I, M.Murat Ozer, hereby submit this original work as part of the requirements for the degree of Doctor of Philosophy in Criminal Justice.

It is entitled:
Assessing the Effectiveness of the Cincinnati Police Department’s Automatic License Plate Reader System within the Framework of Intelligence-Led Policing and Crime Prevention Theory

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Assessing the Effectiveness of the Cincinnati Police Department’s Automatic License Plate Reader System within the Framework of Intelligence-Led Policing and Crime Prevention Theory

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ABSTRACT

This study aims to explore the effectiveness of ALPR systems within the framework of intelligence-led policing in two specific ways. First, the impact of ALPR systems on policing will be analyzed through assessments of crime clearance rates (follow-up arrests). In addition to impact analysis, ALPR mobile units and traditional policing will be compared for their manpower and cost effectiveness. Second, this study will identify and recommend the most effective strategies for deployment of ALPR units based on optimal crime reduction benefits through arrests and crime prevention techniques. Using the tenets of specific theories of crime prevention, including offender search theory and crime pattern theory, this study examines whether crime prevention theory can assist researchers and police leaders to optimally allocate ALPR mobile units to prevent crime before it occurs. Based on this analysis, specific recommendations regarding deployment of ALPR units will be provided.

The current study is organized into five remaining chapters. Chapter 2 begins with a brief review of policing strategies to create a basis for the distinction of policing philosophies and the organizational structure of police work. Specific attention will be given to intelligence-led policing (ILP) strategies. The underlying premises of ILP will be used to develop a framework that directs discussions regarding effective crime control models.

Chapter 3 specifically focuses on ALPR as an example of an approach that furthers the goals of the data-driven, ILP model. Following a descriptive overview of ALPR technology, the scant literature regarding the effectiveness of ALPR is reviewed. Given the implications of ALPR for possible crime prevention, specific tenets of relevant crime prevention theories are reviewed in the context of how they might be utilized to improve the effectiveness of ALPR systems.

Chapter 4 presents in detail the study’s specific research questions and hypotheses, and provides a description of the multiple data sources used to examine these questions. The proposed analytical strategy, as well as the strengths and limitations of the study’s methodology, are reviewed. The results of the proposed analyses will be Chapter 5 in the final dissertation, while the discussion and implications of these findings will comprise Chapter 6.

It is anticipated that this research will bring two new insights into the policing literature. First, the evaluation of the effectiveness of data driven approaches (using ALPR units as an example) will provide a guide for police departments seeking to empirically determine the value of other data-driven techniques. Second, policing scholars have stressed that the importance of data management methods in crime prevention is generally neglected (Manning, 2001; Webb, Smith, & Laycock, 2004). This study intends to bridge this gap by focusing on strategic deployment of ALPR mobile units using crime prevention theory as a guide.
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CHAPTER I
INTRODUCTION

In recent decades, law enforcement organizations have consistently reinvented themselves to adequately respond to public safety demands through innovative approaches like community policing, problem-oriented policing, COMPSTAT, and hot spots policing (McGarrell, Freilich, & Chermak, 2007; Rosenbaum, 2007). While certain police innovations led to a radical intellectual revolution in policing such as community policing (Duman, 2007; Gul, 2009), their effectiveness for reducing crime is questionable due to the weak organizational support and vague policy implications (Capowich & Roehl, 1994; Sadd & Grinc, 1994). For this reason, police departments are still continuing to seek effective policing strategies for effective crime control methods, while ensuring community satisfaction.

Given this context, recent intellectual innovations in policing, such as community policing, changed the mindset of the police from professional policing1 to community-oriented policing; however, they have contributed less to effective crime control. The main reason for this dilemma is that many recent policing innovations do not fit into traditional conceptualizations of police work, since they are contingent upon organizational changes like decentralization (Meares, 2002), which are incompatible with the nature of police (Braga & Weisburd, 2006). Indeed, descriptions and critiques of these incompatibility issues have been raised by many scholars (e.g., see Henry, 2002; Hunter & Barker, 1993; Kappeler & Kraska, 1998; Kelling & Coles, 1996; Klockars, 1998).

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1 In the early 1900s, policing was often associated with lawlessness, corruption, and close ties with political patronage. During the reform era beginning in the 1920s, the police were separated from political control and held accountable for their actions. In addition, police organizations more strongly resembled quasi-military organizations through the use of uniforms, rank structures, and communication devices (i.e., radio). However, even though the police became more professional during the reform era, the police drifted from the public, in part due to their emphasis on a more professional style (Manning, 1977; Walker, 1977).
1988; Magers, 2004; Manning, 1995; Manning, 1988; Walsh, 2001; Walsh & Vito, 2004). These criticisms, however, have not reached the level of creating a new paradigm shift in policing science (Kuhn, 1996). In addition, most criticisms against recent innovations in policing are generally ignored in the larger academic field (Vito, Walsh, & Kunselman, 2004). It has been generally assumed that innovative philosophies, such as community policing\(^2\), will automatically result in reductions in crime (Walsh & Vito, 2004). In practice however, community policing strategies have encountered organizational resistance despite police officers’ acceptance of the general philosophy (Braga & Weisburd, 2006; Engel & Worden, 2003; Greene, 2000; Magers, 2004; Zhao et al., 2001; Zhao, Lovrich, & Thurman, 1999). For similar reasons, the prevalence and sustainability of recent policing innovations remained very limited in practice (Maguire, Shin, Zhao, & Hassell, 2003; Vito, Walsh, & Kunselman, 2004; Zhao et al., 2001).

In conjunction with strategies like community and problem-oriented policing, data-driven policing applications have gained popularity with the promise of increased effectiveness and community satisfaction while ensuring organizational support as well. More specifically, intelligence-led policing (ILP) has recently developed as the newest data-driven policing approach to smartly enforce laws, optimally allocate scarce resources, and maximize crime prevention while minimizing organizational resistance from both middle managers and police officers (John & Maguire, 2004). Several policing scholars view intelligence-led policing as one of the field’s most promising new approaches.

\(^2\) The community policing model suggests that policing should include community as the most important part of the crime fighting, a proposition that is minimized by the era of professional policing (Crank, 1994). In this context, the philosophy of community policing yielded a radical departure from the professional policing model, which considered itself as a mere player in crime fighting (Greene, 2000). The notion of community policing has also led to radical intellectual change for police officers and administrators.
approaches (Kelling & Bratton, 2006; Maguire & John, 2006). The two core themes of intelligence-led policing are to analyze all relevant crime data and to generate proactive strategies in light of effective crime prevention theories and best practices. To maintain the core requirements of intelligence-led policing, law enforcement agencies are constantly seeking ways to increase their data collection and analysis capabilities. In this sense, rapid technological developments, which enable police departments to collect and analyze data quickly, have become very popular in police departments around the world (Ratcliffe, 2002).

