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Efficiency of Algorithmic Policing Tools: a nod to C.N. Parkinson

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Abstract

Jurisdictions around the world have adopted algorithmic policing technologies. The response to concerns about fairness and privacy often includes a claim that these tools are necessary to control crime without ballooning the size of police departments. Thus, effectiveness and payroll are put forward as factors to balance against fairness concerns. However, there is little evidence to suggest that the deployment of such tools without significant new hiring can improve policing outcomes. AI tools increase the volume and flow rate of police information. In order for these tools to be effective, police must be able to keep up with that flow, while also ensuring the integrity of the algorithm and incoming data over time. We argue that algorithmic policing tools require the hiring of additional resources. These new resource demands represent a digital variant of Parkinson's Law. Given the documented risks these tools pose to some populations, it is necessary to work towards a mathematical understanding of the minimum incremental staffing needed to enable such tools to operate successfully, potentially providing benefits greater than their harms. In an effort to stimulate further research in this area, we offer a preliminary "digital Parkinson's law" reflecting a first attempt to quantify the mathematical relationships between the factors involved.

Keywords: algorithmic policing, ethics, Parkinson's Law

1. Introduction

1.1. Context: Algorithmic Policing - The Ethical Consequences of Ineffectiveness

AI-enabled algorithmic monitoring and surveillance tools have seen significant adoption by domestic law enforcement. Despite their theoretical promise, these tools have largely failed to reduce violent crime [1–3]. A variety of reasons for this failure have been proposed, most of which can be traced to a failure by cities to commit the incremental resources necessary to support the data and algorithms and to provide a full and appropriate response to algorithmic predictions.

This paper argues that it is time to begin the process of quantifying the incremental resourcing demands of algorithmic policing tools, not merely as a budgetary matter, but as an ethical imperative. Although the conditions for the domestic use of algorithmic tools vary between jurisdictions (with Canada being significantly more restrictive than the United States [4]), uses of algorithmic policing tools are controversial in most western jurisdictions for reasons related to fairness, privacy, and effectiveness [5]. There is ample evidence that the use of algorithmic policing tools can increase certain types of risks for at least some populations [2, 6]. Those advocating for the adoption and use of algorithmic tools by domestic law enforcement frequently argue that the tools will improve law enforcement efficiency by providing improved outcomes with existing police resources [7, p. 32] [8]. However, recent history suggests that deployment of such tools without incremental resources is more likely to lead to failure.

There are known challenges in measuring policing effectiveness [9]. In order to reduce such challenges, this work focuses primarily on rate-by-population, and in-year clearance rates (% of crimes "solved" within the same reporting year) for murders and burglaries as reported

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by the Chicago Police Department (CPD) according to Federal Bureau of Investigation and published CDP requirements.

The ethical concept of proportionality provides that individuals should only be put at risk of harm (including privacy risk) where the activity giving rise to the risk is necessary and the risk is proportionate to the intended benefits of the individual or society [10]. Given that: (a) the adequacy of resources dedicated to supporting the deployment of these tools appears to be a determinant of their effectiveness; and, (b) such tools pose at least some risks (even and perhaps especially when ineffective); it therefore follows that the sufficiency of incremental resourcing to support the success of these tools is a question of both efficiency and ethics. In order to address this issue it is necessary to enable a mathematical description of the relationship between factors giving rise to incremental resource requirements as a tool for leaders and planners considering their adoption.

1.2. **Context: Parkinson's Law**

Readers will be familiar with the colloquial expression of Parkinson's Law, namely that work expands to occupy the available resources. Parkinson's actual work was considerably more nuanced. He analyzed resourcing within the British navy and other bureaucracies and found that resourcing levels appeared independent of operational outputs. He posited that the addition of new resources had the effect of reducing efficiency because the expanded teams make work for each other, increasing the time required with little or no gain in operational output [11]. Parkinson's Law has been documented in well-known project management texts and widely referenced in the literature [12–15].

