THE ETHICAL CONSIDERATIONS OF CRIMINAL PREDICTIVE TECHNOLOGY

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By

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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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Year after year, the United States is the world's leader in incarceration with over 2.1 million total prisoners in 2020 (World Population Review, 2020). The United States currently holds about 25% of the world's prisoners at a rate of 737 prisoners per 100,000 people (World Population Review, 2020). A large portion of this population consists of individuals who are detained and jailed due to an action caused by serious mental illness such as major depression, schizophrenia, and bipolar disorder. As of 2020, nearly 15% of men and 30% of women booked into jail have a serious mental health illness (National Alliance on Mental Illness, 2020). Currently, mentally ill individuals are not receiving the support they need, often resulting in events that place them in jail.

The technical project seeks to identify areas of injustice or a lack of resources for the mentally ill inmate population through an analysis of data from Region 10 mental health community service providers, Albermarle-Charlottesville Regional Jail (ACRJ), Charlottesville Offender Aid and Restoration (OAR), Jefferson Area Community Corrections (JACC), Thomas Jefferson Area Coalition for the Homeless (TJACH) and Virginia Department of Corrections (DOC). By connecting with criminal justice organizations, the technical research attempts to provide policy makers with comprehensive data analysis about the mentally ill inmate population in hopes they can make more informed resource allocation decisions.

The Science, Technology and Society (STS) project focuses on Big Data technology in the criminal justice system. The Big Data field is quickly expanding with the global data subject to analysis growing by a factor of 50 to 5.2 zettabytes by 2025 (Lynkova, 2019, para. 22). Companies and organizations are continuing to see the value in AI and machine learning with 96.4% of companies investing in Big Data technologies compared to 68.9% in 2017 (Lynkova, 2019, para. 33). Recently, an increasing number of law enforcement agencies have adopted predictive technologies to identify geographic areas with an increased probability of crime. The STS project looks to identify the ethical biases present with the usage of these predictive technologies in the criminal justice system. The STS research also examines whose role it is to ensure individuals are fairly represented within Big Data technologies in the criminal justice system. The STS topic investigates how to best ensure data subjects are represented and respected with criminal predictive technology using a model by W. Bernard Carlson of "Technology Transfer and Social Constructivism" based on Bijker's thesis of the Social Construction of Technology (1984, p. 399).

These two topics are closely related, with the STS topic taking a more holistic and societal view of a specific part of the technical project. While the technical topic involves a more data-driven approach, the STS topic will focus more on reading literature and studies already completed by others. By the end of the analysis, these two topics coupled together complement each other and provide a more comprehensive view of the injustices within the criminal justice system.

AN INTRODUCTION TO THE ANALYSIS OF CRIMINAL PREDICTIVE TECHNOLOGY

The introduction of criminal predictive technologies has created a new way to interact and understand crime. With the integration of these new technologies, society must adapt and ensure that the predictive tools are considerate of human rights and fundamental liberties promised by our criminal justice system. Two frameworks, Technology Transfer and Social Constructivism, will be used to map both the problem and solution respectively, and to analyze whose role it is to ensure a fair and ethical criminal justice system. The paper will be a scholarly article, referencing other academic work that discusses technology in the criminal justice system.

DISCUSSION AND ANALYSIS OF CRIMINAL PREDICTIVE TECHNOLOGY

DEFINITION OF BIG DATA

The current definition of Big Data must first be understood before analyzing its involvement in the criminal justice system. In "Undefined by Data: A Survey of Big Data Definitions", professors at the University of St Andrews in Scotland, Jonathan Stuart Ward and Adam Barker (2013) provide three words to describe Big Data: volume, velocity and variety (p.1). Ward and Barker comment on the increasing size of data collected, the increasing rate at which it is processed and produced and the increasing variety of usages. The authors comment on how it is from this increasing size that questions of trust and uncertainty arise. Ward and Barker (2013) also praise Microsoft's definition of Big Data as "the term increasingly used to describe the process of applying serious computing power – the latest in machine learning and artificial intelligence – to seriously massive and often highly complex sets of information" (p. 2). The authors praise this definition of Big Data for its inclusion of machine learning and artificial intelligence.

