



PERSPECTIVES

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COMMUNITY SUPERVISION AND ARTIFICIAL INTELLIGENCE

SPRING 2026

president's message



MARCUS M. HODGES
PRESIDENT

Community corrections has always been a profession grounded in people, purpose, and the belief in second chances. Our work is built on relationships, accountability, and the daily commitment to helping individuals change the trajectory of their lives. Today, we find ourselves at a defining moment—one where technology, specifically artificial

intelligence (AI), is rapidly reshaping how we carry out that mission. AI is no longer a concept of the future. It is here. It is evolving. And it is already influencing decision-making across justice systems nationwide.

Artificial intelligence has the potential to fundamentally transform community corrections from reactive supervision to proactive engagement. With the right tools, agencies can identify risk patterns earlier, allocate resources more effectively, enhance case planning and intervention strategies, and improve operational efficiency

These advancements allow officers to spend less time navigating administrative burdens and more time doing what matters most—engaging directly with the individuals they supervise. AI, when used responsibly, can strengthen our ability to deliver smarter, more targeted supervision that improves outcomes for individuals and communities alike.

As we embrace innovation, we must remain grounded in a fundamental truth—AI will not replace community supervision professionals; it will elevate them. No algorithm can replicate professional judgment. No data system can replace human connection. No technology can substitute the trust built between an officer and the individual they supervise. Our role as practitioners is not diminished by AI—it is strengthened by how we choose to use it.

With innovation comes responsibility. AI systems are only as effective and as fair as the data and design

behind them. Without intentional oversight, these tools can unintentionally reinforce bias, compromise privacy, and erode trust in the justice system. As leaders in the field, we must establish clear guardrails—transparency in how tools are developed and used; accountability for decisions and outcomes; equity in data inputs and system design; and human oversight in all critical decisions. AI should inform decisions, not make them.

The question before us is not whether AI will shape community corrections. It is whether we will lead this transformation or allow it to define us without our input. For 50 years, APPA has been the voice of community corrections—bringing together practitioners, researchers, and policymakers to advance the field. That leadership requires us to invest in workforce education and training on AI; develop standards for ethical and effective implementation; and promote innovation while protecting the core values of our profession. We cannot afford to be passive participants in this moment of change.

At its core, community corrections is about people, accountability balanced with opportunity, structure paired with support, and helping individuals succeed where they once struggled. Technology can enhance our work—but it cannot define it.

As we move forward, we must ensure that innovation strengthens, not replaces, the human element that is the foundation of our profession. AI presents us with an opportunity to improve outcomes, increase efficiency, and better serve the individuals and communities entrusted to us. But success will depend on how we lead. We must approach this moment with intention, act with integrity, and remain focused on our mission. The future of community corrections is not something that will happen to us—it is something we will shape.

This is our moment to lead. Let's embrace innovation with clarity, set the standard for responsible use of technology, and ensure that, no matter how advanced our tools become, our commitment to people remains at the center of all we do.

Marcus M. Hodges

executive director/ceo's message



VERONICA CUNNINGHAM
EXECUTIVE DIRECTOR/
CEO APPA

This issue of Perspectives is especially timely. Artificial Intelligence (AI) is quickly capturing our attention. Its ability to improve productivity is becoming clearer. In community corrections, the discussion about AI focuses not just on what it can do but on how it can be used effectively and ethically. Important questions revolve around how AI might change individuals' experiences under supervision, as well as its effects on staff workload and decision-making.

In a discussion with a friend who works on developing AI applications, he stated that AI adoption takes many forms, including limited-memory systems, generative AI, predictive analytics, automation, and content creation. Honestly, a lot of words I don't understand. Albeit, I am trying, and full disclosure: I used AI to shorten my message from 5,000 words to under 3,000. This demonstrates both AI's strength and the importance of carefully deciding when and how to use it.

APPA has played a key role in advancing discussions on AI in community supervision. At the 2022 Executive Leadership Summit, an AI expert helped clarify the technology's complexities, and we've asked our Technology Committee to keep the topic prominent. We also include AI-focused sessions in our webinars and training institutes to explore its growing role. Recent training institutes in New York and Atlanta covered topics such as integrating AI into supervision practices, using AI to support client transformation, maintaining professional judgment, and addressing ethical considerations.

As always, I want to thank APPA's staff and the incredible editors who volunteer their time and talents to create a meaningful product. Of course, special thanks to the contributors for their insightful articles — each offering a unique perspective. First, Harnessing AI for Developmentally Supportive Feedback for System-Involved Youth highlights AI's role in juvenile justice, emphasizing supportive growth for youth by focusing on their strengths, skills, and potential. Secondly, AI in Community Corrections: The Promise of Smart Supervision, emphasizes AI's transformative role as a

supportive tool for probation officers. Third, the article on AI-Driven Risk Assessments calls for cautious implementation with ethical safeguards to ensure fairness. Lastly, The Future of Community Supervision: Where AI Meets Human Judgment advocates for a balanced integration of AI and human judgment, suggesting optimal outcomes come from combining data analytics with personal experience.

Together, these contributions enhance our understanding and encourage us to think critically about how AI can be responsibly incorporated into community supervision. As we progress, it is crucial to prioritize ethics and preserve the human element by ensuring that AI serves as a tool for empowerment rather than a replacement.

A handwritten signature in black ink that reads "Veronica Cunningham". The script is fluid and cursive.

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Perspectives disseminates information to the American Probation and Parole Association's members on relevant policy and program issues and provides updates on activities of the Association. The membership represents adult and juvenile probation, parole, and community corrections agencies throughout the United States and abroad. Articles submitted for publication are screened by an editorial committee and, on occasion, selected reviewers, to determine acceptability based on relevance to the field of criminal justice, clarity of presentation, or research methodology. Perspectives does not reflect unsupported personal opinions.

Articles must be emailed to perspectives@csg.org in accordance with the following deadlines:

- Unless previously discussed with the editors, submissions should not exceed 12 typed pages, numbered consecutively, and double-spaced. All charts, graphs, tables, and photographs must be of reproduction quality. Optional titles may be submitted and selected after review with the editors.
- All submissions must be in English and in American Psychological Association (APA) Style.
- Authors should provide a one-paragraph biography, along with contact information.
- Notes should be used only for clarification or substantive comments, and should appear at the end of the text.
- References to source documents should appear in the body of the text with the author's surname and the year of publication in parentheses, e.g., to (Mattson, 2015, p. 73).
- Alphabetize each reference at the end of the text using the following format:
 - Mattson, B. (2015). Technology supports decision making in health and justice. *Perspectives*, 39(4), 70-79.
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ARTIFICIAL INTELLIGENCE IN COMMUNITY CORRECTIONS: THE PROMISE OF SMART SUPERVISION

by Steve Jenkins, Lindsay Smith, Bengisu Tulu, and Faye Taxman

The field of community corrections, a system ready for transformation, stands at a critical crossroads. Probation and parole agencies face mounting caseloads, constrained budgets, and rising expectations to reduce recidivism while promoting rehabilitation. Probation officers in many jurisdictions supervise large caseloads, often averaging 85 to 120 individuals, many of whom present multiple criminogenic needs, including substance use, employment instability, family or social stressors, and other factors that influence recidivism (Martin & Zettler, 2021; Wooditch et al., 2014). Despite significant progress in risk assessment science and evidence-based practices, translating those insights into daily supervision tasks remains an enduring challenge (Appleton & Rudes, 2022).

Artificial Intelligence (AI) has begun to change that equation. Around the world, corrections agencies are experimenting with data-driven tools to support decision-making, help identify risk in real time, and personalize supervision, as discussed in a 2024 “Artificial Intelligence and Criminal Justice” report (U.S. Department of Justice, 2024). Yet the greatest potential of AI lies not in prediction alone, but in how it can help people change by supporting motivation, structure, and sustained engagement. This new approach is exemplified in emerging technologies such as the Probation and Reintegration Coach Application (PARCA), a digital platform built—with support from the National Institutes of Health—by leading criminal justice experts from George Mason University and RTI in collaboration with digital innovation specialists from Worcester Polytechnic Institute (WPI).

PARCA illustrates how AI can be used to operationalize decades of behavioral science in ways that extend, rather than replace, human supervision. By transforming static assessments into adaptive case plans, translating risk and need data into achievable goals, and linking those goals to meaningful incentives, AI systems like PARCA can help community corrections evolve toward a model of “smart supervision,” one that is more personalized, data-informed, and human-centered.

THE CHALLENGES OF TRADITIONAL SUPERVISION

Probation and parole officers have always worn many hats: monitor, mentor, social worker, and enforcer. Balancing those roles has never been easy (National Institute of Justice, 2021). Research shows that successful supervision requires frequent contact and positive reinforcement (Wodahl et al., 2021). Yet the modern realities of workload, documentation, and data management often limit the time officers can spend face to face with probationers and, therefore, their ability to coach clients’ behavioral change (Martin & Zettler, 2020). Officers today must navigate vast amounts of information from multiple databases and reporting systems, much of which is incomplete, inconsistent, or outdated. Poor data quality can obscure important risk factors or progress indicators, while excessive data entry demands reduce opportunities for meaningful engagement with clients (Waring et al., 2022). Addressing these issues requires not only improving data systems and training but also rethinking how technology can support, rather than hinder, the human aspects of supervision.

While risk-need-responsivity (RNR) models have improved how agencies classify and prioritize clients, recent reviews note that many of these tools continue to rely on static, low-quality predictive evidence and lack responsiveness to change over time (Bijlsma et al., 2024). Officers receive detailed reports identifying criminogenic needs such as substance use, antisocial peers, or unstable employment, yet these snapshots quickly lose relevance as clients make progress or encounter new challenges. In practice, officers must translate these fixed assessments into ongoing case plans without real-time feedback or adaptive guidance. This lack of continuous processing means that interventions may lag behind clients’ evolving needs, leading to inconsistent outcomes that depend heavily on officer discretion, local resources, and timing.

The difficulty of turning insight into action creates a critical gap. Clients may leave meetings unclear about their next

steps. Officers may struggle to track progress between appointments. Motivation wanes, and the system's reactive nature can lead to cycles of noncompliance rather than sustained rehabilitation. AI offers new ways to close this gap by introducing systems capable of continuous processing, thereby providing structure, feedback, and reinforcement at the moments they matter most. Unlike static assessments, AI-driven tools can adapt to behavioral changes in real time, supporting officers and clients through dynamic, data-informed decision-making.

