Source: Chicago Police Department

Person-Based Predictive Policing
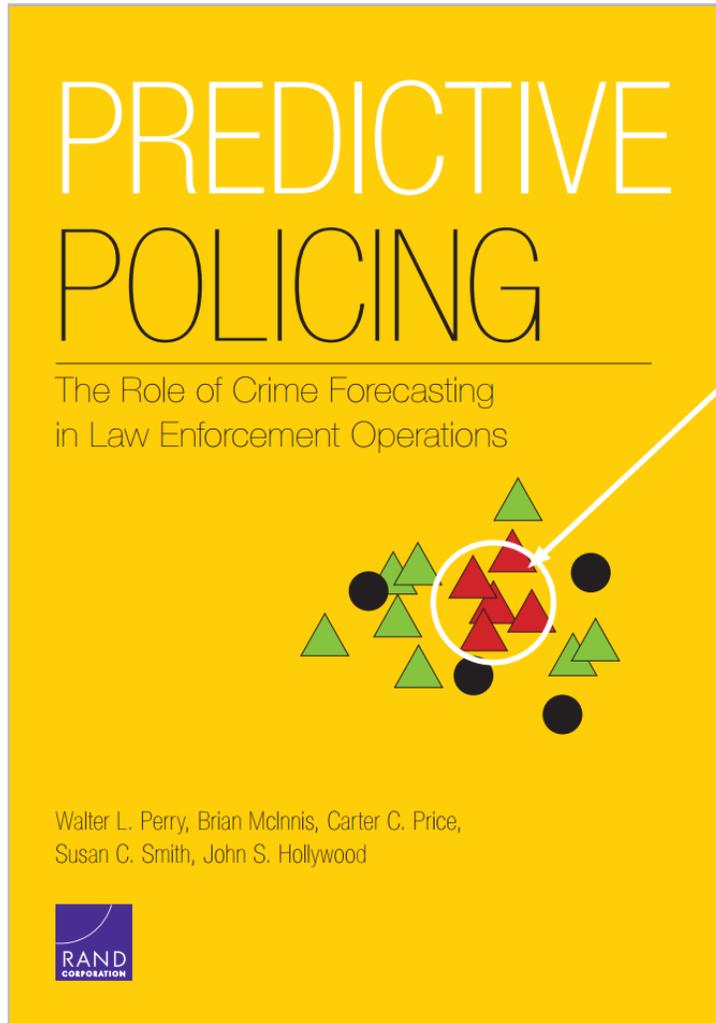
John S. Hollywood

Presentation to the National Academies' Law Enforcement Use of
Predictive Policing Approaches Workshop

Where These Findings Are From

Outline and Bottom Line Upfront

What person-based predictive policing is

Presence: huge in the policy world– but its *operational presence* is near zero

The example of the Chicago Police Department's models

What we can learn from the above

What we might do instead

Predictive Policing

Data, *which might include:*
- **Multiple types of crime**
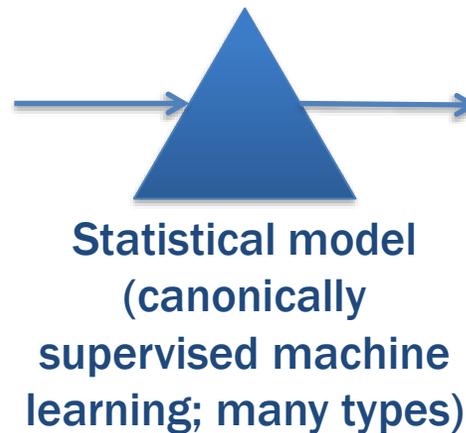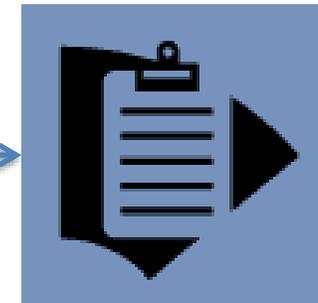- **Disorder calls**
- **Suspicious activity**
- **Field interviews**
- **Time and date**
- **Weather**
- **Geographic features**
- **Gang information**
- **Criminal histories**
- **Etc.**

