2022-09

LAW ENFORCEMENT RISK MODEL TO COMBAT OPIOID RECIDIVISM

Whiting, Christopher L.

Monterey, CA; Naval Postgraduate School

http://hdl.handle.net/10945/71037

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

LAW ENFORCEMENT RISK MODEL TO COMBAT OPIOID RECIDIVISM

by

Christopher L. Whiting

September 2022

Thesis Advisor: Anke Richter
Second Reader: Lauren Wollman (contractor)

Approved for public release. Distribution is unlimited.

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE	*Form Approved OMB No. 0704-0188*

1. AGENCY USE ONLY ***(Leave blank)***	**2. REPORT DATE** September 2022	**3. REPORT TYPE AND DATES COVERED** Master's thesis

4. TITLE AND SUBTITLE LAW ENFORCEMENT RISK MODEL TO COMBAT OPIOID RECIDIVISM	**5. FUNDING NUMBERS**
6. AUTHOR(S) Christopher L. Whiting	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000	**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A	**10. SPONSORING / MONITORING AGENCY REPORT NUMBER**

11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.	**12b. DISTRIBUTION CODE** A

13. ABSTRACT (maximum 200 words)

Bergen County, New Jersey, has seen opioid-related overdoses and deaths spike in the last few years. One of the challenges in addressing this epidemic is that “at-risk” individuals may encounter multiple segmented domains such as law enforcement, recovery services, and healthcare institutions, but no one agency has oversight of all the contacts. Each encounter with at-risk populations, including those who suffer from opioid addiction or who may recidivate, becomes a data record in a system. This thesis asks how can law enforcement leverage such data sets to address the opioid epidemic and battle recidivism? This research examined law enforcement arrest data and overdose reporting in Bergen County, analyzing which risk factors in recidivism could be discerned using statistical information, cross-tabulations, Pearson’s chi-squared tests, and data modeling from the Cox proportional hazards model. The results showed that no demographic profile was more likely to have another overdose or death, and theft arrests coincided with a decreased chance of overdose, despite law enforcement’s presumption of the contrary. The strongest predictor of an overdose was a prior overdose, with the risk increasing for each additional overdose. Additionally, having any contact with law enforcement was an indicator of a significantly higher chance of overdose or death. Thus, each interaction between law enforcement and an observed opioid abuser is a critical point for intervention.

14. SUBJECT TERMS risk model, opioid, recidivism, law enforcement, Bergen County	**15. NUMBER OF PAGES** 77
	16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	**18. SECURITY CLASSIFICATION OF THIS PAGE**	**19. SECURITY CLASSIFICATION OF ABSTRACT**	**20. LIMITATION OF ABSTRACT**
Unclassified	Unclassified	Unclassified	UU

NSN 7540-01-280-5500 Standard Form 298 (Rev. 2-89) Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release. Distribution is unlimited.

LAW ENFORCEMENT RISK MODEL TO COMBAT OPIOID RECIDIVISM

Christopher L. Whiting
Sergeant, Counterterrorism Coordinator, Bergen County Prosecutor's Office New Jersey
BS, Manhattan College, 2003
MS, Fairleigh Dickinson University, 2009

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF ARTS IN SECURITY STUDIES
(HOMELAND SECURITY AND DEFENSE)

from the

NAVAL POSTGRADUATE SCHOOL
September 2022

Approved by: Anke Richter
Advisor

Lauren Wollman
Second Reader

Erik J. Dahl
Associate Professor, Department of National Security Affairs

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

Bergen County, New Jersey, has seen opioid-related overdoses and deaths spike in the last few years. One of the challenges in addressing this epidemic is that "at-risk" individuals may encounter multiple segmented domains such as law enforcement, recovery services, and healthcare institutions, but no one agency has oversight of all the contacts. Each encounter with at-risk populations, including those who suffer from opioid addiction or who may recidivate, becomes a data record in a system. This thesis asks how can law enforcement leverage such data sets to address the opioid epidemic and battle recidivism? This research examined law enforcement arrest data and overdose reporting in Bergen County, analyzing which risk factors in recidivism could be discerned using statistical information, cross-tabulations, Pearson's chi-squared tests, and data modeling from the Cox proportional hazards model. The results showed that no demographic profile was more likely to have another overdose or death, and theft arrests coincided with a decreased chance of overdose, despite law enforcement's presumption of the contrary. The strongest predictor of an overdose was a prior overdose, with the risk increasing for each additional overdose. Additionally, having any contact with law enforcement was an indicator of a significantly higher chance of overdose or death. Thus, each interaction between law enforcement and an observed opioid abuser is a critical point for intervention.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

I. INTRODUCTION 1
  A. PROBLEM STATEMENT 1
  B. RESEARCH QUESTION 2
  C. SIGNIFICANCE OF RESEARCH 2
  D. OVERVIEW OF CHAPTERS 3

II. REVIEW OF EXISTING MODELS 5
  A. AT-RISK MATRIX DELIVERY MODEL 5
  B. OTHER RELEVANT RISK MODELS 6
  C. RECIDIVISM MODELS AND ASSESSMENT TOOLS 7
  D. SUMMARY OF DATA ELEMENTS USED IN EXISTING MODELS 8

III. STATISTICS AND DATA SETS 11
  A. BACKGROUND 11
    1. Operation Helping Hand 13
    2. Heroin Addiction Recovery Team 14
    3. Bergen County Data Exchange 15
    4. Overdose Detection Mapping Application Program 16
  B. DATA ORIGINATION AND APPROVALS 16
    1. Data Removed 17
    2. Data Kept 18

IV. DESCRIPTIVE STATISTICS OF THE DATA 23
  A. CROSS-TABULATIONS AND CHI-SQUARED STATISTICS 24
  B. COX PROPORTIONAL HAZARDS MODEL 28

V. CONCLUSION AND FUTURE RESEARCH 33
  A. LIMITATIONS 34
  B. NEXT STEPS 34

APPENDIX A. ORT FORM 37

APPENDIX B. HART FORM 39

APPENDIX C. DATA REMOVED 41

APPENDIX D. CHI-SQUARED CALCULATIONS: NO STATISTICAL SIGNIFICANCE 43

APPENDIX E. COX PROPORTIONAL HAZARDS MODELS 49

LIST OF REFERENCES 53

INITIAL DISTRIBUTION LIST 57

LIST OF FIGURES

Figure 1. Baseline Survival Model 30

Figure 2. Comparative Survival Models: Arrest vs. No Arrest 31

Figure 3. Comparative Survival Models: Number of Overdoses 32

Figure 4. Proposed Four-Phase Decision Support System 36

Figure 5. Opioid Risk Tool 37

Figure 6. HART Intake/Release Form 39

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF TABLES

Table 1. Factors from Prior Studies for Model Consideration 9

Table 2. Bergen County Opioid Statistics 12

Table 3. Arrest Data Fields Utilized 18

Table 4. Overdose Reporting Data Fields Utilized 19

Table 5. Criminal Charge Summary 20

Table 6. Overdose and Drug Categories 21

Table 7. Further Data Fields Removed 22

Table 8. Age Brackets 23

Table 9. Differences between Male and Female concerning Treatment Drug Usage 25

Table 10. Differences between Male and Female concerning Prostitution Arrests 26

Table 11. Differences between Overdose and Arrest versus Township 27

Table 12. Differences between Opioid and Non-opioid Use vis-à-vis Theft Arrests 27

Table 13. Differences between Opioid and Non-opioid Use vis-à-vis CDS, Theft, and Assault Arrests 28

Table 14. Differences between Opioid and Non-opioid Use vis-à-vis CDS and Theft Arrests 28

Table 15. Data Removed: Arrest Data Fields—Data Set 1 41

Table 16. Data Removed: Overdose Reporting Data Fields—Data Set 2 42

Table 17. Differences between Male and Female concerning Opioid Usage 43

Table 18. Differences between Male and Female concerning Alcohol Usage 43

Table 19. Differences between Male and Female concerning Antipsychotic Drug Usage 43

Table 20. Differences between Male and Female concerning Stimulant Drug Usage....44

Table 21. Differences between Male and Female concerning Sedative Drug Usage....44

Table 22. Differences between Male and Female concerning Domestic Violence Arrests....44

Table 23. Differences between Male and Female concerning Theft Arrests....45

Table 24. Differences between Male and Female concerning Theft Arrests before Overdose....45

Table 25. Differences between Male and Female concerning Theft Arrests after Overdose....45

Table 26. Differences between Male and Female concerning Firearm Violations....46

Table 27. Differences between Male and Female concerning CDS Violations....46

Table 28. Differences between Male and Female concerning Assault Arrests....46

Table 29. Differences between Opioid and Non-opioid Users concerning CDS Arrests....47

Table 30. Differences between Opioid and Non-opioid Users concerning Firearm Arrests....47

Table 31. Differences between Opioid and Non-opioid Users concerning Assault Arrests....47

Table 32. Cox Proportional Hazard Models: Variables and Coefficients....49

Table 33. Summary Statistics by Incident....50

Table 34. Summary Statistics by Individual....51

LIST OF ACRONYMS AND ABBREVIATIONS

ARMD	at-risk matrix delivery
CAD	computer-aided dispatch
CAFS	Children's Aid and Family Services
CDS	controlled dangerous substance
DMI	Drug Monitoring Initiative
DOB	date of birth
DSS	decision support system
GJXDM	Global Justice XML Data Model
HART	Heroin Addiction Recovery Team
HIPAA	Health Insurance Portability and Accountability Act
IRB	Institutional Review Board
NJSP	New Jersey State Police
NPS	Naval Postgraduate School
OD	overdose
OHH	Operation Helping Hand
ORT	Opioid Risk Tool
PHI	protected health information
PII	personal identifiable information
RMS	record management system
TCADR	The Center for Alcohol and Drug Resources

THIS PAGE INTENTIONALLY LEFT BLANK

EXECUTIVE SUMMARY

In 2016, the Bergen County Prosecutor's Office in New Jersey implemented several programs to help reduce recidivism among opioid users, including Operation Helping Hand, the Heroin Addiction Recovery Team (HART), and a data exchange initiative. Despite the successes seen with these prevention and intervention programs, numbers of overdoses, Narcan (naloxone) saves, and fatal overdoses have continued to rise.[1]

No existing research has employed a risk model to combat opioid abuse by leveraging law enforcement data to identify at-risk persons. This research represents the first of its kind to answer which factors drive opioid recidivism based on an examination of law enforcement data. The data were compiled from two data sets utilized by the Bergen County Prosecutor's Office—overdose reporting data and daily arrest data. The Naval Postgraduate School's Institutional Review Board approved the use of these data sets.

Cross-tabulations, assessed with Pearson's chi-squared test and the Cox proportional hazards model, were used to estimate the impact of several factors on the probability of an individual already in a drug treatment program having a future overdose. This analysis revealed that law enforcement's assumptions about opioid addiction are incorrect.[2] Namely, gender roles were found not to be a significant factor, nor was one demographic profile more likely to have another overdose or die from an overdose, according to the analysis.

Additionally, what law enforcement has perceived as valuable indicators of opioid recidivism, such as theft arrests as they correlate to gender, have no statistical significance regarding recidivism. Moreover, a history of theft arrests was found to decrease the risk of overdose by 26% while prostitution increased the risk of overdose by 46%. However, in

---

[1] "Response to the Opioid Epidemic: Bergen County Opioid Statistics," Bergen County Prosecutor's Office, accessed July 20, 2022, https://www.bcpo.net/opioid-response/.

[2] William H. Fisher et al., "Co-Occurring Risk Factors for Arrest among Persons with Opioid Abuse and Dependence: Implications for Developing Interventions to Limit Criminal Justice Involvement," *Journal of Substance Abuse Treatment* 47, no. 3 (September 2014): 197–201, https://doi.org/10.1016/j.jsat.2014.05.002.

comparing opioid users to non-opioid users, the statistical analysis supported current beliefs that opioid users are more likely to be involved in theft arrests than non-opioid users.

The Cox models clearly show that every overdose victim is at higher risk of subsequent overdose, and survival decreases significantly with every new overdose. Additionally, the more arrests a person has, the greater the chance of having a subsequent overdose or death. This finding suggests that each law enforcement interaction with an observed opioid user is a critical point, thus offering the greatest chance of saving an addict's life. These data further support initiatives such as Operation Helping Hand, whereby increased officer interactions with opioid users means a greater likelihood of survival.

ACKNOWLEDGMENTS

"The farther we get from 9/11, the closer we get to 9/10/2001." This quote, from an unknown Port Authority of NY/NJ officer, has resonated and guided me most of my career in counterterrorism. The events and aftermath of 9/11 profoundly impacted my career path—from my service as a volunteer firefighter responding to New York City on that horrific day to my joining the law enforcement community and ultimately serving in counterterrorism.