The application of ILP requires timely and valid data that is examined using advanced analytical tools. In this vein, Automatic License Plate Reader (ALPR) systems provide timely and valid data to police departments. ALPR is an infrared camera system that can scan the image of license plates and convert them into numbers and letters by using Optical Character Recognition (OCR). Once the image is converted to data, they are compared with pre-identified license numbers of vehicles involved in criminal activity. If the sent information matches (e.g., identification of stolen vehicles), an alert appears on the computer of police officer to pull over the vehicle (Chen, Lin, and Yang, 2006; Manson, 2006). Given this context, the use of ALPR is one of the latest innovations in use by police departments across the United States to further the goals of intelligence-led policing. Specifically, ALPR systems vastly increase the data collection capabilities of police departments, providing them with a greater knowledge base from which to develop new, data-driven strategies. The application of ALPR systems in the United States is fairly new to the intelligence-led policing movement, but there is an

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3 Existing literature contains considerable debate whether intelligence-led policing is a different form of traditional policing (Tilley, 2003). Advocates of the ILP argue that a broad definition/conceptualization of intelligence led policing provides new insights to current policing strategies (McGarrell et al., 2007).
increasing trend towards ALPR systems in police departments due to anecdotal reports of its ease of use and success.

**Current Study**

Despite the importance of ALPR units, and the dramatic increase in their usage in police departments across the country, as with many law enforcement technologies, very little is known about their effectiveness. The purpose of this study is to evaluate whether the use of technological innovations like ALPR can help police departments to smartly enforce the law, optimally allocate scarce resources, and maximize crime prevention efforts. One of the aims of intelligence-led policing is to utilize expert knowledge (i.e., network analysis, relational database management, geographic information systems) across the police department to prevent future crimes and potential threats. In this context, exploring the utility of ALPR systems may also reveal the current promise of intelligence-led policing for optimal crime reduction.

This study aims to explore the effectiveness of ALPR systems within the framework of intelligence-led policing in two specific ways. First, a comparison of the effectiveness of ALPR systems over traditional policing practices will be conducted through assessments of crime clearance rates, implementation of proactive measures, and reductions in manpower and other costs associated with crime reduction. Second, this study will identify and recommend the most effective strategies for deployment of ALPR units based on optimal crime reduction benefits through arrests and crime prevention techniques. Using the tenets of specific theories of crime prevention, including offender search theory and crime pattern theory, this study examines whether crime prevention theory can assist researchers and police leaders to optimally allocate ALPR mobile units
to prevent crime before it occurs. Based on this analysis, specific recommendations regarding deployment of ALPR units will be provided.

**Dissertation Overview**

The current study is organized into five remaining chapters. Chapter 2 begins with a brief review of policing strategies to create a basis for the distinction of policing philosophies and the organizational structure of police work. Specific attention will be given to intelligence-led policing (ILP) strategies. The underlying premises of ILP will be used to develop a framework that directs discussions regarding effective crime control models.

Chapter 3 specifically focuses on ALPR as an example of an approach that furthers the goals of the data-driven, ILP model. Following a descriptive overview of ALPR technology, the scant literature regarding the effectiveness of ALPR is reviewed. Given the implications of ALPR for possible crime prevention, specific tenets of relevant crime prevention theories are reviewed in the context of how they might be utilized to improve the effectiveness of ALPR systems.

Chapter 4 presents in detail the study’s specific research questions and hypotheses, and provides a description of the multiple data sources used to examine these questions. The proposed analytical strategy, as well as the strengths and limitations of the study’s methodology, are reviewed. The results of the proposed analyses will be Chapter 5 in the final dissertation, while the discussion and implications of these findings will comprise Chapter 6.

It is anticipated that this research will bring three new insights into the policing literature. First, the evaluation of the effectiveness of data driven approaches (using
ALPR units as an example) will provide a guide for police departments seeking to empirically determine the value of other data-driven techniques. Second, policing scholars have stressed that the importance of data management methods in crime prevention is generally neglected (Manning, 2001; Webb, Smith, & Laycock, 2004). This study intends to bridge this gap by focusing on strategic deployment of ALPR mobile units using crime prevention theory as a guide.
CHAPTER II
ORIGINS OF INNOVATIVE POLICING STRATEGIES

The evolutionary history of policing suggests that modern day policing strategies have developed directly from issues confronting law enforcement officials over time (Greene, 2000; Kelling & Moore, 1988). Lawlessness of policing, for instance, at the beginning of 1900s forced policing into professional policing era (Trojanowicz & Bucqueroux, 1990). However, the adverse effect of military style of administration during the professional policing era yielded riots in the 1960s (Sherman & Eck, 2002). Therefore, community-oriented policing emerged from the deficits of professional policing to develop bilateral relations with the community. Likewise, problem-oriented policing built its principles on the philosophy of community-oriented policing; but concentrated more on problems (i.e., crime hot spots) rather than administrative style of policing. Finally, technological developments introduced COMPSTAT policing (Walsh, 2001) and intelligence-led policing (ILP) (Ratcliffe, 2008) to police departments as an effective crime control model while ensuring community satisfaction as well. In brief, police organizations, administration, and strategies have evolved through specific responses to the concerns raised by preceding policing approaches. Briefly introducing the recent history of policing provides an opportunity to evaluate the current importance of ILP and other policing strategies in context.

Standard Applications of Policing

In the last forty years, policing organizations and the strategies they employ have changed dramatically. Research in the 1970s revealed that standard applications of policing such as increased police strength through additional officers (Sherman & Eck, 2004), preventive patrol (Kelling, Pate, Dieckman & Brown, 1974), and rapid response to
calls for service (Spelman & Brown, 1981) did not reduce crime rates, especially for violent crimes (Rosenbaum, 2007). The main misconception of standard applications of policing during the 1970s was that increasing reactive response capability of the police would bring success in crime control.

As a different approach to crime control, police departments also employed “aggressive police enforcement” methods, such as field interrogations, directed patrols to stop suspicious persons and vehicles, and aggressive traffic enforcement (Cordner, 1998; Sherman, 1992; 1995). Compared to standard applications of policing, aggressive police enforcement includes aggressive proactive methods through directed patrols. Although this method initially appeared to be promising (Sampson & Cohen, 1988; Wilson & Boland, 1978), scholars criticized aggressive police enforcement due to concerns about discrimination and violation of liberties (Sherman, 1997; Walker, 1984). Specific concern has been raised regarding directed patrol efforts that often targeted places populated by individuals of low socio-economic status and racial minority groups (Kennedy, 1997).

**Community Oriented Policing**

In light of the empirical findings regarding traditional methods of policing, by the end of the 1970s, police agencies and scholars alike began to explore new policing strategies. During this period, Goldstein (1979) used the term “community oriented policing” (COP) in order to emphasize that crime can be controlled by improving bilateral relationships with the community. Goldstein (1987) stressed that COP requires organizational decentralization and a fundamental change in both management and organizational culture for better two-way communication with the public.
Community-oriented policing became a very dominant policing strategy in a short time in the U.S. With the funding of the Crime Control Act of 1994, 100,000 police officers were hired to implement community-oriented policing (He, Zhao, & Lovrich, 2005). Despite the popularity of community-oriented policing in the U.S. and the world, research regarding its effectiveness in reducing and controlling crime is mixed (MacDonald, 2002; Skogan & Frydl, 2004). Goldstein (1987) argued the primary reason for the inability of community-oriented policing to control crime was the low commitment from police agencies to the core themes of COP, including organizational decentralization and changes in management style. Eck and Maguire (2000) similarly attributed the ineffectiveness of community-oriented policing to its improper implementation by police agencies. Alternatively, the applications of community-oriented policing (i.e., foot patrol) demonstrated positive impacts on citizens’ perceptions of police legitimacy and reduced their fear of crime. Specifically, empirical studies report that community-oriented policing applications reduce fear reduction and disorder in communities (Rosenbaum & Lurigio, 1994; Skogan, 1990). In short, even though community-oriented policing improves police and public relationships, its impact on crime is well below the expectations due to the slow change in police structures, culture, and management style (MacDonald, 2002).