FROM PREDICTION TO PARTNERSHIP: THE NEW ROLE OF AI

In public discourse, AI is often associated with risk prediction, algorithms (in the form of machine learning) that are designed to forecast recidivism or flag potential noncompliance. While such predictive analytics can inform resource allocation, this narrow application risks reinforcing existing inequities and reducing supervision to a form of surveillance. A more constructive vision positions AI not as a replacement for officer judgment, but as a collaborative partner that enhances human decision-making, supports engagement, and adapts to clients' changing needs over

time. For example, systems like PARCA can automatically translate risk-need assessments into goal plans, send structured reminders to clients between visits, flag when engagement drops, and suggest timely interventions or incentives based on individual progress. Officers retain full discretion but gain a clearer, data-informed view of where to focus their time and support. This partnership allows supervision to shift from reactive monitoring toward proactive, personalized coaching that strengthens accountability and engagement.

Agentic artificial intelligence, referring to autonomous, goal-directed systems that receive, reason, and act proactively, can be applied in community corrections to interpret assessments, synthesize supervision data, and anticipate emerging risks and support needs (Acharya et al., 2025). By evaluating the completeness, timeliness, and reliability of each data source, these systems ensure that recommendations reflect accurate, actionable insights rather than incomplete or misleading information. Beyond passive analytics, these systems can operate as contextual agents, AI-driven digital partners that communicate through secure text, app-based chat, or voice prompts to provide guidance, reminders, and motivational feedback between

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visits. By maintaining continuous, adaptive interaction, Agentic AI can reinforce case goals, sustain engagement, and alert officers when circumstances shift, helping supervision become more responsive and person-centered. Emerging models in the UK and other jurisdictions are already exploring these applications in probation contexts (United Kingdom Ministry of Justice, 2025; RTI International, 2025).

This approach mirrors advances in healthcare and behavioral health, where AI-driven digital companions develop a nuanced digital understanding of individual learning from that individual's behaviors, communication patterns, and responses over time and then use that information to improve adherence and promote positive habit formation (Torous et al., 2025). In community corrections, Agentic AI can apply these same principles to goal setting, cognitive-behavioral skill practice, and prosocial engagement. By integrating digital understanding with adaptive interaction, these systems can personalize support, anticipate barriers, and reinforce progress.

A persistent concern in justice reform is that technology might depersonalize supervision. When properly designed, AI enhances rather than replaces the human connection. By automating administrative tracking, reminders, and documentation, systems like PARCA free officers to focus on relationship building, motivational interviewing, and problem solving, the core elements of effective supervision.

Moreover, AI provides officers with actionable insights that improve efficiency. Dashboards summarizing goal completion, engagement patterns, and risk changes help with prioritizing by flagging where human attention is most needed. Instead of reacting to violations, officers can proactively intervene when early signs of disengagement appear. This shift from reactive enforcement to proactive coaching embodies the philosophy of smart supervision.

INTRODUCING PARCA: A CONTEXTUAL AGENT FOR COMMUNITY CORRECTIONS

PARCA represents this emerging paradigm of adaptive, relationship-centered supervision powered by Agentic AI. PARCA is a digital platform designed to support both officers and clients through secure communication and personalized goal tracking. Clients access the PARCA mobile app to view and complete individualized goals and earn incentives, while officers monitor client progress through a secure online dashboard that displays

milestones and engagement trends across their caseload. Designed as an extension of the supervision process, PARCA leverages Agentic AI to translate case plans and risk-need assessments into structured, goal-oriented action steps that individuals can understand, track, and achieve. Through continuous digital understanding, PARCA personalizes guidance, identifies progress or setbacks, and provides timely feedback between officer contacts. By aligning daily actions with broader rehabilitative goals, PARCA strengthens accountability and engagement while preserving the officer's central role in judgment and building of relationships.

At its core, PARCA functions as an intelligent intermediary connecting the officer, the client, and the broader network of community resources. When a case plan identifies key needs, such as employment readiness, substance use treatment, or cognitive restructuring, PARCA translates those needs into concrete goals that can be approached in a stepwise fashion. Each goal is broken down into manageable actions, sequenced according to individual readiness and local service availability. PARCA continuously refines its understanding of each client's progress, adapting guidance and feedback in real time to sustain motivation and ensure alignment with case objectives.

For example, if a client's risk assessment identifies unstable employment as a criminogenic factor, PARCA might generate a goal sequence such as completing a resume module, submitting applications to three local employers, attending an interview skills workshop, and checking in with a workforce counselor. Each step is paired with concise "how-to" guidance or links to relevant resources from PARCA's digital bookshelf, a curated library of local and online supports tailored to the user's context. PARCA can adapt this sequence in real time based on the client's progress, engagement patterns, and feedback, ensuring that support remains personalized and actionable. Officers are kept informed of milestones and obstacles, enabling collaborative, timely interventions when needed. For example, if a client falls behind on assigned steps, PARCA sends a supportive reminder encouraging them to stay on track with their goals and updates the officer through a visual dashboard showing current progress. Conversely, when milestones are achieved, the system reinforces success and automatically generates the next set of goals. Through its conversational interface, clients can ask questions

such as “When is my next treatment appointment?” or “Where can I find free job training?” They will then receive clear, supportive guidance powered by natural language processing. Over time, PARCA learns individual engagement patterns and motivation levels, refining its recommendations to maintain momentum and strengthen the officer-client partnership between visits.

TRANSLATING DATA INTO ACTION: AI AND THE CASE PLAN

Traditional supervision tools generate a wealth of data, risk assessments, treatment referrals, contact logs, and compliance reports, but these datasets often exist in isolation and vary in completeness, accuracy, and timeliness, limiting their practical value (Waring et al., 2022). PARCA’s Agentic AI layer addresses these challenges by integrating multiple data sources while assessing the quality and reliability of each input. The system identifies gaps or inconsistencies, flags uncertain information, and adapts its recommendations accordingly. By developing a digital understanding of each client’s needs, progress, and engagement patterns, PARCA translates imperfect data into actionable, personalized guidance, proactively highlighting priorities, anticipating potential barriers, and supporting officers in making informed, context-sensitive decisions.

When a risk-need assessment identifies substance use as a high-priority target, PARCA draws from its knowledge of evidence-based interventions and resources to propose corresponding goals, such as attending recovery meetings, engaging in cognitive-behavioral modules, or completing a relapse prevention plan. Similarly, dynamic data, such as missed appointments or positive progress reports, can prompt PARCA to adapt goals, intensify support, provide incentives, or adjust reinforcement schedules.

This capacity to dynamically align case plans with real-world behavior creates a feedback loop that benefits both client and officer. Officers gain clearer visibility into progress between sessions, while clients receive consistent reinforcement and structure. The system acts as a translation layer between the abstract logic of assessments and the concrete actions required to achieve rehabilitation.

GOAL SETTING, DIGITAL LITERACY, AND THE “HOW-TO” BOOKSHELF

Digital behavior-change interventions that combine specific goal setting with self-monitoring and feedback tools

are associated with improvements in physical activity, sedentary behavior, and related health outcomes (Martín-Martín et al., 2021). PARCA embodies this principle through its “digital bookshelf,” a curated library of short guides, videos, and links that teach skills aligned with supervision goals, such as opening a bank account, managing anger, obtaining identification credentials, or communicating effectively with employers. As clients engage with the resources, PARCA learns which formats and sequences are most effective, adapting future recommendations in real time. This approach not only fosters self-efficacy and consistent skill building but also reduces the burden on officers to continually source educational materials. Over time, aggregated data on usage patterns and outcomes can identify which materials and delivery methods yield the strongest engagement and goal completion, informing updates to PARCA’s content library and broader supervision practices.

INCENTIVES AND THE SCIENCE OF POSITIVE REINFORCEMENT

While accountability is central to community supervision, research consistently shows that positive reinforcement is a more powerful driver of sustained behavior change than punishment alone. The principle is simple: behavior that is rewarded is more likely to be repeated (Petty, 2011; Prendergast et al., 2015; Rudes et al., 2012; Ward & Durrant, 2022). PARCA embeds this principle through a digital contingency management system powered by AI. When individuals complete verified goals, such as attending treatment sessions, maintaining employment, or achieving sobriety milestones, the system issues immediate, proportional rewards. Incentives may take the form of small digital gift cards for essentials (e.g., groceries or transportation) or points redeemable for agency-approved privileges within established supervision parameters, such as reduced community service hours or fees/fines.

Importantly, these incentive structures are not arbitrary. They are grounded in decades of behavioral economics and contingency management research, which demonstrates that timely, transparent, and fair reinforcement can improve outcomes in substance use, employment, and health domains. In corrections, applying these principles digitally ensures consistency and scalability, reducing administrative burden and enhancing fairness. Within PARCA, incentives are delivered through the app as digital acknowledgments or rewards (e.g.,

milestone badges, small gift-card credits, or earned privileges), automatically triggered when clients complete verified actions such as submitting documentation, attending treatment sessions, or achieving goal milestones. Officers can review and approve these reinforcements through a secure dashboard, ensuring accountability and compliance with program policy.

ETHICS, FAIRNESS, AND HUMAN PARTNERSHIP

As AI becomes increasingly integrated into community supervision, ethical considerations, fairness, and regulatory compliance are paramount. Algorithms must be transparent, explainable, and free from biases that could disadvantage already marginalized populations (Marko et al., 2025). Systems like PARCA address these concerns by keeping officers actively “in the loop,” AI provides recommendations and structured guidance, but ultimate discretion and decision-making remain with human supervisors. Each AI-generated goal or incentive suggestion is traceable to its underlying data, allowing officers to understand the rationale and intervene when necessary. Built-in governance protocols monitor all AI recommendations, ensuring traceability from input data

to output actions. Officers can audit system decisions, review flagged anomalies, and override suggestions when necessary, creating a loop of accountability and continuous improvement.