It has been a tremendous privilege, honor, and opportunity to participate in the CHDS program. To Dr. Chris Bellavita, Dr. Lauren Fernandez, Director Heather Issvoran, and all the CHDS instructors and advisors whom I met during this program, please accept my thanks for a profound and incredible academic journey.

To the members of Cohort 2001/2002, what an unbelievable journey we have traveled. Beginning at the onset of COVID-19, our cohort persevered, adapted, and overcame all obstacles that we faced. We became remarkably close, despite having had but one session on campus! I recognize the role of the "Zoom Trident Room" and our "Slack banter" in fostering these relationships and allowing unfettered debate on any given point. I will cherish these relationships. I thank each and every one of you for your support, and I wish you all the very best!

I extend a special thank you to Prosecutor Mark Musella, Chief Robert Anzilotti (now retired), Chief Jason Love, Lieutenant David Agar, UASI Director James Sheehan (ELP 2002), and the Bergen County Prosecutor's Office Command Staff and ICTU, especially Analyst Heather Norman. I would not have had the opportunity to apply to this program were it not for the support and encouragement of Chief Anzilotti; I thank you very much, Chief. I would also like to express my most profound appreciation and thanks to NJSP Lt. Colonel Raymond Guidetti, ret. (Cohort 0403/0404), for his unwavering support, guidance, and friendship throughout the years; you are an inspiration and mentor.

To Dr. Lauren Wollman, I appreciate all the support, direction, and reviews that you gave me in preparing this thesis, and to Dr. Laura Armey, I owe you a debt of gratitude for all your assistance and expertise in modeling for this research. Also, thank you, Noel Yucuis, for the editorial assistance, wordsmithing, and wizardry of the template. But, most importantly, Dr. Anke Richter, this research would not have been possible without your constant encouragement, support, and guidance; you have been an invaluable champion of this project and have continually provided your support, questions, expertise, and direction. At the end of the day, you never let me fall behind! You are a remarkable confidant.

This life-changing experience could not have been possible without the unconditional support and encouragement of my family. First and foremost, to my wife, Jodie, and daughter, Anna, I express an enormous special thanks for all your love, sacrifice, patience, and support always! You both endured a lot during this program, constantly pushing and motivating me to do my best! I love and adore you both very much. Second, to my father-in-law, John Bessich, thank you for the many peer review sessions we shared and for your perspectives.

In closing, I leave you with a quote from the great statesman, Sir Winston Churchill: "Never give in, never give in, never, never, never, never—in nothing, great or small, large or petty—never give in except to convictions of honour and good sense."

I. INTRODUCTION

New Jersey, including Bergen County, has seen opioid-related overdoses and deaths spike in the last couple years. One of the challenges in addressing this epidemic is that an “at-risk” individual may encounter multiple segmented domains such as law enforcement, recovery services, and healthcare institutions, but no one agency has oversight of all the contacts. At-risk populations include those who suffer from opioid addiction or have the potential for recidivism in opioid abuse. Each of these encounters results in the recording of a data record in a system. Nevertheless, because of siloed data repositories, information is not readily available or shareable as a proactive intervention resource. The lack of proactive intervention further contributes to recidivism in opioid users. Some of these data sources include investigative data sets from warrants or arrests, technology-driven data (e.g., automated license plate readers and body-worn cameras), forensic data (e.g., cellular data extractions), overdose-related information, and mental health data. Most studies, data analyses, regression analyses, artificial intelligence, and machine learning focused on drug activity traditionally concentrate on the data’s criminal elements (e.g., possession, use, arrests, and transactions). However, often overlooked is the wealth of data on the population at risk of opioid overdose or death in providing proactive interventions.

A. PROBLEM STATEMENT

The purpose of this thesis is to examine and identify data elements found in law enforcement data sets that can be utilized for a risk model to combat opioid abuse proactively before an overdose or reoffending episode. The success of a law enforcement risk model depends on using all data available to improve the process of identifying a person at risk of overdosing or committing a drug-related crime, thereby potentially reducing the at-risk persons’ vulnerability or potential for relapse. Individuals with opioid addictions may have multiple contacts with several county or local agencies across numerous domains such as law enforcement, recovery services, or health care institutions. Moreover, a significant challenge in law enforcement’s successfully addressing opioid abuse in a proactive manner is accessing individual health information. Unfortunately, sharing cross-domain information among various agencies is often fragmented and episodic, thus hindering proactive intervention.

Alerting authorities to intervention opportunities for any at-risk person requires creating a risk model with access to law enforcement data sets and some health information. Once data are made available on a common platform, the objective would be to develop a decision support system (DSS) to integrate the various components and data sets. The DSS would facilitate the capability of analyzing large volumes of data by utilizing a risk model to alert authorities to any at-risk person vulnerable to opioid abuse.

B. RESEARCH QUESTION

What risk factors are pertinent for law enforcement to combat opioid abuse, and how can they be used to create a risk model to alert police to those considered at risk of recidivism?

C. SIGNIFICANCE OF RESEARCH

Although a fair amount of literature has been published examining tools to predict the likelihood of opioid addiction, one of the key limitations of the literature is the lack of research on a risk tool for use by law enforcement to combat opioid abuse. A 2019 RAND report indicates that data-sharing between law enforcement and health professionals is critical insofar as opioid abusers fall between both domains.[1] A study by Winkelman, Chang, and Binswanger finds that opioid users are more likely to be involved with the criminal justice system than non-users.[2] Additionally, Fisher et al. note in their published

[1] Sean Goodison et al., *Law Enforcement Efforts to Fight the Opioid Crisis: Convening Police Leaders, Multidisciplinary Partners, and Researchers to Identify Promising Practices and to Inform a Research Agenda* (Santa Monica, CA: RAND Corporation, 2019), https://doi.org/10.7249/RR3064.

[2] Tyler N. A. Winkelman, Virginia W. Chang, and Ingrid A. Binswanger, “Health, Polysubstance Use, and Criminal Justice Involvement among Adults with Varying Levels of Opioid Use,” *JAMA Network Open* 1, no. 3 (2018): e180558, https://doi.org/10.1001/jamanetworkopen.2018.0558.

research the statistical significance of gender and age in opioid abuse and arrest.[3] However, no information specifically addresses the factors most associated with opioid overdose or death, and which might be observed in data combined from the criminal justice system and the healthcare system for opioid addicts, as suggested by the RAND. Also, no research has explored a joint risk model to combat opioid abuse by leveraging law enforcement data to identify at-risk persons. The research in this paper represents the first attempt to answer questions with respect to both.

D. OVERVIEW OF CHAPTERS

Chapter II reviews existing risk models to identify factors that have correlated with overdose and death in opioid addicts. The goal is to ensure that, to the extent possible, these data elements are found and gathered in the data collected for this study. Additionally, this chapter provides a summary of data elements in the existing models.

Chapter III presents the data sources available in Bergen County and the process of obtaining access to the data. Under the direction of the Naval Postgraduate School's Institutional Review Board, the data were anonymized and retained for use in an academic research setting. Chapter III describes these processes and their implementation and explains in detail the final data set available for analysis.

Chapter IV presents the data analysis conducted with the data set, including descriptive statistics, cross-tabulations, Pearson's chi-squared tests, and a Cox proportional hazards model.

Chapter V presents the findings and their impact on developing a risk prediction model, limitations of the analysis, suggestions for future work, and the overall study conclusion.

---

[3] William H. Fisher et al., "Co-Occurring Risk Factors for Arrest among Persons with Opioid Abuse and Dependence: Implications for Developing Interventions to Limit Criminal Justice Involvement," *Journal of Substance Abuse Treatment* 47, no. 3 (September 2014): 197–201, https://doi.org/10.1016/j.jsat.2014.05.002.

THIS PAGE INTENTIONALLY LEFT BLANK

II. REVIEW OF EXISTING MODELS

This chapter examines the risk models currently available in written studies, as well as the available recidivism models. While these models are not directly applicable to the current study, the discussion details their aims and the data elements examined and found to be important in the question of opioid use, overdoses, death, and criminality.

A. AT-RISK MATRIX DELIVERY MODEL

The first risk analysis tool reviewed was the at-risk matrix delivery (ARMD) model of the Drug Monitoring Initiative (DMI), commissioned by the New Jersey State Police (NJSP) in 2013.[4] The ARMD model is used by the DMI to calculate a "risk score" based on naloxone administration, controlled dangerous substance (CDS) arrests, and theft arrests. The ARMD model was developed to address the increasing opioid epidemic in 2013. The risk score calculation utilized by the DMI is as follows:

- Naloxone administrations within past 6 months = 20
- Naloxone administrations between past 6–12 months = 15
- Naloxone administrations prior to 12 months = 10
- CDS arrest = 3
- Theft arrest = 1
- Arrest involving both CDS and theft charges = 3[5]

The risk score calculation was recently updated to give more weight to recent naloxone administrations than to earlier administrations of naloxone. The greater the number calculated, the greater the risk. The NJSP noted that incorporating additional data sets or response variables would increase the predicator's accuracy and improve modeling outcomes. However, one obvious limitation of the DMI data model is that it was created from professional observations and expertise and has not been validated or statistically assessed. In addition, although it is likely the model's predictive accuracy must have been tested at some point, this information is not provided. While such data are extremely

[4] "New Jersey's Drug Monitoring Initiative: Comprehensive Approach to Community Drug Harms," Rx Drug Abuse & Heroin Summit, accessed September 12, 2022, https://www.eventscribe.com/2021/RxSummit2021/fsPopup.asp?Mode=presInfo&PresentationID=805720.

[5] New Jersey State Police Drug Monitoring Initiative, email message to author, August 25, 2020.

sensitive, statistical testing, model validation, and predictive assessments can easily be reported without revealing any data source. However, none of this information is publicly available.

B. OTHER RELEVANT RISK MODELS

In a study published by Fisher et al., 2010 arrest data from the State of Massachusetts were merged with Medicaid data of known opioid users to assess the effects of co-existing mental illness, substance abuse, and previous arrests on the likelihood of new arrests among that population. As noted, the study found that gender and age are statistically significant in predicting arrests among the opioid dependent population.[6] While the researchers did not include race/ethnicity due to a lack of data, they would have included this important variable had it been available. Earlier studies in criminology reached similar conclusions about the propensity for arrest when a person has an opioid dependency.[7] Fisher et al. reviewed the following data points in the analysis: age, gender, co-occurring mental illness, co-occurring substance use disorder, other drug, alcohol, prior arrests, crimes against persons, drug offenses, public order offenses, nonviolent sex offenses, and "other" low-level or low-incident offenses.[8]

Fisher et al. maintain that addressing an individual's medical issues as well as employing behavioral assessments will reduce the risk associated with the abuse of opioids. This study is useful in that it explores variables related to opioid use and arrests, but its focus (and its study endpoint) is to predict future arrests. For the risk model proposed in this thesis, the study endpoint is opioid overdose or death, with the focus of predicting those at risk of reaching either endpoint.

[6] Fisher et al., 199.

[7] David N. Nurco et al., "Differential Criminal Patterns of Narcotic Addicts over an Addiction Career," *Criminology* 26, no. 3 (1988): 407–23, https://doi.org/10.1111/j.1745-9125.1988.tb00848.x.

[8] Fisher et al., 198.

C. RECIDIVISM MODELS AND ASSESSMENT TOOLS

In 2019, the Centers for Disease Control and Prevention updated the guidelines for prescribing opioids, including assessing and mitigating patient risk.[9] One of the assessment tools utilized by medical practitioners for this purpose when prescribing opioids is the Opioid Risk Tool (ORT), which has been the subject of academic research. Developed by Lynn R. Webster and vetted by the medical community, a medical questionnaire (see Appendix A) assesses the risk of opioid addiction.[10] The ORT's risk score is derived from a patient's answering predetermined questions regarding substance abuse, medical history, and psychological disease. A score is computed based on the answers, assessing the patient's risk of becoming addicted if prescribed opioid drugs. However, this model is limited because it relies on the veracity of a patient's answers. Passik, Kirsh, and Casper also point out that the ORT is susceptible to deception but rationalize its use in lieu of other, more cumbersome or labor-intensive tools for such assessments in the medical profession.[11] Moreover, Webster and Webster's research takes the view that opioid abusers tend to display one or more abnormal behaviors when abusing opioid prescriptions or drugs.[12]

A 2019 article by Martin Cheattle for Practical Pain Management claims that while the ORT risk model functions as a decision support tool, no conclusive evidence suggests that it works to reduce opioid abuse.[13] Research lacks conclusive data on the effect of the tool in driving down opioid abuse. Subsequent research has observed that the ORT is the

[9] "About CDC's Opioid Prescribing Guideline," Centers for Disease Control and Prevention, August 16, 2022, https://www.cdc.gov/drugoverdose/prescribing/guideline.html.

