The History of Crime Analysis Through Data Visualization

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**Abstract**

In this paper, I examine the role of data visualization in modern crime analysis, blending theoretical perspectives with applied examples across law enforcement, forensic science, public policy, and systems reform. Visualization not only simplifies complex data but also frames the narratives through which crime is perceived and responded to. Following the history of data visualization in crime data, I explore the influence of visual representation on geographic profiling, predictive policing, courtroom communication, and public accountability. I also examine ethical dilemmas associated with surveillance, biased data, and misinterpretation. These issues are contextualized within criminology theory and support the use of ethically grounded and participatory visualization practices in criminal justice.

**The History of Crime Analysis Through Data Visualization**

Data visualization has emerged as a powerful instrument in crime analysis. From heatmaps showing burglary rates to 3D reconstructions of crime scenes, visual tools translate quantitative and qualitative data into formats that can be easily interpreted by a lay audience. However, creating data visualizations involves framing, selecting, emphasizing, and omission of data —processes that carry political and ethical implications. Visualizations not only enhance clarity and operational efficiency but also shape public understanding of crime and justice, reinforcing or challenging institutional power.

The use of visualization in criminology dates to the early 19th century. For example, statisticians André-Michel Guerry and Adolphe Quetelet used choropleth maps to represent crime rates across geographic regions. Their pioneering work laid the groundwork for environmental criminology by showing that crime correlated with structural factors like poverty, education, and urban density (Friendly, 2007). Guerry’s maps, shaded by color intensity, not only illustrated where crimes occurred but implicitly questioned the notion of individual criminal pathology. This reframed crime as a social phenomenon.

A diagram of a curve

AI-generated content may be incorrect.

Figure 1. Quetelet’s 19th-century age-crime curve illustrating the statistical relationship between age and propensity to commit crime.

A map of england with different shades of brown

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Figure 2. Guerry’s 1830s choropleth map visualizing crimes against the person across English counties, pioneering the link between geography and moral statistics.

This approach would influence the Chicago School of Sociology in the 20th century. Shaw and McKay (1942) mapped juvenile delinquency in Chicago, revealing spatial patterns that supported their theory of social disorganization. Their maps demonstrated that crime was concentrated in transitional urban zones with high rates of poverty, ethnic heterogeneity, and residential mobility. By translating data into spatial form, they made visible the structural causes of crime, laying the foundation for ecological criminology.

A map of the state of illinois

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Figure 3. Shaw and McKay’s maps of juvenile delinquency in Chicago (1900–1933) illustrating spatial patterns that supported the theory of social disorganization and urban zone analysis.

Crime data visualizations are also closely tied to criminology theory, such as where or why crimes may occur. Routine activity theory (Cohen & Felson, 1979) suggests that crimes are likely to occur when a motivated offender, a suitable target, and the absence of a capable guardian converge in time and space. This framework has inspired visualizations of crime "hot spots," temporal clustering, and guardianship coverage. For example, GIS platforms, or Geographic Information Systems platforms, are software tools used to capture, store, analyze, and visualize spatial or geographic data. They allow users to map data points onto real-world locations and uncover patterns, relationships, or trends that are tied to geography. In modern crime data visualization, GIS platforms now incorporate routine activity theory in mapping police patrols or scheduling CCTV monitoring based on peak hours of risk. Environmental criminology has provided conceptual tools to understand the importance of nodes (e.g., homes, workplaces), paths (commuting routes), and edges (boundaries between neighborhoods) in shaping criminal behavior (Brantingham & Brantingham, 1993). Visualizations using these concepts help identify vulnerable areas where specific crime prevention strategies can be applied. Network analysis, informed by social learning and strain theory, has enabled law enforcement to visualize the structure of criminal organizations. Node-link diagrams illustrate the flow of resources, orders, and influence across gang hierarchies or trafficking networks (Xu & Chen, 2005). These visualizations help identify central actors or choke points for disruption.

