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Scoping review on the integration of artificial intelligence and machine learning with structured instruments to predict juvenile recidivism

Revisión de alcance sobre la integración de inteligencia artificial y aprendizaje automático con instrumentos estructurados para predecir reincidencia juvenil

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Abstract

Predicting the risk of recidivism in juvenile justice has traditionally relied on structured instruments, while the incorporation of AI/ML models has been proposed as a means of improving their performance. However, the actual added value of these models, their integration with structured tools, and their implications for practice remain a subject of debate. This scoping review evaluates whether integrating AI/ML models with structured risk assessment tools in juvenile justice meaningfully enhances recidivism prediction and practice. Five studies that met these criteria were included. Overall, the results show a consistent pattern of moderate discrimination and generally marginal improvements as model complexity increases, suggesting the existence of a certain empirical limit to predictive capacity in this field. Improvements are more likely when the comparator is strictly linear or when contrasted with unstructured judgment, suggesting that the added value of AI/ML may lie in modeling interactions between variables rather than in a substantial increase in accuracy. Nevertheless, aggregate performance may mask relevant differences among subgroups, including disparities associated with sociodemographic variables, which raises implications regarding equity and institutional legitimacy. Added to this are the challenges arising from their implementation, including model traceability, the interaction between professionals and these automated systems, and the need for frameworks that ensure oversight and auditing.

Key words: Artificial intelligence; machine learning; risk assessment; juvenile recidivism; juvenile justice.

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Resumen

La predicción del riesgo de reincidencia en justicia juvenil se ha apoyado tradicionalmente en instrumentos estructurados, mientras que la incorporación de modelos de IA/ML se ha propuesto como una vía para mejorar su rendimiento. No obstante, el valor añadido real de estos modelos, su integración con herramientas estructuradas y sus implicaciones para la práctica siguen siendo objeto de debate. La presente revisión de alcance sintetiza la evidencia empírica disponible sobre la aplicación de IA/ML en población juvenil cuando existe una vinculación con instrumentos estructurados de evaluación del riesgo. Se incluyeron cinco estudios que cumplían estos criterios. En conjunto, los resultados muestran un patrón consistente de discriminación moderada y mejoras generalmente marginales al incrementar la complejidad de los modelos, lo que sugiere la existencia de cierto límite empírico en la capacidad predictiva en este ámbito. Las mejoras son más probables cuando el comparador es estrictamente lineal o cuando se contrasta con juicio no estructurado, lo que apunta a que el valor añadido de la IA/ML puede residir en modelar interacciones entre variables más que en un incremento sustancial de la precisión. Sin embargo, el rendimiento agregado puede ocultar diferencias relevantes entre subgrupos, incluyendo disparidades asociadas a variables sociodemográficas, lo que introduce implicaciones en términos de equidad y legitimidad institucional. A ello se suman los desafíos derivados de su implementación, incluyendo la trazabilidad de los modelos, la interacción entre profesionales y sistemas automatizados, y la necesidad de marcos que garanticen supervisión y auditoría.

Palabras clave: Inteligencia artificial; aprendizaje automático; valoración del riesgo; reincidencia juvenil; justicia juvenil.

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1 Introduction

In the late 19th and early 20th centuries, various jurisdictions began to recognize that children and adolescents did not fit within the criminal justice system designed for adults. In the United States, the origin of the juvenile justice system dates back to 1899 with the enactment of the Illinois Juvenile Court Act legislation, which led to the creation of the first specialized court in Chicago (Thompson & Morris, 2016). In Spain, the legislative starting point is generally considered to be the Law of August 12, 1904 on child protection, and a few years later the move towards a specific institutional framework was taken with the Law of August 2, 1918, concerning courts for children.

Beyond mere chronology, the significance of these beginnings lies in the paradigm shift they entail. Juvenile justice was established as a distinct jurisdiction, separate from the adult criminal justice system, legitimizing its intervention through a balance between the demand for accountability and an eminently educational and socializing purpose. In the current Spanish legal system, this model is embodied in Organic Law 5/2000, of January 12, regulating the criminal responsibility of minors. This law defines the scope of application by age and systematizes the legal response through a flexible catalog of measures, establishing rules for their determination and duration.