Another factor is that AI systems used in community supervision are only reliable when they operate within clearly defined boundaries. Rather than drawing from the open internet, systems like PARCA are restricted to a curated, agency-approved knowledge base that includes case plan structures, supervision policies, goal and step templates, local resources, and evidence-based intervention content. This “closed world” design ensures that the information clients receive is accurate, aligned with policy, and grounded in established behavioral and supervision science. PARCA’s Agentic AI uses this vetted content, along with engagement patterns, goal progress, and other permitted supervision data, to generate guidance that is consistent, explainable, and tailored to each person’s needs. Safety filters and governance rules prevent the system from offering advice outside its authorized scope. By limiting the model’s knowledge sources, enforcing strict oversight, and anchoring all guidance in

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approved materials, AI becomes a reliable extension of the supervision process, offering timely, structured, and policy-consistent support without replacing human judgment.

In addition to these ethical safeguards, PARCA aligns with major regulatory and standards frameworks, including ISO/IEC 42001, the Health Information Trust Alliance (HITRUST) security framework, the EU AI Act, and the EU's General Data Protection Regulation (GDPR). These frameworks ensure robust governance, data protection, transparency, and human oversight.

IMPLEMENTATION AND SYSTEM INTEGRATION

Integrating AI into existing corrections infrastructure requires careful planning and adherence to privacy, security, and governance standards. Key considerations include data quality, interoperability, and staff training. PARCA's architecture is designed to integrate securely with case management systems, accessing only relevant information while maintaining compliance with frameworks such as GDPR and HITRUST. Built-in governance mechanisms monitor data for accuracy, completeness, and consistency, flagging gaps or anomalies and ensuring that AI recommendations are traceable and reliable. Interoperability standards allow PARCA to communicate effectively across existing databases and service platforms, while its Agentic AI operates within clearly defined protocols, providing actionable insights that augment human decision-making. Comprehensive training ensures that officers can interpret recommendations, validate outputs, and maintain ethical, equitable supervision practices.

Training officers to use systems leveraging AI effectively is equally critical. Successful implementation depends on ensuring that staff view AI as a partner, not a threat. Early evaluation of AI-supported supervision tools shows that officers are receptive when the technology aligns with their casework goals, integrates smoothly into daily workflow, and provides clear and interpretable insights, reinforcing that AI is meant to support, not automate, supervision (Lattimore & Inkpen, 2024).

ECONOMIC AND SYSTEMIC BENEFITS

Beyond individual rehabilitation, AI-driven supervision carries significant economic implications. Digital behavioral interventions demonstrate strong cost-benefit ratios, often

saving multiples of their operating costs through reduced recidivism and avoided incarceration days (Kyaw et al., 2023).

PARCA's digital incentive management system minimizes administrative costs traditionally associated with paper-based or manual reward systems. Automated distribution, fraud prevention algorithms, and real-time analytics ensure resources are used efficiently. At scale, these systems can transform how jurisdictions allocate funds, shifting resources from reactive sanctions to proactive reinforcement and community engagement.

FUTURE DIRECTIONS: TOWARD ADAPTIVE, PERSON-CENTERED SUPERVISION

The next decade of community corrections will look very different. As AI systems continue to evolve, incorporating data like biometric data from wearables to detect stress or substance use risk can support adaptive learning models that tailor interventions to cognitive style, and predictive analytics that anticipate crises before they occur.

The goal is not technological sophistication for its own sake; it is responsivity: tailoring supervision to each person's unique context, motivation, and capabilities. Systems like PARCA represent a step toward that vision, enabling a model of probation and parole that is data-informed, ethically grounded, and deeply human.

CONCLUSION: THE PROMISE OF SMART SUPERVISION

AI is often described as the future, but in community corrections, it is already reshaping the present. The promise of "smart supervision" lies not in replacing human judgment but in augmenting it, using data and automation to deliver the right support at the right time.

By translating case plans into daily actions, connecting individuals to resources, and reinforcing positive behavior through timely incentives, systems like PARCA demonstrate how technology can operationalize evidence-based principles at scale. They bridge the gap between assessment and action, between supervision and support. In doing so, AI offers community corrections a path toward greater effectiveness, fairness, and humanity, a system where accountability and compassion coexist, and where every success is both measurable and meaningful.

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Steven Jenkins is the CEO of Q2i and Contingency Management Innovations (CMI), leading national efforts to modernize behavioral health and community supervision through evidence-based reinforcement and AI-driven personalization. He has built Q2i into a trusted partner for state agencies and health systems, powering major statewide contingency management programs and delivering measurable improvements in engagement and outcomes. Jenkins also leads CMI's innovation portfolio, advancing next-generation digital and AI-supported interventions across behavioral health and community corrections. His work bridges scientific rigor and practical implementation, creating scalable, compliant, and human-centered technology that improves outcomes at population scale.

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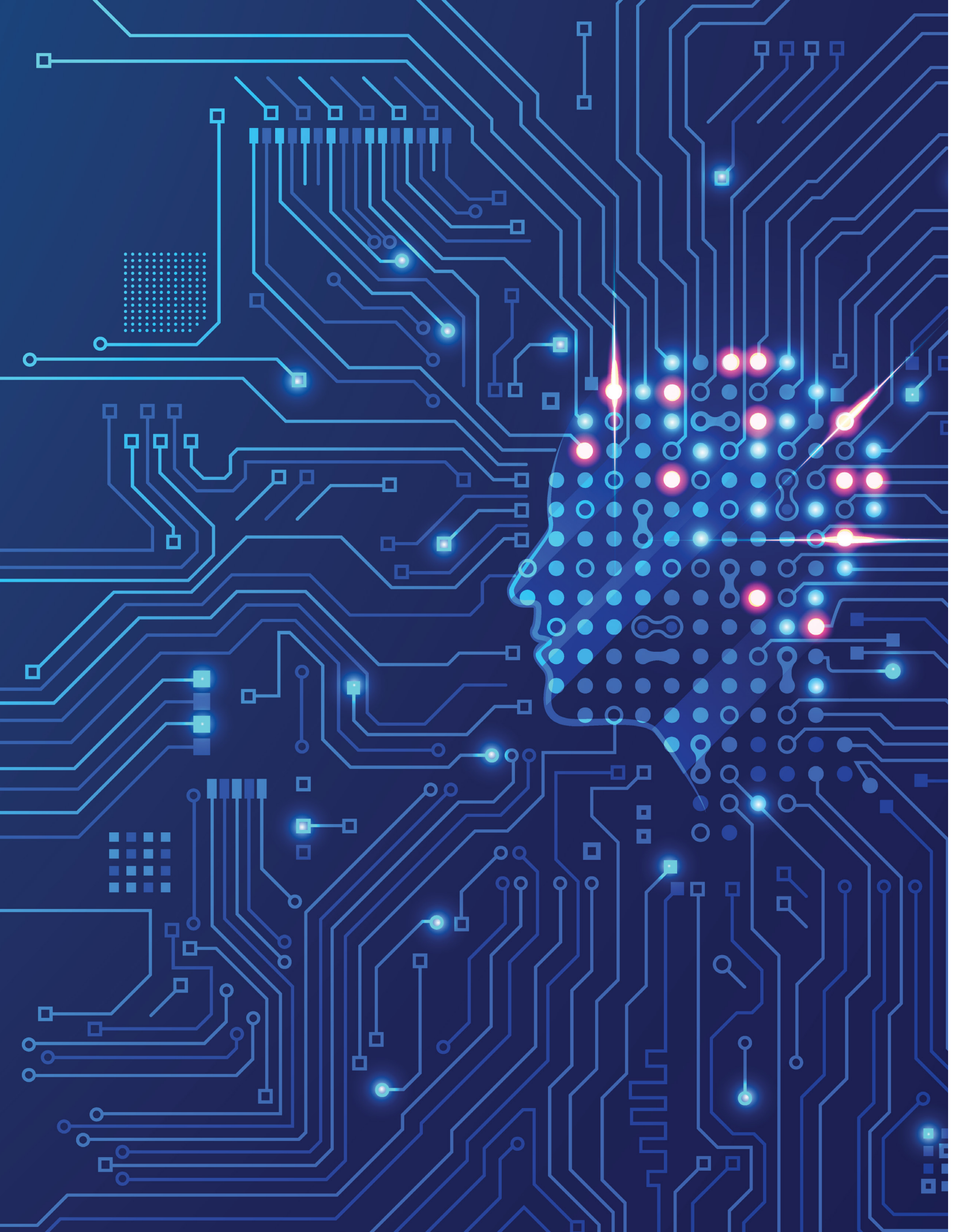
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THE FUTURE OF COMMUNITY SUPERVISION: WHERE ARTIFICIAL INTELLIGENCE MEETS HUMAN JUDGEMENT

by Jack Martin, Former Probation & Parole Chief, Current Client Executive, Tyler Technologies

After more than three decades working in community supervision, I have witnessed firsthand the evolution of our field from a largely reactive, paper-based system to one increasingly driven by data and technology. This transformation has been necessary to meet the growing demands of our profession as we aim to rehabilitate clients, reduce recidivism, and promote public safety while at the same time preserving the connection between individuals and their families.

When I started in this field in the late 1980s, our tools were limited. We relied heavily on face-to-face meetings, paper files, and gut instincts. The introduction of standardized risk assessment tools in the 1990s marked a significant shift toward evidence-based practices. These tools helped inform our decisions for supervision intensity or treatment needs, but they were only the starting point.

The real game-changer came with the widespread adoption of electronic case management systems (CMS) in the early 2000s. These systems revolutionized how we managed client information, tracked supervision activities, and used data to help us make more informed decisions. I remember the mix of excitement and trepidation among my colleagues when we first implemented a CMS. Some immediately embraced it, while others feared it would replace their professional judgment. This paradox remains even today with the emergence of new technology — more on this soon.

Prior to implementing a CMS at my agency, a high-risk client with an extensive criminal history and complex needs might have been lost in a sea of paperwork. With the new system, we were able to quickly access the client's complete profile, including past violations, treatment history, and risk factors. This comprehensive view allowed us to develop a more targeted supervision plan, combining intensive monitoring with cognitive-behavioral therapy. The newer system helped clients successfully complete their probation terms without reoffending — an outcome that might not have been possible without improved data management.