[10] Lynn R. Webster and Rebecca M. Webster, "Predicting Aberrant Behaviors in Opioid-Treated Patients: Preliminary Validation of the Opioid Risk Tool," *Pain Medicine* 6, no. 6 (November 2005): 432–42, https://doi.org/10.1111/j.1526-4637.2005.00072.x.

[11] Steven D. Passik, Kenneth L. Kirsh, and David Casper, "Addiction-Related Assessment Tools and Pain Management: Instruments for Screening, Treatment Planning, and Monitoring Compliance," *Pain Medicine* 9 (July 2008): S145–66, https://doi.org/10.1111/j.1526-4637.2008.00486.x.

[12] Webster and Webster, 440.

[13] Martin D. Cheattle, "Risk Assessment: Safe Opioid Prescribing Tools," Practical Pain Management, April 29, 2019, https://www.practicalpainmanagement.com/resource-centers/opioid-prescribing-monitoring/risk-assessment-safe-opioid-prescribing-tools.

ideal assessment tool because it is concise and straightforward.[14] Nevertheless, Chou et al. note—based on a review of several assessment tools and subsequent studies—the absence of evidence that the ORT addresses risk mitigation for the intentional abuse of opioids.[15]

Research conducted in 2018 by Jacquelyne Guerra, a doctoral student at Walden University, evaluates several validated health practitioner tools for assessing the risk of addiction in opioid users. This secondary research study for nursing practitioners supports the conclusion that the ORT is the assessment tool of choice for ambulatory outpatient clinics.[16] Notably, Guerra's research identifies a difference between abuse, meaning non-medical usage, and misuse of opioids, meaning aberrant behavior, such as non-compliance with a treatment plan. Accordingly, the scholars represented in this literature analysis support the ORT's use despite any defined shortcomings.

For this research, the ORT model contains valuable information on potential drivers of the initial addiction to opioids, but it is not directly relevant to the question of opioid recidivism once a person is addicted. It also does not consider criminal data. The factors this researcher has found to be relevant and explores in this thesis include gender, age, prior substance abuse, alcohol, and psychological disorders.

D. SUMMARY OF DATA ELEMENTS USED IN EXISTING MODELS

In an article for the *Journal of Law, Medicine & Ethics*, Catherine Martinez concludes that to understand the opioid epidemic, systems designed to combat opioid abuse need to aggregate multiple data sets from different disciplines.[17] Martinez asserts that the proposed data-sharing is for tackling the crisis with intervention, not prosecution. Furthermore, a 2016 report by the Police Executive Research Forum suggests that the

[14] Passik, Kirsh, and Casper, S155.

[15] Roger Chou et al., "Opioids for Chronic Noncancer Pain: Prediction and Identification of Aberrant Drug-Related Behaviors: A Review of the Evidence for an American Pain Society and American Academy of Pain Medicine Clinical Practice Guideline," *Journal of Pain: Official Journal of the American Pain Society* 10, no. 2 (February 2009): 131–46, https://doi.org/10.1016/j.jpain.2008.10.009.

[16] Jacquelyne Guerra, "Evaluation of an Opioid Risk-Assessment Screening Tool" (PhD diss., Walden University, 2018).

[17] Catherine Martinez, "Cracking the Code: Using Data to Combat the Opioid Crisis," *Journal of Law, Medicine & Ethics* 46, no. 2 (Summer 2018): 454–71, https://doi.org/10.1177/1073110518782953.

safeguards meant to prevent confidentiality breaches are hurdles to both law enforcement and the medical communities in sharing data.[18] The New York City RxStat program, which is funded through the Bureau of Justice Assistance, has been the subject of publications by the RAND Corporation and the Office of Community Oriented Policing Services, among others. This law enforcement initiative has established a data-sharing protocol between law enforcement and public health entities to reduce opioid overdose and deaths.[19]

However, no published research identifies risk factors for opioid overdose or death that would be directly applicable to an opioid risk tool for law enforcement to alert authorities to at-risk persons. The factors or "triggers" from the outlined risk models and recidivism tools were considered for analysis of the collected data, as described in Chapter III. These factors helped to guide data collection and were part of the analysis as much as possible, as shown in Chapter IV, to determine their relevance and importance in a risk model. The initial set of factors are shown in Table 1. Notably, while psychological diseases/disorders have been deemed important predictors in the other models, such data were not available in the databases used in this research.

Table 1. Factors from Prior Studies for Model Consideration

Demographic Factors	**Substance Abuse Factors**	**Criminal Factors**
Age	Alcohol abuse	Prior arrests
Gender	Opioid abuse	Crimes against persons
Race/ethnicity	Other substance abuse	Drug offenses
	Prior overdose	Theft
		Nonviolent sex offenses

[18] Police Executive Research Forum, *Building Successful Partnerships between Law Enforcement and Public Health Agencies to Address Opioid Use* (Washington, DC: Office of Community Oriented Policing Services, 2016).

[19] Goodison et al., 10.

THIS PAGE INTENTIONALLY LEFT BLANK

III. STATISTICS AND DATA SETS

A. BACKGROUND

New Jersey has 21 counties and 565 municipalities, representing over 550 law enforcement agencies statewide.[20] Traditionally, law enforcement agencies utilize and analyze data to improve efficiency, reduce or mitigate crime, and enable predictive policing. Drug activity is one of the data areas that analysts examine in the law enforcement domain. For example, Bergen County's analytical products provide near-real-time information on overdoses and "hot spots" of illicit drug activity.

However, traditionally, these products are not designed to concentrate on at-risk populations or individuals who are susceptible to recidivist activities, specifically opioid abuse. Furthermore, in Bergen County, individuals with opioid addictions may have multiple contacts with several county or local agencies across numerous domains such as law enforcement, recovery services, and health care institutions. Nonetheless, law enforcement cannot proactively address opioid abuse without individual health information, which poses a huge challenge.

In 2015, Bergen County experienced 288 reported overdoses, of which 231 were heroin or opioid related.[21] In the same year, 87 individuals died of overdoses, including 71 related to heroin or opioid use.[22] Finally, 170 lives were saved in 187 deployments of Narcan by law enforcement.[23]

Subsequently, with the goal of decreasing or eliminating opioid abuse, the Bergen County Prosecutor's Office implemented several programs to help reduce recidivism among opioid users. The programs implemented include Operation Helping Hand, the Heroin Addiction Recovery Team, the Bergen County Data Exchange, and the New Jersey

[20] "2020 New Jersey Uniform Crime Report," New Jersey State Police, accessed September 12, 2022, https://nj.gov/njsp/ucr/uniform-crime-reports.shtml.

[21] "Response to the Opioid Epidemic: Bergen County Opioid Statistics," Bergen County Prosecutor's Office, accessed July 20, 2022, https://www.bcpo.net/opioid-response/.

[22] Bergen County Prosecutor's Office.

[23] Bergen County Prosecutor's Office.

DMI's Overdose Detection Mapping Application Program. As part of this effort to battle opioid misuse, both Operation Helping Hand and the Heroin Addiction Recovery Team were developed directly by Bergen County. Although these programs are extremely valuable in this mission, they rely on interactions with at-risk persons during arrests or overdoses or through self-reporting. From 2016 to 2019, the Bergen County Prosecutor's Office and its partners completed 10 targeted operations and encountered more than 200 individuals in connection with these programs.

Despite these operations and numerous other prevention and intervention programs piloted by the Bergen County Prosecutor's Office and local law enforcement agencies, the number of overdoses, Narcan (naloxone) saves, and fatal overdoses continues to rise. Narcan, as it is commonly referred to, is a naloxone drug administered by first responders, medical personnel, and everyday citizens to reverse the effects of opioids in an overdosing victim. As illustrated in Table 2, overdoses and drug-related fatalities have risen despite law enforcement's and health practitioners' efforts, and the data available track Narcan deployments and saves. Ideally, more work should be done.

Table 2. Bergen County Opioid Statistics[24]

Year	Overdoses	LE Narcan Deployments	LE Narcan Saves	Drug-Related Fatalities
2021	711	368	255	155
2020	665	324	239	146
2019	660	388	276	141
2018	587	344	256	145
2017	504	325	245	129
2016	320	208	180	99
2015	288	187	170	87

[24] Adapted from Bergen County Prosecutor's Office.

1. Operation Helping Hand

In 2016, under the direction of then-Prosecutor Gurbir Grewal, the Bergen County Prosecutor's Office partnered with Bergen New Bridge Medical Center to reserve detox beds for any individuals battling drug addiction who were arrested by law enforcement during a proactive, targeted detail—later coined Operation Helping Hand (OHH).[25] As a collaboration between the Bergen County Prosecutor's Office and the New Bridge Medical Center, OHH enables the agencies to work together to enroll opioid users in a post-arrest detox program.[26]

The initial OHH details were designed as a five-day targeted enforcement operation in areas predominately known for the sale of heroin, where members of a multi-agency task force could conduct enforcement actions in the hope of providing a detox option to narcotic users.[27] During these operations, the task force arrested the individuals and presented the option of participating in a voluntary detox program at Bergen New Bridge Medical Center.[28] The center ensured that detox beds were available to any of the individuals arrested who were willing to receive assistance.[29] The detox program is not offered in lieu of criminal charges but instead operates to help put those in need on a pathway to recovery with a support system in place.[30]

The first OHH detail in 2016 resulted in 40 individuals arrested, of which 12 immediately availed themselves of the detox option.[31] A task force of officers transported

[25] Gurbir Grewal, "Operation Helping Hand Press Conference," New Jersey Office of the Attorney General, streamed live on June 27, 2018, YouTube video, 33:42, https://www.youtube.com/watch?v=rzelcyoVti8.

[26] Bergen County Prosecutor's Office, *Heroin Addiction Recovery Team*, Law Enforcement Directive No. 2017-3 (Bergen County, NJ: Bergen County Prosecutor's Office, 2017).

[27] Allison Pries, "Heroin Busts Come with an Offer of Detox to Help Break Cycle of Addiction," North Jersey Media Group, September 1, 2016, https://www.northjersey.com/story/news/2016/09/01/heroin-busts-come-with-an-offer-of-detox-to-help-break-cycle-of-addiction/92983804/.

[28] Pries.

[29] Grewal.

[30] "Response to the Opioid Epidemic: Operation Helping Hand," Bergen County Prosecutor's Office, accessed July 20, 2022, https://www.bcpo.net/opioid-response/.

[31] Grewal.

each individual to Bergen New Bridge Medical Center to enter the detox program. Three more individuals entered detox programs within a few days of their arrest.[32] Subsequent OHH details involved additional community partners incorporated into the operation to provide a full spectrum of services.[33]

Each of these subsequent initiatives has brought together multiple law enforcement agencies in Bergen County law enforcement with recovery specialists from both Children's Aid and Family Services (CAFS) and the Center for Alcohol and Drug Resources (TCADR).[34] To sufficiently help those dealing with addiction, other partner agencies were added, including the Bergen County Department of Health Services, the Division of Addiction Services, and the Bergen New Bridge Medical Center in Bergen County.[35] Additionally, a patient navigator from CAFS/TCADR arranges for beds in various treatment centers throughout the state.[36]

2. Heroin Addiction Recovery Team

Another initiative designed by the Bergen County Prosecutor's Office for the integration of health practitioners on the pathway to recovery with law enforcement agencies is the Heroin Addiction Recovery Team (HART) program.[37] The HART program joins CarePlus New Jersey with a recovery coach program in partnership with CAFS to provide aid to at-risk individuals who request assistance from the police or contact a county office for help.[38] CarePlus New Jersey is a non-profit organization that provides substance

[32] Grewal.

[33] Steve Janoski, "Special Report: A Week with the Bergen Prosecutor's Narcotics Task Force," North Jersey Media Group, April 10, 2017, https://www.northjersey.com/story/news/bergen/2017/04/10/special-report-week-bergen-prosecutors-narcotics-task-force/99887292/.

[34] James, "Operation Helping Hand 4," *Ridgewood Blog*, March 24, 2018, https://theridgewoodblog.net/operation-helping-hand-4/.

[35] James.

[36] Steve Janoski, "After 142 Overdose Deaths, Bergen Tests Program to Fight Addiction with Treatment, Not Jail," North Jersey Media Group, March 4, 2020, https://www.northjersey.com/story/news/bergen/2020/03/04/bergen-county-tests-program-fight-addiction-treatment-not-jail/2833908001/.

[37] Bergen County Prosecutor's Office.