This paper argues that algorithmic policing technologies give rise to new digital analogs to Parkinson's law, wherein incremental algorithmic policing tools create additional work for other resources (human and technological), with the result that ever increasing resources are required to maintain the same level of overall performance (as measured by serious crime clearance rates, as well as the rates of serious crime compared to comparable jurisdictions not using such tools). Moreover, inadequate resourcing can undercut the suitability of data and modes of response, further reducing efficiency and worsening outcomes.

The rest of the paper is organized as follows. Section 2 provides an overview of algorithmic policing tools and the context in which related technological investments occur. Section 3 provides background information on Parkinson's Law, and Section 4 examines changes in the Chicago Police Department's growth and technology adoption against the backdrop of trends in crime rates. In section 5, we discuss resource implications for effective and efficient algorithmic policing. Finally, section 6 concludes and indicates future research work.

2. **Algorithmic Policing Tools, an Overview**

Algorithmic policing tools can be characterized into three main types: location-focused tools, person-focused tools, and algorithmic surveillance tools [5]. Location-focused tools build on past police practices and data to identify probable "hot-spots" for criminal activity. An example implementation in this category of tools is PredPol. The software is based on an algorithm that was adapted from the study of earthquakes. It makes use of near repeat theory which assumes the likelihood of subsequent events of a same category will increase after a first occurrence. Research has shown the theory to work for some serial crimes such as burglaries [16]. This technology is intended to enable the more efficient deployment of patrol officers. Location-focused tools have been criticized for their tendency to reflect and reinforce patterns of historical bias and disadvantage, and for their tendency to increase charges for minor offences with no meaningful impact on serious crime. Moreover to the extent that such models ingest data on these new charges, they can lead to an increasingly myopic focus on particular areas and the individuals within them [3, 6, 17]. While more police on the street can reduce serious crime, the level of police presence, manner of implementation and engagement appear crucial for success [3, 18–20].

Person-focused tool have also encountered issues with fairness, bias, and effectiveness. For example, Saunders et al. [21] used ARMIA models to examine the effectiveness of the CPD Strategic Subjects List system. The CPD's list system is reportedly based on social network research and leverages connections between homicide victims in Chicago. The authors found the system did not appear to have met its objective of decreasing gun violence. Moreover, it was not clear how such predictions should be used in the future, especially given the privacy and civil rights impacts on vulnerable groups, and suggestions that the lists amounted to racial profiling. Studies in other contexts have suggested that there may be hard limits on the ability to predict an individual's risk of violence, even with substantial psychological data [22]. Thus, even in the case of good tools properly deployed, a significant level of inefficiency in terms of misdirection of police toward false-positive individuals and circumstances may be inherent in such systems and must be included in resource planning.

Nonetheless, advances in machine learning methods, their successful application in other fields, and the deluge of data supporting service digitization have fueled the enthusiasm around algorithmic policing tools. From a technological standpoint, this makes sense: crime is neither a random nor a deterministic process. Some features exist to characterise it [23–25]. Given that machines are better than humans at processing multiple inputs simultaneously, computers running appropriate algorithms should be able to assist police officers and leadership. Algorithmic policing tools could complement traditional investigative methods by reducing the cognitive demand in making complex situational assessments. Machine learning is often touted as a path to improved technical efficiency and a solution to resource scarcity. However, despite the enthusiasm, warnings over 'blind adoption' of any technology are still applicable.

2.1. AI Tools in Context

A healthy dose of quality control is necessary when applying AI to a problem, particularly in situations where the rights of individuals are at stake. Machine learning techniques are becoming increasingly complex. Despite their widespread adoption, transparency issues remain. Scattered regulatory efforts are beginning to focus official attention on related transparency and accountability questions. Arguably, these are steps toward eventual technological maturity. Gartner's Hype Cycle curve [26] characterizes the typical progression of an emerging technology. It can be argued that AI is benefiting from increased scrutiny, is passing the peak of the inflated expectations section on the curve and headed into the area where there is an increased understanding of the technology's relevance and role in the market.