Statistical model (canonically supervised machine learning; many types)

Estimates of future crime & victimization risk (*predictions*)

Interventions & assessment

PREDICTIVE POLICING
The Role of Crime Forecasting in Law Enforcement Operations

Walter L. Perry, Brian McInnis, Carter C. Price,
Susan C. Smith, John S. Hollywood

RAND
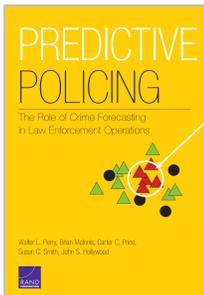
"Predictive policing is the application of analytical techniques… to identify likely targets for police intervention and prevent crime or solve past crime by making **statistical predictions**" (emphasis added, p. xiii)

Some Applications

Predict crimes
- Places and times at increased risk
- Geography associated with risk

(Vast majority of predictive policing here)

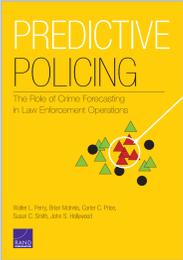Predict offenders
- **Individuals at greatest risk**
- **Families at risk**
- **Groups at risk**

Predict victims
- **Risks from location**
- **Risks from personal risk factors**

"Person-based predictive policing" – especially for **offenders**

Predict perpetrators
- Crimes likely by same perpetrator
- Suspects who most likely committed a set of crimes

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N.B., there are traditional crime analysis and clinical approaches for all of these

On the Prevalence of Person-Based Predictive Policing

- Results of a Google search on "person-based predictive policing", June 20, 2024

- Notice something (or some types of results) missing?

Person-Based Predictive Policing Appears to be Rare

Chicago Police Department Strategic Subjects List and Crime and Violence Reduction Model (SSL / CVRM)

- Today's focus

Los Angeles Police Department Strategic Extraction and Restoration Program (LASER)

- Identified gun crime hot spots (via traditional techniques)
- "Chronic offenders" defined as those who had most quality police contacts plus other criminal history items
- Patrol and special units told to look out for selectees and arrest them when warranted

Pasco County, FL, Sheriffs Office Prolific Offender Designation Programs

- Selected "prolific offenders" by scoring arrests & suspicions; decreased by age & time since last arrest
- Selectees received visit and letter; further police actions were low on average (BJA-sponsored assessment), but with cases of intimidation and harassment reported (*Tampa Bay Times*)

Chicago Predictive Policing Experiment, Ver. 1.0: The Strategic Subjects List ("Heat List") Spreadsheet

- Regression model to predict risk of becoming a homicide victim based on the numbers of 1st and 2nd degree *co-arrest links*
  - Based on social network analysis research showing that homicide victims tended to have been co-arrested with other victims

- Top-ranking persons (n = 426) added to a *Strategic Subject List (SSL)*
  - Spreadsheet never changed during RAND's evaluation, March 2013-2014
  - **3 of 405** Chicago homicide victims on SSL
  - **21%** of homicide victims over this period had one or more links

1st Degree

Subject   Victim

2nd Degree

Inter.

Subject   Victim

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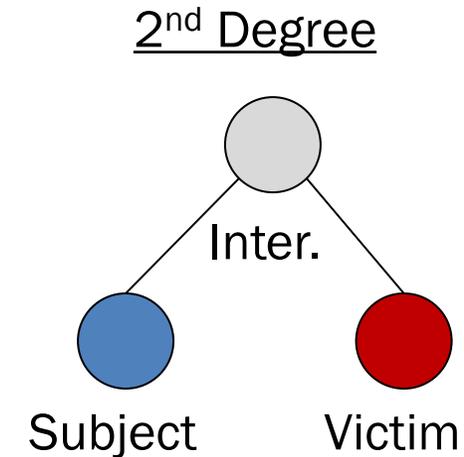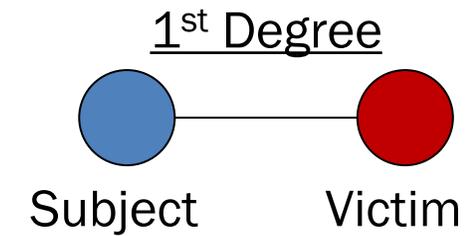
Chicago Predictive Policing Experiment, Ver. 2.0: The Crime and Victimization Risk Model Web App

