Flagged for Failure: Surveillance, Schools, and the Automation of Injustice

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***Abstract*—Algorithmic decision-making systems are increasingly used in public services yet concerns persist about their potential to reinforce bias and inequality. This paper critically examines the At-Risk Youth Program (ARYP), a predictive policing model implemented by the Pasco County Sheriff's Office to identify students deemed likely to engage in criminal behavior. Through an algorithmic audit and comparative case studies—including COMPAS, PredPol, the Allegheny Family Screening Tool, and Decision Support Algorithm—this study reveals how the ARYP relies on racially and socioeconomically biased indicators, such as school records, child welfare data, and adverse childhood experiences. These inputs create a feedback loop that disproportionately targets marginalized youth, exacerbating the school-to-prison pipeline. The findings demonstrate that predictive risk models often encode systemic inequities, legitimizing discriminatory outcomes under the guise of objectivity. The paper concludes with recommendations for reform, emphasizing transparency, community oversight, and resource reallocation to address root causes of harm.**

Keywords—predictive policing, algorithmic bias, school-to-prison pipeline, criminal justice reform

I. Introduction

Algorithmic decision-making systems are increasingly being utilized by governments and public service agencies to make decisions about people and their life outcomes. However, scholars and social justice activists have voiced concerns over the potential harms and biases embedded within these systems, calling into question whether these models do more harm than good. Furthermore, these systems are often used without transparency in the data used to train these models, how they work, and how they are being utilized.

Predictive risk models have been deployed across various sectors, influencing decisions made by child welfare services on determining risk in Pennsylvania [1], landlords on choosing tenants [2], and by homeless services on housing in Los Angeles [3], to name a few. These kinds of predictive models have been controversial, as the unchecked adoption of these systems risks automating discrimination under the guise of risk prevention [4, p. 1].

The criminal justice system reflects this tension, specifically in policing in schools. While equitable outcomes in the education and criminal justice system are fundamental to a just society, the recent integration of algorithmic policing in public schools risks exacerbating existing disparities like the school-to-prison pipeline. If design flaws and racial bias are encoded within these tools, they can result in disproportionate surveillance, disciplinary actions, and over-policing of marginalized students.

In this paper, I will be focusing on the Pasco County Sheriff's Office's implementation of an Intelligence-Led Policing (ILP) program, where a predictive model called the At-Risk Youth Program (ARYP) was used to identify "high-risk" students for criminal behavior. According to their internal manual, the algorithm integrated data from the Pasco County School Board and the Department of Children and Families to generate a list of kids deemed likely to "fall into a life of crime" [5, p. 14].

The Sheriff's Office cites that the primary motivation for developing this algorithm is to reduce crime rates. However, when this model is racially and socioeconomically biased, it can lead to increased incarceration rates in marginalized communities and further entrench the inequalities that contribute to crime.

This paper will critically examine the ARYP's design, implementation, and consequences. By looking at the ARYP and comparing it to other predictive risk models on policing and children, the paper will evaluate the extent to which these models contribute to inequality and marginalization. This analysis aims to illuminate the risks of predictive algorithms and the urgent need for reform and accountability.

II. Background

A. Tampa Bay Times

In 2020, the Pasco Sheriff's Office in Florida came under scrutiny following an investigative report by the Tampa Bay Times. The report, authored by journalists Neil Bedi and Kathleen McGrory, revealed that the Sheriff's Office had implemented the ARYP within their wider Intelligence-Led Policing program that involved the algorithmic identification of students "who are destined to a life of crime" [5, p. 14]. The agency compiled this list by cross-referencing school enrollment records with sensitive data obtained through partnerships with the Pasco County School District and the Florida Department of Children and Families. This was all done without the knowledge or consent of students or their families [6]. Notably, the ARYP received federal funding through the Department of Justice's

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(DOJ) Students, Teachers, and Officers Preventing (STOP) School Violence Program, highlighting how the federal government supports and finances predictive algorithms like the ARYP under the objective of violence prevention [7].

The manual noted that while most law enforcement agencies lack access to certain personal data, the Pasco Sheriff's Office had obtained records that allowed it to assess factors such as academic performance, family structure, and socioeconomic backgrounds. The model was inspired by David Farrington and Jerry Ratcliffe's analysis of the psychological explanations of crime which considered these variables predictive of future delinquency [8, p. 45]. The ARYP then encouraged law enforcement to build relationships with flagged students to identify "the seeds of criminal activity" [5, p. 67]. According to the Tampa Bay Times, deputies often found and interrogated the people on the list, often without probable cause.