However, as Taxman and Belenko (2011) pointed out, even the best CMS is only as good as the data it contains and the people using it. Inconsistent data entry or reluctance to fully adopt data standards can undermine the potential benefits of these tools. In my early years, we might have considered a dozen factors when assessing a client's risk. Today, machine learning algorithms can process hundreds of variables to predict recidivism risk or identify intervention needs (Berk et al., 2018). This evolution reflects broader trends in criminal justice technology, where data-driven decision-making and predictive analytics are becoming increasingly important. While advanced analytics has its benefits, an overreliance on technology can be an agency's downfall. As Desmarais and Lowder (2019) emphasize, artificial intelligence (AI) and automation tools are meant to aid, not replace, professional judgment.

In this article, we compare traditional data analytics and AI-driven approaches in community supervision. Drawing on both research and real-world experiences, we examine how these tools are reshaping our field and what this means for practitioners, policymakers, and the individuals we supervise.

TRADITIONAL DATA ANALYTICS VS. AI-DRIVEN APPROACHES IN COMMUNITY SUPERVISION

Traditional Data Analytics as the Foundation of Evidence-Based Practices

The introduction of computerized systems in the 1990s marked a significant leap forward, shifting away from handwritten reports and moving toward automatically scheduled reports on various aspects of operations, including caseload statistics, contact compliance, program participation rates, risk assessment summaries, and violation and recidivism rates. Today, these reports provide a standardized view of system performance and client progress (Latessa and Smith, 2015), which is crucial for monitoring accountability and long-term trends. However, reporting limitations have also emerged. I recall a case where the client seemed to be ticking all the right boxes on our standard reports, with regular check-ins,

clean drug tests, and steady employment. However, the probation officer had a gut feeling something was off. It wasn't until the client was arrested for a new offense that we realized our reports weren't able to capture subtle changes in behavior and social associations that might have signaled increased risk. This case highlighted the reactive nature of our reporting, as those standard reports could not replicate human intuition or intercept pure thinking, and was a reminder that people are at the heart of what we do as officers. It sparked a needed discussion for more dynamic analytics and a system that could capture complex, interrelated factors that influence behavior.

The Rise of AI-Driven Approaches

Processing vast amounts of data, identifying complex patterns, and generating predictive insights that were previously unimaginable, AI and machine learning have the potential to revolutionize community supervision. Key applications where AI is most ripe in our field include:

- 1. Risk Assessment:** AI algorithms can analyze hundreds of variables to predict recidivism risk with increasing accuracy (Berk et al., 2018).
- 2. Resource Allocation:** AI can help optimize officer caseloads and program placements based on client needs and risk levels.
- 3. Early Intervention:** Predictive analytics can identify patterns indicative of potential violations or increased risk, allowing for proactive interventions.
- 4. Automated Reporting:** Natural Language Processing can generate detailed reports from unstructured data sources, such as case notes or interview transcripts.

However, the transition to AI-driven approaches comes with challenges. Skepticism and resistance are present among some officers, as they fear these tools might replace their professional judgment. Transparent communication about where AI belongs in community supervision — and where it doesn't — are crucial in gaining staff buy-in.

There is also a concern about bias in AI systems, as highlighted by Chouldechova and Roth (2018) in their work on algorithmic fairness. They advised caution with machine learning, stating that it trains on (or learns using) only present data, which has the potential to compromise its reliability.

For example, if arrest data skews toward minority populations, it will naturally replicate any bias present by flagging or predicting the likelihood of a newly released offender committing a crime. These biases can hinder informed bail or parole decisions, making human decision-making, ongoing monitoring, and regular recalibration of the tool more critical to maintain accuracy and fairness.

Comparative Analysis

Based on experience and research, here is how traditional and AI-driven approaches compare:

	Traditional Approaches	AI-Driven Approaches
Data Processing	Excels at handling structured data within predefined parameters.	Processes both structured and unstructured data from diverse sources, allowing for more comprehensive analysis of a client's situation.
Predictive Capability	Provides retrospective analysis.	Offers advanced predictive modeling. As Flores et al. (2016) demonstrated, some AI models can significantly outperform traditional risk assessment tools in predicting recidivism.
Adaptability	Static and requires manual updates.	Continuously learns and adapts based on new data and outcomes.
Resource Efficiency	Time-consuming to create and maintain.	Automates many analytical tasks, freeing up officer time for more direct client engagement.
Interoperability	Generally easy to interpret.	Deep learning systems can seem like a mysterious "black box," making interpretation challenging and causing significant concern in a field where transparent decision-making is critical.
Implementation	Well-established and relatively simple to implement.	May require methodical change management and training.

CASE STUDY: A HYBRID DATA ANALYTICS AND AI APPROACH IN A WEST COAST URBAN PROBATION DEPARTMENT

From my years as a consultant and chief, the most effective approach is often a hybrid model that leverages the strengths of both traditional and AI-driven analytics. From 2019 to 2021, I advised a large urban probation department on the West Coast as it implemented a hybrid approach, combining traditional reporting with AI-driven analytics. The department's success reflects real-world implementation, illustrating the potential of combining approaches, as suggested by Baumer (2021) in his work on hybrid justice systems.

System Components:

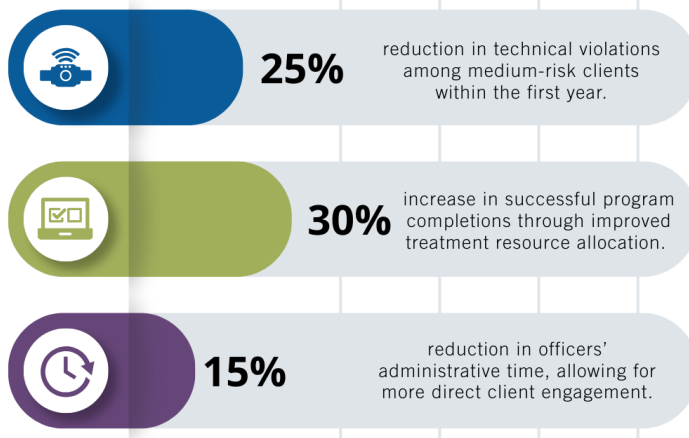
- Traditional scheduled reports for basic performance metrics and compliance tracking.
- An AI-driven risk assessment tool for initial client classification and resource allocation.
- Machine learning algorithms for analyzing case notes and identifying potential red flags for an officer to review.

Implementation Process:

- Phased rollout over 18 months, starting with the risk assessment tool.
- Extensive staff training, including the benefits and limitations of AI in decision-making.
- Regular feedback sessions with officers to refine the system.

Results:

- Leveraging the predictive insights from the AI tool while maintaining human oversight in final decision-making, the department saw:



Lessons Learned and Success Factors:

- There were initial data integration issues between the traditional and AI systems. Regular validation of the AI components against real-world outcomes helped maintain trust in the system.
- The hybrid approach enabled a gradual transition, alleviating staff concerns about overreliance on AI. However, clear protocols for when to rely on AI versus officer judgement helped validate AI-driven recommendations and establish decision-making built with outcomes in mind.

RECOMMENDATIONS

As data analytics and AI evolve in community supervision, this case study illustrates several key points:

1. AI-driven approaches can significantly enhance predictive accuracy and efficiency, but their implementation requires staff buy-in, careful planning, and ongoing evaluation.
2. Traditional reporting systems, while limited in their analytical capabilities, provide a stable foundation for basic performance monitoring and accountability.
3. A hybrid approach can respect both the power of AI technology for complex analysis and the irreplaceable value of human judgment and transparent traditional reports. This approach, as suggested by Baumer (2021), balances the strengths of both methodologies while mitigating their weaknesses.

LOOKING AHEAD: THE FUTURE OF COMMUNITY SUPERVISION

With the evolution of data analytics and AI, we have the potential to make more informed decisions, allocate resources more effectively, and better serve both our clients and the communities we are sworn to protect. However, it is crucial that we approach new technologies with both enthusiasm and caution. The future of community supervision lies in striking the right balance between predictive analytics and human judgment to enhance decision-making and improve outcomes, while remaining vigilant about potential biases and preserving the human nature that is at the core of what we do as officers.

No AI system, no matter how sophisticated, can replace the empathy, intuition, and life experience that skilled probation and parole officers bring to the table. Algorithms can't interpret the subtle body language of a client who is about to spin a tall tale about why they missed their check-in. That is a skill honed by years of experience and countless cups of coffee — some things not even AI is capable of.

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Jack Martin, former director of the Clark County Department of Juvenile Justice Services, has served more than 30 years in law enforcement, ranging in adult, juvenile, and parole services.

Martin began his career rebuilding troubled correctional systems experiencing civil rights violations. Over time, he succeeded in speaking nationally about operational issues surrounding cultural change initiatives and designing and teaching classes for all working in the justice system. Martin has also served on the Southern Nevada local workforce board as Vice Chair, Program Chair, and operational expert and is currently serving as National Chair for the Coalition of Juvenile Justice.

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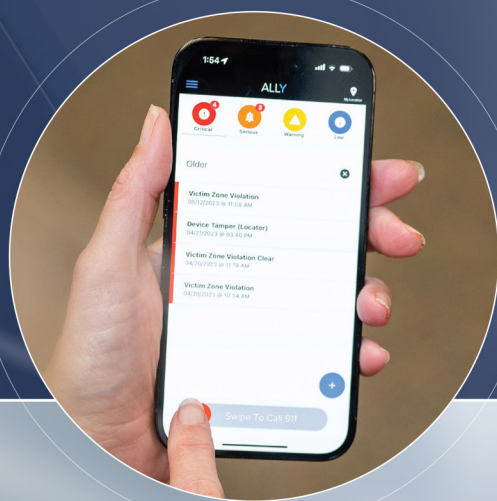
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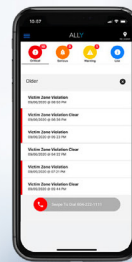
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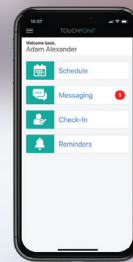
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HARNESSING ARTIFICIAL INTELLIGENCE TO PROVIDE DEVELOPMENTALLY SUPPORTIVE FEEDBACK FOR SYSTEM-INVOLVED YOUTH

by Justin T. Richardson, Bellamy Williams, Royce Hill, Sasha Kuhl, and Adam D. Fine

The juvenile justice system was founded on the idea that youth are fundamentally different from adults in their developmental capacities and need a tailored system to meet their needs (Cauffman et al., 2018). However, a gap remains between what the juvenile justice system was designed to do and what many justice-involved youth experience day-to-day. Detention settings often prioritize surveillance and control over developmental support, and detention has previously been related to worse outcomes and increased likelihood of future system involvement (Walker & Herting, 2020).

