# Understanding Law Enforcement and Common Peoples' Perspectives on Designing Explainable Crime Mapping Algorithms


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## ABSTRACT

In recent years, with growing concerns of making predictive policing less-biased and less-risky, the HCI and CSCW research communities have focused on designing more explainable and accountable algorithms in the criminal justice system. In this extended abstract, we present a preliminary, qualitative analysis of the perceptions of people with different backgrounds (n=60) from Milwaukee, USA on algorithmic crime mapping. Our initial results suggest the need for algorithmic interaction and the database transparency of the system. Taken these suggestions together will inspire to design an explainable crime mapping algorithms that pay attention to the values and needs of law enforcement and common peoples.



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| Demographic Criteria | Participant Description | count |
|---|---|---|
| Gender | Male | 23 |
| | Female | 36 |
| | Transgender Male | 1 |
| Age Range (in Years) | 18 -21 | 29 |
| | 22-30 | 20 |
| | 31-40 | 4 |
| | 40+ | 7 |
| Education | High School Diploma or GED | 2 |
| | Undergraduate (Enrolled) | 32 |
| | Bachelors | 20 |
| | Masters | 5 |
| | Doctorate | 1 |
| Job Type | Full-Time | 17 |
| | Part-Time | 14 |
| | Unemployed | 4 |
| | Self Employed | 3 |
| | Student | 21 |
| | Retired | 1 |

**Table 1: An overview of the participants' (n=60) demographics**

## INTRODUCTION

Today, predictive policing is getting significant attention in the fields of criminal justice and computer science. Among the several approaches to predictive policing, police departments are now analyzing crime through crime mapping algorithm, a process that aims to uncover high-density crime areas or hotspots [7] for resource allocation purpose. [7, 8].As police adopt data-driven strategies, they have to deal with the social criticisms such as limitations and strengths of algorithmic crime mapping's knowledge claims [16]. Recently the HCI and CSCW community has shown great interest in these open issues in order to address the social criticisms against police [5, 15, 16].

In this extended abstract, we present an initial qualitative analysis of a work-in-progress project where we built an application that helps us study human interaction with a crime mapping algorithm. We have recruited 60 participants in total from diverse such as non-technical, technical, and law enforcement backgrounds. Our primary analysis suggests how people from different backgrounds can contribute to making the model better through their respective technical and professional abilities.

## BACKGROUND

Algorithmic crime mapping is the usage of modern information processing technology to combine GIS data, digital maps, and crime data to facilitate the understanding of the spreading of crime [17]. It enables law enforcement agencies to analyze and correlate data sources to create a detailed snapshot of crime incidents and related factors within a community or other geographical area [17]. It has already been applied to different crime types, including drug incidents [13], environmental crimes [3], burglary [3], gang violence [10], burglary repeat victimisation [9], residential burglaries [11] etc.

However, in terms of interacting with a predictive algorithm, there is a distinct gap between street-level bureaucrats[1] (law enforcement agents [LEA]), people with a technical background (crime analysts) who usually build that model and policymakers who decide how the outcome will be used [1, 8]. Data-driven systems work off with data from police reports and tips that might not be uniform or reliable at all times. Even though law enforcement agents might know how to address those issues because of the gap between them and the crime analysts while building and interacting with the algorithm, it can't be accounted for. So, it is very important to know the perception of people with different backgrounds while interacting with such a predictive model and extract the information from it on how they can contribute to the system through experience and technical abilities.

## METHOD

We conducted an IRB-approved study in the city of Milwaukee, Wisconsin, USA. In total 60 participants were recruited for our study in 3 months. Our first category of participants, group 1 ($n_1$ = 39 has no technical background in crime-mapping algorithms and are not from LEA background. Our second

*"Mostly how the data is being collected. So not necessarily the algorithm itself, but what kind of data and how that data was generated is more important. ... I: So you you feel the data is more important than the model? Or then the math behind it, per se? Right? ... P18: Yeah, definitely... the integrity of the data is the most important thing." - Conversation between P18 (non-technical) Interviewer*

*"I think the number of crimes or incidents in crime events, the type of event that is being reported, the number of them, but I think it's also important to know, not just how that the event is being reported, but the actual outcome of it. So, you know, someone may report a robbery, but it's not actually a robbery, but it could be coded as a robbery as an initial call. So I think it's really important to make sure that there is attention to the classification of an event and making sure that it was what it was actually founded or found to be, as opposed to how it was reported." -P61, LEA*

category of participants, group 2 ($n_2 = 14$) are knowledgeable in overall programming and algorithmic analysis. Our third and final category, group 3 ($n_3 = 7$) are from law enforcement and criminal justice background. Detailed demographics of the participants have been presented in table 1. Our goal of separating participants into three different groups was to analyze the ability to interact and interpret crime analysis methods, specifically KDE through their different uses and needs for the algorithm, as KDE is one of the most popular techniques in terms of precision and prediction [4] and has been used in various commercial software such as [14]. This paper focuses on the qualitative part of the study that we collected from the participants through semi-structured interviews after they finished a controlled experiment interacting with a crime mapping algorithm.These data were then analyzed using thematic analysis [2]. After several iterations of coding, the first author identified patterns and converged them into initial appropriate themes by taking all authors' suggestions together.