Table 1. Model coefficients and risk factors in CVRM

Risk factor (after time-sensitivity weighting and data normalization)	Model coefficient	
	Current CVRM	Previous CVRM
Incidents as shooting victim	0.3071	0.2029
Age at latest arrest	0.3056	0.5152
Incidents as victim of aggravated battery or assault	0.2627	0.6567
Trend in involvement in crime incidents	0.1413	0.1466
Violent incidents as arrestee	0.1339	0.4099
Arrests for unauthorized use of a weapon	0.1330	0.1430
Narcotics arrests	Not used	0.4091
Affiliation with a gang	Not used	0.0066

Self-reported predictive performance

Tier	Risk Level	Risk (Probability)
1	Very High	27-35%
2	High	15-27%
3	Moderate	5-15%
4	Low	1-5%
5	Very Low	0-1%

Conditional random fields approach used to adjust risk scores so that persons with a high number of co-arrest links (i.e., were arrested together) have similar risk scores

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Finding 1: Predictive Models Were Operationally Unsuitable

– Risk levels scores did not provide sufficient information to guide interventions

  • N.B., models are largely *victim prediction systems* – and reasons why someone is at high risk for being shot vary widely

– Assessments are time-critical – models ran on intervals of months to years

– **CPD never able to integrate the models into operations, much less validate them**

  • Minimal guidance on specific interventions

  • Two types of actions emerged during SSL: try to contact all SSL members at least once, and have officers stop SSL members when noticed

  • Intervention model never emerged during CVRM – CPD stopped work and had us evaluate their real time crime centers instead

Finding 2: SSL and CVRM Were Misunderstood, Contributing to Unnecessary Public Fear

The minority report: Chicago's new police computer predicts crimes, but is it racist?

Chicago police say its computers can tell who will be a violent criminal, but critics say it's nothing more than racial profiling (M. Stroud, *The Verge*, 2014)

- One of many articles, conferences, and political discussions along these lines (some in progress were rewritten after interviews with us)

- Widespread concerns about CVRM & SSL being *Minority Report* and/or computer-assisted discrimination

- Reality is that CVRM is, largely, a de facto *victim prediction system* with interventions never well-defined or managed

- Initial communications issues and timing may have played a role
  - SSL as the "bad guy list"
  - Limited details about the model
  - At a time when predictive policing had captured attention

What Can We Learn From These Examples on Why Person-Based Predictive Policing Has (Likely) Been Rare?

Speculation only:

- Ethical, legal, reputational, and institutional risks from apparently punishing people for something they have not done
  - Even in small numbers, have caused a great deal of public fear
  - Pretrial, probation, and parole risk assessment tools can be framed as *reducing supervision and punishment* based on findings that people are less likely to offend; also offer promise of *reducing subjectivity* of decisions that must be made during criminal justice processes

- What to do with said forecasts operationally is an open issue
  - While statistically valid, models' forecasts have been too weak and general to directly inform further action

- Place-based predictive policing (e.g., PredPol, IBM Smarter Planet) got most of the attention early and kept it

What Do We Do Instead? Let's Start With the Basics: Policing Should Deliver *Freedom from Fear*

Lovida H. Coleman Jr.. Photo by Diane Baldwin/The RAND Corporation

Americans should experience freedom from both the fear of crime and the fear of the government protecting them

- As championed by Lovida H. Coleman, Jr., longtime RAND Board member

"The basic mission for which police exist is to *prevent crime and disorder*… The ability of the police to perform their duties is dependent upon *public approval* of police existence, actions, behavior, and the ability of the police to secure and maintain *public respect*… the *police are the public and the public are the police*…"