Positive youth development (PYD) and social influence frameworks offer an alternative approach. PYD emphasizes building youths' strengths, fostering reflection, and supporting competence across life domains (Bowers et al., 2015), while social influence research highlights adolescents' heightened responsiveness to feedback and validation (Blakemore, 2008; van der Meulen et al., 2023). Together, these perspectives suggest that access to caring adults, opportunities for reflection, and consistent positive reinforcement can support meaningful growth, even in restrictive environments such as juvenile detention. However, recognizing these needs is insufficient without practical mechanisms to deliver them consistently.

Journey.do, a social growth learning platform, integrates these developmental frameworks into a structured system designed to help youth learn, reflect, and build skills they find meaningful. Youth navigate modules that involve reading relatable stories, learning key concepts, and applying these concepts by writing reflective narratives. Staff then provide written feedback on the youths' stories to encourage growth, validate strengths, and help the youth process their experiences. This feedback is central to the platform's goal of promoting positive personal change by reinforcing youths' capacity for change.

Unfortunately, expecting staff to do thoughtful, emotionally present work on top of their already demanding jobs is not realistic without additional support. In this context, artificial intelligence (AI) may offer a promising tool to support staff by creating consistent, strength-based, and trauma-

informed feedback that staff can then tailor to individual youths. An important first step, however, is to determine how the quality of feedback written by AI compares to feedback written by staff.

JUVENILE DETENTION

Despite the knowledge that youth are developmentally different than adults, many existing practices within the juvenile justice system remain misaligned with developmental science. The emphasis of control within many detention facilities fails to set up youth for prosocial futures. For instance, the institutional structure of detention often emphasizes compliance, surveillance, and control rather than supporting development (National Research Council, 2013). In addition, justice involvement more broadly can have negative impacts on youths' mental health (Ramchand et al., 2009), their psychosocial maturation (Ward et al., 2023), and perceptions of future opportunities (Cauffman et al., 2021).

Short-term juvenile detention plays a particularly complex role because it temporarily removes youth from their previous developmental setting yet often fails to provide effective intervention and equally meaningful developmental support. Most youth spend only a few days or weeks in detention (Annie E. Casey Foundation, 2020), yet the impact can be profound. Detention can disrupt education, isolate youth from family support, and expose youth to violence or victimization (Davidson-Arad et al., 2009; Lo et al., 2025). However, that is not to say that detention is incapable of promoting positive outcomes.

Detention facilities have a unique opportunity to influence youth during a pivotal moment. Juvenile detention can present youth with a host of challenges but also provide opportunities for reflection (Ashkar & Kenny, 2008; Paton et al., 2009). Because of youths' reflection and reevaluation, detention provides an opportunity for rehabilitation. With appropriate developmentally informed engagement, facilities can implement models that emphasize youths' strengths and help them build positive relationships and work toward their future goals.

Achieving this shift is challenging. Staff are frequently overburdened (Rhineberger-Dunn & Mack, 2020), and the culture of detention tends to lean toward behavioral management (Gray, 2009). Thus, interventions that support staff in fulfilling a rehabilitative role without increasing their workload are essential.

SUPPORTING YOUTHS' DEVELOPMENT

Positive Youth Development

Positive youth development (PYD) is a strengths-based framework that emphasizes the inherent potential within all adolescents to grow, learn, and thrive (Bowers et al., 2015). Rather than focusing on correcting deficits or behavioral control, PYD prioritizes supporting youths' strengths, addressing their developmental needs, and reinforcing their sense of agency. This approach stands in stark contrast to traditional punitive models within juvenile justice settings.

PYD is most commonly conceptualized through the "Five Cs" model (Bowers et al., 2015). These "Cs" are:

- **Competence:** The ability for youth to navigate different complex environments (e.g., school, families, peer groups, workplaces) and use the resources they have in these environments.
- **Confidence:** The feeling youth experience when they can navigate complex environments and their belief in their ability to impact the world around them.
- **Connection:** When youth feel they are a valued and important member of their community.
- **Character:** How youth internalize and adhere to social norms and standards of behavior and develop a sense of right and wrong.
- **Caring:** How youth empathize and sympathize with others' feelings and experiences.

Among these, connection and character are especially relevant for the current study and youth in detention.

For youth in detention, opportunities for meaningful connection with staff or other youth can be limited. Therefore, engaging youth through supportive, mentoring interactions that emphasize validation and recognition for positive change could help foster positive connections and promote prosocial change. Supportive mentoring interactions have been associated with notable benefits, including decreased aggressive

behavior and substance misuse (Jolliffe & Farrington, 2007; Raposa et al., 2019).

Youth rarely develop responsibility and adopt new values and beliefs simply by being punished. Such changes are more reliably fostered by providing youth with opportunities to engage in positive behaviors and providing affirming and specific feedback when they exhibit them. When youth are praised for their insights, acknowledged for their efforts, and encouraged to build on emerging strengths, they are more likely to internalize prosocial norms and behaviors (Bowers et al., 2015).

The effectiveness of PYD in detention, therefore, depends on staff's ability to have consistent and timely affirming and strength-based interactions with youth. However, due to high workloads, emotional fatigue, and time constraints, staff may struggle to do so. This highlights how AI may be a potentially helpful tool for supporting PYD-aligned communication and day-to-day facility practice.

Journey.do

Journey.do is a social growth learning platform designed to help youth reflect on their experiences, explore life areas, and build prosocial skills through structured learning activities. Its design aligns with principles from positive youth development, developmental psychology, and learning science. For justice-involved youth, Journey.do offers an opportunity to develop insight, self-efficacy, and skills in life areas they find personally meaningful.

The Journey.do platform guides youth through a simple learning process:

- **Journeys:** Broader life areas addressing key important domains (e.g., Owning My Past Actions, Building Strong Relationships, Pursuing Health & Wellness).
- **Modules:** Under each Journey are eight or nine focused lessons that guide youth through reflection, skill-building, and real-world application

Each module comprises three central steps:

- **Connect:** Youth read and engage with peer-written narratives that illustrate the module's concepts in application. These stories promote relatability, provide examples of how to apply their new skills, and prime youth to engage with the material.

- **Learn:** Youth complete concise, developmentally appropriate materials that are designed to deepen their understanding of the topic. They can also learn strategies for coping, managing emotions, identifying triggers, or mastering other skills related to prosocial behavior.
- **Apply:** Youth write their own reflective narratives in response to guided prompts, which allow them to apply new concepts to past, hypothetical, or reimagined scenarios. This step supports youth in internalizing their knowledge and builds their ability to relate previous experiences to their desired future outcomes.

The Apply step is crucial for an additional reason. In this step, staff provide individualized, strength-based,

and trauma-informed feedback to youth regarding their submitted stories. Responses from staff seek to validate youths' experiences, reinforce the prosocial growth they are demonstrating, and encourage them to reflect further on what they have learned. This feedback serves as a form of positive social influence, leveraging adolescents' developmental sensitivity to social evaluation and interpersonal feedback in a beneficial manner (Blakemore, 2008; Telzer et al., 2018). Due to changes in the brain during adolescence (Andrews et al., 2021; Morningstar et al., 2019), youth become more attuned to how others view them and more responsive to praise, validation, and encouragement. Therefore, supportive environments where adults provide consistent validation and encouragement become a powerful engine for youths' positive development.



The Standards will guide community supervision agencies in strengthening and improving services, policies, and practices. The Standards are meant to help ignite conversations and guide our field to increased successes.

MORE INFORMATION



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Social influence can be especially powerful, because it reinforces moments when youth make responsible choices (Foulkes et al., 2018; Knoll et al., 2015), increasing the likelihood that these positive behaviors will be repeated. In doing so, youth learn that their stories matter, their growth is acknowledged, and they are capable of bringing about real change. For justice-involved youth, this kind of affirmation from adults may be particularly impactful. In detention settings, however, opportunities for consistent, intentional positive feedback tend to be limited. If most staff–youth interactions are primarily corrective, youth may come to believe they are defined by their mistakes rather than their potential. Technology offers a way to shift this dynamic, and AI could help staff deliver the prosocial, growth-oriented reinforcement that youth rarely receive but deeply need.

The Importance of Feedback within Journey.do

The written feedback youth receive through Journey.do is not an add-on but rather a core mechanism through which the program supports emotional and cognitive development. High-quality feedback can promote self-efficacy, as youth see how their engagement translates into positive reinforcement. Additionally, it can validate the feelings the youth are sharing or the challenges they have experienced. Lastly, it can motivate youth to continue engaging in their growth and development while feeling seen and valued.

For many youths in detention, staff feedback may be one of the few times adults acknowledge their progress without judgment. It is therefore crucial that feedback is warm, supportive, and developmentally informed. Producing consistently high-quality feedback, especially at scale, can be quite challenging. This challenge is heightened by structural realities within detention facilities, including time constraints and staff's preexisting duties. Therefore, AI support offers a way to preserve the developmental benefits of the Journey.do learning cycle while reducing the burden on staff.

Staff, Journey.do, and AI

Staff are essential to the success of Journey.do, because they are the ones who read youths' reflections and provide feedback that validates growth and encourages further development. However, the process of crafting feedback is both cognitively and emotionally demanding. To provide high-quality feedback, staff must read youth stories closely, identify themes of insight, growth, or vulnerability, and write individualized

responses that acknowledge these elements. Additionally, staff seek to maintain a trauma-informed and strength-based tone. While doing this for a single youth can be demanding, doing this for dozens or hundreds of submissions can feel like a herculean feat.

However, staff are not alone in this task. When AI tools are properly designed and trained, they can help staff provide consistent, developmentally appropriate, and timely responses. Instead of starting from scratch, staff can revise AI-generated drafts to reflect their personal voice, insights, and relationship with the youth. This collaborative approach ensures staff maintain authenticity while benefiting from the efficiency and consistency of AI. In this scenario, AI does not replace the human element. Instead, it ensures that staff have a strong foundation from which to build and helps provide them with the capacity to support youth who are making prosocial changes in their life. However, this approach is only effective if the feedback provided by AI is actually helpful and of high quality.