The challenge lies in translating this objective into concrete judicial decisions. The choice between detention and community-based measures, as well as determining the intensity of supervision or the duration of intervention, requires a high degree of individualization and justification (Berríos, 2022; Fernández-Molina & Bartolomé, 2020). To support this work and reduce discretion, the legal process draws on technical information regarding the minor's personal and social circumstances, thus complementing the strictly normative assessment (Gómez-Fraguela et al., 2021). In this context, risk and needs assessment transcends its classificatory function to become a language that organizes heterogeneous information, guides the proportionality of the response, and links the judicial decision with intervention planning (Bonta & Andrews, 2023).

However, achieving this capacity to integrate diagnosis with case management has not been an immediate process, but rather the result of a progressive methodological evolution. The specialized literature, compiled in the work of Andrews et al. (2006), describes this development through four generations of assessment, each emerging to overcome the technical and ethical limitations of its predecessor.

The first generation, dominant until the mid-20th century, was based on unstructured clinical judgment. At this stage, the evaluation depended on the subjectivity of the professional (psychologist, social worker, or correctional officer), who issued a prognosis based on their intuition, personal experience, and training, without the support of standardized guidelines or explicit criteria (Loinaz, 2017). Although this approach allowed for flexibility, it suffered from serious reliability issues; for example, two evaluators could reach opposing conclusions about the same minor, making the judicial measure more dependent on who was evaluating than on the characteristics of the case (Helmus & Babchishin, 2017).

In response to this lack of guarantees, a second generation of actuarial tools emerged in the 1970s, focusing on statistical objectivity. The objective shifted toward the search for empirical evidence through the development of instruments that assigned quantitative values to predefined items, thereby imposing an arithmetic logic and reducing the scope for interpretation. One example was the *Salient Factor Score* (Hoffman & Beck, 1974), used to objectify parole decisions. This instrument operated via a checklist of static factors where points were assigned based on the number of prior convictions, the age at first arrest, a history of escape and drug dependency. The final score placed the individual in a static risk category, regardless of their current behavior. Although Andrews et al. (2006) demonstrated that these tools outperformed clinical judgment in terms of predictive capacity, they presented a significant limitation for the juvenile justice system because, by relying almost exclusively on static factors, they could predict risk but did not provide guidance on how to reduce it, since the minor's past could not be changed.

This gap led to the development of the third generation of assessment tools starting in the 1980s, when dynamic factors or criminogenic needs were incorporated. These instruments, based on the Risk-Need model, represented a conceptual revolution by evaluating not only static (unchangeable) history, but also the subject's current and modifiable situation (Loinaz, 2017). It is no longer simply a matter of knowing what the minor did, but of understanding what circumstances sustain their behavior today. The assessment focuses on identifying deficits in areas such as parental supervision, educational performance or the nature of their relationships with peer groups-variables that recent research confirms as predictors of juvenile recidivism (Garrido et al., 2017). The major contribution of this stage was instrumental: by distinguishing which factors can be modified, it facilitates the design of specific treatment goals, overcoming the pessimism of purely actuarial models (Bonta & Andrews, 2023).

Finally, the fourth generation integrates the advances of previous generations into a case management system. One of the international benchmarks for these tools is the Youth Level of Service/Case Management Inventory (YLS/CMI) developed by Hoge and Andrews (2002), designed to guide the entire process for young people, from assessment through to case closure. In the Spanish context, this approach is implemented through protocols such as the VRAI, which structures risk and protection variables to inform educational and socialization interventions (Gómez-Fraguela et al., 2020). The innovation of this stage lies in the fact that the tool requires periodic reassessment to verify the effectiveness of the intervention and detect changes in the minor's profile. In this way, the assessment ceases to be a bureaucratic procedure and becomes a dynamic mechanism that allows for adjusting the judicial response by aligning resources with the adolescent's changing needs (Argudo et al., 2021).

In practice, this approach is often accompanied by the Risk-Need-Responsiveness model (Bonta & Andrews, 2007). The risk principle requires adjusting the intensity of the intervention to the level of probable recidivism, reserving intensive judicial measures for the highest-risk cases and avoiding over-intervention in low-risk cases, where it can even be iatrogenic by disrupting certain protective factors (Hilterman et al., 2019). The need principle, for its part, determines what to treat, focusing on direct criminogenic factors (such as antisocial attitudes or substance use) rather than nonspecific clinical aspects (Wormith & Zidenberg, 2018). Finally, the responsiveness principle adapts the method, requiring that strategies be tailored to the minor's learning capacity and motivation to ensure the effectiveness of the treatment (Taxman & Smith, 2021).