This investigative article led to widespread discussion on both the ethics and legality of programs like the ARYP with students, families, teachers, and human rights activists becoming vocal about their concerns and outrage. However, the Sheriff's Office continued to defend their program along with the superintendent of Pasco County [9].

B. The School-to-Prison Pipeline

The school-to-prison pipeline describes the relationship between harsh school discipline policies, such as zero-tolerance rules and increased police presence in schools, and its disproportionate effect on vulnerable students and contributes to their involvement in the criminal justice system [10].

Over the past few years, police presence in schools has surged. According to the 2017-18 Civil Rights Data Collection, approximately 41% of high schools, 38% of middle schools, and 17% of elementary schools had a School Resource Officer (SRO) stationed on campus at least part-time [11]. While SROs are often framed as protective figures, their presence has led to greater student arrests for nonviolent behaviors, such as classroom disruptions or minor rule violations [12]. When schools refer students to law enforcement, or allow SROs to arrest them, they initiate a student's first contact with the juvenile justice system, making it more likely for them to acquire a permanent record and face harsher penalties for future incidents.

Despite declining juvenile crime rates (juvenile incarceration dropped 41% between 1995 and 2010), school discipline has become more punitive. Out-of-school suspensions have increased by 10% since 2000 and more than doubled since the 1970s, with Black students bearing the brunt of these policies. Federal data reveals that Black students are three times more likely to be suspended or expelled than white students [10].

III. METHOD/APPROACH

To critically assess the effectiveness, fairness, and ethical implications of Pasco County's At-Risk Youth Program, this study employs a mixed-method approach combining algorithmic auditing and comparative case studies.

1) Audit of the ARYP

Using primary documents, including the Pasco County Sheriff's Intelligence-Led Policing Internal Manual, we will:

- Evaluate model design
- Assess its fairness and validity
- Examine implementation

After analyzing the ARYP, we will evaluate the extent to which it contributes to the disproportionate targeting and criminalization of marginalized communities.

2) Comparative Case Studies

To situate the ARYP within broader debates on predictive risk algorithms, we will analyze four additional models:

- COMPAS (Correctional Offender Management Profiling for Alternative Sanctions)
- PredPol
- Allegheny Family Screening Tool (AFST)
- Denmark's Decision Support Algorithm (DSS)

By comparing the ARYP to other predictive risk algorithms we can identify recurring systemic flaws and draw evidence-based conclusions about what improvements should be made.

IV. ANALYSIS

1) Audit of the ARYP

The ARYP internal manual describes how youth are identified through the analysis of their risk in three primary categories: educational risk factors, criminogenic risk factors, and adverse childhood experiences. The Sheriff's Office explains, "The criteria and scoring in each category are grounded on empirically based research of behaviors and other indicators that are indicative of a juvenile at risk for developing into a chronic recidivist offender" [5, p. 71]. The model is based on Farrington who assert that "potential offenders can be identified at an early age with a reasonable degree of accuracy" [13, p. 105].

The Sheriff's Office constructed its list of children to monitor by combining data from its own Records Management System (RMS) with information from the Florida Department of Children and Families' child welfare database and the County School Board's Early Warning System (EWS), which tracks all students' grades, attendance, and behavior. For each child, the variables are assigned one of four labels: on track, at risk, off track, or critical [5]. There are three primary categories of variables used in the model: educational risk factors, criminogenic risk factors, and Adverse Childhood Experiences (See Appendix A).

I. Educational Risk Factors

The educational risk factors used include course performance, GPA, credits, attendance, and office discipline referrals (See Appendix A). The thresholds used to flag students as "At-Risk" are notably low: earning a single D, falling one credit behind, having three absences in a quarter, and having one office discipline referral in a quarter can all result in an "At-Risk" label.

It is important to interrogate the assumption that academic indicators such as GPA or credit accumulation have a direct causation with future criminal behavior. In reality, poor academic performance can stem from a wide range of socio-economic and structural issues, including food insecurity, housing instability, undiagnosed learning disabilities, and under-resourced schools, none of which are inherently criminogenic [14]. None of these factors are inherently criminogenic, yet by treating them as proxies for criminal propensity, the model leads to the "the criminalization of poverty," referring to the various legal and social mechanisms that enforce penalties on those in poverty [15]. While studies demonstrate correlational trends between aggregate academic performance and delinquency rates, this does not mean that individual students with poor grades are likely to offend [16].