2.2. Considerations for AI Model Accuracy

Algorithmic policing technologies are trained on historical data sets, using traditional batch-mode machine learning techniques, in order to ultimately generate predictions on new, unseen input data. An algorithm's training process discovers the relationship between data inputs and outputs. However, this relationship can evolve beyond the patterns learned in the training phase. These models can suffer from concept drift; where changes to the underlying data distribution can develop over time once deployed [27, 28]. Changes in the relationship between the input data and target output can negatively impact the accuracy of the model. Mitigation steps for this include: setting up a process for concept drift detection, maintaining baseline models for performance comparisons, regularly retraining and updating models and evaluating the importance of new data. Updating such models in production can be a costly, arduous and resource-intensive task.

Alternatively, algorithmic policing tools can ingest new policing data and use it to update models in near real-time. This can directly address concept drift and allows for analytical tasks on streaming data [29]. Adaptive learning algorithms promise earlier access to insights with fewer computing capacity requirements and simpler production deployments. However, processing data in a stream presents challenges. Streaming data is essentially unbounded or infinite and does not fit in memory. The stream processing often only stores a relatively small window into the past. Data in the wild is often multi-source, multi-scale, noisy and heterogeneous. Thus, preparing data for algorithmic predictions requires extensive preprocessing, implicating additional human resources and complexity. As an alternative, online algorithms open up the possibility of data processing at the edge in less powerful computing environments. This can eliminate the need to send all data upstream for processing and preserve available bandwidth for other police functions. However, distributed stream processing introduces other intricacies, and specific deployment and maintenance requirements. Thus, even this approach demands a certain level of expertise and manpower to ensure that the systems are up and functioning properly.

The allure of using predictions in a policing context relates to the cost-effective deployment of scarce patrolling resources. However, predictive policing tools are not simple, off-the-shelf and maintenance-free plug and play appliances. The algorithms and data require quality control and maintenance. Additionally, the predictions they enable necessitate expert interpretation regardless of which models are used and where they are deployed.

Thus, in many cases, success will require not only the addition of more police officers, but the use of individuals with specific training in other areas. This includes both the social services experts needed to implement risk reduction strategies, as well as technology and data experts to maintain models and ensure their ongoing accuracy and utility. While it is possible to draw officers away from other areas of the city to attempt this, that approach can create vulnerabilities in other areas without ensuring the necessary expertise to create lasting change.

Person-focused policing tools use a range of data about individuals, their past behaviours, legal entanglements, and contacts to predict their likelihood of committing or being the victim of a future crime. Once identified, the person may be the subject of enhanced police attention. As with hot-spot policing, the enhanced focus on an individual increases the likelihood that they will be charged with something, which in turn reinforces the algorithm [5, 6] [7, p. 32]. The thinking is that by focusing attention on high-risk individuals, police may be able to either deter the commission of crimes, or to more easily make the case against the perpetrator. Thus, if this approach is successful, one would expect to see a reduction in serious crimes and / or an increase in "clearance" rates where crimes were committed.

Algorithmic surveillance tools can be used on their own, or in association with other algorithmic policing tools. They can be applied to specific suspects, or, they can be applied in dragnet fashion to the population in general, potentially giving rise to privacy issues. [5, 30]. Examples of algorithmic surveillance tools include automatic licence plate readers, social media surveillance, social network analysis, and facial recognition tools. If deployment of these technologies is effective, one would expect to see reductions in serious crimes and higher clearance rates.

2.3. **Data Considerations**

While problems with bias in data are well known, other serious issues are not as thoroughly understood. Police data systems are very uneven and only marginally inter-operable even within a given department [8]. Adding to this is the sheer number of different individuals adding data to the system over time and in various contexts, and the challenges in maintaining consistency in format, interpretations, and language [16]. Virtually every officer will enter data in the course of their work. For human users who understand the policing context, these differences may not be very concerning. However, in a machine learning context without dedicated resources to ensure consistency and completeness, issues can be expected.

Thus, there is a "pay me now or pay me later" quality to the resourcing question for data analysis and decision support systems: in order to ensure that the tool is efficient and does not waste officer time, it is necessary to invest in resources to tend to the data. These resourcing considerations should hardly be surprising. CompStat, a major non-AI statistical approach to police management accountability and localized crime control originating in New York City in 1994 has experienced variable success in different cities, attributable in large part to the details of implementation and resourcing [7, pp.267–283]. Despite this, as of 2019, the Chicago Police Department had budget for only 8 data entry operators and three programmer / analysts. This is clearly insufficient to ensure accuracy, standardization, and completeness of data in a department of nearly 14,000 officers [31].