Currently, the potential evolution of the fourth generation opens the door to the incorporation of artificial intelligence (AI) and machine learning (ML) techniques. This shift does not imply the disappearance of standardized instruments or case management logic, but rather a change in focus towards models trained on large databases and longitudinal records (Travaini et al., 2022; Yukhnenko et al., 2025). In other words, ML is the branch of AI that trains algorithms using millions of previously observed cases to learn which combinations of variables are associated with a relevant outcome, such as recidivism or re-engagement with the system, and to estimate that risk in new cases (Berk, 2021; James et al., 2021; Wang et al., 2023).

Unlike a traditional structured instrument, where criteria and their weighting are predefined, a machine learning model automatically adjusts its parameters during training by comparing its predictions with actual outcomes to minimize error (Colliot, 2023; Verrey et al., 2025). In operational terms, these models integrate heterogeneous information (judicial, educational, family, and clinical) to generate a continuous probability or score, which is then translated into decision categories to prioritize intensive supervision or referrals to specific programs. However, recent literature warns that comparing results across models is not straightforward. This is because there is a wide variety of methods used, ranging from the type of artificial intelligence chosen to how exactly recidivism is defined or at what stage of the trial the prediction is made (Eaglin, 2016; Engel & Grgić-Hlača, 2021; Greene et al., 2022; Kigerl et al., 2022; Travaini et al., 2022).

Consequently, current interest seems to be shifting toward understanding the relationship between automated machine learning and standardized assessment tools. This convergence is usually studied by comparing whether the algorithms are more accurate than the tools (e.g., YLS/CMI) or by using the content of the latter to train the AI. In this second approach, the model takes the items from the tool and processes them to adjust their significance or to combine them with other administrative records. In this way, the aim is to connect computing power with the practical language of intervention, allowing us to assess what the technology contributes to addressing the same problem and how it can be integrated without losing the technical justification for decisions (Ghasemi et al., 2021; Raiche et al., 2023; Sheppard et al., 2024; Tasharrofi & Barnes, 2022).

In this context, the present scoping review aims to map the available empirical evidence on the use of AI/ML in predicting juvenile recidivism, restricting inclusion to those studies that establish an explicit link with structured risk assessment instruments. This criterion addresses the need to analyze the actual integration between computational approaches and established evaluative practices in clinical and judicial settings.

Specifically, the review proposes: (a)to describe the AI/ML models employed and the data sources used in the included studies, and (b) to analyze their predictive performance, methodological limitations, and implications for their implementation in juvenile justice contexts.

2 Method

2.1 Design

The study design and implementation followed the methodological guidelines outlined in the chapter on scoping reviews by Peters et al. (2020), supplemented by the classic methodological framework of Arksey and O'Malley (2005). The drafting of the final report was structured in accordance with the PRISMA-ScR statement checklist (Tricco et al., 2018).

The question guiding this review is: What empirical evidence exists on the use of AI/ML techniques to predict recidivism in the juvenile justice system, and to what extent do these models compare with or explicitly integrate with structured juvenile risk assessment instruments?

2.2 Eligibility Criteria

The inclusion and exclusion criteria were established in accordance with the PCC (Population, Concept, and Context) framework. Table 1 below details the eligibility criteria applied for the selection of studies.

Table 1. Inclusion and exclusion criteria

DOMAIN	INCLUSION CRITERIA	EXCLUSION CRITERIA
Population	Youth in the juvenile justice system (semi-	Adult population or mixed samples

	open facilities, detention, probation).	without a breakdown of data for minors.
Concept	AI/ML-based predictive models with an explicit link to structured risk instruments.	ML models that do not involve structured instruments. Traditional instruments that do not utilize AI techniques.
Context	Contact with the system	Antisocial or clinical behavior without an associated criminal record.
Publication Type and Period	Peer-reviewed empirical articles. Published from 2016 onwards.	Grey literature, technical reports, theoretical reviews, editorials or legal opinions lacking data.