**Problem Oriented Policing**

A similar policing approach to community-oriented policing is problem-oriented policing (POP). Problem-oriented policing concentrates police attention on problems that the community faces in everyday life and develops effective solutions for these recurring problems (Eck & Maguire, 2000; Eck & Spelman, 1987; Goldstein, 1990).
Like community oriented policing, Goldstein (1979; 1990) argues that problem-oriented policing requires organizational transformation, such as decentralization, to detect problems in the community. That is, it requires transposing of discretion and decision making processes from headquarters to operational level police officers to detect problems and to generate relevant solutions (Eck, 2006). In the identification of recurring problems, problem-oriented policing incorporates the principles of several crime prevention theories, such as crime pattern theory (Brantingham & Brantingham, 1981; 1982; 1999; 2003), routine activity theory (Cohen & Felson, 1979), and situational crime prevention theory (Clarke, 1997; 1999), into its problem analysis/scanning procedure (Skogan & Frydl, 2004).

Empirical assessments of problem-oriented policing produce mixed results, but reveal that problem-oriented policing is more promising than community-oriented policing in terms of crime control and crime reduction (Rosenbaum, 2007). Researchers emphasize that when problem-oriented policing is implemented to narrowly focused problems (i.e., robberies at particular street blocks), its effectiveness increases (Braga, 2002; Weisburd & Eck, 2004; Hope, 1994). Other scholars argue that organizational change has little or no impact on reducing crime (Eck & Maguire, 2000; Gianakis & Davis, 1998; Maguire, Shin, Zhao, & Hassell, 2003), and that it is enough to concentrate on repeat offenders, repeat victims, and hot spots to reduce crime without changing organizational style (Braga & Weisburd, 2006).

**Pattern Focused Strategies**

There are other forms of policing strategies that focus on recurring problems, such as repeat offending, repeat victimization, and repeat criminal activities in places.
Specifically, there are two main policing strategies that target recurring crime problems in the community: Hot spot policing and COMPSTAT policing.

**Hot spot policing**

In the literature, hot spot policing is considered to be a separate, though related, policing strategy from problem-oriented policing (Skogan & Frydl, 2004). For instance, both strategies focus their efforts on places where crime shows patterns. As previously mentioned, problem-oriented policing borrows the notion that crime is non-randomly distributed, both rather spatially and temporarily distributed (Cohen & Felson, 1979; Sherman, Gartin, & Buerger, 1989). In this respect, hot spot policing can be considered as a part of problem-oriented policing because hot spot policing focuses on spatially and temporally patterned criminal activities (i.e., robberies, burglaries) as well. Similar to studies examining problem oriented policing, randomized empirical studies demonstrate that policing that focuses on hot spots results in a considerable crime reduction (Braga & Bond, 2008; Sherman & Weisburd, 1995, Weisburd & Green, 1995).

**COMPSTAT Policing**

COMPSTAT is the abbreviation for a policing strategy known as either “computer statistics” or “comparative statistics.” COMPSTAT gained nation-wide attention from police administrators and scholars after its successful implementation in New York City during the early 1990s (McGarrell et al., 2007). As the name suggests, COMPSTAT analyzes patterned or recurring criminal activities with the help of computerized data collection and analysis methods, such as crime mapping (Geographic

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4 There is no clear explanation in the literature regarding why certain policing scholars categorize hot spot policing as a different policing style from problem-oriented policing. It can be indirectly derived from Braga’s (2005) hot spots policing article that hot spot policing is the way of identifying crime concentration in a given region. Alternatively, problem oriented policing is the tool that is applied to crime hot spots.
Information Systems) and statistical tools (Moore, 2002; Ratcliffe, 2004). Then, it helps to direct police resources to the identified problematic places (hot spots). The other focus of COMPSTAT policing is the incivility thesis proposed in the “Broken Windows” theory. Wilson and Kelling (1982) contend that more serious crime develops if the citizens and the police do not pay attention to urban decay and social incivility. Hence, COMPSTAT policing techniques also targets urban decay to prevent more serious crime in the long run.

The main difference between COMPSTAT policing and its counterparts (i.e., problem-oriented policing, hot spot policing) is that it relies more on the bureaucratic/managerial accountability model (Magers, 2004; Walsh & Vito, 2004) of the police organization. That is, once the problematic areas (hot spots) are identified, precinct commanders are expected to find pragmatic solutions during the weekly meetings (Walsh & Vito, 2004). In this way, precinct commanders are held accountable for their focused interventions, which in turn bring effectiveness for the police efforts (Famega, Frank, & Mazerolle, 2005). Weisburd and his colleagues (2003, 423) identify the following six principles of COMPSTAT:

1. Clarify the agency’s mission by focusing on its basic values and by embodying them in tangible objectives.
2. Give priority to operational objectives over administrative ones.
3. Simplify managerial accountability for achieving those objectives.
4. Become more adept at scanning the organization’s environment to identify problems early and develop strategies to respond (e.g., being data-driven).
5. Increase organizational flexibility to implement the most promising strategies.

Weisburd, Greenspan, Mastrofski, and Willis (2008) posit that COMPSTAT policing refined and reinforced the bureaucratic nature of policing in favor of
community-oriented policing and problem-oriented policing. In addition, the authors argue that COMPSTAT reconciles many of the management prescriptions into single program which is customized for police organizations. In general, COMPSTAT policing is seen as reconciliation of police organizational structure (hierarchy, formalized, and specialized) with the community policing and problem solving policing. With COMPSTAT policing, middle managers are held accountable for their decisions while implementing the doctrine of community-oriented and problem solving policing (Walsh, 2001). In addition, middle managers or supervisors are the key players that are capable to implement an innovative approach in the departments (Engel, 2002; Engel & Worden, 2003; Kelling and Bratton, 1993). Since COMPSTAT policing introduced the importance of organizational structure of police departments in implementing the philosophy of community-oriented policing, it is seen as a new paradigm shift in policing (Weisburd et al., 2008; Walsh, 2001; Walsh & Vito, 2004). This paradigm shift can be summarized with the words of Walsh and Vito (2004, 66): COMPSTAT “is an attempt to synthesize the elements of the rational-legal bureaucratic and community problem-solving paradigms with strategic management concepts taken from the business world.”

Evaluations of COMPSTAT for crime reduction are promising. As discussed above, the New York City Police Department (NYPD) reported a significant drop in the city’s crime rates from 1993 to 1997 (Greene, 1999). Bratton (1998) argued, however, that COMPSTAT was only a part of generalized intensive enforcement in the city. Thus, any crime reduction cannot be solely attributed to COMPSTAT. Empirical studies also revealed that some external factors, such as a decline in the crack market and the tendency of crime to fall before the implementation of COMPSTAT, played a key role in
the declining crime rate during this period (Blumstein, 1995; Bowling, 1999; Eck & Maguire, 2000).