Statistical Analysis System (SAS), a multinational developer of analytics software, provides a more comprehensive definition of Big Data. The company states that Big Data are "extremely large data sets that may be analyzed computationally to reveal patterns, trends and associations, especially relating to human behavior and interactions" (What is Big Data section, para. 2). This definition shows that it is Big Data coupled with machine learning and AI that allow for conclusions to occur which can help inform decision makers.

PREDICTIVE POLICING: AN APPLICATION OF BIG DATA TO THE CRIMINAL JUSTICE SYSTEM

Big Data is integrated in the criminal justice system by a tool called Predictive Policing. In “The ethical dangers of merits of predictive policing”, Moish Kutnowski (2017), professor at University of Toronto, defines predictive policing as “an emerging law enforcement technique that uses data and statistical analysis to aid in the identification of criminal activity” (p. 1). Furthermore, predictive policing pairs analytical techniques with Big Data to discover areas of probable criminal offenders.

Kutnowski gave Atlanta's usage of predictive policing as an example of this distinction. In 2013, the Atlanta Police Department (APD) launched a predictive policing tool called PredPol. The tool created region specific predictions for higher probabilities of criminal activity based on an algorithm using municipal data. PredPol then identified areas of highest crime rates, based on previous data, for officers to focus their efforts. The author outlines how APD then attempted to show the benefit of PredPol "via a significant reduction of crime rates compared to marginal rises in non-PredPol zones". In result, the tool was integrated city wide and became part of officer's daily routine (p. 154). According to Atlanta Police Chief, George Turner, University of California professor Jeff Brantingham, and Santa Clara University professor George Mohler (2014), aggregate crime decreased a total of 8 percent and 9 percent in the two zones in which predictive policing was used, based on a 90-day time period (p. 72).

CRITICISMS AND RISKS OF BIG DATA IN THE CRIMINAL JUSTICE SYSTEM

It is important to analyze the possible ethical and societal impacts of predictive policing. Kutnowski points out this distinction in the Georgia example previously explained. He begins by explaining how 2014 US Census data showed how in Georgia, African American rates of poverty levels are almost double other demographics, in addition to lower employment, lower home ownership and a large population of uneducated young men (p. 14). Kutnowski continued his argument by showing maps illustrating the greater crime concentration in the Hispanic and African American areas. He continued by stating that “this also correlates with housing affordability and school rankings; white areas have more expensive houses and better schools while the inverse is true for African American and Hispanic dominant regions (Trulia Maps, accessed 08/2016),” (Kutnowski, p.14). Kutnowski concludes by stating that with perpetuated poverty paired with housing and schooling difficulties in segregated areas, those populations are put at a higher risk of “crime, developmental stagnation, and perpetuated cycles of diminishing wellbeing (Kubisch, 2010)” (p. 14). In this way, the author argues that predictive policing is more of a tool of confirming existing suspicions than preventing future criminal events. Furthermore, cycles of institutional biases against certain populations can emerge by continuing to highlight the struggles of ethnic and poor populations. The predictive policing tool is reproducing patterns of discrimination and historical biases because that is what the data it is using reflects. That is the root of the problem.

The Royal United Services Institute (RUSI) found similar biases with predictive technology in their paper “Data Analytics and Algorithmic Bias in Policing”. The paper, written by Alexander Babuta and Mario Oswald (2019), analyzes the biases that arise with the usage of predictive policing in England and Wales. The paper’s conclusions were drawn from 13 informant interviews with representatives of various UK law enforcement agencies and five academics and legal experts (p. 3) as well as roundtables with several police representatives. Babuta and Oswald comment on the using data already collected in the policing algorithms can replicate existing biases. A police officer they interviewed stated “young black men are more likely to be stop and searched than young white men, and that’s purely down to human bias. That human bias is then introduced into the datasets, and bias is then generated in the outcomes of the application of those datasets" (p. 12). The authors then emphasize how the use of these predictive tools creates a feedback loop where "future *policing* is predicted, not future crime" (p. 12). The authors also draw on the fact that areas with certain sociodemographic backgrounds are more likely to interact with public services, providing police with more data on these individuals. In result, the algorithm can highlight these groups as higher risk (p. 12).