2.3 Sources and Search Strategy

Literature searches were conducted across four electronic databases: Web of Science, Scopus, PsycINFO, and PubMed. A block-based search strategy was employed, using terms relating to Juvenile population and juvenile justice, recidivism or re-engagement with the system, AI and ML techniques, and structured risk assessment instruments for juveniles. The most recent search was carried out on February 2, 2026. The search strings used and the number of records identified in each database are presented in Table 2.

Table 2. Search strategies

Source	Boolean descriptors and connectors	No. of records identified
PubMed	(juvenile OR youth OR adolescent* OR "juvenile justice" OR "young offender*" OR "youth offender*") AND (recidiv* OR reoffend* OR "re-offend*" OR rearrest* OR "re-arrest*" OR adjudicat* OR convict* OR "justice contact" OR "justice system contact") AND ("machine learning" OR "artificial intelligence" OR algorithm* OR "random forest" OR "gradient boosting" OR boosting OR xgboost OR svm OR "support vector*" OR knn OR "k nearest" OR "neural network*" OR "deep learning" OR stacking OR lasso OR "elastic net" OR ridge) AND (SAVRY OR "Structured Assessment of Violence Risk in Youth" OR "YLS/CMI" OR "Youth Level of Service" OR "Youth Level of Service/Case Management Inventory" OR PACT OR "Positive Achievement Change Tool" OR YASI OR "Youth Assessment and Screening Inventory" OR PAT OR "Prevention Assessment Tool" OR MJCA OR "Ministry of Justice Case Assessment Tool" OR "Washington State Juvenile Court Assessment" OR "Juvenile Court Assessment" OR "risk assessment instrument" OR "risk assessment tool" OR "risk assessment scale" OR "actuarial risk assessment" OR "structured professional judgment" OR SPJ)	2
PsycINFO	(juvenile OR youth OR adolescent* OR "juvenile justice" OR "young offender*" OR "youth offender*") AND (recidiv* OR reoffend* OR "re-offend*" OR rearrest* OR "re-arrest*" OR adjudicat* OR convict* OR "justice contact" OR "justice system contact") AND ("machine learning" OR "artificial intelligence" OR algorithm* OR "random forest" OR "gradient boosting" OR boosting OR xgboost OR svm OR "support vector*" OR knn OR "k nearest" OR "neural network*" OR "deep learning" OR stacking OR lasso OR "elastic net" OR ridge) AND (SAVRY OR "Structured Assessment of Violence Risk in Youth" OR "YLS/CMI" OR "Youth Level of Service" OR "Youth Level of Service/Case Management Inventory" OR PACT OR "Positive Achievement Change Tool" OR YASI OR "Youth Assessment and Screening Inventory" OR PAT OR "Prevention Assessment Tool" OR MJCA OR "Ministry of Justice Case Assessment Tool" OR "Washington State Juvenile Court Assessment" OR "Juvenile Court Assessment" OR "risk assessment instrument" OR "risk assessment tool" OR "risk assessment scale" OR "actuarial risk assessment" OR "structured professional judgment" OR SPJ)	7
Scopus	(juvenile OR youth OR adolescent* OR "juvenile justice" OR "young offender*" OR "youth offender*") AND (recidiv* OR reoffend* OR "re-offend*" OR rearrest* OR "re-arrest*" OR adjudicat* OR convict* OR "justice contact" OR "justice system contact") AND ("machine learning" OR "artificial intelligence" OR algorithm* OR "random forest" OR "gradient boosting" OR boosting OR xgboost OR svm OR "support	11