CURRENT STUDY

The study's purpose was to evaluate whether AI-generated written feedback could match or exceed the quality of staff-written responses to youths' Journey.do submissions. This question is important not because AI is intended to replace staff, but because staff often face structural and emotional constraints that limit their ability to produce consistent, high-quality feedback. If AI can produce strong first drafts, staff may then personalize those drafts, thereby conserving cognitive and emotional resources without sacrificing the relational value of individualized feedback. However, we need to determine whether AI-generated feedback is comparable or superior to human feedback.

Method

Data came from a large juvenile detention facility in the southwestern United States. Between January and May of 2024, detention staff, programming staff, and members of the probation department reviewed and approved about 330 youth-written stories to be shared with their Journey.do community. From these, we selected the first 50 approved stories spanning the platform's three most used learning modules.

Each story received two sets of written feedback—one from a staff member and one from an AI system (ChatGPT-4o paired with a secure, customized language model designed to reflect human training). This resulted

in 150 matched pairs of feedback. To minimize bias, five trained scorers received all 150 matched pairs in random order and were blinded to whether feedback was written by a human or by AI.

The scorers rated each response across five key domains using 20 items on a five-point Likert scale. These domains reflect forms of communication intended to help justice-involved youth feel understood, supported, and motivated to grow, and they allow for an assessment of whether AI-generated feedback could serve as a useful tool for supporting staff interactions with youth.

- Empathetic and active listening: Assesses how well the response demonstrates a genuine understanding of what the youth shared.
- Support and affirmation: Evaluates how much the feedback validates youths' feelings and helps them feel valued.
- Clarity and tone: Examines the feedback's clarity, accessibility, and suitability for youth.
- Encouraging growth and progress: Focuses on how effectively the response promotes continued reflection and positive change.
- Developmentally informed guidance: Assesses how trauma-informed, strength-based, and empowering the feedback would be for youth.

Results

Across every area we compared, AI-generated feedback was rated significantly higher in quality than human-generated feedback ($p < .001$; see Table 1 for details). While these findings do not imply that AI understands youth needs with the same depth as humans or that AI is an appropriate or suitable replacement for staff, they do suggest that AI can be programmed to reliably apply trauma-informed, empathetic language patterns and foundational feedback, thereby assisting staff with feedback. The potential benefits of these results for both youth and staff are significant.

DISCUSSION

Research consistently shows that positive social influence, validation, and supportive adult relationships play a critical role in shaping adolescent behavior and development (Bowers et al., 2015; Blakemore, 2008; van der Meulen et al., 2023). These elements

are central to both juvenile justice reform efforts and positive youth development frameworks. However, supporting youth development in detention settings remains difficult. Structural limitations, emotional demands, and institutional constraints often limit staff's ability to provide the consistent, individualized attention needed to foster meaningful growth. Journey.do offers a promising platform for structured reflection, feedback, and development, but its impact depends on staff being able to maintain high-quality engagement, which is both emotionally and cognitively demanding.

This study suggests that AI can provide a viable pathway to bridge this gap. By generating initial drafts for feedback that incorporate empathetic language, trauma-informed approaches, and strength-based principles, AI can help staff maintain consistency and quality, even under demanding conditions. Rather than replacing staff, AI amplifies their capacity to fulfill their supportive role, enabling them to build stronger relationships with youth without incurring additional cognitive and emotional burdens.

Key Takeaways

- Consistent, supportive feedback from adults can help youth in detention feel seen and capable, while also supporting shifts in self-perception toward greater agency, responsibility, and motivation for prosocial change.
- Time constraints, logistical challenges, and staff burnout can make it difficult to consistently provide developmentally informed feedback. Findings from this study suggest that AI-assisted feedback may offer a practical way to support staff by generating strength-based, trauma-informed drafts that help sustain high-quality engagement without adding to cognitive or emotional burden.
- AI is likely most effective when used to support rather than replace staff–youth relationships, with personalized feedback and authentic engagement maintained through clear guidance, training, and attention to youths' needs and perceptions of how AI is used.

Implications for Positive Youth Development

Not only do youth in detention have limited contact with the outside world, but they also face the challenge of coping with an unnatural environment, one that differs markedly from their life on the outside. Positive youth development offers a framework that supports youths' growth through autonomy, connection, and competence-

building (Bowers et al., 2015). Journey.do aligns well with this framework by offering youth a meaningful way to connect and grow.

AI-assisted feedback enhances PYD through ensuring the feedback youth receive is consistent, timely, and aligned with developmental best practices. When youth are validated and supported, their self-perceptions can shift toward seeing themselves as capable of growth, responsible for their choices, and motivated to pursue a prosocial future. These shifts represent key PYD outcomes that can reduce recidivism, improve well-being, and increase prosocial behavior.

Supporting Staff Through AI Tools

The benefits of AI-assisted feedback extend beyond youth to the staff who support them. Juvenile detention staff often experience high levels of burnout (Rhineberger-Dunn & Mack, 2020; Sheppard et al., 2022) and emotional fatigue (Rhineberger-Dunn & Mack, 2020) while balancing their duties, which often emphasize facility security. Therefore, Journey.do with AI assistance offers staff a different approach to how they engage with youth. This study suggests that AI can assist staff in generating high-quality feedback. This approach could help prevent staff from feeling burned out by engaging in new tasks, such as using Journey.do, and by creating a more sustainable and balanced relationship between security and developmental support.

Strengths of the Approach

The integration of AI-assisted feedback into youth-facing platforms such as Journey.do has several notable strengths, both conceptually and practically. First, the developmental framing of the intervention, aligned with positive youth development, trauma-informed care, and adolescent social influence, creates a strong theoretical foundation. Journey.do is not simply a learning application; it is a reflective, relationship-centered experience that supports youths' ability to grow in ways they find meaningful. AI's role in enhancing aspects of this experience is therefore built atop an established evidence base regarding what helps youth thrive.

Another strength lies in the study's focus on ecological validity. By using real youth stories and the actual reviews provided by detention staff, the research examined feedback within the authentic context of juvenile detention work. The challenges youth express in

their stories regarding vulnerability, trauma, and potential abuse reflect many of the real-world issues these kids experience. Therefore, by using real narratives, we ensured that the evaluation of AI-generated feedback reflects these complexities.

Furthermore, the approach acknowledges the unique challenges of justice-involved youth, as those in this population have often experienced trauma and adversity (Ford et al., 2013) and may benefit most from trauma-informed and strength-based language. Traditional detention feedback, if it appears at all, may prioritize behavioral compliance or rule following. Journey.do, in contrast, situates adult feedback as a vehicle for acknowledging growth, promoting reflection, and reinforcing youths' positive behaviors. Thus, AI is well-positioned to help staff shift detention environments from control-oriented settings to ones that promote positive change and growth.

Finally, our results demonstrate scalability and adaptability. AI-generated drafts can be applied across various modules and work in different justice modalities (i.e., detention, probation, and diversion) with relative ease in multiple jurisdictions. Because properly trained AI can generate consistent, strengths-based language, its implementation reduces the variability that often arises from differences in staff training, experience, or emotional bandwidth. At the same time, AI drafts remain customizable, ensuring that feedback can be tailored to the unique relationship between staff and youth and that the human voice is not lost.

Limitations and Future Directions

Despite its promise, using AI-assisted feedback in juvenile justice settings presents several limitations that must be considered. These limitations are not insurmountable, but they require careful consideration, intentionality, and planning. First, one observed limitation is that AI-generated responses can produce detectable patterns, such as similar phrasing across different reviews. If youth detect patterns during real-world implementation, they may perceive responses as impersonal or automated. This could undermine trust or reduce the emotional impact of feedback. As such, staff must personalize and tailor their responses to each youth's unique story and based on their relationship with that youth. Future work should explore how to optimize the ways AI enhances authentic staff feedback grounded in relationships, so it is not as mechanical or repetitive.



Second, there is an important unanswered question about how youth themselves perceive AI-assisted feedback. It is possible that some youth may view AI involvement with skepticism, fear, or concerns about privacy. Others may feel that feedback arrives “too quickly,” which could suggest to them that their stories are not being read carefully. If youth feel that there is an overreliance on AI in generating feedback, they could find their reviews impersonal and thus unmotivating. Future studies should investigate youths’ thoughts on the use of AI-assisted feedback, examine whether there are differences in the emotional impact when comparing human-generated and AI-generated feedback, and determine whether youths will share their experiences and narratives if they know such shared information will be processed by AI. Exploring these topics is essential before AI tools are adopted by jurisdictions.

A third consideration involves the practical implementation of AI tools in daily staff routines. While AI can reduce the time burden of writing responses, it remains unclear whether AI integration actually does lead to meaningful reductions in overall workload, burnout, or emotional fatigue in real-world operations. Utilizing AI in this way would likely relieve some of the cognitive and emotional burdens that staff experience, but this needs to be tested. Similarly, while AI can help staff respond to youth more efficiently and effectively, this requires staff to possess adequate technical literacy. Ensuring such literacy and comfort may require additional training and institutional support. Addressing some of these potential obstacles will help clarify best practices and facilitate the practical integration of AI into detention and juvenile justice.

Lastly, despite how AI-generated responses can be tailored to a specific reading level, initial drafts may not automatically adjust to the literacy needs of all youth. Detention populations often exhibit a wide range of literacy skills, including those reading significantly below the grade level of their non-justice-involved peers. In this instance, staff should work with AI to match feedback to the reading level of the youth, ensuring that feedback remains accessible while maintaining its emotional depth and impact.

Conclusion

Given the significant impact that juvenile detention experiences can have on youths’ development (Ward et al., 2023; Walker & Herting, 2020), it is essential to approach time spent in detention as an opportunity for positive behavioral development. Few studies to date

have explored how AI could be a tool for supporting rehabilitation and growth in the juvenile detention setting. The present study, which examined use of AI as part of an innovative and scalable approach for supporting juvenile rehabilitation—an approach guided by positive youth development principles—points to the potential benefit of using emerging technologies. Those working within juvenile justice systems now have an opportunity to reconsider how they support youth during one of the most vulnerable times of their lives by use of such technologies. With the right approach, AI can be an invaluable resource in helping such juvenile justice staff engage with youth and realign programs with increased focus on the goal of rehabilitation.