Absenteeism is another deeply flawed indicator. Students may miss school due to circumstances beyond their control—caretaking responsibilities, unstable transportation, or unsafe home environments—rather than a disengagement from learning [17]. Using these absences as predictors of future criminality skews the model to target vulnerable and low-income students.

Importantly, these indicators disproportionately affect students of color and students with disabilities. For example, one of the variables is "Office Discipline Referrals." In Pasco County, Black students comprise just 7.4% of the student population but are significantly overrepresented in all forms of school discipline: 14.9% of in-school suspensions, 14.4% of out-of-school suspensions, 23% of expulsions, 13.9% of law enforcement referrals, and 18.5% of school-related arrests [18]. Additionally, studies have found that police in schools were associated with an additional arrest of 1.22 Black students, but only 0.38 White and 0.48 Hispanic students per 1,000 [12]. Furthermore, a landmark study in Texas revealed that 97% of school suspensions were discretionary, meaning they were subject to bias and individual decision-making, with Black students 31% more likely to receive such suspensions, even after controlling for 83 variables [10].

Disciplinary actions, represented by the "Office Discipline Referral" variable, often have cascading effects on other educational risk variables. A suspension not only results in office referrals but also increases absences, reduces credit accumulation, and lowers GPA, all of which further raise a student's risk score. This cyclical interaction between punitive measures and risk factors feeds into ARYP's feedback loop. Ultimately, the model falsely presumes academic metrics are neutral indicators rather than products of systemic bias.

II. Crimionogenic Risk Factors

Furthermore, the model also uses criminogenic risk factors. Criminogenic means the factors or situations that increase the likelihood of someone committing a crime [19]. These factors include variables like "Number of Convictions", "Drug or Alcohol", and "Crime Type"; other variables such as "Victim of Personal Crime," and "Custody Disputes" are out of a child's control (See Appendix A).

One of the central issues is that these variables may reinforce existing disparities in law enforcement practices. Empirical research has consistently demonstrated that police presence and enforcement activity are disproportionately concentrated in predominantly Black and low-income communities, both in Florida and across the United States [20]. As a consequence, children from these communities are more likely to have contact with law enforcement and appear in sheriff's office records because of targeted policing strategies. When predictive models treat frequency of law enforcement contact as a proxy for future criminality, they risk encoding and perpetuating existing racial and socio-economic biases in policing.

Furthermore, the use of victimization data, whether a child has been a victim of personal crimes like assault or battery, as a risk indicator is problematic. Research shows that Black youth and other children of color are more likely to be victims of certain types of violent crime [21]. Including victim status as a risk factor inadvertently penalizes children who have already experienced trauma, thereby contributing to their further marginalization.

The inclusion of family circumstances such as custody disputes further illustrates the problematic assumptions embedded in the model. Custody disputes are legal matters between guardians and are entirely outside of a child's agency or control. The notion that a child becomes "At-Risk" for future criminal behavior due to parental custody disputes imposes an unjustified burden on the child. By this model, a child will automatically be labeled as "At-Risk" simply because of that.

III. Adverse Childhood Experiences

Lastly, the At-Risk Youth List also relies on a children's exposure to Adverse Childhood Experiences (ACEs), which include traumatic events such as physical abuse, neglect, sexual abuse, and witnessing domestic violence (See Appendix A), drawn the Sheriff's Offices' records.

While research on ACEs has consistently demonstrated that childhood trauma increases the risk of a wide range of adverse social, health, and behavioral outcomes, using these indicators to inform predictive policing models is deeply problematic. Originally developed as a public health tool, ACEs are strongly correlated with educational disruptions, substance use, and mental health disorders—not with criminal behavior [22]. When predictive policing conflates trauma exposure with a propensity for crime, it effectively criminalizes victims of trauma.

Moreover, Black families are disproportionately entangled with the child welfare system, a primary source of ACE data. In Florida, for instance, Black children made up 19.9% of the child population in 2021 but accounted for 29.1% of reported child maltreatment victims and 28.5% of those in foster care [23]. Nationally, over 50% of Black children will undergo a child welfare investigation before the age of 18, nearly double the rate for white children [24]. Importantly, research indicates that rates of child maltreatment do not significantly differ across racial groups. Instead, disparities arise from systemic biases in reporting and decision-making within child protective services [25]. For example, one study found that medical professionals often held strong stereotypes linking child abuse with both race and poverty [26]. These stereotypes can lead to biased diagnoses and overreporting of abuse among Black and low-income families.