	vector*" OR knn OR "k nearest" OR "neural network*" OR "deep learning" OR stacking OR lasso OR "elastic net" OR ridge) AND (SAVRY OR "Structured Assessment of Violence Risk in Youth" OR "YLS/CMI" OR "Youth Level of Service" OR PACT OR "Positive Achievement Change Tool" OR YASI OR "Youth Assessment and Screening Inventory" OR PAT OR "Prevention Assessment Tool" OR MJCA OR "Ministry of Justice Case Assessment Tool" OR "Washington State Juvenile Court Assessment" OR "Juvenile Court Assessment" OR "risk assessment instrument" OR "risk assessment tool" OR "risk assessment scale" OR "actuarial risk assessment" OR "structured professional judgment" OR SPJ)	
Web of Science	(juvenile OR youth OR adolescent* OR "juvenile justice" OR "young offender*" OR "youth offender*") AND (recidiv* OR reoffend* OR "re-offend*" OR rearrest* OR "re-arrest*" OR adjudicat* OR convict* OR "justice contact" OR "justice system contact") AND ("machine learning" OR "artificial intelligence" OR algorithm* OR "random forest" OR "gradient boosting" OR boosting OR xgboost OR svm OR "support vector*" OR knn OR "k nearest" OR "neural network*" OR "deep learning" OR stacking OR lasso OR "elastic net" OR ridge) AND (SAVRY OR "Structured Assessment of Violence Risk in Youth" OR "YLS/CMI" OR "Youth Level of Service" OR PACT OR "Positive Achievement Change Tool" OR YASI OR "Youth Assessment and Screening Inventory" OR PAT OR "Prevention Assessment Tool" OR MJCA OR "Ministry of Justice Case Assessment Tool" OR "Washington State Juvenile Court Assessment" OR "Juvenile Court Assessment" OR "risk assessment instrument" OR "risk assessment tool" OR "risk assessment scale" OR "actuarial risk assessment" OR "structured professional judgment" OR SPJ)	8
Total		28

2.4 Screening Process

The retrieved references were exported to the Mendeley platform for centralization and management. The deduplication process combined an initial automated phase using the platform's tools with a subsequent manual verification to ensure the integrity of the database. The selection of studies was carried out independently by two reviewers in two consecutive stages. Initially, titles and abstracts were screened to discard clearly irrelevant records. Subsequently, the preselected articles were examined in full text to verify strict compliance with the eligibility criteria. Any disagreements regarding the decision to include a study were resolved through discussion and consensus among the authors.

2.5 Data Extraction

Data extraction was carried out using a standardized form specifically developed for the purpose of this review. The study reference was recorded, along with the country, the sample size, the relevant structured instrument, and the main AI/ML models evaluated.

Furthermore, the strategy for using the instrument was coded, distinguishing between comparison against the instrument's score or against professional judgement, the integration of instrument items or variables as predictors, and mixed options where both models coexisted. Performance was summarised using the AUC, with the value of the comparator also recorded. Finally, one key finding per study was recorded, written operationally to synthesize the work's central message.

3 Results

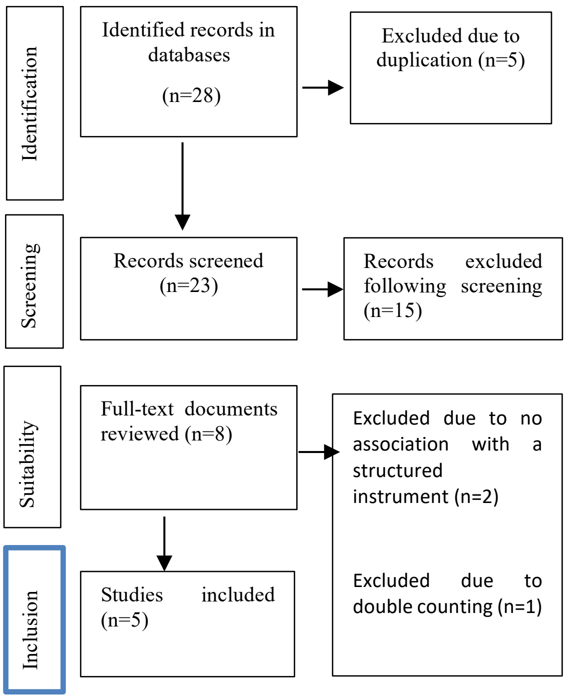
3.1 Study Selection

The literature search identified 28 records, distributed across PsycINFO (n= 7), PubMed (n= 2), Web of Science (n= 8), and Scopus (n= 11). Following deduplication, 5 duplicate records were removed, leaving 23 unique records for screening.

During the title and abstract selection phase, 15 records were excluded for not meeting the eligibility criteria. Eight reports were reviewed in full text, of which three were excluded: two for not having an explicit link to a structured risk assessment instrument and one for being additional publication due to doublecounting, thus avoiding the duplication of evidence.

Consequently, five studies were ultimately included. The complete selection process is presented in the PRISMA-ScR diagram displayed in Figure 1.