3. **Parkinson's Law and Algorithmic Policing Tools**

C. Northcote Parkinson, in his 1955 paper [11] described, in humorous but painfully credible terms, how bureaucracies tend to grow over time. Parkinson described the human factors giving rise to gradual increases in staff, which in turn increases the time required for internal communication and coordination. The result of Parkinson's work (the details of which, distressingly and somewhat suspiciously, are never shown) is a formula purporting to predict the growth of any bureaucracy, based entirely on factors distinct from the department's actual operational responsibilities. In the absence of external constraints, Parkinson predicts growth in bureaucracies of between about 5 and 6.5% annually. All this begs the question: how will algorithmic tools impact organizational growth?

Since the invention of the wheel, humans have sought to use tools to increase their efficiency. The organizations examined by Parkinson most certainly used advances in communications and military technologies in an effort to increase their efficiencies. Algorithmic technologies are a new breed however. Whereas a new telegraph system or gunship might add speed or power to operations, algorithms add information. Information demands analysis and, sometimes, action. Certainly, one can layer multiple powerful systems together to reduce the analytical load on humans. However, at some point, a human must go to the location, visit the person, or plan and execute the raid. By-and-large, the contribution of algorithmic policing tools is to add to the list of suspects and areas of concern. They do not provide assurances that nothing bad will happen in Manor Park tonight or that Joe Smith won't seek revenge for his friend's murder until next week. Thus, police must still address much of their historical workload, while also responding to these new algorithmic prompts.

Undoubtedly, when properly deployed, well designed algorithmic tools have potential to assist detectives in identifying connections and developing leads. However, even accurate information represents an acceleration of the pace of work, driving up the intensity of demand on rank-and-file resources to verify and act on it. Just as Parkinson described in 1955, the new resources create work for those around them. To the extent that new tools improve policing outcomes, this additional effort might be warranted. However, it still requires additional resources in terms of officers, technical experts, and possibly additional algorithmic tools to carry out further analysis and linkages. Thus, a digital Parkinson's Law would say that the use of algorithmic policing tools cannot simultaneously improve policing outcomes and hold police resources steady.

4. An Examination of the Chicago Police Department's Growth and Technology Use, 1965 to 2019

In order to examine the applicability of a digital Parkinson's Law to algorithmic policing, we considered the growth of the Chicago Police Department over two periods: a pre-algorithmic period of 1965 to 1995, and a period of increasing use of algorithmic tools from 2002 to 2019. Through a mix of CPD Annual Reports [32], City of Chicago budget documents [33], and other materials, it was possible to assemble a high-level view of the resourcing changes, technology adoption, and serious crime indicators over this period.

4.1. CPD 1965 - 1995

Technologies : During the pre-AI period, the CPD adopted a range of new technologies. For example, the CPD adopted an intensive hot-spot-like policing program for transit hubs in 1975, adopted a computerized case management system in 1985, and began using an automated fingerprint scanner in 1986-87.

Human Resources : Over this thirty-year period, the CPD experienced slow growth, well below that predicted by Parkinson's Law. The number of sworn police officers increased at an average rate of 0.9% per year, whereas growth in the civilian ranks was 0.6%, for a weighted average annual growth of 0.8%.

Serious Crimes and Clearance Rates : During the 1964-65 to 1994-95 period, the murder clearance rate declined by an average annual rate of about 1.3%. The average murder clearance rate in 1965 and 1966 was 92.5%, and in 1994 and 1995 was 63.25%.

The burglary clearance rate declined by an annual average rate of about 4.2% between 1964/65 and 1994/95. The average burglary clearance rate in 1964 and 1965 was 36.8%, and the average in 1994 and 1995 was 10.5%. These and related trends are shown in Figure 1 of Appendix B.

There has been a general trend of decreasing clearance rates for serious crimes over this same period and forward to the present [34, 35]. Thus, while Chicago was not able to beat this trend, these declines are not entirely remarkable.