Another argument against predictive policing is that by identifying high risk areas or individuals, the start and finish of a criminal justice procedure is blurred. An individual is now not identified for purely doing something illegal. They are identified through a predictive technology before a crime has been committed. As Ales Zavrsnik (2019) from the University of Ljubljana in Sloevnia stated in "Algorithmic justice: Algorithms and big data in criminal justice settings", "the start of the criminal procedure became indefinite and indistinct and it was no longer clear when a person 'transformed' into a suspect with all the attendant rights," (p.6). Furthermore, predictive technologies have allowed for police to imagine potential crimes for a 'person of interest' instead of focusing on suspects. In Zavrsnik's article, he explains a machine learning tool used on Twitter in Sloevnia to track 'persons of interest'. He further argues that by using this tool, police are chasing the "imagined indefinable future" (Zavrsnik, p.6). The focus is not only on what the person might commit, but what the individual might become. Some argue this blurs the line of a fair criminal justice system.

Babuta and Oswald saw the bias in England's and Wales' police force as well. The authors (2019) stress how dependence on the results of the predictive policing algorithm can cause contextual information during an arrest to be disregarded (p. 14). Babuta and Oswald defined this bias as automation bias, "the tendency to over-rely on automated outputs and discount other correct and relevant information" (p. 15). An officer they interviewed explained

“Officers often disagree with the algorithm. I’d expect and welcome that challenge. The point where you don’t get that challenge, that’s when people are putting that professional judgement aside” (p. 15).

Finally, inevitably due to the amount of crime committed, criminality is never fully reported and is a normative phenomenon. This in turn can jeopardize the accuracy of predictive criminal technology. Algorithmic technology is most reliable in fields where ground-truth data is accurate and fully reported. An example of this is earthquake detection technology. The machines used in earthquake detection technology can detect the P and S waves which help detect how strong the shaking will be (Lee, 2013, para. 10). Instruments are also used to collect the magnitude of earthquakes after they have occurred. In this example if machine learning uses past data collected by earthquake instruments, there can be a large amount of certainty knowing that the data is both accurate and fully reported. When the data is not accurate or fully reported, the chance of false predictions is higher. Zavrsnik explains how criminality is never fully reported, resulting in an unreliable ground truth data set. Zavrsnik states that “the future is then calculated from already selected facts about facts” (Zavrsnik, p. 7). Criminal justice information is also normative, meaning it depends on human values and changes over time. Thus, a predictive tool will not produce the most accurate results, as the ground truth data may change. In result, those changes could alter predictions.

CRIMINAL PREDICTIVE TECHNOLOGY AND SOCIAL CONSTRUCTIVISM

Predictive crime tools should not be used in isolation by the criminal justice system. The ethical responsibility of criminal predictive technology should be extended to a variety of stakeholders, not just criminal justice officials. By pairing with community stakeholders, predictive crime tools can be used to both decrease crime and ensure ethical considerations and community wellness. By doing this, not only will more stakeholders be aware of the biases and inaccuracies in predictive crime technologies, the new stakeholders can also produce better uses of the predictions that aren't targeting the predicted individuals.