– Sir Robert Peel's Principles, 1829 *(as popularly known as)*

Data & Statistics / ML to Assess What We "Know" Works in Policing
(From RAND's *Better Policing Toolkit*)
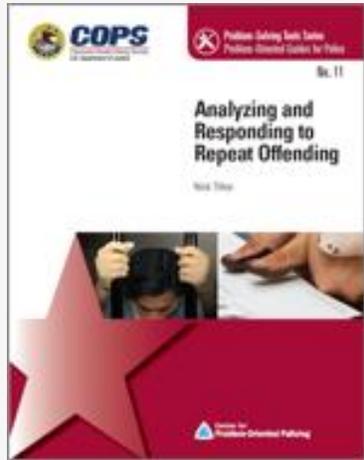
Problem & Community-Oriented Policing
- Talk to the community to ID problems
- Bring in services & partners

Violence Prevention Programs (e.g., GVI / Boston Ceasefire)
- Follow guidance closely
- Have ongoing community & partner involvement

Best Practices in Investigations
- BJA has a guidebook on how agencies solving 80%+ of homicides do it
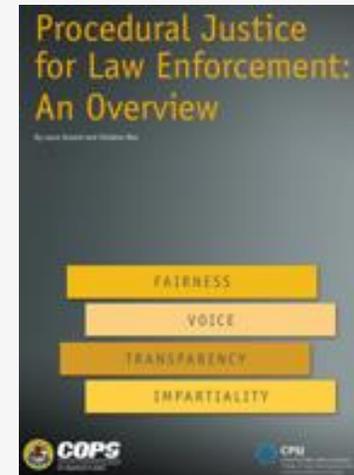
Legitimacy Policing
- Procedural justice: have citizen participation, perceived neutrality, respect, trustworthy motives
- Ongoing dialogue

What not to do: **aggressive policing** – maximizing stops and arrests

Towards Data & Analytics-Informed Community Safety

Collaborate with public about data, analysis, decisions, actions (many likely not enforcement), and protections

Situational Awareness	Generic	• Increase resources in areas at greater risk
Provide tailored information to all levels	Crime-specific	• Conduct crime-specific interventions
	Problem-specific	• Address **specific** locations and factors driving crime risk

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Questions? John S. Hollywood, johnsh@rand.org