4.2. CPD 2002 - 2019

Technology : The CPD increased its use of various technologies over the 2002 to 2019 period. While public records likely omit a number of internal initiatives, they are adequate to identify this as a crucial period for CPD's engagement with algorithmic policing technologies.

CPD's data systems division began statistical crime analysis at least as early as 2001. The Information Collection for Automated Mapping (ICAM) system for area-specific crime prediction was deployed in 1995. From 2000 to 2007, Chicago employed a targeted policing strategy based on an analysis of crime and intelligence data, and identifying hots spots, with an emphasis on activities related to gangs, guns, and drugs. A 2012 study found that, despite having been deployed as intended, this data-driven approach had failed to reduce violent crime [20]. CPD has been monitoring social media in a serious way since about 2010 [36].

In 2012, Chicago became among the first U.S. jurisdictions to adopt a person-focused algorithmic policing system. This system was intended to identify individuals at high risk for gun violence and place them on a strategic subjects list (SSL) [21, 37]. By 2016, evidence of an impact on serious crime was lacking, and it was decommissioned in 2020 due to a lack of reliability [5, 21].

It appears that such tools may be useful at predicting individuals in need of assistance to improve their situation, but not sufficiently reliable in predicting crime to be of concrete assistance to police. Thus, a policing-centric approach which neglected the underlying social issues was ineffective.

Human Resources: Calculating CPD staffing levels in the 2002 to 2019 period is complicated by structural and data factors. Details can be found in Appendix A.

The total sworn membership of CDP did not grow significantly from 2002 to 2019, rising at an average annual rate of only 0.07%. Over this same period, the population of the City of Chicago shrank by an average of 0.4%. However, even accounting for the shrinking population, growth in the sworn officer ranks has been very modest.

A careful analysis of Annual Reports and budget documents suggests shrinkage of police-related positions in Chicago over the 2002 to 2019 period. Police-related staffing in 2019 was estimated to be 16,259 including about 2,375 civilians between the CPD and the Office of Emergency Management and Communications. This represents a total (sworn and civilian) shrinkage rate of about 0.076% over the 2002 to 2019 period. An examination of only sworn officer positions over the period shows only very modest growth of 0.13% per year on average.

Serious Crimes and Clearance Rates: Chicago murder rates have ranged between about 15 and 30 murders per 100,000 residents since the 1970s. While there are significant year-to-year variations, there is no obvious trend, either before or after the introduction of algorithmic policing tools. This is consistent with studies showing no impact of these tools, or statistical approaches in reducing serious crimes [20, 21].

By way of comparison, New York City's combined murder and non-negligent homicide rate has declined from about 8 deaths per 100,000 residents in the mid 1990s to about 4 per 100,000 residents in 2015 and 16 [38, 39]. Solid information about the NYPD's use of AI-enabled policing tools is not easily available. However, it appears that their use of such tools was limited prior to 2016 [40]. If the NYPD was using algorithmic policing tools successfully in the 2009 to 2017 period (where the greatest decline in murder rate was seen), their resourcing strategies should be studied as guidance for other cities. Any such study would need to account for the pre-existing transformation in structure and data already in place as a result of the NYPD's long term use of CompStat, as there is an argument to be made that the discipline of good quality, timely data being used thoughtfully is at least as important to improved policing outcomes as any AI-enabled tool.

Crimes which the police considered solved, usually by the arrest of the suspect, are considered "cleared". Clearance rates for homicides have been declining in the United States and elsewhere for some time [34, 35]. The in-year murder clearance rate in Chicago fell at an average rate of 6.2% per year between 2001-2 and 2016-17 (CPD changed their reporting methodology in 2018). The CPD's average murder clearance rate in 2001 and 2002 was about 50%, with an average of 656 murders per year, and in 2016 and 2017, there were an average of 711 murders per year with an average in year clearance rate of about 19%. Burglary clearance rates also declined during this period, by an average annual rate of about 3%. The average burglary clearance rate in Chicago in 2001 and 2002 was 11% and in 2016 and 2017 it was 7%. These rates are shown in Figure 1 of Appendix B. The population of Chicago declined by about 200,000 over this period [41]. Thus, it is evident that Chicago's deployment of algorithmic policing tools was not effective at increasing clearance rates for these crimes.