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Table 1. Comparison of AI and Human Reviews by Domain

Quality Domain	AI-Reviewer		Human-Reviewer		<i>t</i> (749)	<i>p</i>
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>		
Empathetic and Active Listening	4.15	0.32	3.88	0.71	9.76	< .001
Support and Affirmation	4.14	0.35	3.86	0.74	9.84	< .001
Clarity and Tone	4.24	0.38	4.06	0.53	9.31	< .001
Encouraging Growth and Progress	3.75	0.49	3.46	0.81	9.99	< .001
Developmentally Informed Guidance	4.00	0.30	3.68	0.75	11.69	< .001

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AI-DRIVEN RISK ASSESSMENTS: BALANCING ACCURACY, TRANSPARENCY, AND FAIRNESS

by Christopher Inkpen, Ph.D., Pamela K. Lattimore, Ph.D., Nicholas Powell, Ph.D., Bria D. Cross, A.B.D, Ryan M. Labrecque, Ph.D.

Justice officials often rely on criminal propensity information to inform their sentencing and supervision decisions. Although risk assessment tools and algorithms are designed to provide objective details in a fair and equitable manner (Bonta, 2002), authorities must exercise great caution when making decisions that affect personal liberties and public safety (Singh et al., 2014). Over the last half century, there have been several significant advancements and attending criticisms regarding the assessment of risk in criminal legal settings (Bonta & Andrews, 2024). Most recently, developers have started employing artificial intelligence (AI) strategies to increase the predictive accuracy of risk instruments (e.g., Ghasemi et al., 2020; Kigerl et al., 2022). As with all new technologies, however, AI is not a panacea. Legal scholars and advocates warn that such use may inadvertently worsen disparities and lead to other adverse outcomes (e.g., Angwin et al. 2016; McKay, 2019).

In this article, we describe the Integrated Dynamic Risk Assessment for Community Supervision (IDRACS) project that was conducted in partnership between RTI International, the Georgia Department of Community Supervision (DCS), and Applied Research Services, Inc. (ARS) (Lattimore & Inkpen, 2024). As part of this work, the research team constructed and compared the performance of three different risk models on a range of metrics, including predictive accuracy, racial fairness, and interpretability between AI-driven techniques and traditional inferential statistical models. This study identifies serious practical and ethical questions for justice officials to consider when selecting and implementing a risk assessment tool. Before addressing these issues, we begin with a brief review of the major historical developments in correctional risk assessments to contextualize the study's findings and their implications for policy, practice, and research.

HISTORICAL DEVELOPMENTS

Scholars often discuss the evolution of correctional risk assessments in terms of “generations” (Bonta, 1996). First-generation assessments typically involve

unstructured interviews by trained staff members who make determinations about risk based on their professional judgment. Despite its intuitive appeal, this approach is often discredited for being subjective and producing poor predictive accuracy (Brennan et al., 2009). Second-generation instruments calculate risk scores based on static factors, such as current offense information and prior criminal history. Although still in use, these instruments have been criticized for relying solely on unchanging factors (Hannah-Moffat, 2005).

A guiding principle of correctional rehabilitation is that individuals can reduce their likelihood for engaging in new criminal conduct (Cullen & Gendreau, 2000). As such, third-generation risk tools combine both static and dynamic variables, such as antisocial personality patterns, procriminal attitudes, procriminal associates, and substance misuse (Bonta & Andrews, 2024). The incorporation of criminogenic need factors not only helps authorities identify appropriate targets for treatment but also provides the ability to monitor changes in an individual's risk over time (Labrecque et al., 2014). Implementation research suggests that probation officers often struggle to link this risk and need information to their key supervision decisions (Viglione et al., 2015). To aid in that effort, fourth-generation systems seek to help staff more directly connect assessment information with case management decisions (Andrews et al., 2006). The extent to which this strategy can improve decision-making and reduce recidivism remains a ripe topic for further academic inquiry.

Whether AI will come to define a fifth-generation or simply serve as an analytical strategy for helping to improve the performances of second-, third-, and fourth-generation instruments remains to be seen. One thing is clear, however. AI is here, and it is actively being used by some developers to increase the accuracy of their risk prediction scales. We argue that even if AI-generated tools provide greater predictive accuracy, that is but one factor that justice officials should consider when selecting a risk instrument for any given purpose. It is also important that authorities prioritize

interpretability and fairness. If a tool is not easily understood by staff, clients, and other stakeholders, it is less likely to garner buy-in or elicit confidence in its results. In addition, a failure to address biases that exist within the data used to develop algorithmic tools may disproportionately impact different groups of people. To help illustrate these issues with a practical example, we next present the findings of the recent IDRACS project.

CURRENT STUDY

The IDRACS study was supported by a research and development grant from the National Institute of Justice with the intent of fostering the development of AI software tools for use in community supervision. As part of this project, researchers from RTI International, Georgia DCS, and ARS collaborated to expand upon the primarily static classification tools that were being used to assess risk and determine the supervision levels of probationers and parolees in Georgia. The goal of this effort was to develop a fourth-generation risk instrument that incorporated criminogenic needs and strength factors—such as the results of drug tests and changes in employment status—and to integrate it into

DCS's case management system so that more informed classification and treatment decisions could be made. Before summarizing the main findings of this project, we first provide a brief description of community supervision practices in Georgia.

Community Supervision in Georgia

The Georgia DCS, which supervises more than 200,000 people, was founded in July of 2015 with the foundational purpose of enhancing criminal justice outcomes across the state. The establishment of DCS consolidated several community supervision responsibilities: (a) felony probation supervision; (b) parole supervision; and (c) supervision for select Class A and Class B juvenile offenses. Georgia has the largest per capita community supervision population in the nation, with 1 in every 23 individuals on probation or parole compared to the national average of 1 in every 71 (Kaeble, 2025). To help allocate resources to supervise such a large population, individuals' supervision levels are determined by their risk score. Individuals are generally supervised in accordance with the supervision requirements of the corresponding level, with those on a



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high supervision level receiving more frequent in-person check-ins, collateral contacts (i.e., family/friend check-ins), and employment and residence verifications. DCS employs risk models that are stratified by client sex and supervision type, creating risk scores that are normed for men and women on straight probation, those sentenced to incarceration followed by a term of probation (split probation), and individuals on parole.

Study Summary

In this study, we adopted a systematic approach to the development and evaluation of risk assessment models for community supervision by first identifying the best-fitting models through testing a variety of predictive features and time-specific periods. Building on this foundation, we sought to maximize predictive accuracy by evaluating several AI techniques alongside traditional statistical methods. Lastly, recognizing the importance of fairness in predicting recidivism, we also implemented bias-aware modeling strategies to ensure that our models did not yield disparate predictions by race. This multi-step process, described below, provides insights for considering when and why to incorporate AI into risk assessment prediction.

Identifying Well-Fitting Models

One motivation behind the IDRACS project was to develop models that could capture and capitalize on the dynamic nature of an individual's progress on community supervision. To do so, the research team carried out two distinctive but related processes using longitudinal supervision histories for individuals: (1) testing the utility of building period-specific models and (2) testing different predictive features (i.e., model specification). More specifically, we used the supervision histories of roughly 168,000 individuals who started straight or split probation or began a term of parole between 2016 and 2019 to assess the likelihood of experiencing a felony or violent misdemeanor arrest or revocation during the observation period.

To aid in identifying accurate predictions of felony and violent rearrest during community supervision, we tested traditional logistic regression models that predicted risk across different time intervals, including both monthly and quarterly periods. Using a period-specific modeling approach allowed for variation in the relationships between the risk and protective factors and the outcome over time. Through this process, we determined that time-period specific models that closely aligned with

DCS's supervision practices were most effective. Specifically, these models reflect the agency's approach of providing intensive supervision during the first 90 days, gradually shifting to less frequent check-ins, and eventually transitioning to more periodic "contact" supervision after the first year. This strategy allowed our models to capture the dynamic nature of supervision and the changing risk profiles of individuals over time.

In addition to capturing static information (e.g., underlying charge, criminal history, age at the start of supervision), the supervision histories include dynamic measures that can change over time (e.g., positive drug tests within a specific timeframe or employment status). Building time-period specific models can account for the fact that an individual's values across dynamic measures can change depending on the time period examined. For example, someone on probation could be employed during the first 90 days but lose that job in the second quarter. In a traditional approach that uses an individual's last observed values, this categorical change would not be captured. Furthermore, the count of someone's positive and negative drug tests, technical violations, or non-violent misdemeanor arrests can also vary over time, and the relationship between those measures and recidivism may be influenced by the time period. Testing period-specific models where someone's values could change depending on their time on supervision allowed us to capture the unique variation of risk and protective factors with the outcome within these periods.

The IDRACS model development process yielded two key findings. First, the models that included features that could change over time on supervision were substantially more accurate than those that used only information gathered at intake. Second, the time-period-specific models were more accurate compared to models built on all the data (i.e., using someone's last observed values). This was most evident in the first year of supervision, where models built from data gathered during those time periods outpaced those built on all the observed data. Taken together, these findings suggest that developing period-specific dynamic models yields a more accurate tool when compared to static tools or those built only on someone's final observed day in the dataset.

Testing the AI-Driven Models

Beyond testing the suitability of dynamic features and period-specific models, the IDRACS project also

compared the predictive performances of two AI-driven machine learning approaches to traditional inferential logistic regression models. Machine learning is a sub-field of AI that focuses on employing algorithms to generate predictions based on identified patterns within the data (Hastie et al., 2009). Although there are many types of machine learning techniques that could be used to predict a dichotomous outcome such as rearrest, this study selected two robust methods that perform well on tabular data: random forest and gradient-boosted machines. Random forests are an extension of decision trees and employ an ensemble approach that averages predictions across multiple decision trees. They excel at identifying non-linear interactions within tabular data (Bou-Hamad et al., 2011). Gradient-boosted machines are another ensemble technique that takes an iterative approach known as gradient boosting, building and learning from weak models to improve overall predictions (Natekin & Knoll, 2013). Ensemble techniques that average the predictions of many models built on a subset of the observations or measures in the data are often found to be more accurate than a single model built on all the data (Dietterich, 2000; Rincy & Gupta, 2020).