[38] Melanie Anzidei, "Paramus Police Launch HART Program," North Jersey Media Group, May 6, 2017, https://www.northjersey.com/story/news/bergen/paramus/2017/05/06/paramus-police-launch-hart-program/311629001/.

abuse services in addition to other recovery-focused care.[39] A participant in the HART program is required to complete a consensual questionnaire (see Appendix B), which documents the participant's substance abuse problems and, after completion of the form, is then entered into a database to track the participant.[40] Nevertheless, the data generated from HART participants present challenges for data-sharing since each record involves individually identifiable health data.

3. Bergen County Data Exchange

Since New Jersey is a home-rule state, most of the agencies house their own record management systems (RMSs) and computer-aided dispatch (CAD) systems. In Bergen County alone, there are 72 law enforcement agencies with siloed data sets, which include RMS data. Unfortunately, the sharing of cross-domain information among these agencies is fragmented, thereby hindering proactive interventions based on county-generated data. To address this challenge proactively, the Bergen County Prosecutor's Office developed a data exchange platform, referred to as the Bergen County Data Exchange (BC DEx).

BC DEx is a vendor-neutral platform that leverages the county's existing network by connecting the many disparate CAD/RMS vendors to facilitate data-sharing regardless of the vendor. Connectivity among organizations is made possible through a standards-based approach. A critical piece in this process involves using standards from the National Information Exchange Model and the Global Justice XML Data Model (GJXDM) to describe the syntax and format of the shared data sets, which are required to develop a common language for various data systems.[41] The Justice Information Sharing Initiative implemented by the Bureau of Justice Assistance, an office of the U.S. Department of Justice, designed the GJXDM specifically as a standard for criminal justice information exchanges. The GJXDM provides a schema or outline to share timely essential data.[42] By

[39] "About," CarePlus New Jersey, accessed July 21, 2022, https://careplusnj.org/about/.

[40] Bergen County Prosecutor's Office.

[41] "About NIEM," National Information Exchange Model, accessed September 13, 2022, https://www.niem.gov/about-niem.

[42] "Global Justice XML (Archiving)," Bureau of Justice Assistance, accessed September 13, 2022, https://it.ojp.gov/initiatives/gjxdm.

leveraging data in a common platform, law enforcement could apply artificial intelligence and machine learning to analyze the data and produce actionable information.

4. Overdose Detection Mapping Application Program

Another initiative to address opioid abuse in Bergen County is the Overdose Detection Mapping Application Program (ODMAP), a federal overdose collection system managed by the Washington/Baltimore High-Intensity Drug Trafficking Area.[43] ODMAP leverages data-sharing between health and law enforcement.

In Bergen County, each Narcan deployment is documented in the county's CAD/RMS system and accessible as a searchable data record, as well as recorded in ODMAP through an application programming interface from the BC DEx system to the ODMAP interface. Bergen County uses the ODMAP initiative to track overdose information and provide strategic analysis to stakeholders. While these programs are extremely valuable in the battle against drug addiction, they continue to rely on interactions with at-risk persons during arrests and overdoses and through self-reporting.

B. DATA ORIGINATION AND APPROVALS

The data utilized in the analysis of this thesis were compiled from two data sets overseen by the Bergen County Prosecutor's Office. The first data set was compiled from the Bergen County's overdose reporting data from January 2018 to March 2021. The second data set was compiled from Bergen County's daily arrest reporting data from October 2017 to March 2021. Both data sets were already compiled and available in Excel spreadsheets. However, before this researcher could utilize the data in this research, the data sets were anonymized by a third party. The two data sets were merged into one spreadsheet by the third party, and a unique identifier was then applied to all data records to remove personal identifiers from the data set.

No personal identifiable information (PII) was used in the analysis of this research. Fields that included names, streets, criminal justice identifiers, case numbers, or any other

[43] Jeff Beeson, "ODMAP: A Digital Tool to Track and Analyze Overdoses," National Institute of Justice, May 14, 2018, https://nij.ojp.gov/topics/articles/odmap-digital-tool-track-and-analyze-overdoses.

identifiable records were removed. None of the records examined created a situation in which an individual could be identified from the analyzed data. Access to this data was granted through existing laws and protocols for data access at the Bergen County Prosecutor's Office.

The Naval Postgraduate School (NPS)'s Institutional Review Board (IRB) and Human Research Protection Program are the authorities designated to review all research that involves or potentially involves human subject research at the institution. According to NPS's official website, "The NPS IRB is authorized to review, recommend approval to the NPS President, require modifications in, or withhold approval or suspend approval of research involving human subjects. No human subject research in any form (including recruitment, consent, or data collection) can take place without proper review and approval by the NPS IRB and NPS President."[44]

This researcher submitted a review request to the NPS IRB for the research intended in this thesis, including a copy of both data sets, all column header information available, columns that would be deleted, columns that would be anonymized, and columns that would be combined by a third party to ensure anonymization. The NPS IRB approved the utilization of the requested anonymized data sets and subsequent removal of several data fields, as outlined in the following subsection of this chapter. The NPS IRB issued determination #NPS.2021.0119-DD-N on May 22, 2021, which, after review, found that the examination of the data in this thesis did not constitute human subject research and that no individuals or PII could be ascertained from the data sets analyzed.

1. Data Removed

Per the NPS IRB approval, several records were removed by a third party from the original data sets before they were combined. See Appendix C for a list of fields removed from the data sets.

[44] "Human Research Protection Program Office & Institutional Review Board (IRB)," Naval Postgraduate School, accessed September 13, 2022, https://nps.edu/web/research/irb-home.

2. Data Kept

The two data sets are "Arrest Data Fields—Data Set 1" and "Overdose Reporting Data Fields—Data Set 2."

a. Arrest Data Fields—Data Set 1

The fields in Table 3 were retained for analysis after the third party anonymized the data.

Table 3. Arrest Data Fields Utilized

1.	DATE OF OFFENSE
2.	STATUTE (NJ LAW STATUTE)
3.	DESC
4.	DOB (Date of Birth)
5.	SEX
6.	ZIP CODE OF RESIDENCE
7.	GANG RELATED
8.	DOMESTIC VIOLENCE
9.	MUN CD (Municipal Charging District)
10.	MUNICIPALITY NAME
11.	COUNTY OF ARREST
12.	COUNTY OF ARREST NAME
13.	RESIDENCE COUNTY NAME
14.	INCIDENT ZIP

b. Overdose Reporting Data Fields—Data Set 2

The fields in Table 4 were retained for analysis after the third party anonymized the data.

Table 4. Overdose Reporting Data Fields Utilized

1.	CREATE DATE	23.	EMS DOSES
2.	CE AGENCY	24.	OTHER DOSES
3.	DISPOSITION DATE	25.	DID NALOXONE WORK
4.	INVOLVEMENT	26.	TIME FOR NALOXONE TO WORK
5.	INCIDENT DATE	27.	TAKEN TO HOSPITAL
6.	INCIDENT ZIP	28.	DRUG NAME 1
7.	INCIDENT COUNTY	29.	DRUG FORM 1
8.	PACKAGING PRESENT	30.	PILL BRAND 1
9.	DRUG SEIZED	31.	PACKAGING TYPE 1
10.	PARAPHERNALIA SEIZED	32.	PACKAGE COLOR 1
11.	DOB	33.	STAMP DESCRIPTION 1
12.	VICTIM SEX	34.	STAMP TEXT 1
13.	VICTIM RACE	35.	STAMP COLOR 1
14.	NALOXONE ADMINISTERED	36.	DRUG NAME 2
15.	HISTORY OF PRIOR ODS	37.	DRUG FORM 2
16.	PREVIOUSLY ADMINISTERED NALOXONE	38.	PILL BRAND 2
17.	NUM OF PRIOR NALOXONE DOSES	39.	PACKAGING TYPE 2
18.	VICTIM ZIP	40.	PACKAGE COLOR 2
19.	VICTIM COUNTY	41.	STAMP DESCRIPTION 2
20.	TREATMENT INFO PROVIDED	42.	STAMP TEXT 2
21.	LE DOSES	43.	STAMP COLOR 2
22.	FIRE DEPT DOSES	44.	OTHER DRUGS

The two data sets were then combined and correlated with a unique identifier by a third party to ensure that no identifying information could be revealed by the utilization of the combined data sets. During this process, several data fields were further summarized during the data correlation. The DATE OF OFFENSE and CREATE DATE fields were converted from the actual date to a number relative to day zero. In other words, the first encounter of the unique identifier became day zero, and subsequent encounters in the data after day zero were calculated by the number of days from the incident. For example, if for unique identifier 1234 the first encounter in the data was an arrest, it would be day zero. If the next event was an overdose several weeks later, it would be calculated as *x* days from zero. Furthermore, the DOB fields were combined and further converted from actual DOB to AGE at the first observance of the data by the third party. A single data set was then provided for analysis.

Upon further review and familiarization with the combined anonymized data, this researcher removed and summarized several fields. The GANG RELATED field was removed after it was determined not to have sufficient data or relevant information.

Furthermore, the DOMESTIC VIOLENCE field was summarized to a yes or no flag. Additionally, the STATUTE and STATUTE DESC fields were further categorized in groupings from the listed New Jersey criminal code charges, as shown in Table 5.

Table 5. Criminal Charge Summary

Type of Arrest	Number of Charges
Assault	138
Assault - Disorderly Conduct	8
CDS - Distribution	18
CDS - General	1
CDS - Heroin/Cocaine	23
CDS - Inhale	4
CDS - Marijuana	79
CDS - Methamphetamine	1
CDS - Paraphernalia	420
CDS - Possession General	29
CDS - Possession Schedule I - IV	380
CDS - Possession Schedule V	4
CDS - W/O Prescription	110
CDS - Wandering	6
Conspiracy	8
Criminal Mischief - Damage Property	27
Criminal Restraint	4
Cyber	4
Domestic Violence	36
Drug Testing Fraud	5
Endangering Juvenile	18
Endangering - Underage Alcohol	2
False Public Alarm	26
Firearm Violation	22
Weapon Possession	48
Forgery	7
Impersonation	6
Interception of Communications	3
Money Laundering	2
Motor Vehicle Offense	12
Obstruction	57
Obstruction - Resisting	52

Type of Arrest	Number of Charges
Privacy Invasion	1
Prostitution	4
Sexual Assault	1
Lewd Act	1
Theft	382
Theft - Trespass	19
Threats	28
Total	**1996**

Additionally, overdose drug and drug name fields in the data set were further summarized into categories (see Table 6). The data set was then updated with the appropriate category for each unique identifier profile. Note that a profile contains multiple categories if the original data listed multiple drugs.

Table 6. Overdose and Drug Categories

Category	Type	Count
1	Opioid	442
2	Alcohol	38
3	Antipsychotic	64
4	Stimulant Drug	104
5	Sedative	52
6	Cannabis	33
7	Depressant Drug	7
8	Pain Medicine	25
9	Prescription Drugs	96
10	Treatment Drug	93
11	Unknown	13
12	Involved a Mix of Categories 1–10	109
	Total*	**967**

*Category 12 not included

A flag was created in the data to indicate when the town of the incident was the same as the town of residence for the unique identifier profile. Last, after further review of the data set, while approved for usage, more fields were removed before analysis (see Table 7). The final data set was then compiled and retained for further analysis, as presented in Chapter IV.

Table 7. Further Data Fields Removed

1.	PACKAGING PRESENT	14.	PACKAGE COLOR 1
2.	TREATMENT INFO PROVIDED	15.	STAMP DESCRIPTION 1
3.	LE DOSES	16.	STAMP TEXT 1
4.	FIRE DEPT DOSES	17.	STAMP COLOR 1
5.	EMS DOSES	18.	DRUG NAME 2
6.	OTHER DOSES	19.	DRUG FORM 2
7.	DID NALOXONE WORK	20.	PILL BRAND 2
8.	TIME FOR NALOXONE TO WORK	21.	PACKAGING TYPE 2
9.	TAKEN TO HOSPITAL	22.	PACKAGE COLOR 2
10.	DRUG NAME 1	23.	STAMP DESCRIPTION 2
11.	DRUG FORM 1	24.	STAMP TEXT 2
12.	PILL BRAND 1	25.	STAMP COLOR 2
13.	PACKAGING TYPE 1		

IV. DESCRIPTIVE STATISTICS OF THE DATA

The data population was 475 individuals, of which 99 were identified as female, 373 were identified as male, and 3 were unknown. The demographic breakdown of the data pool was 1.26% Asian, 5.68% Black, 0.84% Black/Hispanic, 4.21% Mixed Race, 0.42% Native American, 76.63% White, and 10.95% White/Hispanic. Ages ranged from 16 to 73 in the data set. The average age of the data pool was 34 for female and 34 for male. A further breakout of the data appears in Table 8. The median household income of the county in which the individuals lived ranged from $32,459 to $194,536.