**Policing Efforts Targeting Repeat Victimization**

Previous empirical studies suggest that victimization is a good predictor of subsequent victimization (Farrell & Pease, 1993). That is, places and individuals victimized at some point in time are more likely to be exposed to subsequent victimization compared to non-victimized places and individuals (Osborn & Tseloni, 1998). In addition, certain empirical studies report that a burgled dwelling increases the likelihood of nearby victimization (Townesley, Homel, & Chaseling, 2003). For places, Polvi, Looman, Humphries, and Pease (1991) found that the likelihood of burglary victimization is 12 times greater for previously victimized houses than non-victimized ones within a one month period. In addition, their findings also indicate that half of repeat victimization occurs within 7 days. Finally, the effects of repeat victimization for subsequent victimization diminish after 6 months.

Based on the findings of empirical studies, police interventions targeting repeat victimization (i.e., repeat residential burglary) reported significant crime reduction. For instance, Australian and British Police reduced residential burglary by 25-30 % by focusing on previously burglarized places (Chenery, Holt, & Pease, 1997; Pease, 1991; Townesley, Homel, & Chaseling, 2000). Similarly, empirical studies examining repeatedly victimized individuals reveal that like chronic (repeat) offenders, a relatively small percentage of individuals (4%) suffer approximately 50% of the offenses (Hindelang, Gottfredson, & Garofalo, 1978; Laycock & Farell, 2003; Pease & Laycock, 1999; Wittebrood & Nieuwbeerta, 2000). While prior victimization is a good predictor
of subsequent victimization, police efforts that target individual repeat victimization are scarce in the literature (see for exception, Kirkholt burglary experiment, Laycock & Farrell, 2003).

**Assessments of Current Policing Strategies**

*Incident-driven vs. Data-driven*

As suggested by the review of police strategies above, empirical assessments of these strategies reveal varied success in crime reduction (Braga & Weisburd, 2006; Sherman & Eck, 2002). The existing literature suggests that the focal point of current policing strategies is incidents (Manning, 2001; McGarrell et al., 2007). Responding to calls for service occupy a majority of police officers’ time. Even in problem-oriented policing, preventive approaches are generated as a response to high accumulations of recurring crime in specific places (hot spots).

As Walsh and Vito (2004) argue, COMPSTAT policing can be thought as a different policing strategy; however, COMPSTAT policing also generates its implications from previously occurred incidents. The difference between COMPSTAT policing and problem-oriented policing is that COMPSTAT policing aggressively pushes bureaucratic/managerial lines and uses advanced data analysis tools to identify problematic places within the city. Indeed, COMPSTAT policing is the desired model for problem-oriented policing as proposed by Goldstein (2003) because it refines organizational structure in favor of community-oriented policing and problem-oriented policing (Braga & Weisburd, 2006; Toch, 2008; Walsh & Vito, 2004).

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5 Goldstein (2003) argues that the success of problem-oriented policing requires long term commitments by police leaders, adequate skills of the agency for problem solving (i.e., analysis, evaluation), and well-established academic connections to follow recent innovations of problem solving.
Taken together, the current application of policing is demand-led (i.e., responding to incidents that have already occurred), which takes it roots from calls for service and specific problems (hot spots) in the community. Therefore, their focus is mostly on the here and now (Manning, 2001). Although the terms data-driven and incident-driven/are used interchangeably in policing literature, they have different meanings. For instance, in mathematics and computer science, demand-led or incident-driven method requires a previous incident or demand to perform the next steps. However, the data-driven approach independently develops the necessary steps before an actual demand/incident arises (Ashcroft, 1986; Treleaven, Brownbridge, & Hopkins, 1982).

Manning (2001) argued that current policing strategies (as reviewed above) can be improved if the here and now applications (incident-based policing) is replaced with more proactive policing strategies. Specifically, a data-driven approach like ILP may bring new insights to policing, since it considers all available data and analyzes patterns among repeat victims, repeat offenders, and cluster of problems.

**Intelligence-Led Policing As a New Data-Driven Approach**

Intelligence-led policing (ILP) has emerged within the last two decades as a new policing method and gained sharp momentum in police agencies due to its success in increasing crime prevention and crime control capability (McGarrell et al., 2007). Indeed, Kelling and Bratton (2006, 6), the architects of COMPSTAT policing, contend that intelligence-led policing “has the potential to be the most important law enforcement innovation of the twenty-first century.”

The term “intelligence-led policing” originated in the United Kingdom by Kent Constabulary (Sir David Philips) in the early 1990s (Clarke & Newman, 2007; Hale,
Heaton, and Uglow, 2004). The force behind the development of intelligence-led policing was a rapid increase of burglary and vehicle theft at a time of police budget cuts. In 1993, the British Audit Commission issued “Tackling Crime Effectively,” which stressed the necessity of quality policing for the money spent (Maguire & John, 2006).

To tackle crime more effectively, more rationally, and more proactively with scarce resources, Constabulary placed intelligence at the heart of local decision making to direct daily police activities according to community priorities (i.e., target offenders, hot spot locations and activities, sufficient level of threat for the community) rather than mere reactive responses, such as calls for service (Maguire & John, 2006). For example, it was believed that the majority of crimes were committed by a relatively small number of prolific offenders; therefore, concentrating proactive policing tactics (intelligence, surveillance, and informants) on prolific offenders might provide considerable crime reduction. After applying this approach in Kent, crime rates dropped by 25% within three years (Clarke & Newman, 2007; Maguire & John, 2006).

After the preliminary success of the Kent experiment, a new royal report titled “Policing with Intelligence” emphasized the importance of intelligence-led policing in crime reduction. The report also stressed the importance of an integrated intelligence structure and collaboration with outside agencies for optimal crime reduction (Maguire & John, 2006).

In 2000, the U.K. adopted the “National Intelligence Model (NIM)” for all police agencies, which is built around two principles of the business model: risk assessment and risk management for crime control (Lint, 2006). In this regard, The National Intelligence Model identified main assets of this business model as “managing crime and
criminals,” “managing localized disorder,” “managing enforcement and community issues,” and “reducing opportunities for crime” (Maguire & John, 2006, p.71). As detailed in the model, the goals of NIM are to ensure community safety, to reduce crime, to arrest prolific criminals, to manage hot spots, and to control potentially dangerous offenders (Maguire & John, 2006).

Core Elements of Intelligence-Led Policing

What makes ILP an important innovation is that its core elements operate within the existing rational bureaucratic structure of police organizations for community policing and problem solving policing. These core elements are reviewed in detail below.

Levels: Intelligence-led policing has three operational levels; each level with its own responsibilities. As the level increases, the complexity of information and analysis also increases. In addition, Level-3 is the top management level, where strategic planning can be generated for future-oriented threats (John & Maguire, 2004).