A screenshot of a computer

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Figure 4. The interaction patterns (and overall structures of networks) discovered from two criminal networks. (a) The network consists of 60 criminals dealing with narcotic drugs. It is difficult to manually detect subgroups and interaction patterns from this original network. (b) A chain structure becomes apparent using clustering and blockmodeling (see the red mark). Circles represent groups, which are labeled by their leaders’ names, and straight lines represent between-group relationships. (c) The system can also show the inner structure of a selected group, identify its central members (leaders by degree, gatekeepers by betweenness, and outliers by closeness), and presents the centrality rankings of the members in a table in a separate window. (d) The network consisting of 57 gang members. (e) The star structure found in the gang network. (f) The details of a selected group in the gang network (Xu & Chen, 2005).

Visual representation plays a growing role in criminal trials. Forensic experts use digital animations to simulate bullet trajectories, blood spatter dynamics, and crime scene reconstructions. These visuals help jurors understand spatial relationships and causality. However, jurors may overestimate the accuracy of animated reenactments because of their visual realism (Kassin et al., 2018). Technologies such as photogrammetry and LiDAR allow precise 3D scans of crime scenes, which can be viewed in VR headsets during trials. Some jurisdictions have introduced immersive exhibits to recreate the scene from the perspective of the victim or the accused. While these tools provide clarity, they may also be introducing potential bias through camera angles, color, or sound effects. Facial composite software and AI-generated likenesses are also part of forensic workflows. These systems rely on verbal descriptions to generate visual outputs, often used in "Be On the Lookout" (BOLO) alerts. However, machine learning models trained on unbalanced datasets may produce racially biased or exaggerated features (Buolamwini & Gebru, 2018).

Crime data visualization can also be used to promote transparency and citizen engagement. Programs such as the FBI’s Crime Data Explorer or initiatives like the Police Data Project allow users to explore statistics by location, type, and time. Journalists and activists use visualization tools to uncover racial disparities in stop-and-frisk incidents, police shootings, and arrest rates. The National Registry of Exonerations provides visualizations of wrongful convictions across multiple dimensions: race, crime type, jurisdiction, and cause of error. These tools highlight patterns of systemic injustice and help scholars identify policy gaps. Similarly, projects like Mapping Police Violence transform raw incident data into intuitive charts and maps, making opaque phenomena visible to a lay audience. Public-facing platforms also include citizen-generated content, such as Nextdoor crime maps or ShotSpotter alert visualizations. While these visualization tools offer valuable insights, it is important to recognize that, without proper context, they may perpetuate biased views of certain neighborhoods.

Crime visualization may also introduce epistemological and ethical challenges. Choices about color, legend thresholds, and spatial granularity significantly affect perception. Misleading visuals can distort public understanding and policy priorities (Richardson, Schultz, & Crawford, 2019). Furthermore, predictive visualizations risk pathologizing communities. When certain neighborhoods are consistently flagged as high-risk, residents may experience heightened surveillance, reduced investment, and social stigma. Rather than addressing root causes, authorities may respond with increased enforcement. Another concern with crime visualization is that visualizations often erase uncertainty. Heatmaps and forecasts rarely include margins of error, confidence intervals, or alternate explanations. The illusion of precision can encourage overreliance on technical tools, sidelining human judgment and contextual knowledge.

In crime analysis, visualizations have the potential to uncover patterns, inform policies, and support meaningful reform. At the same time, they can mislead audiences, reinforce stereotypes, and present incomplete or biased narratives, especially when the decisions about what to display and how to display it are not carefully considered. Visualization is not just a technical process; it reflects values, priorities, and assumptions. It can shape how we understand crime, influence public opinion, and impact how resources and attention are distributed across communities. As data tools become more automated and widely adopted, it is essential to remain aware of their broader social consequences. Visualizations that rely on biased or incomplete data can unfairly target certain neighborhoods and reinforce harmful patterns in policy and policing. When these tools are treated as objective, they risk harming rather than helping communities most affected by crime and justice policies. This makes it all the more important to build visual literacy that goes beyond interpretation and into critical analysis—who created the visualization, whose voices are missing, and what impact it may have. To ensure crime visualization contributes to a more just society, it must be developed through collaboration among communities, researchers, and designers, grounded in transparency and accountability. When done ethically, visualization can support more equitable decision-making and serve as a catalyst for systemic change.

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