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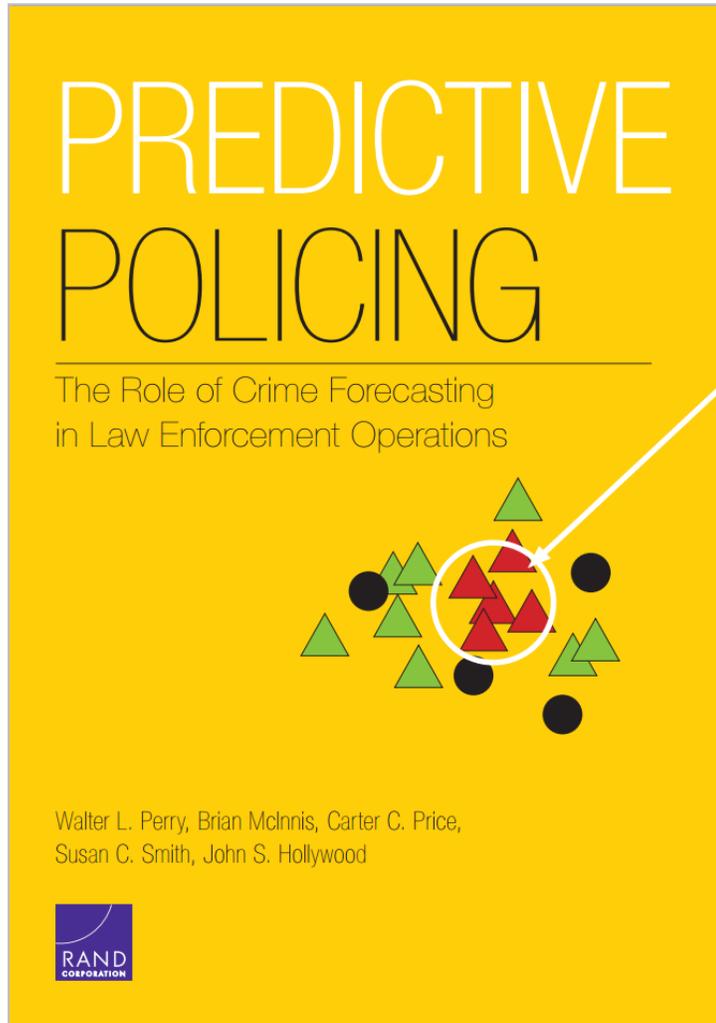
J Exp Criminol (2016) 12:347–371
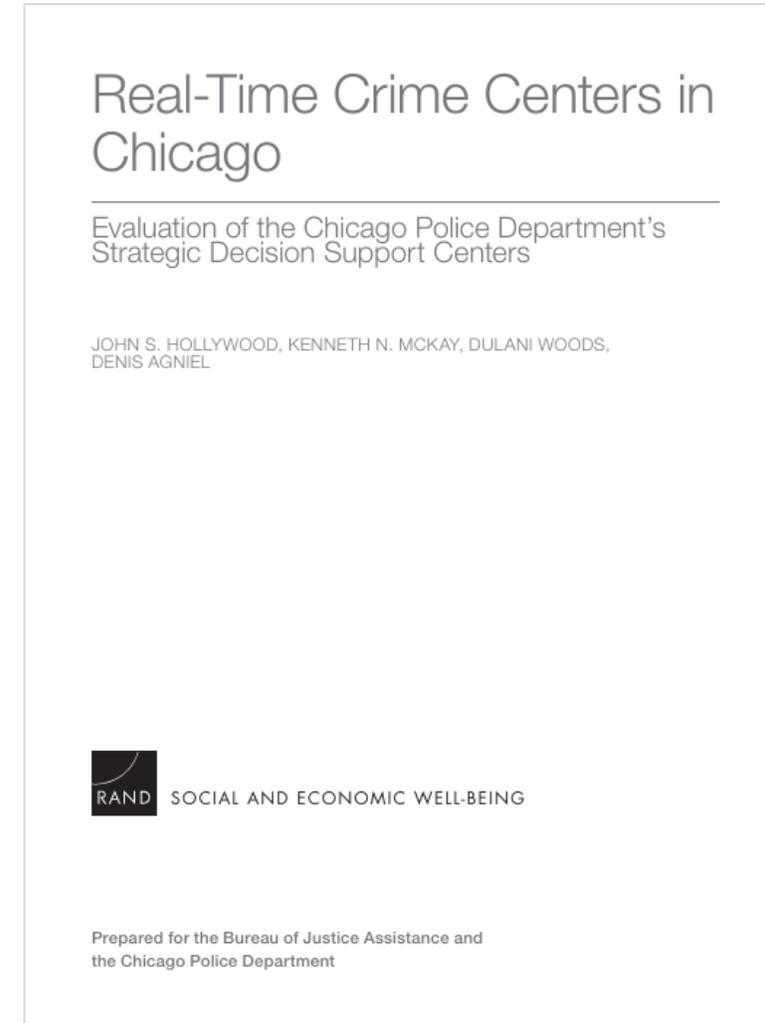DOI 10.1007/s11292-016-9272-0

CrossMark

Predictions put into practice: a quasi-experimental evaluation of Chicago's predictive policing pilot

Jessica Saunders[1] · Priscillia Hunt[1] · John S. Hollywood[1]

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Real-Time Crime Centers in Chicago

Evaluation of the Chicago Police Department's Strategic Decision Support Centers

JOHN S. HOLLYWOOD, KENNETH N. MCKAY, DULANI WOODS, DENIS AGNIEL

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