The idea of including more stakeholders is outlined in Philip Brey's "The Strategic Role of Technology in a Good Society" (2017). Brey's paper is an article published in *Technology in Society*, an international journal analyzing the social, economic and business changes caused by technological advancements. The article explores the proper role of technology in a good society and discusses how to analyze whether technology is contributing to society's overall quality of life. The author, Philip Brey, is a professor of the philosophy of technology at the University of Twente, the Netherlands. He is also president of the International Society for Ethics and Information Technology and on the editorial board of eleven widely recognized technology and philosophy journals ("University," 2020, para. 2). In the article, Brey recommends including more stakeholders in the development and usage of a product to help ensure a technology contributes to a good society. He states how the emergence of new technologies, such as Big Data technology, requires the government to create new laws and policies (2017, p. 40). Applying this to predictive policing, lawmakers and legislators, not just law enforcement officials, should be included as a stakeholder ensuring the ethical usage of criminal predictive technology. The inclusion of lawmakers will provide a check on whether biases or inaccuracies exist in criminal predictive technologies, through the creation of laws and policies. For example, new regulations could be proposed that requires law enforcement officials to meet and discuss the possible risks present with the usage of these predictive algorithms every month. The discussion would be a good first step to help bring attention to these risks. It is the hope that with an awareness of possible biases in predictive policing tools, law enforcement officials could alter their behavior or reliance on these tools to perform their job with less bias.

Predictive crime analytics should also be paired with health organizations to decrease ethical biases and produce better preventative measures. In his article, “The ethical dangers of merits of predictive policing”, Kutnowski outlines possible benefits of pairing predictive crime analytics with healthy initiative policies. One possible solution proposed, respective to individuals identified by predictive policing, is that “accessible care could be provided as a preventative measure, without burdening hospital infrastructure, by strategically placing modular care centers at risk communities (as identified by the predictive policing software), and having them interact within a network as a series of independent nodes” (Kutnowski, p. 15). Therefore, health care organizations should be another stakeholder in this network, as they can provide better resources for individuals highlighted with predictive policing.

Carlson’s Technology Transfer model based on Bijker’s thesis of the Social Construction of Technology provides a solution to the ethical problems outlined in the current criminal justice system (1984, p. 399). Figure 1 below maps the current problem being discussed using the framework. With the way the system is now, the technologies’ predictions for high risk individuals is produced without input of other stakeholders. It is produced with past data alone, causing

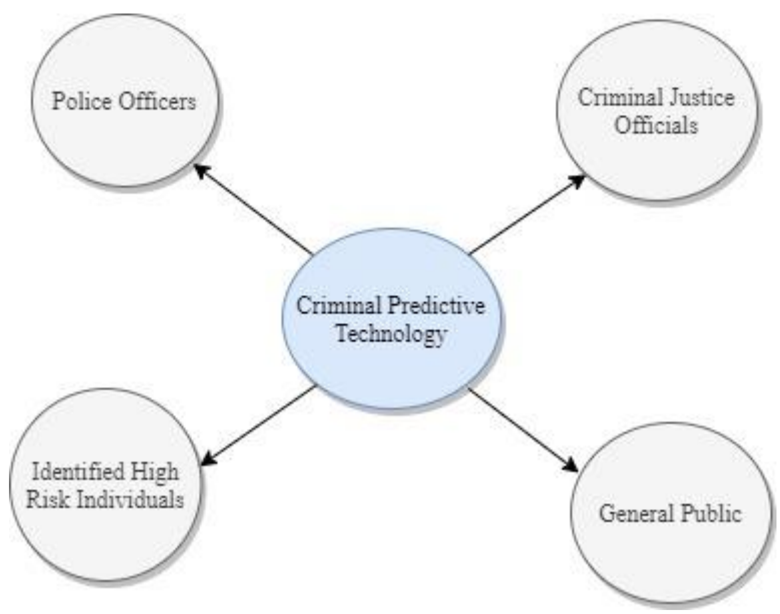

Figure 1. Technology Transfer Model for Criminal Predictive Technology: An adaption of Carlson’s Technology Transfer Model (adapted by Claire Deaver, 2020 from B. Carlson, 2008)

some of the issues highlighted in the analysis above. Once predictions are made it affects high-risk individuals that were identified as they are now highlighted to criminal officials. It affects police officers as it can be argued that it gives them some bias on who to oversee and monitor. It affects the general public as they receive the injustices to their society as a whole.