Table 8. Age Brackets

Age	F	M	U	Total	%
16–25	20	70		90	19%
26–35	44	174	3	221	47%
36–45	19	71		90	19%
46–55	12	45		57	12%
56–65	4	12		16	3%
66–75		1		1	0.2%
Total	**99**	**373**	**3**	**475**	

The total number of arrests per individual ranged from 0 (which meant the person entered due to an arrest but was not arrested again) to 10. The average number of arrests per person was 1.65. Table 5 in Chapter III details the number and type of incidents that were cause for arrest. From a population perspective, 30% of individuals were arrested on theft charges, 18% on assault charges, 6% on domestic violence charges, and 57% on drug-related charges, at least once.

All profiles in the data set, regardless of how they entered—overdose (OD) or criminal record—had an overdose during the observation period. According to the data, 84% suffered an overdose after their entry into the data set. In addition, 102 people died of overdose, 100 people had multiple overdoses, and Narcan was administered 919 times in 663 overdose reports recorded. The average number of overdoses per person was 1.389.

The number of days from first entry into the data set (via OD or arrest) to subsequent OD or death ranged from 0 days to 1,181 days.

Table 6 in Chapter III presents figures on substance use recorded by type. In this data population, 109 people used multiple drugs, 302 used only opioids, 106 used a combination of opioids and other drugs, 5 used only alcohol, 33 used a combination of opioids and alcohol, 3 used alcohol with prescription drugs, 8 used only prescription drugs, and 10 used only one drug of another type.

In examining the location of incidents, this researcher could determine whether an overdose or arrest occurred in the same township as the individual's residence. Regarding overdoses, 67% occurred in the same township while 33% occurred in a different township. In contrast, 23% of arrests occurred in the same township whereas 77% of arrests occurred in a different township. These findings align with standard assumptions of law enforcement.

A. CROSS-TABULATIONS AND CHI-SQUARED STATISTICS

Data familiarization and a visual inspection were important steps in the analytical process. The next steps of this research required statistical analysis for more in-depth results of the data pool. Cross-tabulation, a technique used to reveal relationships among categorical (nominal) data elements, was employed to examine relationships between different variables in the data set.[45] Additionally, Pearson's chi-squared test was utilized as a non-parametric method to determine whether the observed differences were statistically significant.[46] Several chi-squared tests were conducted utilizing different variables in the data set.

The first chi-squared calculations examined whether there was a statistical difference between the male and female populations with the use of certain drugs. Several

[45] Douglas R. White, "A Student's Guide to Statistics for Analysis of Cross Tabulations," *World Cultures* 14, no. 2 (2004): 179–93, https://escholarship.org/uc/item/8xn2s349.

[46] Karl Pearson, "On the Criterion That a given System of Deviations from the Probable in the Case of a Correlated System of Variables Is Such That It Can Be Reasonably Supposed to Have Arisen from Random Sampling," *London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science* 50, no. 302 (1900): 157–75, https://doi.org/10.1080/14786440009463897.

calculations were conducted, of which only one finding of statistical significance was observed, where the p-value was less than .05; that was in the category of male and female drug use of treatment drugs. The p-value in this instance was .024255 (see Table 9). All other drug observations had a p-value greater than .05 and no statistical significance observed (see Appendix D). These calculations included opioid usage, alcohol usage, antipsychotics, stimulants, and sedative drugs. This finding suggests that the only difference between male and female subjects regarding substance abuse is that the latter are more likely to be on treatment medications than males.

Table 9. Differences between Male and Female concerning Treatment Drug Usage

Results			
	ALL	Drug 10	***Row Totals***
FEMALE	89 (93.55) [0.22]	10 (5.45) [3.79]	99
MALE	357 (352.45) [0.06]	16 (20.55) [1.01]	373
Column Totals	446	26	**472 (Grand Total)**

The chi-square statistic is 5.0763. The p-value is .024255. The result is significant at $p < .05$.

Given no differences between males and females in terms of substance abuse, additional calculations were completed to determine whether there were any differences by gender in the arrest data. Cross-tabs and chi-squared statistics were calculated to identify any statistical significance in the data. Domestic violence, controlled dangerous substances, prostitution, assault, firearms, and theft arrests, including before and after overdose, were examined. The only statistical significance observed was in prostitution arrests, where the p-value was .007692 (see Table 10). Unsurprisingly, female subjects were significantly more likely to be arrested on prostitution charges than male subjects.

Table 10. Differences between Male and Female concerning Prostitution Arrests

Results			
	ALL	Prostitution	***Row Totals***
FEMALE	96 (98.16) [0.05]	3 (0.84) [5.57]	99
MALE	372 (369.84) [0.01]	1 (3.16) [1.48]	373
Column Totals	468	4	**472 (Grand Total)**

The chi-square statistic is 7.1038. The p-value is .007692. The result is significant at $p < .05$.

More surprising, outside of prostitution, there were no other differences in types of arrest by gender. All other arrest observations correlated to gender had a p-value greater than .05 and no statistical significance (see Appendix D).

The chi-squared calculations were valuable in disproving common biases held about the statistical importance of certain observations. For example, a common belief among law enforcement is that theft arrests are a potential indicator of recidivist activity for a previous overdose subject. However, only 148 of the 475 subjects were involved in the 397 reported theft arrests in the data population. Furthermore, only 32 were involved in a theft arrest after an overdose incident. As 84% of the population suffered an overdose or death after entry into the data set, theft arrests are likely not a good predictor of a future overdose. The next section of this chapter explores these trends further with analysis from the Cox model.

There was a statistically significant difference between the most likely location for arrests and overdoses (see Table 11). Arrests are statistically more likely to occur in townships where the subject does not reside. In addition, overdoses are statistically more likely to occur in the same township as the subject's residence. These findings match law enforcement expectations.

Table 11. Differences between Overdose and Arrest versus Township

Results			
	Overdose	Arrest	***Row Totals***
Same Township	441 (270.15) [108.05]	218 (388.85) [75.07]	659
Different Township	219 (389.85) [74.87]	732 (561.15) [52.02]	951
Column Totals	660	950	**1610 (Grand Total)**

The chi-square statistic is 310.0123. The p-value is < .00001. The result is significant at p < .05.

Further, chi-squared calculations examined the differences between opioid and non-opioid users as they correlated to various crimes. In this instance, theft arrests were found to be statistically significant with a p-value of .002451. Additionally, several combinations of arrests were found to be statistically significant. As illustrated in Table 12, CDS, theft, and assault arrests were found to be statistically significant with a p-value of .012339; in Table 13, CDS and theft arrests were found to be statistically significant with a p-value of .024213; and in Table 14, CDS, theft, assault, and firearms arrests were found to be statistically significant with a p-value of .026066. All other arrest observations correlated to opioid and non-opioid—including firearms, CDS, and assault arrests—had a p-value greater than .05, and no statistical significance was observed (see Appendix D).

Table 12. Differences between Opioid and Non-opioid Use vis-à-vis Theft Arrests

Results			
	Theft	Other	***Row Totals***
Opioid	390 (378.26) [0.36]	1507 (1518.74) [0.09]	1897
No Opioid	8 (19.74) [6.98]	91 (79.26) [1.74]	99
Column Totals	398	1598	**1996 (Grand Total)**

The chi-square statistic is 9.1768. The p-value is .002451. The result is significant at p < .05.

Table 13. Differences between Opioid and Non-opioid Use vis-à-vis CDS, Theft, and Assault Arrests

Results					
	CDS	Theft	Assault	Other	***Row Totals***
Opioid	1010 (1013.13) [0.01]	390 (378.26) [0.36]	135 (138.76) [0.10]	362 (366.85) [0.06]	1897
No Opioid	56 (52.87) [0.18]	8 (19.74) [6.98]	11 (7.24) [1.95]	24 (19.15) [1.23]	99
Column Totals	1066	398	146	386	**1996 (Grand Total)**

The chi-square statistic is 10.8894. The p-value is .012339. The result is significant at $p < .05$.

Table 14. Differences between Opioid and Non-opioid Use vis-à-vis CDS and Theft Arrests

Results				
	CDS	Theft	Other	***Row Totals***
Opioid	1010 (1013.13) [0.01]	390 (378.26) [0.36]	497 (505.61) [0.15]	1897
No Opioid	56 (52.87) [0.18]	8 (19.74) [6.98]	35 (26.39) [2.81]	99
Column Totals	1066	398	532	**1996 (Grand Total)**

The chi-square statistic is 11.0447. The p-value is .026066. The result is significant at $p < .05$.

These findings suggest that opioid users are statistically more likely to be involved in theft arrests than those who do not use opioids. As shown in Tables 12–14, 21% of the arrests of opioid users were for theft whereas only 8% of the arrests of non-opioid users were for theft. Of the total theft arrests, 98% were for thefts committed by opioid users, and only 2% were for thefts committed by non-opioid users. As Table 14 demonstrates, there was a distinctive pattern of arrests for opioid users that was different from those who do not use opioids. The Cox proportional hazard model, as detailed in the next section, was used to determine whether a driver in this pattern was a precursor to overdose or death.

B. COX PROPORTIONAL HAZARDS MODEL

This part of the analysis involved applying the Cox proportional hazards model (Cox model) to estimate the impact of several factors on the probability of an individual already in the drug treatment program having a future overdose. The Cox model is part of a family of statistical models often called "survival models," which estimate the cumulative risk of a hazardous event, such as death or an overdose, occurring over time after initial treatment. One might characterize such analysis as a "time to failure" model. The Cox model allows researchers to include independent variables that can influence the time to—and the probability of—failure.

The Cox model is frequently used in cases involving drug overdose, for which researchers are primarily interested in the impact of independent variables, not the passage of time, on the probability of failure. This is because the Cox model has the advantage of not imposing a functional form on the unobserved baseline hazard rate, allowing researchers to isolate the impact of the independent variables from any assumption about the shape of the hazard over time. Moreover, hazard models offer a key advantage in this case over a simple logit or probit model with a yes-or-no dependent variable—chiefly, right censoring can be expected as some persons in treatment may have a future overdose even if they have not had one already, and hazard models are more forgiving of this possibility than other approaches.[47]

All individuals in this data universe already had an overdose at some point, no matter their status with the program, because they had an overdose or an arrest. (Roughly 24% of such individuals had an overdose as the first incident, 73% had an arrest as a first incident, and 3% had both as a first incident; 82% would have an overdose before starting the program). This high propensity of overdoses gives rise to a baseline survival function that approximates a nearly 100% probability of an eventual overdose (see Figure 1). However, the ability to add covariates to the Cox model could retard or accelerate the likelihood of overdose.

[47] Mario Alberto Cleves, *An Introduction to Survival Analysis Using Stata*, 3rd ed. (College Station, TX: Stata Press, 2010).

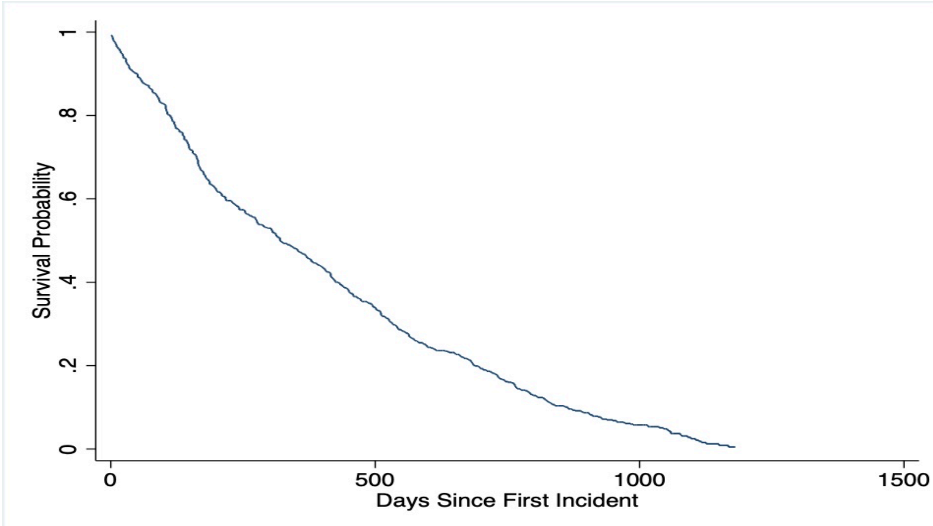

Figure 1. Baseline Survival Model

The basic Cox model was built from demographic characteristics, together with the number of overdoses, past arrests for a crime, age, and age-squared because the preponderance of overdoses occurred between the ages of 20 and 40, spiking at around 30. The inclusion of a quadratic equation created this shape. In addition to a baseline model, this researcher estimated a model that included income by residence zip code. However, because this variable was not available for all observations, it was included only in Model 2. For Model 3, the types of arrests were added to determine whether additional information could be gleaned from it. For robustness, this researcher ran the same set of models but focusing on opioid overdoses (94% of overdoses in the data involved opioids) and individuals with past overdoses, both with mostly similar results.