Incorporating ACEs into predictive policing ignores the structural inequities that shape both trauma exposure and system involvement. It risks re-traumatizing vulnerable children through increased surveillance and punitive interventions based on their life circumstances.

IV. Feedback Loop

The ARYP operates under the assumption that it can objectively identify children likely to become future offenders. However, the program's reliance on educational risk factors, criminogenic risk factors, and ACEs, all of which are shaped by bias and inequity, undermines the model's credibility. At the heart of this issue is a self-perpetuating feedback loop: historically over-policed communities produce more "risk" indicators, which in turn justify increased surveillance and intervention. These interventions then lead to higher rates of law enforcement contact, which then reinforce the original predictions of criminal behavior, further entrenching the cycle. Thus, historical patterns of biased policing are used to justify future biased policing practices.

Moreover, by conflating poverty with criminal risk, the model effectively punishes socio economic hardship, contributing to the very instability and desperation it claims to prevent. This dynamic exemplifies what sociologist Ruha Benjamin terms the "New Jim Code," a process by which technologies that claim neutrality and objectivity ultimately serve to reproduce and legitimize racial hierarchies under the guise of data-driven governance [4, p. 24].

2) Comparative Case Studies

Beyond the ARYP, the use of predictive analytics has evolved and expanded in the last two decades. This is in part because the National Institute of Justice, the Department of Justice (DOJ)'s research, development, and evaluation arm, regularly funds pilot projects on predictive policing. Additionally, another DOJ entity, the Bureau of Justice Assistance, funds projects with direct financial grants [27]. With this, many police departments and law enrichment agencies have implemented predictive policing programs with mixed results.

The next section situates ARYP within the broader field of predictive risk algorithms by comparing with four other models: COMPAS (Correctional Offender Management Profiling for Alternative Sanctions), PredPol, Allegheny Family Screening Tool (AFST), and Denmark's Decision Support Algorithm (DSS).

I. COMPAS

COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) is one of the first predictive policing algorithms to be widely utilized and has been used across the U.S. to assess a defendant's likelihood of recidivism and inform pretrial release, sentencing, and parole decisions [28]. The use of algorithms to decide this was seen as a fair and neutral option as opposed to human opinion.

However, a 2016 ProPublica report challenged the assumption that algorithms like COMPAS are neutral. The authors argued that despite claims of fairness, the algorithm systematically disadvantages Black defendants while underestimating risk for white defendants. Some key findings were that White defendants who did reoffend were 48% likely to be incorrectly deemed low-risk vs. 28% for Black defendants. They also found that even after controlling for criminal history, age, and gender, Black defendants were 45% more likely to receive higher general recidivism scores and 77% more likely to receive higher violent recidivism scores [28].

A major issue with COMPAS is its lack of transparency as the algorithm's methodology remains undisclosed. However we can deduce that because it relies on machine learning, its outputs depend heavily on input data. If the data used to train the model is racially biased (e.g., due to disparate policing of Black communities), the results will reflect those biases. This aligns with findings from the ARYP analysis, suggesting that COMPAS may be skewed by historical disparities in arrest and incarceration data.

II. PredPol

The concerns in COMPAS are further highlighted in PredPol, a widely used crime-prediction algorithm that predicts crime hotspots to direct police patrols. An investigation by Gizmodo found that PredPol reinforces racial and socioeconomic biases under the guise of objectivity by using historical crime data that reflected existing biases in policing; finding that PredPol's predictions systematically over-police Black and Latino neighborhoods by up to 400% more than wealthier, Whiter areas [29].

Like the ARYP, PredPol generated a feedback loop that falsely validated its predictions while exacerbating existing inequalities. The algorithm's predictions concentrated police patrols in already over-policed neighborhoods, leading to increased arrests that were then fed back into the system, reinforcing their "high-risk" status. At the same time, wealthier White neighborhoods, overlooked by law enforcement, were reinforced as "low-risk" areas [29]. This created a self-perpetuating cycle: heightened policing generated more crime reports, which in turn justified additional policing, deepening racial and economic divides.

Further mirroring another key issue with the ARYP, PredPol operated without meaningful public awareness or oversight. Gizmodo also found that community members had no idea their neighborhoods were being targeted by these algorithmic predictions, raising concerns about transparency and accountability in predictive policing systems.