Figure 1. PRISMA-ScR Flowchart



3.2 Characteristics of the Studies Included

The five selected studies were conducted in the United States (n= 2), Spain (n= 1), Japan (n= 1), and Singapore (n= 1), with sample sizes ranging from N= 855 to N= 227,451. The structured instruments used were: WSJCA (Barnoski, 2004), SAVRY (Borum et al., 2006), MJCA (Correction Bureau, Ministry of Justice of Japan; see UNAFEI, 2019), PAT (Florida Department of Juvenile Justice, 2014), and YLS/CMI 2.0 (Hoge & Andrews, 2011).

Regarding the methodological link between AI/ML and these tools, the evidence is grouped into three categories:

Integration: where the instrument items feed into the algorithm as predictor variables (e.g., WSJCA; YLS/CMI 2.0).

Comparison: where the model's performance is compared against the instrument score or the assessor's judgment (e.g., MJCA).

Optimization: where AI/ML is used to rescale items or derive new indices from the original structure (e.g., SAVRY; PAT). Table 3 summarizes the main characteristics, predictive performance (AUC), and key findings of each study.

Table 3. Characteristics of the included studies and predictive performance

Study Country No	Instrument	AI/ML Models (Main)	Usage Strategy	Performance (AUC)	Key Finding
Kigerl et al. (2022) U.S *(N = 227.451)*	WSJCA	LR, Penalized Reg., RF, MLP, SVM, Stacking.	Integration (items from the instrument as predictors).	0.72 (Stacking) vs. 0.71 (LR).	The differences between model families are marginal (<0.01). Sample size has a greater influence than algorithmic complexity.
Miron et al. (2021) Spain *(N = 855)*	SAVRY	Logit, MLP, kNN, SVM, DT, NB, RF.	Mixed (item comparison and integration)	0.73 (ML) vs. 0.64 (SAVRY)	Machine learning improves predictive accuracy, but introduces disparities based on nationality and gender.
Mori et al. (2024) Japan *(N = 5.942)*	MJCA	kNN, SVM, RF, GBDT (*Gradient Boosting*), MLP.	Comparison (machine learning vs. scoring).	0.75 (GBDT) vs. 0.67 (MJCA)	The ML model outperforms the MJCA score in terms of discrimination (ΔAUC = 0.08).
Sheppard et al. (2024) U.S *(N = 11.472)*	PAT	Stepwise LR, Penalized Reg., RF.	Optimization /Recalibration (rescaling items to derive new scales).	0.74 (RF) vs. 0.74 (LR)	Similar performance across techniques.
Ting et al. (2018) Singapore *(N = 3.744)*	YLS/CMI 2.0	Random Forest.	Inclusion of YLS variables and administrative data used to train the model.	0.69 (RF) vs. 0.64 (LR)	The model captures non-linear relationships between risk factors, thereby improving screening compared to traditional statistical methods.

Note. Acc = Overall Accuracy; AUC = Area Under the Curve; DT = Decision Trees; GBDT = Gradient Boosting Decision Trees; kNN = k-Nearest Neighbours; LR = Logistic Regression; ML = Machine Learning; MLP = Multi-Layer Perceptron (Neural Network); NB = Naive Bayes; RF = Random Forest; Stacking = Model ensembling technique; SVM = Support Vector Machines. MJCA = Ministry of Justice Case Assessment Tool (Ministry of Justice, Japan); PAT = Prevention Assessment Tool (Florida Department of Juvenile Justice); SAVRY = Structured Assessment of Violence Risk in Youth (Borum et al., 2006); WSJCA = Washington State Juvenile Court Assessment (Barnoski, 2004); YLS/CMI 2.0 = Youth Level of Service/Case Management Inventory (Hoge & Andrews, 2011).

3.3 Synthesis of Findings

3.3.1 Magnitude of Performance and Incremental Value

Overall, the models achieved AUC values ranging from 0.69 to 0.75. When evaluated against a direct comparator, the incremental value ranged from 0.00 to 0.09 AUC points. This variability ranged from no predictive differences (0.74 vs. 0.74 in Sheppard et al., 2024) to moderate improvements (0.75 vs. 0.67 in Mori et al., 2024; 0.73 vs. 0.64 in Miron et al., 2021; and 0.69 vs. 0.64 in Ting et al., 2018).