The results appeared in terms of hazard ratios, as shown in Appendix E. Thus, a coefficient of 1 was a hazard equal to the baseline, greater than one an increase in the hazard of overdose, and less than 1 a reduction of the hazard. Notably, age was the only demographic characteristic, including income, that was statistically significant. Age was significant only in Model 1 at the 10% level and only when age-squared was included. The coefficients suggest a maximum risk age of 36.

History does matter, however, for overdose risk. Past arrests more than doubled the risk of overdose; Figure 2 shows a graphical representation of this risk in terms of the survivor function. This result was significant at the 1% level in Models 1 and 3, and 5% level in Model 2. Overdoses seemed to beget more overdoses, with an increased risk of additional overdoses of about 20%–25% (significant at the 1% level in all models) associated with each overdose (see Figure 3).

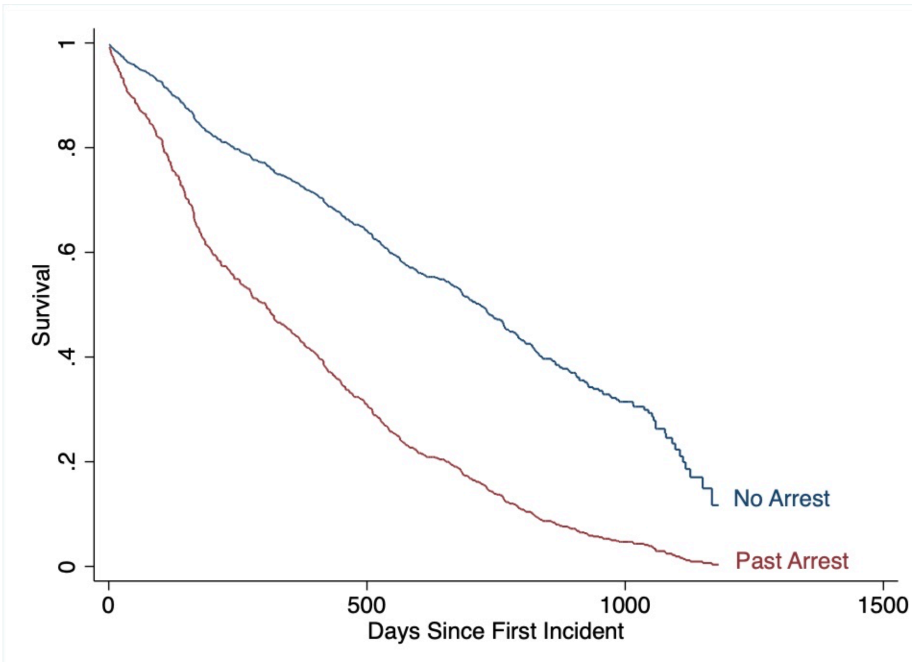

Figure 2. Comparative Survival Models: Arrest vs. No Arrest

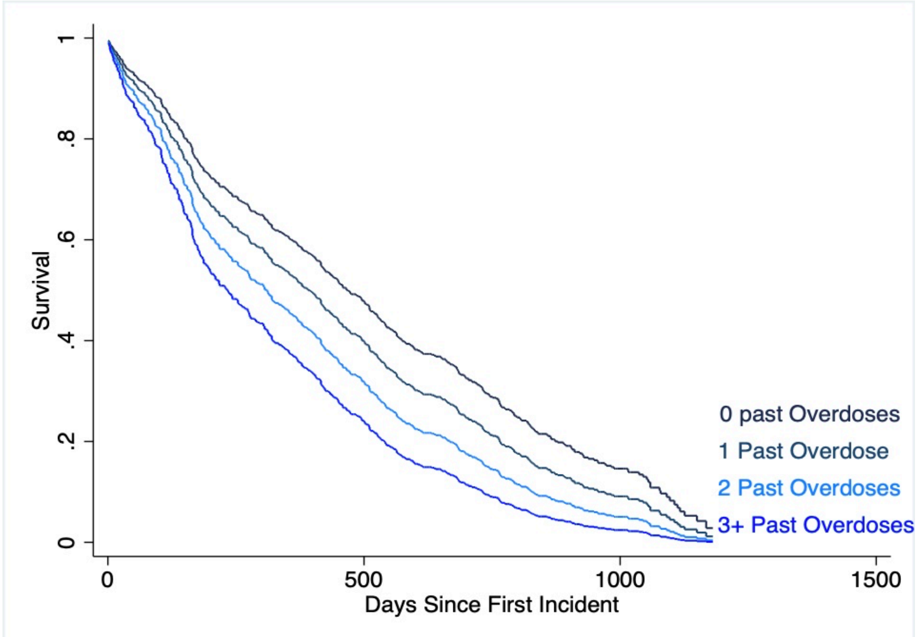

Figure 3. Comparative Survival Models: Number of Overdoses

Finally, there was some evidence that the type of crime mattered. A history of theft reduced the likelihood of an overdose by 26%, but prostitution increased it by 46%. These results were significant at the 1% and 5% levels, respectively.

V. CONCLUSION AND FUTURE RESEARCH

For law enforcement and other first responders to combat opioid recidivism, they need to either validate or refute their biases regarding opioid users. As revealed in this analysis, law enforcement's inherent biases are not accurate. No demographic profile was found more likely to have another overdose or death in the analysis. Additionally, what law enforcement has perceived as valuable indicators of opioid recidivism, such as theft arrests correlated to gender, revealed no statistical significance for recidivism in this study. A history of theft arrests correlated with a decreased risk of overdose by 26% while prostitution correlated with an increased risk of overdose by 46%.

However, glaringly evident in this study is that all overdose victims are at higher risk, and their chance of survival decreases significantly, with every new overdose. Additionally, the more arrests, the greater the chance of a subsequent overdose or death. Each interaction between law enforcement and the observed opioid user is, therefore, a critical point where intervention by law enforcement has the greatest potential to combat a significantly diminishing chance of survival. These data further support initiatives such as Operation Helping Hand, whereby increased officer interactions with opioid users mean a greater likelihood of users' living another day—or even recovering from addiction. Future work should concentrate on a larger data set to determine whether the same observations are found among larger groups of people.

The success of a law enforcement risk model will depend on using all data available to improve the ability to identify a person at risk of overdosing or committing a drug-related crime, thereby potentially reducing the at-risk person's vulnerability or susceptibility to relapse. Individuals with opioid addiction may encounter several county or local agencies across numerous domains such as law enforcement, recovery services, or health care institutions.

These data highlight that those who show up on law enforcement's radar most frequently are in the greatest need for assistance—as they are more likely to overdose or die—but a significant challenge for law enforcement in proactively addressing opioid abuse is establishing connectivity with individual health information. Unfortunately, the sharing of cross-domain information among the responsible law enforcement and health agencies is fragmented, thus hindering proactive intervention. To alert the authorities to any at-risk person, the system's model requires access to both law enforcement data sets and health information.

A. LIMITATIONS

The most significant limitation in the data set was that only 475 subjects were observed. Although this was a relevantly small data set, it did represent all the people encountered in Bergen County's opioid suppression programs. Notably missing from the data set were the people who did not appear in either the arrest data set or the overdose set, or who appeared in only one of the two data sets—only those who appeared in both lists were in the merged data set utilized for analysis. There might have been people on the arrest lists that have a drug problem but did not have an overdose or an overdose instance in Bergen County. Again, as researchers, we cannot analyze those who we do not observe in the data, and some people die from overdose without having previous incidents or appearing on the "radar" for addiction.

B. NEXT STEPS

As emphasized in this thesis, to address data-sharing needs, Bergen County now is in the process of implementing a data exchange portal, referred to as BC DEx. The next step is to leverage the data in the platform for use in a risk model to combat opioid recidivism. Further research is needed to explore the use of a law enforcement risk model based on RMS data, automated license plate readers, arrests, overdoses, medical aid, and Narcan deployments. However, there are hurdles to the initiative. Among the most crucial steps in facilitating this process is addressing the challenge of integrating data from disparate systems, including health practitioner data.

A 2016 report by the Police Executive Research Forum suggests that the safeguards meant to prevent breaches of confidentiality are hurdles that both law enforcement and the medical communities must overcome in sharing data.[48] Access to individual health information is covered by the Health Insurance Portability and Accountability Act (HIPAA) of 1996. HIPAA created a national standard to safeguard an individual's protected health information (PHI). Contained in HIPAA is the Privacy Rule, which balances the individual's right to privacy with the ability to share PHI data in certain circumstances. Under the Privacy Rule, data-sharing with law enforcement agencies and personnel is permitted under six conditions (note that this does not include recent guidance for COVID-19).[49] Since the proposed collection of health information in an "at-risk" model is not covered under the six enumerated instances, data-sharing under this program would require an identified individual's permission.

The next steps in this research program include studies to identify pertinent data elements or triggers for use in the risk model that would assist in alerting authorities to an at-risk person to combat opioid recidivism. Additionally, the need exists to examine key factors in a predictive model that may be based on police records, which this analysis did not capture, as it concentrated on arrest and overdose incidents only.

The goal of this research, after data are made available in a common platform, is to develop a decision support system (DSS) to facilitate the capability of analyzing large volumes of data with a machine learning risk model to identify any at-risk person vulnerable to opioid abuse. This DSS framework incorporates data modeling, decision modeling, model analysis, and investigation, all of which depend on relationships in the data.[50] As shown in Figure 4, the proposed framework comprises four phases: 1) identification, 2) monitoring, 3) analysis, and 4) alert and intervention.

---

[48] Police Executive Research Forum, 73.

[49] Uses and Disclosures for Which an Authorization or Opportunity to Agree or Object Is Not Required, 45 C.F.R. 164.512(f) (2016).

[50] Andrés Boza et al., "A Framework for a Decision Support System in a Hierarchical Extended Enterprise Decision Context," in *Enterprise Interoperability*, ed. Raúl Poler, Marten van Sinderen, and Raquel Sanchis (Berlin: Springer, 2009), 113–24.

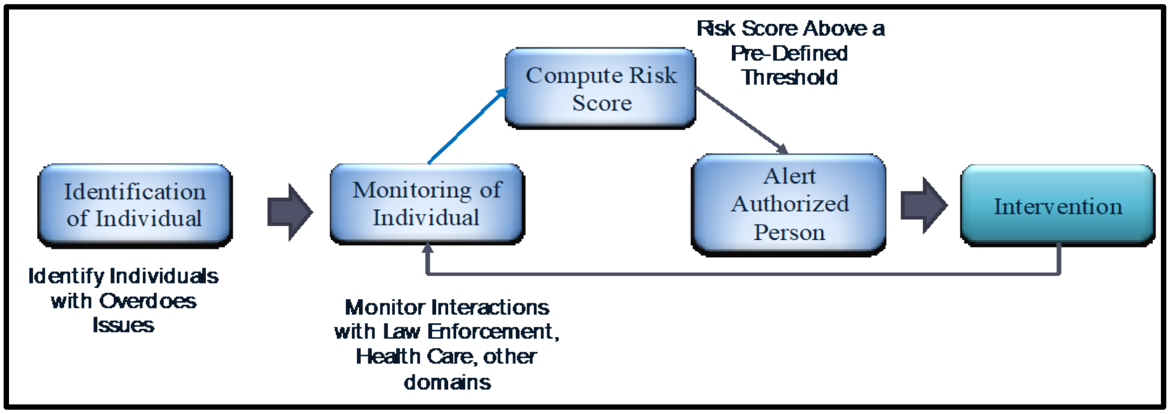

Figure 4. Proposed Four-Phase Decision Support System

In reviewing the pertinent literature, this researcher found that this study was the first of its kind to answer the question about the factors that drive opioid recidivism based on law enforcement data. The findings of this examination are an essential step toward understanding the driver of opioid recidivism.

The initial arrest elements examined were discerned from law enforcement's common beliefs and interactions with opioid users, some of which were not an accurate reflection of their recidivist paths. Gender roles, an example of such bias, were found not to be a significant factor (except for prostitution). In addition, while most overdoses were in the same township, about one-third of the overdoses were in different townships. However, the statistical analysis conducted regarding theft arrests supported current beliefs and revealed that opioid users are more likely to be involved in theft arrests than non-opioid users. However, interesting still is that a person involved in theft arrests in this data set had a reduced likelihood of overdose.