III. Allegheny Family Screening Tool

The AFST is a predictive risk model designed to identify children at highest risk of abuse or neglect in Allegheny County, Pennsylvania. Similar to the ARYP, the algorithm pulls over one billion records from Pennsylvania county and state agencies to make its predictions. However, as Virginia Eubanks demonstrates, the tool suffers from significant methodological flaws that compromise its validity.

Eubanks identified several flaws and biases within the system, including the use of proxy variables such as re-referrals from others rather than actual maltreatment statistics. This means the AFST doesn't predict harm directly; instead, it predicts decisions made by the community, agency, and family courts, reflecting biases in reporting and decision-making.

Furthermore, by treating access to public service as risk factors, the AFST systematically over-identifies low-income and minority families as high-risk while excluding wealthier households that access private services, a phenomenon Eubanks terms "poverty profiling" [1].

Once flagged by the system, families are subjected to additional investigations that then produce more referrals, data which further validates their "high-risk" classification. Furthermore, a child's interaction with protective services permanently elevates their future risk score should they become parents, creating a cycle where families are perpetually flagged as high-risk.

IV. Decision Support Algorithm

Once flagged by the system, families are subjected to additional investigations that then produce more referrals, data which further validates their "high-risk" classification. Furthermore, a child's interaction with protective services permanently elevates their future risk score should they become parents, creating a cycle where families are perpetually flagged as high-risk.

The Decision Support (DSS) Algorithm is another predictive risk model designed to identify children at highest risk of abuse or neglect. Utilized in Denmark, the model also suffers from methodological flaws that undermine its validity. An audit found that the model exhibits age-based discrimination, systematically assigning higher risk scores to older children even when their risk factors are identical to younger children, a disparity stemming from the model's reliance on flawed proxies like foster care placements and preventive service usage [30].

The algorithm's design creates a self-validating feedback loop: high DSS scores trigger interventions from social workers, which are then fed back into the system as "evidence" of risk, reinforcing the model's predictions. DSS also disproportionately targets low-income families, treating public service utilization, such as financial aid or participation in youth clubs, as risk indicators.

Notably, DSS was developed without input from caseworkers, who were only presented with the model after its completion. Families were also never notified that their cases were being evaluated, nor were they given the option to opt out. During pilot testing, social workers overrode DSS's risk scores in 21% of cases, highlighting the model's unreliability. In one example, a neglected two-year-old received a DSS score of 1 (low-risk), while social workers assessed the case as a 9 (high-risk) [30].

V. Discussion and Concluding Thoughts

The audit of the Pasco County Sheriff Office's At-Risk Youth Program reveals a pattern of systemic issues rooted in flawed assumptions, biased data, and a lack of accountability, all of which undermine the legitimacy and ethicality of the program.

Central to the program's limitations is its reliance on variables such as school attendance records, disciplinary referrals, and child welfare involvement. These indicators are not neutral; they are shaped by broader systems of inequality and reflect social conditions rather than objective measures of risk.

The consequences of the ARYP are both immediate and long-term. In the short term, youth flagged by the system are often subjected to increased surveillance and intervention by law enforcement. Crucially, when law enforcement responses are prioritized over meaningful support—such as academic assistance, family counseling, or access to mental health services—the underlying conditions that contribute to behavioral or academic challenges remain unaddressed. Over time, repeated interactions with law enforcement are documented, limiting future opportunities and further entrenching social and economic marginalization. Rather than disrupting cycles of disadvantage, the model reinforces them: amplifying structural inequities and accelerating pathways into the justice system.

These findings are consistent with critiques of the other predictive models analyzed. Each of these systems has demonstrated similar vulnerabilities, including reliance on biased variables, disproportionate impact on marginalized populations, feedback loops, and lack of transparency. This is a discrepancy that underscores the algorithm's difficulties to capture real-world needs.

A particularly concerning aspect of ARYP and similar tools is the tendency to deflect attention from broader structural determinants of harm like economic inequality, racism, and resource and opportunity deprivation. These models shift responsibility away from institutions and punish individuals most affected by systemic inequity under the guise of objectivity.

