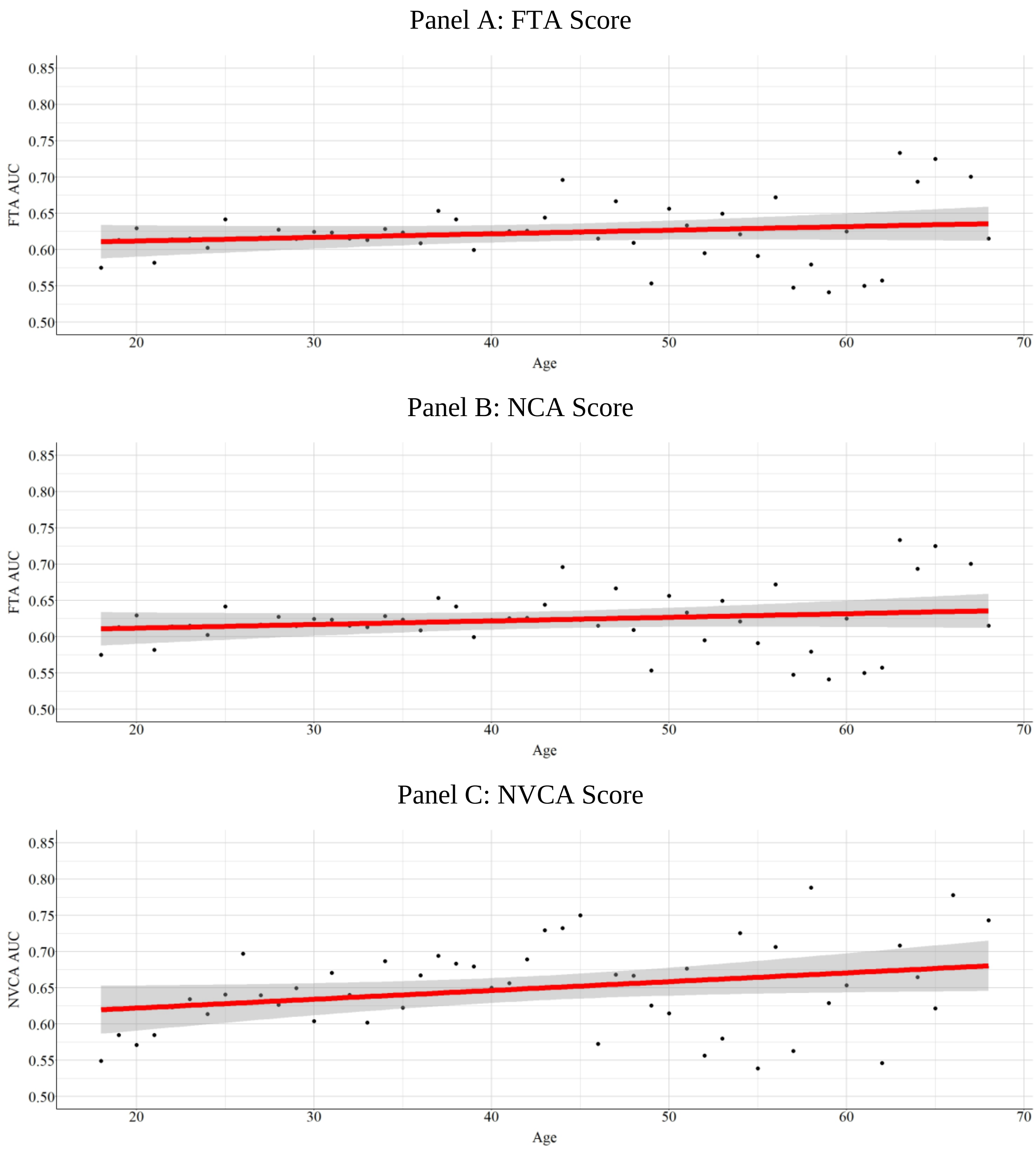

Figure 3.
AUC for PSA Scales by Age (N = 31,527)

Notes: The AUC for the FTA, NCA, and NVCA scale was produced by regressing failure to appear, new criminal arrest, or new violent criminal arrest on the FTA, NCA, or NVCA score (respectively; bivariate models). AUC values of .54 and below are considered poor, .55 to .63 are considered fair, and .64 to .70 are considered good, with values higher than .71 are considered excellent (Desmarais et al., 2018).