Although machine learning techniques offer potential gains in predictive accuracy, interpreting the reasons for predictions can be opaque when compared to a linear regression equation, where coefficients show both the direction and magnitude of a measure and an individual's values can be multiplied by the coefficient's value to produce a prediction. In comparison, results from machine learning techniques can lead to an inability to identify which factors are driving recidivism prediction and how the factors interact with one another (Rudin et al., 2020). Further, there is debate as to whether machine learning models, which have limited interpretability, outperform traditional models such as logistic regression or linear discriminant analysis when it comes to predicting recidivism (Tollenaar & Van der Heijden, 2013). As a result, some researchers suggest relying on more interpretable models when understanding the reasons for the prediction are paramount (Rudin, 2019).

To explore variation in predictive accuracy, this study tested the differences in predictive metrics between the logistic regression and machine learning models. Specifically, we used the Area Under the Curve (AUC) value, which is a threshold-neutral measure of model accuracy that ranges from 0 to 1, with a value of 0.5

representing a coin flip. AUC is a useful measure for a model's performance, as it does not require an arbitrary threshold be set for predictions, instead plotting the model's true positive rate compared to its false positive rate at every possible threshold (Huang & Ling, 2005). To compare AUCs, this analysis employed the DeLong test, which assesses differences in two correlated AUC values (DeLong et al., 1988). Given the performance of traditional models, this study required that machine learning models produce both a statistically significant and substantively meaningful difference in AUCs. Specifically, the difference between traditional and machine learning models had to be greater than 0.03 in AUC and the chance that the difference was an artifact of the data had to be less than 1% (i.e., a p value of less than 0.001 for the DeLong test). Table 1 shows the AUC metrics by time-period, sex, and supervision type for the logistic regression, random forest, and gradient-boosted machine models, listing the differences in AUCs by model type and the p-values (i.e., significance) with the associated DeLong tests.

Based on the rubric described above, neither machine learning model produced a statistically significant improvement in predictive accuracy within the first 90 days. For the remaining three quarters of the first year, there are some statistically significant differences in AUC metrics, but only the random forest model for males on parole reached the substantive threshold of a 0.03 difference. Lastly, when examining differences in predictive accuracy in the greater than one-year models, none of the machine learning techniques outperformed the traditional logistic regression models.

Fairness in Prediction

Beyond developing an accurate model, this study also sought to ensure that the final models did not vary in predictive accuracy across race groups. Several recent studies have addressed the importance of producing similarly accurate predictions for different race groups despite group differences in base rates of the outcome and in the distribution of predictor measures such as criminal history (Berk et al., 2021; Skeem & Lowenkamp, 2016). To account for the difference in base rates and the variation in criminal history items associated with race, this study took a "bias-aware" approach that models group differences explicitly but removes the predictive contribution of race to the final model predictions (Cardoso et al., 2019). Although this approach can lead to less accurate predictions, explicitly modeling race but omitting it from prediction helps to limit inherent biases



in the data. In practice, this entailed modeling race when developing the models but multiplying the coefficient by zero when producing test predictions.

Table 2 shows the results of DeLong tests for model predictions for a White and Non-White sample. Within the first 90-day models, the accuracy for Non-White individuals was higher than those for White individuals, although the differences were not statistically significant. This finding suggests that the models do not perform differently by race. This pattern holds for the other time periods, across sex and supervision type, except for females on parole, where sample sizes were substantially smaller than other supervision types. In this instance, however, the difference in prediction may be attributable to the fewer Non-White individuals who experienced the outcome and the model predicting no arrest for both groups.

DISCUSSION

The findings from this project reveal that while AI and machine learning techniques offer the promise of advanced analytics, their practical improvement over traditional statistical models in risk assessment for community supervision may be limited. Specifically, this study demonstrated that neither random forest nor gradient-boosted machine models consistently outperformed logistic regression in terms of predictive accuracy. Importantly, the logistic regression models featured here reported AUCs above 0.8, indicating a strong level of accuracy even though they do not account for an individual's broader community or legal system context. This high baseline performance suggests that any potential incremental gains from more complex, less interpretable machine learning models may not justify their adoption, particularly in settings where clarity and transparency are essential for decision-making. Furthermore, the use of AI-driven tools must be approached with caution to ensure that they do not reinforce or exaggerate group differences inherent in the data. The bias-aware modeling strategies employed in this study, which explicitly modeled group differences but excluded race from final predictions, underscore the importance of fairness and the need to limit the impact of historical biases.

The study also highlights the significant value of dynamic modeling approaches, which incorporate variables that can change over the course of supervision, such as employment status, completion of supervision

conditions, and results from drug tests. Models that account for these dynamic features and that are tailored to specific time periods demonstrated improved predictive accuracy compared to those relying solely on static intake information and those that modeled risk based on an individual's last observed values in the data. Beyond technical performance, this dynamic approach is important because it acknowledges the potential for individuals on supervision to progress over time.

Given these findings, the implementation of AI-driven risk assessment tools in criminal justice settings should proceed with robust guardrails in place. The decision to adopt such technologies is not solely an empirical question of predictive accuracy. It is also a practical and ethical one that demands careful consideration by correctional authorities. Leaders should resist the temptation to embrace the latest "shiny new thing" without fully understanding its implications. Instead, new AI-based models should be systematically compared to traditional, interpretable approaches in real-world settings, ensuring that any transition prioritizes transparency, fairness, and stakeholder confidence. A cautious, evidence-based approach will help safeguard both the integrity of risk assessment processes and the rights of individuals impacted by these tools.

AUTHOR BIOS

Christopher Inkpen, PhD, is a senior research sociologist and demographer in the Center for Justice Systems Research at RTI International. He served as co-PI for the Integrated Dynamic Risk Assessment for Community Supervision (IDRACS) project, funded by the National Institute of Justice (NIJ) and has been principal investigator or co-PI on three NIJ-funded grants that use cutting-edge analytical techniques. His methodological work focuses on expanding the use of advanced statistical techniques and data-driven methods to improve risk assessment tools within the criminal justice system. In addition to the NIJ, his research has been funded the National Science Foundation, the Institute of International Education's Fulbright Scholarship program, the Department of State's Bureau of International Narcotics and Law Enforcement Affairs, and the Arnold Ventures foundation.

Pamela K. Lattimore, PhD, is a principal scientist (emeritus) at RTI International. She has more than 35 years of experience conducting multidisciplinary research focused on research across the criminal justice system including pretrial policy, community supervision, probation reform, prisoner reentry, and criminal record expungement. She is a past Chair of the American Society of Criminology Division on Corrections and Sentencing, a Fellow of the Academy of Experimental

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Table 1

Comparison of Logistic Regression Model to Random Forest and Gradient Boosted Machines Classifiers

		First 90 Days						Next 270-Day Model						> 1 Year Model					
		LR		RF		GBM		LR		RF		GBM		LR		RF		GBM	
		AUC	p	AUC	p	AUC	p	AUC	p	AUC	p	AUC	p	AUC	p	AUC	p	AUC	p
Straight Probation	Male	.801	.810	.804	.009	.804	.115	.803	.825	.844	.000	.819	.832	.000	.007	.828	.833	.817	.005
	Female	.801	.811	.079	.010	.804	.858	.003	.851	.864	.001	.013	.861	.000	.010	.855	.855	.735	.000
Split Probation	Male	.748	.750	.730	.002	.758	.036	.010	.795	.814	.000	.019	.801	.019	.006	.789	.793	.482	.003
	Female	.759	.740	.351	-.020	.755	.709	-.005	.816	.834	.049	.017	.817	.920	.001	.833	.826	.459	-.007
Parole	Male	.812	.826	.143	.013	.820	.213	.008	.858	.889	.000	.030	.864	.043	.006	.819	.835	.048	.016
	Female	.731	.776	.450	.045	.752	.731	.020	.901	.897	.812	-.004	.888	.303	-.014	.813	.830	.603	.017

Source: LR = logistic regression; RF = random forest; GBM = gradient-boosted machines; AUC = area under the curve. Paired Test AUC value comparisons from longitudinal cohort of individuals on probation and parole in Georgia, 2016–2019. Tests are produced using the gROC package in R and produced using a bootstrapping method with 2000 iterations and using the DeLong method. P value cells are highlighted in green if value is less than 0.001. Difference values between AUCs are highlighted in green if values are greater than or equal to 0.02.

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- ☐ Career Center
- ☐ Executive Summit
- ☐ Leadership Institute
- ☐ Marketing Opportunities
- ☐ Online Training Courses
- ☐ Specialized Services
- ☐ Training Institutes
- ☐ Writing for Quarterly Journal

I AM INTERESTED IN:

- ☐ Case Management/Planning
- ☐ Controlled Substances
- ☐ Criminogenic Risk/Needs
- ☐ Diversity
- ☐ Domestic Violence
- ☐ DUI
- ☐ Electronic Monitoring
- ☐ Evidence-Based Practice
- ☐ Family Justice
- ☐ Fines, Fees & Restitution
- ☐ Gangs
- ☐ International
- ☐ Interstate Compact/Commission
- ☐ Judicial
- ☐ Juvenile Justice
- ☐ Offender Employment
- ☐ Offender Mental Health
- ☐ Officer Safety/Wellness
- ☐ Parole
- ☐ Pretrial
- ☐ Probation
- ☐ Professional Development
- ☐ Public Policy
- ☐ Public Relations
- ☐ Recidivism
- ☐ Research/Evaluation
- ☐ Restorative Justice
- ☐ Sex Offender Management
- ☐ Supervision Strategies
- ☐ Technology
- ☐ Victims Issues
- ☐ Workplace
- ☐ Other _____

PRIMARY WORK SECTOR

- ☐ Academia
- ☐ Adult Correction
- ☐ Adult Parole
- ☐ Adult Probation
- ☐ Community Justice
- ☐ Juvenile Parole
- ☐ Juvenile Probation
- ☐ Judicial
- ☐ Non-Profit
- ☐ Pretrial Services
- ☐ Private
- ☐ Residential
- ☐ Treatment Provider

PROFESSIONAL CATEGORY

- ☐ Administrator
- ☐ Attorney
- ☐ Commissioner/Director/Chief
- ☐ Consultant
- ☐ Educator
- ☐ Grant Coordinator
- ☐ Judge
- ☐ Line Officer
- ☐ Parole Board Member
- ☐ Private
- ☐ Project Director
- ☐ Retired
- ☐ Specialist
- ☐ Student
- ☐ Supervisor
- ☐ Trainer
- ☐ Transition Specialist

A Force for Positive
CHANGE