However, it is important to consider whether predictive models can offer benefits. When problems involve urgent stakes like public safety or child welfare, there is understandable need to act quickly and efficiently. We should focus on using predictive models to allocate community support programs, mentorship opportunities, or educational initiatives, rather than using them to punish. Instead of discarding predictive models altogether, several policy and design reforms are recommended to improve fairness, transparency, and effectiveness:

1. Community Engagement and Participatory Design: Predictive models must actively incorporate the perspectives of impacted communities through participatory design to better understand needs and address flaws.
2. Interdisciplinary Collaboration: Cross-sector collaboration (social workers, educators, civil rights experts, etc.) is critical to designing tools that reflect the complexity of social problems.
3. Ongoing Auditing and Evaluation: Predictive systems must be subjected to regular, independent audits that assess not only their predictive accuracy but also their impact on equity and civil rights.
4. Resource Reallocation: Rather than expanding algorithmic tools, funding should be directed toward community-based, trauma-informed interventions that address root causes of harm.

References

[1] V. Eubanks, *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*. St. Martin's Press, 2018.

[2] E. Rosen, P. M. E. Garboden, and J. E. Cossyleon, "Racial Discrimination in Housing: How Landlords Use Algorithms and Home Visits to Screen Tenants," *Am. Sociol. Rev.*, vol. 86, no. 5, pp. 787–822, Oct. 2021, doi: 10.1177/00031224211029618.

[3] N. Tang *et al.*, "AI Failure Cards: Understanding and Supporting Grassroots Efforts to Mitigate AI Failures in Homeless Services," in *The 2024 ACM Conference on Fairness, Accountability, and*