5. Parkinson Meets Prediction: Musings on the Resource Implications for Effective and Efficient Algorithmic Policing

With over a decade of mixed and largely negative algorithmic policing results to draw from, is it possible to develop a digital Parkinson's Law, which will help police and municipal leaders assess the true salary costs associated with efficient and effective implementation of algorithmic policing technologies? Arguably yes, although not necessarily today.

The core challenge is the difficulty in identifying examples where use of these tools has resulted in significant decreases in serious crimes not attributable to other factors. Existing studies demonstrate a need for high quality data, adequate officer training, and a response to algorithmic recommendations which is both substantial and appropriately skilled [18, 42].

These factors are all amenable to improvement through incremental resourcing: more officers creates the flexibility to pull officers off the beat for the necessary training, and also enables a stronger police response when the algorithm identifies a need for action. Incremental resourcing also provides capacity for better coordination with social services and the planning of a more consistent and coherent response to those individuals and areas at highest risk. It also enables the employment of individuals and systems to monitor and correct data quality, algorithmic drift, and other system factors.

It is therefore clear that meaningful incremental resourcing is a necessary condition for the successful operation of algorithmic policing tools. How much incremental resourcing is required will depend on the mix of tools, as well as the data on which they will depend, the training and skills of those involved, and the social and political realities of the location.

The potential resource implications of algorithmic policing technologies depend a great deal on their intended use. Tools producing new data or making old data more accessible will increase demands on police attention more than, for example, a basic hot-spot prediction algorithm. Tools producing predictions about the future behaviour of individuals will significantly increase demands on police and other professionals' time as they assess the related risks and develop and deploy a surveillance or engagement plan.

In many cases, police services will not be the best suited organization to help those at risk to change aspects of their life and reduce their risk of being involved in a serious crime. Increased social services resources will also be necessary to enable these systems to reduce serious crime and improve outcomes. This is consistent with the success observed in the non-algorithmic Boston "Operation Cease Fire" project [7, pp.171–190] and other problem-oriented policing approaches [7, pp.117–132], as well as previous work [43, 44] demonstrating that in addition to age and gender demographics, socio-economic factors are a leading driver of serious crime. There is a political element to the balance between carrot and stick, between supports and coercion; and, media and political climate is known to influence police activity [45]. Thus, each city will seek a slightly different mix of expertise among incremental hires.

5.1. **Looking Forward: A Digital Parkinson's Law**

While it would be premature to propose an exhaustive formula to describe the resourcing implications of various algorithmic policing technologies, the information available does point to a number of factors which will be relevant, and also hints at the likely nature of their interactions. We share here a preliminary effort to present these factors as a formula to be further refined as more information becomes available. Those familiar with machine learning will recognize the obvious importance of data volume and complexity on the range of likely output and resultant resource requirements. (See "q" and "r" in the formula below.)

Policy and political factors, such as the resourcing balance between addressing social determinants of crime and investigating and deterring specific offences, will inform how existing and incremental resources are divided between police and social services. Together with current data, these factors will inform the number of officers (t) and social services professionals (w) per 1000 population, the target (v) and actual (s) clearance rates for crimes of interest. Given that many crimes currently go unreported, the rate of both reported (p) and estimated unreported crimes (100-u) of interest will be important. (Increased police attention in these areas is likely to lead to increased reporting, increasing the number of police-actionable crimes.) Other contextual factors will also come into play, including the range of crimes to be focused upon, the size and population density of the region, and even the local media and political climate. The type of algorithmic policing tool deployed will be a key factor, as different classes of tools are expected to have different resourcing impacts.

Assessment of these factors will require much more information from successful deployments than is available today. With nearly unlimited surveillance and analytical capabilities come nearly unlimited opportunities to fill police officer time following up on a range of increasingly minor or obscure offences. Thus, prioritization of effort will remain crucial even with algorithmic tools. In the absence of firm fiscal constraints, ultra-rapid algorithmic analysis of an exponentially increasing volume of data could require human resource growth well in excess of Parkinson's proposed 5 or 6 %. Finding the optimal point which provides sufficient resourcing to enable algorithmic tools to deliver their intended benefits while controlling spiralling resource demands will be challenging.