- Level-1: local area policing (i.e., beat level policing or basic command unit level),
- Level-2: regional or cross-border issues
- Level 3: national and international threats (i.e., serious and organized crime)

At each level, risks are assessed and prioritized to manage and allocate limited resources (Maguire & John, 2006). All the information is collated to Level 3 where global assessments can be conducted. For example, the reason behind a drug problem at Level-1 might stem from easy access (importation) to drugs from other states and countries. In this situation, trying to prevent street dealers would not be an effective strategy to manage limited resources of the police because the roots of the problem would continue.
The importance of each level is that police officers specifically focus their attention on their own level in order to manage the common organizational goal.

Tasking and Coordinating Groups: With the function of the Tasking and Coordinated Group (TCG), appropriate resources are optimally allocated and coordinated at each level to carry out a common goal. For instance, at the local level, the head of the TCG can be a captain or precinct commander, while the members of the TCG would be various resource owners, including police personnel, local partners, local authorities, and universities, depending on the complexity of the problem. In this context, “TCG is the owner of business at its particular Level, and is responsible for achieving the relevant outcomes” (Maguire & John, 2006, 72).

Intelligence and analytical products: This element of ILP overlaps with the SARA (Scanning, Analysis, Response, and Assessment) model of problem-oriented policing (Clark & Goldstein, 2003; Eck & Spelman, 1987; Scott, 2000). There are four intelligence products and four analytical techniques. The latter identifies the former one. The key intelligence products include: (1) strategic assessment, (2) tactical assessment, (3) target profiles, and (4) problem profiles (Maguire and John, 2006). Likewise, the four analytical techniques are explained by Innes, Fielding, and Cope (2005, 44) as follows:

1. *Criminal Intelligence*: detailing the activities of “a known” suspect or suspects.
2. *Crime intelligence*: enhancing the police’s understanding about a specific crime or series of crimes.
3. *Community Intelligence*: based upon data provided to the police by “ordinary” members of the public.

6 Alternatively, Maguire and John (2006, p.73) contend that “intelligence products are created on the basis of a range of nine analytical techniques (results analysis, crime pattern analysis, market profile, demographic/social trend analysis, criminal business profiles, network analysis, risk analysis, target profile analysis, operational intelligence assessment).”
4. **Contextual Intelligence**: relating to wider social, economic and cultural factors that may impact upon levels of crime and patterns of offending.

The intelligence or information that comes from analytical tactics help to assess strategies and operational tactics that optimally fit to identified target profiles and problem profiles. Once limited resources are allocated to prioritized problems, the Tasking and Coordinated Group control and evaluate the operational success in a regular time period, usually every six months (Maguire & John, 2006).

Taken together, ILP adopts top-down management or rational bureaucratic model in an enabling way. For instance, it uses formalization of the existing bureaucratic model to standardize only the best practices for future organizational memory. Similarly, it employs enabled hierarchy by activating a “Tasking and Coordinated Group.” Recall that the TCG comprises all resource owners including police officers and community members. In this way, both police supervisors, police officers, and various resource owners meet on the same page to solve problems pertinent to a specific level (i.e., local). Finally, ILP uses rational bureaucracy to utilize expert knowledge (specialization) with its advance analytical tactics. In this way, ILP efficiently utilizes rational bureaucratic model to solve current problems and to prevent future problems.

**Defining Intelligence-Led Policing**

Even though intelligence-led policing is the preferred policing strategy in many police departments, especially in the United Kingdom, there is no consensus among scholars regarding its definition, goals, mission, and objectives (McGarrell et al., 2007; Baker, 2009; Ratcliffe, 2008). The lack of clarity regarding ILP stems from earlier uses of the term, particularly those that refer to policing terrorism-related crimes.
**Intelligence-Led Policing is a Product of Anti-Terrorism Policies**

The term “intelligence” is generally associated with terrorism and homeland security and, due to this association ILP has been often viewed as a function of terrorism rather than daily police activities (McGarrell et al., 2007). The 9/11 terrorist attacks in the United States accelerated the necessity of intelligence-sharing to combat terrorism. For instance, in the U.S., law enforcement agencies have been urged to develop ILP under the plan of “National Criminal Intelligence Sharing Plan (NCISP)” to fight terrorism more effectively (McGarrell et al., 2007). However, the origin of ILP reveals that it was developed as a pure response to increased community crimes during budget crises. Although Level-3 ILP generates strategic planning against organized crime and terrorism, ILP is actually a policing strategy that independently emerged from terrorism and terrorist events. Given this, Taylor, Kowalyk, and Boba (2007) have recently proposed using the term “information-led policing” instead of intelligence-led policing.

**Intelligence-Led Policing is a Sub-form of Competing Policing Strategies**

In some studies, problem-oriented policing is compared with ILP, claiming that “while problem-oriented policing allows space for the intelligence-led policing, the reverse does not hold” (Tilley & Dando, n.d.). More specifically, Tilley (2003) contrasts ILP with problem-oriented policing using the following table:

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Intelligence-led policing</th>
<th>Problem-oriented policing</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.Problem addresses</td>
<td>Poor detection rates</td>
<td>Demand exceeding capacity</td>
</tr>
<tr>
<td>2.Critique of traditional policing</td>
<td>Ineffective at clearing crime</td>
<td>Ineffective in dealing with spiralling demand</td>
</tr>
<tr>
<td>3.Police mission</td>
<td>Law enforcement</td>
<td>Deal with police relevant problems</td>
</tr>
<tr>
<td>4.Scope of policing</td>
<td>Narrowed to law enforcement</td>
<td>Police function defined-broader than enforcement</td>
</tr>
<tr>
<td>5. Core drivers</td>
<td>Intelligence units/Tasking and Coordinating Groups</td>
<td>Analysts/data</td>
</tr>
<tr>
<td>-----------------</td>
<td>---------------------------------------------------</td>
<td>---------------</td>
</tr>
<tr>
<td>6. Openess to others</td>
<td>Enforcement contingent</td>
<td>Problem contingent</td>
</tr>
<tr>
<td>7. Problem diagnosis</td>
<td>Bad people</td>
<td>Unintentional crime opportunities</td>
</tr>
<tr>
<td>8. Intervention focus</td>
<td>Person</td>
<td>Event pattern</td>
</tr>
<tr>
<td>9. Analytic inputs</td>
<td>Evidence/intelligence</td>
<td>Data</td>
</tr>
<tr>
<td>10. Technology</td>
<td>Computerized intelligence relating cases</td>
<td>Computers and software for aggregate analysis</td>
</tr>
<tr>
<td>11. Preferred tactic</td>
<td>Arrest</td>
<td>Any-problem-contingent</td>
</tr>
<tr>
<td>12. Preferred control mechanism</td>
<td>Incapacitation</td>
<td>Any, but especially blocked opportunity</td>
</tr>
<tr>
<td>13. Key police quality</td>
<td>Action/brawn</td>
<td>Reason/brain</td>
</tr>
<tr>
<td>14. Main Indicator</td>
<td>Serious/prolific villains caught</td>
<td>Police functions performed effectively</td>
</tr>
<tr>
<td>15. Expected benefit</td>
<td>Reduced crime</td>
<td>Reduced crime and other police related problems</td>
</tr>
</tbody>
</table>

Source: Adopted from Tilley (2003).