Figure 2 below provides a mapping of the provided solution on Carlson's Social Constructivism model, based on Bijker's thesis of the Social Construction of Technology (1984, p. 399). By having arrows in both directions, the framework shows how the criminal predictive technology must interact with different community entities. These interactions allow for the technology to ensure it is being used ethically and to its full potential. By including multiple stakeholders, no one stakeholder can use the technology alone. This decreases the chance of biases and inconsideration of human rights. The addition of new stakeholders also allows for better criminal preventive measures to be produced. Like stated earlier, by pairing criminal predictive technologies with health care providers, the criminal justice system can work to provide health solutions, avoiding arrest. By pairing with the

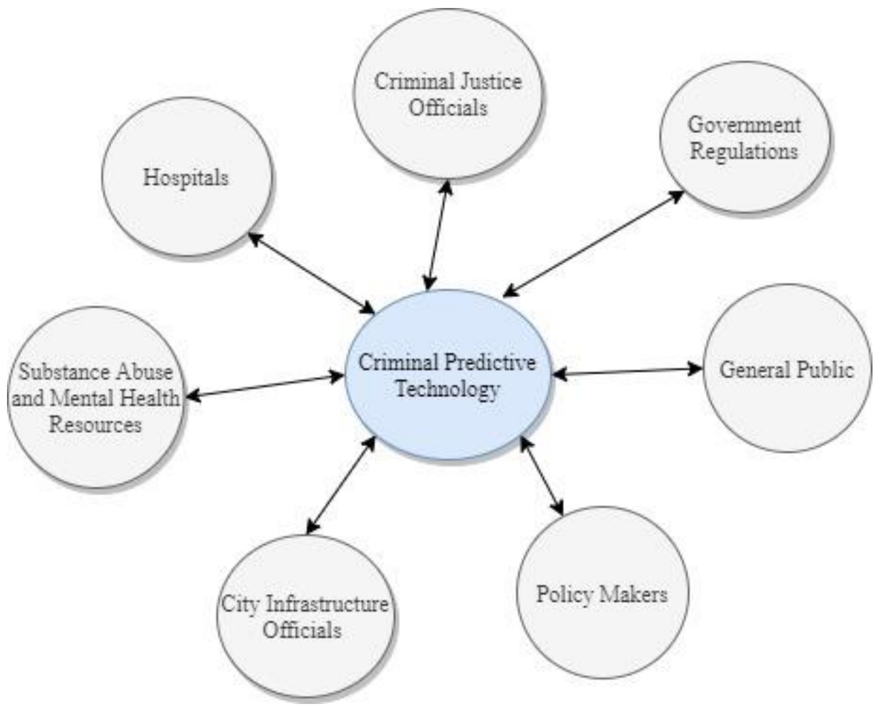

Figure 2. Social Constructivism Model for Criminal Predictive Technology: An adaption of Carlson's Social Constructivism Model (adapted by Claire Deaver, 2020 from B. Carlson, 2008)

lawmakers and legislators, new regulations can be put in place to ensure ethical usage of predictive technologies.

RECOMMENDED CHANGES TO THE CRIMINAL JUSTICE SYSTEM

The STS analysis provides evidence that criminal predictive technologies are inconsiderate of some human rights and fundamental liberties. The analysis also showed that predictive policing is more of a tool for confirming existing suspicions than preventing future criminal events. In order to decrease these risks, more stakeholders like health care providers, government regulators and mental health organizations should be considerate of the usage of criminal predictive technologies. With this expanded network, stakeholders can ensure individuals are being represented and monitored without biases.

RECOMMENDATION FOR FUTURE WORK

Further analysis could be done on how predictive technologies involve bias in other fields like medicine or education. This technology is used in many different fields so it would be interesting to see how bias could possibly be present in other areas. This future work will be especially important as it projected that Big Data will be growing substantially. From 2012 to 2017, Big Data produced more than 8 million jobs in the US and it is projected to only increase (Schmid, 2017, para. 3). While it is easy to see the benefits of Big Data technologies, it will be continually important to ensure the technology is used ethically.

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