It seems probable that a digital Parkinson's law applied in a police department employing algorithmic tools will be along the lines of:

$$x = apq^r(\frac{v}{s})(\frac{2.4}{t})(\frac{1}{2w})(\frac{100}{u}) \tag{5.1}$$

Where,

$x =$ the number of additional full time city employees required per year (includes officers, technical staff, and social services professionals)
$a =$ constant associated with a particular algorithm
$p =$ average number of serious crimes per 1,000,000 in population (annual average over past 5 years)
$q =$ size of data holdings upon which the algorithmic tool draws (petabytes)
$r =$ number of independent data headers in data source accessed by algorithm
$v =$ target clearance rate (in percent) for serious crimes
$s =$ clearance rate for serious crimes* over the prior five years (%, annual, averaged over 5 years)
$t =$ officers per 1000 residents
$w =$ social services professionals per 1000 residents
$u =$ percentage of serious crimes* reported (%, annual average over 5 years)

*A "serious crime" in this case includes all those classes of crime which the police force intends to use the algorithmic tool to study or address.

In application, the equation provides a tool to begin to account for known major factors likely to have resource implications. Thus, the variable "$\boldsymbol{a}$" reflects the need to distinguish between resource concentration recommendation tools (e.g. hot-spot policing) which would have a relatively low value for "$\boldsymbol{a}$" (and only a modest impact on resourcing requirements) versus investigative tools (having a higher value for "$\boldsymbol{a}$" and greater resourcing implications) which can increase lead volume and also reveal previously unknown crimes and suspects requiring action. The value of "$\boldsymbol{a}$" will need to be determined empirically for different kinds of tools. The variable "$\boldsymbol{p}$" reflects the reality that the use of algorithmic tools in areas with more crime to control can be expected to result in more information to be acted on, requiring more resources to respond. The term $\mathbf{q^r}$ reflects the impact of data volume and complexity on the range of possible leads to be followed up by police, as well as the extent of data verification and cleaning required to ensure accurate results. The term $(\frac{\mathbf{v}}{\mathbf{s}})$ reflects the role of crime clearance targets on resourcing. Thus, the greater the degree to which recent clearance rates "$\boldsymbol{s}$" fall below target rates "$\boldsymbol{v}$", the more resources will be required. The term $(\frac{\mathbf{2.4}}{\mathbf{t}})$ reflects the impacts of existing officer staffing levels on incremental resourcing needs. The numerator "$\boldsymbol{2.4}$" was selected for this example as about "$\boldsymbol{2.4}$" officers per 1000 residents has been reported to be the average level of staffing [46]. It is known that community size impacts average officer : resident ratios. Thus, this number will require adjustment for communities of different sizes. The term ($\frac{\mathbf{1}}{\mathbf{2w}}$) reflects the impact of existing social service professional staffing levels on incremental resourcing needs. As with police staffing levels, typical values will vary with location. Finally, the term ($\frac{\mathbf{100}}{\mathbf{u}}$) reflects the fact that algorithmic tools can be expected to provide information relevant to crimes which would have otherwise gone unreported. These crimes represent new work to the police. Thus, the lower the rate of crime reporting (the fewer crimes included in the count represented by "$\boldsymbol{p}$"), the more new work will be located by the algorithms, and the more resources will be required (reporting estimates can be obtained by surveys or other means).

6. **Conclusion and Future Work**

In many domains, model development can take knowledge-centric, data-centric or hybrid approaches. Knowledge-centric models provide a deeper understanding of basic interactions in a system by quantifying the mathematical relationships between the entities involved. They are the product of iterative knowledge discovery validated by empirical observations. The digital analog to Parkinson's law proposed in this work is an effort to stimulate further research with the goal of discovering foundational knowledge around the adoption of algorithmic policing tools. Anecdotal and empirical evidence suggest that the relatively rarity of examples of successful algorithmic policing initiatives is likely due to under-resourcing. An objective method of determining resource requirements based on a mathematical approach is needed.