Transparency, Rio de Janeiro Brazil: ACM, Jun. 2024, pp. 713–732. doi: 10.1145/3630106.3658935.
[4] R. Benjamin, *Race After Technology: Abolitionist Tools for the New Jim Code*. Polity Press, 2019.
[5] Pasco County Sheriff's Office, "Intelligence-Led Policing Manual," May 2018, [Online]. Available: https://s3.documentcloud.org/documents/20412738/ilp_manual012918.pdf.
[6] N. Bedi and K. McGrory, "Pasco's sheriff uses grades and abuse histories to secretly label kids potential criminals." Accessed: Apr. 29, 2025. [Online]. Available: https://projects.tampabay.com/projects/2020/investigations/police-pasco-sheriff-targeted/school-data
[7] "DOJ Grant to District School Board of Pasco Count," USASpending.gov. Accessed: Apr. 29, 2025. [Online]. Available: https://usaspending.gov/award/ASST_NON_2018YSBX0034_1550
[8] J. Ratcliffe, *Intelligence-led policing*, Second edition. London New York: Routledge, 2016.
[9] N. Bedi and K. McGrory, "Pasco superintendent defends sharing data with sheriff, as teachers object." Accessed: Apr. 29, 2025. [Online]. Available: https://www.tampabay.com/investigations/2020/12/15/pasco-superintendent-defends-sharing-data-with-sheriff-as-teachers-object/
[10] L. Nelson and D. Lind, "The school-to-prison pipeline, explained | Vox," Vox. Accessed: Apr. 29, 2025. [Online]. Available: https://www.vox.com/2015/2/24/8101289/school-discipline-race
[11] "2017-18 Estimations | Civil Rights Data," Civil Rights Data Collection Office for Civil Rights. Accessed: Apr. 29, 2025. [Online]. Available: https://ocrdata.ed.gov/estimations/2017-2018
[12] E. M. Homer and B. W. Fisher, "Police in schools and student arrest rates across the United States: Examining differences by race, ethnicity, and gender," *J. Sch. Violence*, vol. 19, no. 2, pp. 192–204, Apr. 2020, doi: 10.1080/15388220.2019.1604377.
[13] D. P. Farrington, "Predicting Individual Crime Rates," *Crime Justice*, vol. 9, Jan. 1987, doi: 10.1086/449132.
[14] Miller, Votruba-Drzal, and Coley, "Poverty and Academic Achievement Across the Urban to Rural Landscape: Associations with Community Resources and Stressors," *RSF Russell Sage Found. J. Soc. Sci.*, vol. 5, no. 2, p. 106, 2019, doi: 10.7758/rsf.2019.5.2.06.
[15] C. R. Larrison, "The Criminalization of Poverty," in *Social Work, Criminal Justice, and the Death Penalty*, L. A. Ricciardelli, Ed., Oxford University Press, 2020, p. 0. doi: 10.1093/oso/9780190937232.003.0008.
[16] S. Han, H. Baek, N. M. Connell, and M. Osborne, "The Relationship Between Academic Performance and Delinquent Behavior: Focusing on Strains Among Students With Unsatisfactory Academic Performance," *Crime Delinquency*, p. 00111287251316520, Feb. 2025, doi: 10.1177/00111287251316520.
[17] E. Armstrong-Carter, S. Osborn, O. Smith, C. Siskowski, and E. Olson, "'I Missed School to Take Care of Someone Else': Middle and High School Students' Caregiving Responsibilities as a Reason for Absenteeism," *J. Sch. Health*, vol. 94, Mar. 2024, doi: 10.1111/josh.13446.
[18] "PASCO 2017-18 | Civil Rights Data," Civil Rights Data Collection Office for Civil Rights. Accessed: Apr. 29, 2025. [Online]. Available: https://civilrightsdata.ed.gov/profile/us/fl/pasco?surveyYear=2017&nces=1201530
[19] LSD.law, "criminogenic definition." Accessed: Apr. 29, 2025. [Online]. Available: https://www.lsd.law/define/criminogenic#
[20] M. K. Chen, K. L. Christensen, E. John, E. Owens, and Y. Zhuo, "Smartphone Data Reveal Neighborhood-Level Racial Disparities in Police Presence," *Rev. Econ. Stat.*, pp. 1–29, Sep. 2023, doi: 10.1162/rest_a_01370.
[21] Office of Victims of Crime, "Youth Victimization." Department of Justice, Office of Justice Programs, 2018.
[22] CDC, "About Adverse Childhood Experiences," Adverse Childhood Experiences (ACEs). Accessed: Apr. 29, 2025. [Online]. Available: https://www.cdc.gov/aces/about/index.html
[23] A. Karthik and D. Moss, "Digitizing the School-to-Prison Pipeline, Pasco County's At-Risk Youth Program." Legal Defense Fund, Dec. 2024.
[24] S. White and S. M. Persson, "Racial Discrimination in Child Welfare Is a Human Rights Violation—Let's Talk About It That Way," American Bar Association. Accessed: Apr. 29, 2025. [Online]. Available: https://www.americanbar.org/groups/litigation/resources/newsletters/childrens-rights/racial-discrimination-child-welfare-human-rights-violation-lets-talk-about-it-way/
[25] "Mandatory Reporting of Child Abuse and Neglect - Florida," Child Welfare Information Gateway. Accessed: Apr. 29, 2025. [Online]. Available: https://www.childwelfare.gov/resources/mandatory-reporting-child-abuse-and-neglect-florida/
[26] C. J. Najdowski and K. M. Bernstein, "Race, social class, and child abuse: Content and strength of medical professionals' stereotypes," *Child Abuse Negl.*, vol. 86, pp. 217–222, Dec. 2018, doi: 10.1016/j.chiabu.2018.10.006.
[27] B. Carleton, B. Cunningham, and Z. Thorkildsen, "The Use of Predictive Analytics in Policing".
[28] J. Larson, S. Mattu, L. Kirchner, and J. Angwin, "How We Analyzed the COMPAS Recidivism Algorithm," ProPublica. Accessed: Apr. 29, 2025. [Online]. Available: https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm
[29] A. Sankin *et al.*, "Crime Prediction Software Promised to Be Free of Biases. New Data Shows It Perpetuates Them," Gizmodo. Accessed: Apr. 29, 2025. [Online]. Available: https://gizmodo.com/crime-prediction-software-promised-to-be-free-of-biases-1848138977
[30] T. Moreau, R. Sinatra, and V. Sekara, "Failing Our Youngest: On the Biases, Pitfalls, and Risks in a Decision Support Algorithm Used for Child Protection," in *The 2024 ACM Conference on Fairness, Accountability, and Transparency*, Rio de Janeiro Brazil: ACM, Jun. 2024, pp. 290–300. doi: 10.1145/3630106.3658906.

APPENDIX A

Table 1: Overview of the variables used in the At-Risk Youth Program.

Risk Factor Categories	Weighted Variables
Educational	• Course Perfomance • GPA • Credits • Attendance • Office Discpline Referrals
Criminogenic	• Age of Onset • Crime Type • Number of Convictions • Drug or Alcohol Use • Lack of Parental Supervision • Victim of Personal Crime • Delinquent Peers • Running Away • Custody Disputes • Certified Gang Member
Adverse Childhood Experiences	• Household member incarceration • Physical abuse • Emotional abuse • Witness household violence • Physical neglect • Household substance abuse • Sexual abuse