3.3.2 Algorithmic Complexity vs Performance

In several studies, performance differences between model families were marginal. Virtually identical performance was documented between complex techniques and traditional approaches such as logistic regression, especially when the sample size is large, or the evaluated scenario reduces predictive variability (Kigerl et al., 2022; Sheppard et al., 2024).

3.3.3 Nonlinearity and Utilization of the Instrument Structure

In studies that incorporate structured information from the instrument as predictor variables, the results are consistent with the identification of non-linear relationships between risk factors. In this context, improvements in performance were found compared to linear approaches in certain assessment scenarios (Ting et al., 2018).

3.3.4 Equity and Disparities

Explicit assessment of group equity was rare in the reviewed literature. In the included sample, it was documented that maximizing predictive performance can introduce disparities based on nationality and sex. Specifically, when comparing the models with the traditional instrument (SAVRY), an increase in false positives was observed, which specifically penalizes vulnerable subgroups, such as young foreigners (Miron et al., 2021).

4 Discussion

The aim of this scoping review was to analyse the existing empirical evidence on the application of AI/ML models in predicting the risk of juvenile recidivism, specifically evaluating their performance and their relationship with structured assessment instruments. The analysis of the five included studies provides evidence on the actual capabilities and limitations of these technologies in clinical and judicial practice.

4.1 Empirical Limitations and Algorithmic Complexity

The first cross-sectional finding of this review is the existence of an empirical limit in the predictive capacity of AI/ML, showing stagnation at levels of moderate predictive discrimination. The results of studies with large samples (Kigerl et al., 2022) and preventative approaches (Sheppard et al., 2024) demonstrate that the transition from traditional statistical models to complex AI/ML architectures yields only marginal improvements. This pattern is consistent with recent methodological critiques in criminal justice that describe predictive inconsistency among algorithmic tools and question the widespread superiority of opaque models when more interpretable and auditable alternatives exist (Greene et al., 2022; Rudin, 2019).

This predictive ceiling suggests that the performance of risk assessment tools is more dependent on the quality, validity, and structure of the available data than on the sophistication of the algorithm (Berk, 2021; Steyerberg, 2019). Juvenile criminal behaviour is subject to fluctuations linked to dynamic risk factors, maturation processes, and contextual contingencies, which may limit the temporal stability of predictions based on one-off measurements (Cuevas et al., 2019). In this regard, as Berk (2021) warns, AI/ML models applied to criminology cannot extract a strong predictive signal if it does not exist in the administrative and historical data sets.

Consequently, the argument that the implementation of AI/ML will lead to a substantial improvement in accuracy within the juvenile justice system does not appear to be consistently supported by the currently available evidence (Kigerl et al., 2022; Sheppard et al., 2024). As Ugwudike (2022) points out, there is a clear limit to technological reformism in justice systems. Reliance on baseline recidivism rates and their variability across time periods and jurisdictions, coupled with data quality limitations, imposes a methodological barrier that AI/ML, on its own, cannot overcome (Berk, 2021; Steyerberg, 2019; Weber et al., 2025).

4.2 Discriminative Capacity and Clinical Utility

Despite the previously described asymptotic limit, the review also confirms that, under certain methodological and comparative conditions, AI/ML models can outperform traditional assessments. Empirical results demonstrate that, when directly comparing computational performance against the score assigned by the human evaluator (Mori et al., 2024) or against strictly linear comparators (Ting et al., 2018), moderate improvements in discriminative capacity are observed. These findings are consistent with the idea that the potential added value of AI/ML, when observed, may lie in capturing nonlinear interactions and relationships between variables, especially when the comparator is linear or when the human score does not explicitly incorporate such combinations (Mori et al., 2024; Steyerberg, 2019; Ting et al., 2018).

However, even if there is a moderate increase in discrimination, methodological evaluation cannot be limited to reporting AUC, given that applied utility depends on how the prediction is used to make concrete decisions (Monahan & Skeem, 2016; Steyerberg, 2019). Within the context of the juvenile justice system, the true value of an AI/ML model depends on the specific clinical or judicial decision it aims to support (e.g., the intensity of supervision, the prioritization of socio-educational programs, or referral to specialist resources), and on how a continuous score translates into operational thresholds with asymmetric consequences between false positives and false negatives (Eaglin, 2017; Garrett & Monahan, 2020; Monahan & Skeem, 2016).