While this study had limitations and examined a finite pool of subjects, which again was based only on overdoses and arrests, its implications will drive future projects in Bergen County and the law enforcement community. Law enforcement agencies will benefit from the findings in this study, as well as the understanding that our biases are not always reliable. Additionally, the results provided in this thesis will encourage the further exploration of literature and research on this topic for law enforcement.

APPENDIX A. ORT FORM

THE OPIOID RISK TOOL (ORT)

Factor		**Score** Female	**Score** Male
1. Family History of Substance Abuse	Alcohol	[1]	[3]
	Illegal Drugs	[2]	[3]
	Prescription Drugs	[4]	[4]
2. Personal History of Substance Abuse	Alcohol	[3]	[3]
	Illicit Drugs	[4]	[4]
	Prescription Drugs	[5]	[5]
3. Age (If between 16 to 45)		[1]	[1]
4. History of Preadolescent Sexual Abuse		[3]	[0]
5. Psychological Disease	ADD, OCD, Bipolar, Schizophrenia	[2]	[2]
	Depression	[1]	[1]
	TOTAL Score		
Low Score = 0 to 3			
Moderate Score = 4 to 7			
High Score = ≥8			

NOTES

- A score of <3 indicates low risk
- A moderate risk score is 4 to 7
- High risk scores are ≥8
- The main drawback of the ORT is its susceptibility to deception.

Figure 5. Opioid Risk Tool [51]

[51] Source: Webster and Webster, 432.

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX B. HART FORM

OFFICE OF THE BERGEN COUNTY PROSECUTOR
HART INTAKE/RELEASE FORM

Date:	Time:
Department:	Officer:
CAD Incident #:	

NOTE TO PARTICIPANT

The below information is solely to assist the police department's Heroin Addiction Response Team (HART) in connecting you to appropriate services. Information reported below is subject to medical verification.

CONTACT INDIVIDUAL

Name:	Phone:
Relationship to Potential Participant:	

POTENTIAL PARTICIPANT

Name:		
Date of Birth:	SSN:	
Gender:	Race/Ethnicity:	
Address:	City/State/ZIP:	
Photo ID? Yes: No:	State:	ID Type:

PERSONAL HISTORY INFORMATION

1. What substance is the participant seeking treatment for? ______________________________
2. When was the last time the participant ingested the substance? __________________________
3. How long has the participant had this substance abuse problem? ________________________
4. Is the participant suffering from any other medical issues at this time, including withdrawal symptoms associated with the substance abuse problem? Yes: _____ No: _____

PARTICIPANT VOLUNTARY CONSENT AGREEMENT

I, ________________________, am voluntarily agreeing to participate in the HART program of my own free will and accord and agree to hand over all weapons, narcotics, and paraphernalia to the police department. I consent to allowing a member of the police department to conduct a security search of my person and belongings for the safety of myself, the police, and the HART provider.

Are you willing to speak with law enforcement about your knowledge of the illegal distribution of narcotics? Yes: _____ No: _____ Participant Initials: ______

________________________________ ________________________________

Participant Officer

EMAIL COPY OF COMPLETED FORM TO HART@BCPO.NET

Figure 6. HART Intake/Release Form[52]

[52] Source: Bergen County Prosecutor's Office, *Heroin Addiction Recovery Team*.

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX C. DATA REMOVED

Table 15. Data Removed: Arrest Data Fields—Data Set 1

1. DATE OF ARREST	13. AKA FIRST
2. GEN OFF CD	14. ORIGINATING ORI
3. GEN OFF CD	15. ORIGINATING ORI NAME
4. LAST NAME	16. BOOKING ORI
5. FIRST NAME	17. BOOKING ORI NAME
6. MI	18. PLACE OF BIRTH
7. RACE	19. INCIDENT STREET NO
8. STREET #	20. INCIDENT STREET NAME
9. STREET NAME	21. INCIDENT CITY
10. CITY	22. INCIDENT STATE
11. STATE	23. AGENCY CASE #
12. AKA LAST	

Table 16. Data Removed: Overdose Reporting Data Fields—Data Set 2

1.	CREATE BY	31.	SUSPECT DOB
2.	PC FULL NAME	32.	SUSPECT SEX
3.	PC EMAIL	33.	SUSPECT PHONE
4.	PC PHONE	34.	SUSPECT PHONE SEIZED
5.	PC AGENCY	35.	SUSPECT PHONE CAP
6.	REQUESTING AGENCY	36.	SUSPECT PHONE DICE/DARTS
7.	CASE NUMBER	37.	SUSPECT ADDRESS
8.	NARRATIVE	38.	SUSPECT APARTMENT
9.	INCIDENT ADDRESS	39.	SUSPECT CITY
10.	INCIDENT APARTMENT	40.	SUSPECT STATE
11.	INCIDENT CITY	41.	SUSPECT ZIP
12.	INCIDENT STATE	42.	SUSPECT COUNTY
13.	INCIDENT LATITUDE	43.	SUSPECT LATITUDE
14.	INCIDENT LONGITUDE	44.	SUSPECT LONGITUDE
15.	BUSINESS ADDRESS	45.	WITNESS FIRST NAME
16.	VICTIM FIRST NAME	46.	WITNESS LAST NAME
17.	VICTIM LAST NAME	47.	WITNESS DOB
18.	VICTIM DOB	48.	WITNESS SEX
19.	VICTIM NOTES	49.	WITNESS PHONE
20.	VICTIM PHONE	50.	WITNESS PHONE CAP
21.	VICTIM PHONE SEIZED	51.	WITNESS ADDRESS
22.	VICTIM PHONE CAP	52.	WITNESS APARTMENT
23.	VICTIM PHONE DICE/DARTS	53.	WITNESS CITY
24.	VICTIM ADDRESS	54.	WITNESS STATE
25.	VICTIM APARTMENT	55.	WITNESS ZIP
26.	VICTIM CITY	56.	WITNESS COUNTY
27.	VICTIM STATE	57.	WITNESS LATITUDE
28.	VICTIM LATITUDE	58.	WITNESS LONGITUDE
29.	VICTIM LONGITUDE	59.	DOCTOR NAME 1
30.	SUSPECT FIRST NAME	60.	DOCTOR NAME 2
31.	SUSPECT LAST NAME		

APPENDIX D. CHI-SQUARED CALCULATIONS: NO STATISTICAL SIGNIFICANCE

Table 17. Differences between Male and Female concerning Opioid Usage

Results			
	ALL	Drug 1	***Row Totals***
FEMALE	8 (6.88) [0.18]	91 (92.12) [0.01]	99
MALE	24 (25.91) [0.14]	349 (347.09) [0.01]	373
UNK	1 (0.21) [3.01]	2 (2.79) [0.22]	3
Column Totals	33	442	**475 (Grand Total)**

The chi-square statistic is 3.5795. The p-value is .167004. The result is not significant at $p < .05$.

Table 18. Differences between Male and Female concerning Alcohol Usage

Results			
	ALL	Drug 2	***Row Totals***
FEMALE	95 (91.03) [0.17]	4 (7.97) [1.98]	99
MALE	339 (342.97) [0.05]	34 (30.03) [0.52]	373
Column Totals	434	38	**472 (Grand Total)**

The chi-square statistic is 2.7218. The p-value is .098983. The result is not significant at $p < .05$.

Table 19. Differences between Male and Female concerning Antipsychotic Drug Usage

Results			
	ALL	Drug 3	***Row Totals***
FEMALE	86 (87.95) [0.04]	13 (11.05) [0.35]	99
MALE	334 (331.38) [0.02]	39 (41.62) [0.16]	373
UNK	2 (2.67) [0.17]	1 (0.33) [1.32]	3
Column Totals	422	53	**475 (Grand Total)**

The chi-square statistic is 2.0626. The p-value is .356536. The result is not significant at $p < .05$.

Table 20. Differences between Male and Female concerning Stimulant Drug Usage

Results			
	ALL	Drug 4	***Row Totals***
FEMALE	87 (87.95) [0.01]	12 (11.05) [0.08]	99
MALE	333 (331.38) [0.01]	40 (41.62) [0.06]	373
UNK	2 (2.67) [0.17]	1 (0.33) [1.32]	3
Column Totals	422	53	**475 (Grand Total)**

The chi-square statistic is 1.6518. The p-value is .437847. The result is not significant at $p < .05$.

Table 21. Differences between Male and Female concerning Sedative Drug Usage

Results			
	ALL	Drug 5	***Row Totals***
FEMALE	95 (95.43) [0.00]	4 (3.57) [0.05]	99
MALE	360 (359.57) [0.00]	13 (13.43) [0.01]	373
Column Totals	455	17	**472 (Grand Total)**

The chi-square statistic is 0.0694. The p-value is .792146. The result is not significant at $p < .05$.

Table 22. Differences between Male and Female concerning Domestic Violence Arrests

Results			
	ALL	DV Arrest	***Row Totals***
FEMALE	86 (83.58) [0.07]	13 (15.42) [0.38]	99
MALE	313 (314.89) [0.01]	60 (58.11) [0.06]	373
UNK	2 (2.53) [0.11]	1 (0.47) [0.61]	3
Column Totals	401	74	**475 (Grand Total)**

The chi-square statistic is 1.2428. The p-value is .53718. The result is not significant at $p < .05$.

Table 23. Differences between Male and Female concerning Theft Arrests

Results			
	ALL	Theft Arrest	***Row Totals***
FEMALE	62 (67.96) [0.52]	37 (31.04) [1.14]	99
MALE	262 (256.04) [0.14]	111 (116.96) [0.30]	373
Column Totals	324	148	**472 (Grand Total)**

The chi-square statistic is 2.1078. The p-value is .146553. The result is not significant at $p < .05$.

Table 24. Differences between Male and Female concerning Theft Arrests before Overdose

Results			
	ALL	Theft Arrest	***Row Totals***
FEMALE	71 (74.88) [0.20]	28 (24.12) [0.62]	99
MALE	286 (282.12) [0.05]	87 (90.88) [0.17]	373
Column Totals	357	115	**472 (Grand Total)**

The chi-square statistic is 1.0438. The p-value is .306944. The result is not significant at $p < .05$.

Table 25. Differences between Male and Female concerning Theft Arrests after Overdose

Results			
	ALL	Theft Arrest	***Row Totals***
FEMALE	91 (92.29) [0.02]	8 (6.71) [0.25]	99
MALE	349 (347.71) [0.00]	24 (25.29) [0.07]	373
Column Totals	440	32	**472 (Grand Total)**

The chi-square statistic is 0.3356. The p-value is .562389. The result is not significant at $p < .05$.

Table 26. Differences between Male and Female concerning Firearm Violations

Results			
	ALL	Firearm Arrest	***Row Totals***
FEMALE	93 (91.66) [0.02]	6 (7.34) [0.24]	99
MALE	344 (345.34) [0.01]	29 (27.66) [0.07]	373
Column Totals	437	35	**472 (Grand Total)**

The chi-square statistic is 0.3349. The p-value is .562815. The result is not significant at $p < .05$.

Table 27. Differences between Male and Female concerning CDS Violations

Results			
	ALL	CDS Arrest	***Row Totals***
FEMALE	25 (26.05) [0.04]	74 (72.95) [0.02]	99
MALE	98 (98.16) [0.00]	275 (274.84) [0.00]	373
UNK	2 (0.79) [1.86]	1 (2.21) [0.66]	3
Column Totals	125	350	**475 (Grand Total)**

The chi-square statistic is 2.5771. The p-value is .275669. The result is not significant at $p < .05$.

Table 28. Differences between Male and Female concerning Assault Arrests

Results			
	ALL	Assault	***Row Totals***
FEMALE	85 (80.66) [0.23]	14 (18.34) [1.03]	99
MALE	300 (303.90) [0.05]	73 (69.10) [0.22]	373
UNK	2 (2.44) [0.08]	1 (0.56) [0.36]	3
Column Totals	387	88	**475 (Grand Total)**

The chi-square statistic is 1.9666. The p-value is .374079. The result is not significant at $p < .05$.

Table 29. Differences between Opioid and Non-opioid Users concerning CDS Arrests

Results			
	CDS	Other	***Row Totals***
Opioid	1010 (1013.13) [0.01]	887 (883.87) [0.01]	1897
No Opioid	56 (52.87) [0.18]	43 (46.13) [0.21]	99
Column Totals	1066	930	**1996 (Grand Total)**

The chi-square statistic is 0.4177. The p-value is .518086. The result is not significant at $p < .05$.