Although Table 1 contains many overlaps between ILP and problem-oriented policing, there are also some distinctions. These distinctions likely stem in part from the vague definition of ILP. It is also likely that these distinctions are based on differences across scholars and practitioners. For instance, advocates of problem-oriented policing view ILP as traditional policing with a fresh name. Alternatively, advocates of ILP view problem-oriented policing as naive and ineffective (Tilley & Dando, n.d.). Regardless, Table 1 above does not accurately reflects the core elements of ILP as discussed previously. For example, ILP uses the same tools of problem-oriented policing (SARA – Scanning, Analysis, Response, and Assessment) to address problems in the community (Ratcliffe, 2008; Ratcliffe, forthcoming; Greene, 2000). In addition, ILP employs an advanced data-driven approach that yields high detection of crimes and criminals. Therefore, poor detections rates for crime and criminals for the ILP is likely an inaccurate description.
An additional disputable proposition resulting from the description of ILP in Table 1 is that ILP is portrayed as a mere enforcement model. Note, however, that origins of the ILP indicate that the strategy focuses on community priorities in an effort to gain community satisfaction and increase police legitimacy. In addition, ILP strategies at Level-1 provide for a close working relationship with the community (basic command level or beat level) to identify community problems and to gather intelligence to identify community priorities in terms of crime reduction (Maguire & John, 2003).

Some scholars have argued that intelligence-led policing is an antithesis of the community policing because of its operational mechanism (top-down management) (Ratcliffe, 2005). This notion is not necessarily true because ILP still prioritizes the needs of the community in its operations. Peterson (2005), for instance contends that ILP and community policing complete each other. The only difference between community oriented-policing and ILP is that ILP uses rational-legal bureaucracy of the police organization for the implementation of community policing. In this respect, ILP more closely resembles COMPSTAT policing. However, Baker (2009) argues that ILP has managerial broadness that makes it unprecedented compared to other policing strategies.

A final likely inaccuracy in Tilley’s comparison of the two approaches is the reporting that ILP focuses only on prolific offenders to tackle crime more effectively. In contrast, ILP also concentrates on other crime patterns (i.e., hot spots, repeat victimization). Many scholars have the misconception that ILP focuses on prolific offenders, stemming from Ratcliffe’s influential (2008:89) definition of ILP. He defines ILP as:

…a business model and managerial philosophy where data analysis and crime intelligence are pivotal to an objective, decision-making framework that facilitates crime and problem reduction, disruption and prevention through both strategic
management and effective enforcement strategies that target prolific and serious offenders.

Since Ratcliffe (2008) limits ILP efforts in his definition to only prolific and serious offenders, ILP has been thought of separately from crime prevention techniques. The origins of ILP, however, reveal that it focuses on “managing crime and criminals, managing localized disorder, managing enforcement and community issues, and reducing opportunities for crime” (John and Maguire, 2006: 71). Given this context, Ratcliffe’s definition of ILP is non-inclusive of the core principles of the ILP. Ratcliffe (2003) does concur that there is no agreed upon definition for ILP in the literature. For purposes of this study, only taking into account Ratcliffe’s (2008) incomplete definition leads to misconceptions about ILP and the likely impact of ALPR units.

In contrast to Ratcliffe’s oft-used definition of ILP, Wigget, Walters, O’Hanlon, and Ritchie (2003: 113), define ILP as allowing for “a clear understanding of crime and criminality by identifying which criminals are active, which crimes are linked and where problems are likely to occur.” This definition does not restrict ILP efforts to only prolific offenders, and more clearly applies to the use of ALPR units for crime prevention efforts.

A more inclusive description of the ILP is “ideally a strategic, ‘rational’ response to crime ‘problems’ based on careful analysis of crime patterns and intelligence data, and involving the ‘targeting’ of people, locations or activities thought to pose future threat, rather than simply reactions to reported past offences” (Maguire and John, 2006: 82). This definition, at first glance, contains similar themes with the earlier policing strategies, including problem-oriented policing, community policing, hot spots policing, and COMPSTAT policing. While ILP builds on the successful themes of the earlier policing
strategies, it also targets future problems. Given this context, ILP distinguishes itself from earlier policing strategies by focusing on persistent problems more proactively. The distinction between ILP and the earlier policing strategies can be also seen in its data-driven methodology. As previously discussed, the data-driven approach develops solutions for persisting problems independent of the current recurring problems (i.e., high accumulation of crime in specific places). ILP focuses on “here and after/future” instead of the “here and now” as was the primary focus of earlier policing strategies. In this context, ILP provides more promising results for crime control. Exploring the origins of ILP allows for more clarity in its goals, mission, and objectives.

Most pertinent to this study is that the framework and the definition of the ILP perfectly fit the usage of ALPR systems. ALPR systems collect and store much information about license plate numbers and associated with individuals. Analyzing patterns of individuals involved in criminal activities (i.e., drug dealing activities, gang activities) may give new insights to police-decision makers about future-related problems in the community. In addition, since ALPR systems collect and store the data independent of previous incidents, ALPR systems inherently focus on likely future-related problems as ILP suggests. Within this context, ALPR systems directly match ILP’s core elements and definition (reviewed above), and therefore provide a strong empirical test of the effectiveness of at least one innovative technology tool used for ILP.

**Summary**

This summary of various policing strategies suggests that proactive policing does work in reducing crime. In addition, as Braga and Weisburd (2006) contend, community-oriented policing and problem-oriented policing represent the most radical departures
from the standard applications of policing. Within the notion of community-oriented policing, the police recognized the necessity of the community’s role in preventing crime and in so doing increased the community’s perceptions of legitimacy of the police.

Even though community-oriented policing is “a perceptual revolution and alignment in understanding the core problems traditional policing has suffered for centuries” (Duman, 2007, 10), police organizations struggled to properly implement it because of their organizational structure (formalized, hierarchical, and specialized) (Bailey, 1988; Braga & Weisburd, 2006). Likewise, Walsh and Vito (2004) believe that community-oriented policing is an important paradigm shift, but its impact is more philosophical than organizational. To manage successful implementation of the philosophy of community-oriented policing in police departments, COMPSTAT policing has introduced managerial accountability. Similarly, ILP heavily draws its roots from the philosophy of community policing (Baker, 2009; McGarrell et al., 2007; Peterson, 2005) but recognizes the importance of managerial accountability for innovative applications.

Taken together, current policing strategies have directly evolved from the previous inadequacies identified in failed strategies. These evolutionary footprints suggest that ILP is currently the most comprehensive style of policing that also contains the principles of prior innovative policing strategies, including community-oriented policing, problem-oriented policing, and COMPSTAT. Due to this broadness of ILP, it is currently being used by many police departments in their daily police activities. The technological advances that will assist in the development and use of ILP are the subjects of this dissertation research.
In this context, technological innovations in policing that collect timely and valid data, like ALPR systems, are the main prerequisites of intelligence-led policing. By introducing integrated technologies to police departments, police should increase their data driven capabilities, independent of past incidents (i.e., call for service, hot spots). ALPR technology is the one way of collecting and storing information independently from past occurring events. In this sense, by applying ALPR systems within the context of ILP, police decision-makers can identify future-related problems more clearly and allocate resources to the places where the need is greatest. Such strategic approaches also reduce the cost of daily police activities, while increasing overall police effectiveness.
CHAPTER III
AUTOMATIC LICENSE PLATE READER (ALPR) TECHNOLOGY AND INTELLIGENCE-LED POLICING

Due to the promising nature of ILP, many police departments have begun to implement this approach to reduce and prevent crime (Ratcliffe & McCullagh, 2001). ILP, however, requires a high volume of data collection and subsequent analysis to develop effective interventions. In an attempt to fulfill the requisite needs of intelligence-led policing (i.e., data collection), police organizations are trying to increase their data-driven policing capability. The Automated License Plate Reader (ALPR) is one technological innovation that many police departments have implemented to enhance their data collection and analysis capabilities. This chapter describes the working system of ALPR technology, including the scope and average cost estimates for ALPR systems, and reports specific details about Cincinnati Police Department’s ALPR deployment. The scant literature on empirical studies of ALPR effectiveness is also reviewed, followed by an application of crime prevention theories.