## INITIAL RESULTS & DISCUSSION

From our preliminary analysis, we have found distinct patterns of perceptions regarding the explainable requirement of algorithmic crime mapping depending on their background.

### Concerns about the data collection & management

Tensions around the database that's being fed to the crime mapping model is two-fold. First, people are concerned about their privacy. As applications such as this are used primarily by LEA, crime mapping tools are available to the general public [6], or individuals not associated with law enforcement, and may be used for their personal benefit [12] and research for various purposes such as buying a house, calculating how safe a particular neighborhood may be for business or even daily commute, etc. This leads to the belief that the infrastructural values of a particular neighborhood is being related to the crime map. People with no technical background (Group 1) showed little desire to learn how the algorithm operates rather expressed their concerns about how this data has been collected and what type of data has been fed into the crime mapping algorithm e.g. the conversation with P18. Sometimes, people do not fully understand the database which allows the individual to lose trust in it. They think the whole process has been kept vague, creating concern for their privacy. Thus, the explanation might release the public frustration around this hidden methodology.

Second, knowing what data is being fed to the system to particular professionals such as people with law enforcement backgrounds might help greatly in terms of interpretability and accuracy by providing their feedback into the system. From the interview with several LEAs, we learned that the LEAs have very little knowledge about how the data is collected and processed. P61 gave insight to some of the data being entered and explained how sometimes information can be coded wrongly in the reports when the officer meant something else. So to them, it is very important to understand how this coded data has been fed into the system and whether or not the algorithm can decipher it.

*"It influences my decision-making process as to where I'm going to spend more of my time researching crimes in this area versus another. ... Why are we seeing such a high increase in crime in gangs? Is it because it's a border for two districts? Is it because we're not allocating enough resources to that area and it's allowing crime to thrive? Is it the socioeconomic background of the citizens that reside there? What is the real root cause? " -P60, LEA*

*"It's important to know how to interpret, you know, the information that you receive from the analysis. Simply giving numbers or, I've experienced this previously, names of people with no context, no interpretation, Is that helpful? So, you know, going beyond just simply mining the data and giving raw numbers, put some interpretation that goes along with that is helpful." -P53, LEA*

### Values & needs for interactive crime-mapping algorithms

With the growing concern of false alarms and becoming inefficient day by day, LEAs want to be able to explain to themselves how this algorithm works. Many LEAs spoke about how crimes are connected. There may be an entry in the system about one specific crime but that can be linked with another. If a crime happens in a specific area, there could be a different follow-up crime in that same area. A certain crime may be reported in order to observe a specific crime itself, but that area could potentially be prone to other types of a similar crime. This is where LEAs felt like the system greatly lagged behind. As the system is static and there is no feedback loop in place (and not to mention the LEAs have very limited to no understanding of the system), the system's path to efficiency is greatly hindered. From the LEA perspective, it is very clear that they want to know a basic understanding of the algorithm LEAs think that information coupled with just the knowledge of the officer who is familiar with the area might be very effective in deployment. P60 explained how knowing some of the facts behind the algorithm would be very useful in planning and decision making.

While interviewing the LEA participants, they also provided some key examples of how the system can be improved. Some of the concerns, thoughts, values, and needs of a crime mapping algorithm are the necessity of a feedback loop, key information for interpretation of the analysis, explainability of the algorithm so that LEA can understand, and an algorithm that has been built beyond mining numbers and statistics. It is not expected that LEAs with no technical background will understand all the technicalities of an algorithm, but from their interviews for example from the quote of P53, it is very clear that LEAs just want to know few important key aspects so that they can relate that information with their field experience, ultimately making the algorithm more efficient. But of course, making the algorithm more efficient doesn't mean necessarily it is less-biased. Future research needs to be done on how to incorporate their professional abilities in improving both.

## CONCLUSION

In this extended abstract, we present initial results from a larger work-in-progress that suggest gaps in building an explainable crime mapping algorithm which has both the need for transparency and self-improvement by having the feedback from the domain experts. In our study, we did build an application where the stakeholders can interact with crime mapping. We thoroughly recorded their interaction and interpretation of the system. by analyzing all of these data, our research might be able to suggest more gaps and needs that are required in creating more efficient and less-bias algorithm.

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