Future research will focus on validating or extending the proposed equation presented in this work (i.e. Equation 5.1) with specific examples of algorithmic policing systems and the related resourcing in terms of various expertise. Given the limited instances of success in these areas, initial studies will need to focus on those pockets of officers, social services, and locations where algorithmic policing tools have unambiguously led to decreases in serious crime rates in comparable areas. The results of these studies will provide guidance to leaders considering the implications of such tools and should be backed by observed empirical phenomena. This work will also help to elaborate what a digital Parkinson's Law would look like when different varieties of tools are adopted, as well as the resource implications of interaction between such tools.

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Appendix A. Chicago Police Department Related Employee Estimates

Civilian employees began to move out of the CPD and into a newly created Office of Emergency Management and Communication (OEMC) beginning in 1995 with the movement of emergency call staff (911), then the transfer of surveillance camera monitoring, and continuing at least until 2016 when nearly one thousand crossing guards were transferred from CPD to OEMC [47]. These and other changes complicate an assessment of the number of City of Chicago employees in roles which were historically part of the CPD. Additionally, The CPD did not consistently report its actual employee numbers in its annual reports during this period. Thus, employee numbers for 2015 and 2019 are based on planned budget numbers, reduced by the average difference between budget and actual in 2016 and 2017 (4.4%).

Accounting for growth in civilian employee numbers requires an assessment of OEMC as well as CPD. OEMC serves not only CPD, but also the Chicago Fire Department and other emergency functions. Thus, an assessment of OEMC contributions to what were previously CPD functions was prepared based on historical functions transferred, as well as current OEMC job titles. (Readers interested in further details are encouraged to contact the authors.) Based on this assessment one finds total (CPD plus OEMC) 2019 police-dedicated staffing of 16259, with civilian staffing for police of at least 2375 individuals. This represents a total (sworn and civilian) shrinkage rate of about 0.076% over the 2002 to 2019 period.

If one limits the analysis to 2011 and forward (when OEMC budget figures are available), and includes all OEMC employees into CPD employee counts (an obvious over-estimate of police-dedicated resources), the cumulative annual growth rate for CPD and OEMC combined between 2011 and 2019 is -0.3%. The growth rate over the same period when assessed for CPD budgeted employees only is -0.7%. It is therefore clear that, however one calculates it, there was no increase in the number of individuals engaged in either historical or actual police department roles in the algorithmic era.

Appendix B. Average Crime and Clearance Rates

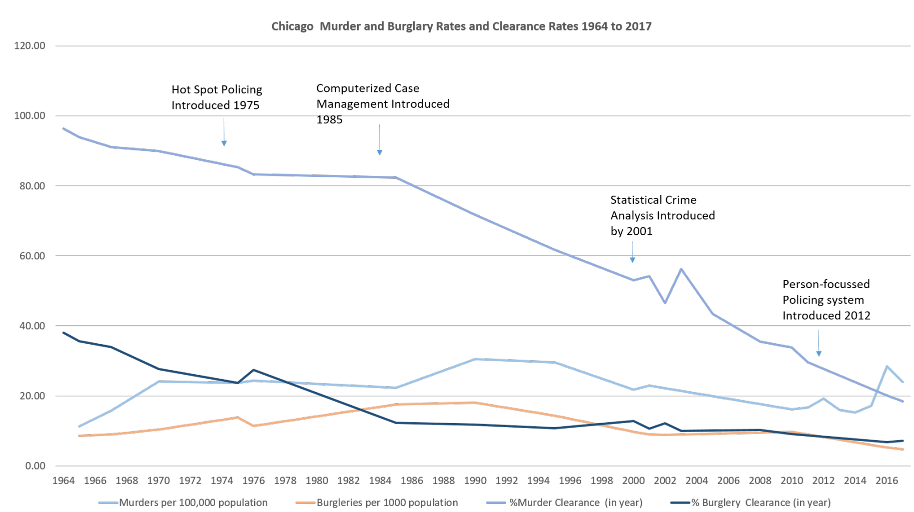

Figure 1. Chicago Murder and Burglary Rates and Clearance Rates Over Time