Automatic License Plate Reader (ALPR) Systems: How it works

The Automatic License Plate Reader (ALPR) technology is an infrared camera system that can scan images of license plates and convert them into numbers and letters by using Optical Character Recognition (OCR). Once the image is converted to text string, this information can be compared with other data/databases. This procedure is summarized in Figure 1. The camera first captures a license plate with its illuminated (infrared) camera. ALPR processors identify the license plate number that comes in a variety forms (i.e., different state license plate numbers, letters, characters, and colors). Then the OCR engine reviews the images identified by the ALPR processor and converts
the best images to text strings. Finally, the converted text string (license plate number) and image of the vehicle are presented in the application software (Federal Signal Public Safety Systems, 2008). After this process, obtained information (text string) is compared to law enforcement databases with pre-identified license plate numbers of vehicles known to be or suspected of being involved in criminal activity. If the sent information matches an entry in an included database, an alert appears on the police officer’s computer or at a command center (if the scan came from a fixed ALPR site) that a suspect or “hit vehicle” is in close proximity to the ALPR system (Chen, Lin, Yang, 2006; Manson, 2006; ELSAGNA, n.d.). The traditional method for police officers to conduct license plate checks involves an officer entering the license plate number of a suspicious vehicle into a mobile data terminal to learn the status of the vehicle. Using this method, an officer can check approximately 150 vehicles during a typical shift (Manson, 2006). In contrast, ALPR technology allows for the automatic scanning of up to 3,600 vehicles during the same time period (ELSAGNA, n.d.; Combs, Neville, & Whitton, 2009).

<table>
<thead>
<tr>
<th>Camera</th>
<th>ALPR Processor</th>
<th>OCR Engine</th>
<th>Application Software</th>
</tr>
</thead>
<tbody>
<tr>
<td>Illuminate and Capture</td>
<td>Detect the Plate</td>
<td>Read the Plate</td>
<td>Present Results</td>
</tr>
</tbody>
</table>

Figure 1. Components of ALPR Technology. Adapted by FSPSS, 2008.

7 In ALPR policing terminology, a “hit vehicle” refers to a vehicle with a license plate number that is scanned by an ALPR unit and matches a law enforcement database.
**Scope of ALPR Systems**

ALPR systems are used to accomplish multiple law enforcement purposes including: Traffic enforcement, parking management, tollbooth operations, secure area access control, collection of delinquent taxes and fines. They also assist with larger law enforcement objectives including: Homeland security and terrorist interdiction, AMBER alerts, gang and narcotic interdiction, the identification of suspended and revoked drivers, and the recovery of stolen vehicles (ELSAGNA, n.d.). One of the fastest growing applications of ALPR systems in police agencies across the United States is in the identification of vehicles whose license plates are involved in some type of criminal activity (ELSAGNA, n.d.). It is estimated that as much as 70 percent of all perpetrated crime involves the use of a vehicle (ELSAGNA, n.d.). In this sense, targeting license plate numbers gives police departments a substantial opportunity to capture criminals and to control future-related crimes. Used in this capacity, ALPR cameras (either mounted to police vehicles or stationary structures) automatically take photographs of vehicle license plates.

**Average cost of ALPR Systems**

Applying ALPR technology to daily police activities requires significant financial investment. The cost of a single ALPR mobile unit (mounted in a police patrol vehicle) is approximately $20,000; fixed or site ALPR units (mounted to stationary structures like bridges) are even more expensive (approximately $100,000). Despite the high cost of ALPR systems, many police departments have put forth the investment of scarce resources in this technology because it is believed to easily increase their data-
driven/intelligence-led policing capability (Gaumont, 2009). Indeed, police departments
in all 50 states have installed or are installing ALPR systems (ELSAGNA, n.d.).

**Cincinnati Police Department’s ALPR Deployment**

Similar to the technological innovations being applied in police departments
around the world, the Cincinnati Police Department (CPD) recognized ALPR technology
as one of the main requisites of intelligence-led policing. The CPD explains the aim of
ALPR technology for their department as follows:

*Intelligence gathering* by creating a *regional* network of fixed ALPR cameras that
capture and track *high interest* vehicles and mobile ALPR units that capture and
track regional criminal activity resulting in significant apprehensions while
increasing *information sharing* by building a powerful regional database of
vehicles available to all SOSINK\(^8\) agencies for investigative purposes (Combs et
al., 2009).

It has been officially reported that the CPD strategically deploys ALPR mobile units to
certain places for different reasons and purposes, including:

- High crime locations, such as bars
  Covert investigations like gang funerals
- Patrol major events such as festivals and parades
- Patrol critical infrastructures
- Operating a Vehicle under the Influence (OVI) check points (Combs et al.,
  2009).

Despite this documented description, based on observations of patrolling patterns and
discussions with CPD line personnel, there appears to be no current systematic daily
deployment pattern for ALPR equipped vehicles. Rather their daily deployment appears
to be idiosyncratic and haphazardly varies across police districts, to the point of being
random.

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8 Southwest Ohio/Southeast Indiana/Northern Kentucky
The Importance of Relational Databases and ALPR Systems

As described above, there are a number of ways to utilize ALPR systems. Regardless of the mission of ALPR, however, the most important component of its use is database management. ALPR systems automatically communicate with a database server; however, the database must be ready for the sent information. For example, if the database does not include suspected gang members’ vehicle plate numbers, ALPR cannot be fully utilized as a tool for gang enforcement. Therefore, database management, which is often neglected in police departments (Webb, Smith, & Laycock, 2004), is crucial for the maximum effectiveness of ALPR.

Furthermore, police departments usually separately store data collected for different purposes. For example, the homicide unit only keeps and stores homicide cases in their database, while the gang unit stores gang data in their respective database. There may, however, be a close relationship between gang affiliations and homicide. Keeping databases separately from each other may hinder crime analysts from seeing this pattern, whereas a more complete picture, based on shared information from multiple databases, might allow for a more effective prioritization of crime problems and allocation of limited resources to relevant interventions (Manning, 2001). Without integrated or relational databases, the roots of many crime problems cannot be thoroughly identified and understood.