For this reason, in addition to overall discrimination, it is necessary to require metrics for calibration, external validation and temporal stability. An AI/ML system may rank subjects relatively well and yet still produce poorly calibrated probabilities or deviate due to changes in data distribution across different contexts and time periods, which seriously compromises its usefulness (Moons et al., 2019; Steyerberg, 2019; Wolff et al., 2019).

4.3 Evaluation of Predictive Performance and Equity Concerns

The third aspect emerging from the results necessitates a rethinking of the criteria for success in juvenile risk prediction. The study by Miron et al. (2021) shows that by integrating AI/ML models with the SAVRY instrument, it is possible to achieve an overall improvement in discriminatory power compared to traditional scoring. However, this study introduces a nuance: this average gain coexists with significant predictive disparities based on the nationality and gender of the minors assessed, underscoring that the overall improvement in performance does not guarantee a uniform impact across subgroups.

This finding shifts the debate to the realm of algorithmic equity, given that the deployment of risk scores in criminal and juvenile justice systems has distributive consequences and directly affects institutional legitimacy (Garrett & Monahan, 2020; Završnik, 2020, 2021). As demonstrated in the specialist literature, when there are historical differences in baseline rates of criminal prevalence between socio-demographic groups, it is mathematically difficult to satisfy all statistical notions of equity (Chouldechova, 2017; Hardt et al., 2016; Kleinberg et al., 2017).

From a perspective of rights and legitimacy, the evidence provided by studies such as that of Miron et al. (2021) requires the justice system to maintain a clear criterion regarding what type of statistical inequality is considered unacceptable. This requirement is particularly important if AI/ML predictions are incorporated into decisions that restrict freedom, alter the educational purpose of the measures, or intensify control over the minor (Eaglin, 2017; Završnik, 2020, 2021).

4.4 Algorithmic Traceability and Professional Interaction

As an extension of the demands for fairness, the deployment of AI/ML in juvenile justice raises challenges regarding traceability. Since processing architectures can hinder the legal rationale behind decisions and the detection of underlying flaws or biases (Wang et al., 2023), criminology argues that systems must be designed to ensure institutional inspection and control (Završnik, 2021). This requirement is perhaps most relevant when the incremental gain in performance is small, because the cost of complexity may outweigh the benefit if it reduces the capacity for auditing and practical explanation (Rudin, 2019; Wang et al., 2023).

However, even when technical transparency is ensured, practical feasibility depends on how professionals integrate the scores into their decision-making and which organizational rules they apply. Although the studies included in this review focus on statistical performance, research warns that the introduction of automated recommendations may alter cognitive decision-making processes. Phenomena such as anchoring bias against machine scoring, overconfidence in technology, and the displacement of responsibility to the algorithm are well-documented (Doleac & Stevenson, 2024; Green & Chen, 2021).

Furthermore, generic policies on human oversight do not guarantee effective control unless they define when and how one may override the system, what justifications are required, and what audits are applied; otherwise, oversight may become a mere formality (Green, 2022; Engel & Grgić-Hlača, 2021). Therefore, the actual impact of integrating AI/ML with structured instruments depends not only on discrimination, but also on decision-making behavior and the framework for use, including training, protocols, thresholds, documentation, and continuous auditing (Doleac & Stevenson, 2024; Green & Chen, 2021; Greene et al., 2022).

4.5 Limitations and Conclusion

This scoping review has limitations that must be considered. First, the small number of included studies (five) limits the statistical generalizability of the results, although this number reflects the nascent state of the empirical literature that specifically examines the intersection of AI/ML with structured instruments in youth populations. Second, the high heterogeneity in modelling techniques, comparators used, and jurisdictional contexts prevented quantitative synthesis from being carried out. Third, publication bias cannot be ruled out, particularly in the literature on predictive models, where transparency in validation, calibration and subgroup analysis is variable.

Therefore, the results should be interpreted with caution and with attention to the methodological quality and applicability of each study.

In conclusion, the synthesized evidence suggests that AI/ML can provide flexible modeling and represent nonlinear relationships, but its improvement in predictive performance in juvenile justice appears limited given the current state of data, evaluation designs, and institutional definitions of recidivism as an outcome variable.

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