Table 30. Differences between Opioid and Non-opioid Users concerning Firearm Arrests

Results			
	Firearms	Other	***Row Totals***
Opioid	65 (66.53) [0.04]	1832 (1830.47) [0.00]	1897
No Opioid	5 (3.47) [0.67]	94 (95.53) [0.02]	99
Column Totals	70	1926	**1996 (Grand Total)**

The chi-square statistic is 0.7333. The p-value is .391804. The result is not significant at $p < .05$.

Table 31. Differences between Opioid and Non-opioid Users concerning Assault Arrests

Results			
	Assault	Other	***Row Totals***
Opioid	135 (138.76) [0.10]	1762 (1758.24) [0.01]	1897
No Opioid	11 (7.24) [1.95]	88 (91.76) [0.15]	99
Column Totals	146	1850	**1996 (Grand Total)**

The chi-square statistic is 2.2146. The p-value is .136714. The result is not significant at $p < .05$.

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX E. COX PROPORTIONAL HAZARDS MODELS

Table 32. Cox Proportional Hazard Models: Variables and Coefficients

Variables	(1) hh	(2) hh	(3) hh
_t			
male	0.900	0.839	0.889
	(0.0980)	(0.0946)	(0.0991)
black	0.903	0.889	0.873
	(0.167)	(0.180)	(0.167)
asian	0.910	0.691	0.956
	(0.345)	(0.232)	(0.384)
hispanic	1.049	1.141	1.068
	(0.141)	(0.176)	(0.141)
native_american	0.730	0.629	0.667
	(0.978)	(0.869)	(0.910)
darrest	2.675***	2.192**	2.899***
	(0.781)	(0.686)	(0.869)
dTheft			0.736***
			(0.0759)
ddrugarrest			0.996
			(0.0887)
dProstitution			1.411**
			(0.198)
dAssault			0.892
			(0.117)
dDomestic_Violence			0.823
			(0.161)
cumod	1.246***	1.214***	1.216***
	(0.0678)	(0.0757)	(0.0791)
age	1.049*	1.037	1.045
	(0.0306)	(0.0303)	(0.0315)
age2	0.999*	0.999	0.999
	(0.000372)	(0.000364)	(0.000385)
MedianHouseholdIncome		1.000	
		(1.92e-06)	
Observations	1,110	831	1,110

For robustness, see form in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 33. Summary Statistics by Incident

Variable	Obs	Mean	Std. dev.	Min	Max
-------------	------------	------------	--------------	-----------	--------
age	1,588	33.15554	9.654216	16	73
male	1,582	0.7939317	0.404608	0	1
black	1,588	0.0510076	0.2200825	0	1
asian	1,588	0.0094458	0.0967601	0	1
hispanic	1,588	0.1284635	0.3347106	0	1
-------------	------------	------------	--------------	-----------	--------
native_ame~n	1,588	0.0037783	0.0613713	0	1
MedianHous~e	1,177	71869.98	25308.97	26936	194536
daysfromfi~t	1,588	250.4225	285.3806	0	1181
overdose	1,588	0.4156171	0.4929833	0	1
cumod	1,588	0.4370277	0.8898726	0	9
-------------	------------	------------	--------------	-----------	--------
arrest	1,588	0.5982368	0.490409	0	1
cumarrest	1,588	1.241184	1.511274	0	10
Theft	950	0.2768421	0.4476734	0	1
Prostitution	950	0.0042105	0.0647859	0	1
Assault	950	0.1136842	0.3175945	0	1
-------------	------------	------------	--------------	-----------	--------
Domestic_V~e	950	0.0326316	0.177764	0	1
drugarrest	1,588	0.2418136	0.4283168	0	1

Table 34. Summary Statistics by Individual

Variable	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
-------------	-----------	-------------	------------	-------------	-------
uniqueid	0				
age	475	34.02737	10.18175	16	73
male	472	0.7902542	0.4075591	0	1
black	475	0.0652632	0.24725	0	1
asian	475	0.0126316	0.111796	0	1
-------------	-----------	-------------	------------	-------------	-------
hispanic	475	0.12	0.3253041	0	1
native_ame~n	475	0.0042105	0.0648201	0	1
MedianHous~e	397	76663.41	27106.26	32459	194536
daysfromfi~t	475	438.7432	307.9421	0	1181
overdose	475	1	0	1	1
-------------	-----------	-------------	------------	-------------	-------
cumod	475	0.6989474	0.9850673	0	9
arrest	475	1	0	1	1
cumarrest	475	1.650526	1.550818	0	10
Theft	475	0.3073684	0.4618898	0	1
Prostitution	475	0.0084211	0.0914754	0	1
-------------	-----------	-------------	------------	-------------	-------
Assault	475	0.1810526	0.3854678	0	1
Domestic_V~e	475	0.0589474	0.2357745	0	1
drugarrest	475	0.4652632	0.4993178	0	1

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF REFERENCES

Anzidei, Melanie. "Paramus Police Launch HART Program." North Jersey Media Group, May 6, 2017. https://www.northjersey.com/story/news/bergen/paramus/2017/05/06/paramus-police-launch-hart-program/311629001/.

Beeson, Jeff. "ODMAP: A Digital Tool to Track and Analyze Overdoses." National Institute of Justice, May 14, 2018. https://nij.ojp.gov/topics/articles/odmap-digital-tool-track-and-analyze-overdoses.

Bergen County Prosecutor's Office. *Heroin Addiction Recovery Team*. Law Enforcement Directive No. 2017–3. Bergen County, NJ: Bergen County Prosecutor's Office, 2017.

———. "Response to the Opioid Epidemic: Bergen County Opioid Statistics." Accessed July 20, 2022. https://www.bcpo.net/opioid-response/.

———. "Response to the Opioid Epidemic: Operation Helping Hand." Accessed July 20, 2022. https://www.bcpo.net/opioid-response/.

Boza, Andrés, Angel Ortiz, Eduardo Vicens, and Raul Poler. "A Framework for a Decision Support System in a Hierarchical Extended Enterprise Decision Context." In *Enterprise Interoperability*, edited by Raúl Poler, Marten van Sinderen, and Raquel Sanchis, 113–24. Berlin: Springer, 2009.

Bureau of Justice Assistance. "Global Justice XML (Archiving)." Accessed September 13, 2022. https://it.ojp.gov/initiatives/gjxdm.

CarePlus New Jersey. "About." Accessed July 21, 2022. https://careplusnj.org/about/.

Centers for Disease Control and Prevention. "About CDC's Opioid Prescribing Guideline." August 16, 2022. https://www.cdc.gov/drugoverdose/prescribing/guideline.html.

Cheattle, Martin D. "Risk Assessment: Safe Opioid Prescribing Tools." Practical Pain Management, April 29, 2019. https://www.practicalpainmanagement.com/resource-centers/opioid-prescribing-monitoring/risk-assessment-safe-opioid-prescribing-tools.

Chou, Roger, Gilbert J. Fanciullo, Perry G. Fine, Christine Miaskowski, Steven D. Passik, and Russell K. Portenoy. "Opioids for Chronic Noncancer Pain: Prediction and Identification of Aberrant Drug-Related Behaviors: A Review of the Evidence for an American Pain Society and American Academy of Pain Medicine Clinical Practice Guideline." *Journal of Pain: Official Journal of the American Pain Society* 10, no. 2 (February 2009): 131–46. https://doi.org/10.1016/j.jpain.2008.10.009.

Cleves, Mario Alberto. *An Introduction to Survival Analysis Using Stata*. 3rd ed. College Station, TX: Stata Press, 2010.

Fisher, William H., Robin Clark, Jeffrey Baxter, Bruce Barton, Elizabeth O'Connell, and Gideon Aweh. "Co-Occurring Risk Factors for Arrest among Persons with Opioid Abuse and Dependence: Implications for Developing Interventions to Limit Criminal Justice Involvement." *Journal of Substance Abuse Treatment* 47, no. 3 (September 2014): 197–201. https://doi.org/10.1016/j.jsat.2014.05.002.

Goodison, Sean, Michael Vermeer, Jeremy Barnum, Dulani Woods, and Brian Jackson. *Law Enforcement Efforts to Fight the Opioid Crisis: Convening Police Leaders, Multidisciplinary Partners, and Researchers to Identify Promising Practices and to Inform a Research Agenda*. Santa Monica, CA: RAND Corporation, 2019. https://doi.org/10.7249/RR3064.

Grewal, Gurbir. "Operation Helping Hand Press Conference." New Jersey Office of the Attorney General. Streamed live on June 27, 2018. YouTube video, 33:42. https://www.youtube.com/watch?v=rzelcyoVti8.

Guerra, Jacquelyne. "Evaluation of an Opioid Risk-Assessment Screening Tool." PhD diss., Walden University, 2018.

James. "Operation Helping Hand 4." *Ridgewood Blog*, March 24, 2018. https://theridgewoodblog.net/operation-helping-hand-4/.

Janoski, Steve. "After 142 Overdose Deaths, Bergen Tests Program to Fight Addiction with Treatment, Not Jail." North Jersey Media Group, March 4, 2020. https://www.northjersey.com/story/news/bergen/2020/03/04/bergen-county-tests-program-fight-addiction-treatment-not-jail/2833908001/.

———. "Special Report: A Week with the Bergen Prosecutor's Narcotics Task Force." North Jersey Media Group, April 10, 2017. https://www.northjersey.com/story/news/bergen/2017/04/10/special-report-week-bergen-prosecutors-narcotics-task-force/99887292/.

Martinez, Catherine. "Cracking the Code: Using Data to Combat the Opioid Crisis." *Journal of Law, Medicine & Ethics* 46, no. 2 (Summer 2018): 454–71. https://doi.org/10.1177/1073110518782953.

National Information Exchange Model. "About NIEM." Accessed September 13, 2022. https://www.niem.gov/about-niem.

Naval Postgraduate School. "Human Research Protection Program Office & Institutional Review Board (IRB)." Accessed September 13, 2022. https://nps.edu/web/research/irb-home.

New Jersey State Police. "2020 New Jersey Uniform Crime Report." Accessed September 12, 2022. https://nj.gov/njsp/ucr/uniform-crime-reports.shtml.

Nurco, David N., Thomas E. Hanlon, Timothy W. Kinlock, and Karen R. Duszynski. "Differential Criminal Patterns of Narcotic Addicts over an Addiction Career." *Criminology* 26, no. 3 (1988): 407–23. https://doi.org/10.1111/j.1745-9125.1988.tb00848.x.

Passik, Steven D., Kenneth L. Kirsh, and David Casper. "Addiction-Related Assessment Tools and Pain Management: Instruments for Screening, Treatment Planning, and Monitoring Compliance." *Pain Medicine* 9 (July 2008): S145–66. https://doi.org/10.1111/j.1526-4637.2008.00486.x.

Pearson, Karl. "On the Criterion That a given System of Deviations from the Probable in the Case of a Correlated System of Variables Is Such That It Can Be Reasonably Supposed to Have Arisen from Random Sampling." *London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science* 50, no. 302 (1900): 157–75. https://doi.org/10.1080/14786440009463897.

Police Executive Research Forum. *Building Successful Partnerships between Law Enforcement and Public Health Agencies to Address Opioid Use*. Washington, DC: Office of Community Oriented Policing Services, 2016.

Pries, Allison. "Heroin Busts Come with an Offer of Detox to Help Break Cycle of Addiction." North Jersey Media Group, September 1, 2016. https://www.northjersey.com/story/news/2016/09/01/heroin-busts-come-with-an-offer-of-detox-to-help-break-cycle-of-addiction/92983804/.

Rx Drug Abuse & Heroin Summit. "New Jersey's Drug Monitoring Initiative: Comprehensive Approach to Community Drug Harms." Accessed September 12, 2022. https://www.eventscribe.com/2021/RxSummit2021/fsPopup.asp?Mode=presInfo&PresentationID=805720.

Webster, Lynn R., and Rebecca M. Webster. "Predicting Aberrant Behaviors in Opioid-Treated Patients: Preliminary Validation of the Opioid Risk Tool." *Pain Medicine* 6, no. 6 (November 2005): 432–42. https://doi.org/10.1111/j.1526-4637.2005.00072.x.

White, Douglas R. “A Student’s Guide to Statistics for Analysis of Cross Tabulations.” *World Cultures* 14, no. 2 (2004): 179–93. https://escholarship.org/uc/item/8xn2s349.

Winkelman, Tyler N. A., Virginia W. Chang, and Ingrid A. Binswanger. “Health, Polysubstance Use, and Criminal Justice Involvement among Adults with Varying Levels of Opioid Use.” *JAMA Network Open* 1, no. 3 (2018): e180558. https://doi.org/10.1001/jamanetworkopen.2018.0558.

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
   Ft. Belvoir, Virginia

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, California