Other scholars have argued that even the effective storing of data into electronic databases does not automatically turn this information into interpretable knowledge capable of guiding decision makers in the development of effective interventions. Bruce (2004, 12) argues that “data become information when it is effectively analyzed, and
Information becomes knowledge when it is effectively communicated,” making clear that accessing and analyzing the data are not meaningful for police departments unless it is effectively communicated and shared among stakeholders (i.e., different units, police officers). Likewise, Ratcliffe (2008) argues that knowledge becomes intelligence when it influences decision makers. In other words, when the knowledge gives clear options for intervention to senior officers, it becomes intelligence for a police department.9 In light of this discussion, any crime analysis should end in intelligence regarding crime patterns and correlates that assists operational and administrative personnel in the appropriate prioritization of and development of investigative decisions, plans, and tactics (Cope, 2004; Gottlieb, Arenberg, & Singh, 1994).

Simply stated, ALPR is only as useful to police agencies as the information included in its searchable databases and the effective analysis and interpretation of these data. Technological advances alone cannot increase police effectiveness when, as Manning (2001, 83) explains: “The lack of infrastructure of support and interpretation; the distribution of the information, isolated and unintegrated databases, and lack of online access by patrol officers, renders the extant software and analytic capacity ineffectual.”

**Empirical Studies of the Effectiveness of ALPR**

Since the use of ALPR systems is still in its infancy in policing, empirical studies of the effectiveness of this technology are very limited, particularly studies of its use in the United States. Anecdotally, most police departments using ALPR report increases in efficacy associated with its implementation. Furthermore, the few empirical studies on

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9 This process, as described by Ratcliffe (2008), is formalized with an acronym DIKI (data-information-knowledge-intelligence).
this topic indicate preliminary success of this technology, improving public safety and increasing effectiveness (Russell, 2009). For example, British Police Forces evaluated ALPR technology for 13 months in 2002. Within this time frame, the team using ALPR stopped 180,543 vehicles. From these stops, officers

- arrested 13,499 persons, including:
  - 2,263 arrests for theft and burglary
  - 3,324 arrests for driving offences (for example driving whilst disqualified)
  - 1,107 arrests for drugs offences
  - 1,386 arrests for auto crime (theft from and of vehicles);
- recovered or seized property, including:
  - 1,152 stolen vehicles (valued at over £7.5 million)
  - 266 offensive weapons and 13 firearms
  - drugs worth over £380,000 from 740 vehicles
  - stolen goods worth over £640,000 from 430 vehicle (Watson & Walsh, 2008: 5).

Using ALPR technology, the British Police Forces increased its number of arrests 10 times compared to national average arrest rate (Watson & Walsh, 2008).

Other studies indicate the evaluation of ALPR systems can vary based on certain factors, such as the type of crime. Specifically, the Royal Canadian Mounted Police (RCMP) used the ALPR systems to focus on an increase in the number of auto thefts in 2006. The analysis of ALPR data, however, indicated that ALPR patrol vehicles only identified 1 percent of stolen vehicles during the time period of October 10 and October 31, 2006. The reason for this low identification rate is that the license plate numbers of stolen vehicles are often altered or the vehicle is left unattended after the commission of the crime (Gaumont, 2009). Therefore, the evaluation of ALPR systems in terms of reducing and preventing crime may vary based on different types of crime.

Although the above studies –evaluating ALPR technology by comparing the number of arrests before and after the implementation of ALPR systems– reported
anecdotal successes, the effectiveness of ALPR systems is still in question because more arrests do not directly ensure the effectiveness of ALPR systems. Moreover, in an effort to evaluate the impact of ALPR technology on crime and arrest rates, crime displacement arises as a threat for crime prevention efforts; conversely diffusion of crime control benefits may also occur (Clarke & Weisburd, 1994; Weisburd, Wyckoff, Ready, Eck, Hinkle, & Gajewski, 2006). Given this context, no empirical study has evaluated the effectiveness of ALPR technology (i.e., specific targeted approaches to reduce crime, increasing reported crime arrest rate) by considering the tenets of crime prevention theories. Therefore, the effectiveness of ALPR technology is still unknown in the policing literature.

**ALPR and Crime Prevention Theory**

Crime prevention studies are designed to change the environmental layout of a place in order to reduce crime (Clarke, 1997). While this method is promising (Eck, 1993; Guerette, forthcoming), other aspects of crime prevention, such as administrative systems and data management, are usually neglected (Webb, Smith & Laycock, 2004). Recent technology-based applications employed by police departments have revealed that data-driven approaches can increase crime prevention effectiveness in terms of cost, time, and accuracy. This section briefly summarizes relevant theories of crime prevention and illustrates how they can apply to the more effective use of data-driven approaches like ALPR.

**Optimal Allocation of ALPR Units with the Principles of Crime Prevention Theory**

The main premise of crime prevention theories is that crime is not randomly distributed across time, place (i.e., address intersections, schools, playgrounds) and
individuals (i.e., repeat victimization) (Astor, Meyer, & Behre, 1999; Brantingham & Brantingham, 1981, 1982; 1993, 1995, 1999; Lauritsen & Quinet, 1995; Sherman et al., 1989). Both individual level theories (i.e., routine activity and life style theories) and contextual level theories, such as defensible space theory, attempt to explain various natures of crime opportunities that produce concentrated patterns of crime.

**Individuals and Community Activity Patterns and Criminal Opportunity**

Individual level theories of crime prevention can also be thought of as theories based on human and community activity patterns (Cohen & Felson, 1979; Eck & Weisburd, 1995). For example, Cohen and Felson’s (1979) routine activity theory developed out of a need to take into account the effects of societal structural changes on the habitual human patterns of individuals (tempo, rhythm, and timing). Cohen and Felson argued that during the 1960s and 1970s, female labor participants and leisure activities increased (tempo), leaving homes unattended more often. This new structural change created a new opportunity for likely offenders to burglarize homes in the absence of dwellers. In addition, augmentation of both leisure and vocational activities also boosted the chance of being exposed to criminals (timing). These new structural changes inspired Cohen and Felson (1979, p. 588) to view criminal opportunity as the “spatial and temporal converges of motivated offenders, suitable targets, and absence of guardianship.”

Rational choice theory (Clarke & Cornish, 1985) and crime pattern theory (Brantingham & Brantingham, 1981, 1993, 1999) also explain individual level victimization along with contextual covariates. In this context, Cornish and Clarke (1986) incorporate both individual (demographics, precipitator factors/motivation,
judgment of offenders for a specific crime, and cognitive psychology) and contextual level factors (background factors, social learning theory, and the impact of informal social control for continuing and desisting from crime) into their theory to explain criminal opportunity by the view of offenders. Given this context, places that offer more opportunity than risk from the view of criminals lead to crime concentration. Empirical studies suggest that background factors, such as street culture (Jacobs and Wright, 1999), and environmental factors for criminal opportunity (Brensilber & Petrosino, 2003) are important in explaining the decision making processes of offenders.

Drawing on psychological research, Cusson (1993) argued that deterrence policies can be more effective if powerful control over situations can be managed. ALPR may significantly reduce the transportation capability of offenders, because they may fear being watched (i.e., an increase in guardianship), which in turn reduces crime. For instance, Los Angeles Police Department significantly reduced the crime in a recreation park area by simply installing CCTV cameras (Davis, 2007).

**Place Features and Criminal Opportunity**

Contextual level theories of crime prevention focus on how place features (e.g., physical design, land use) contribute to criminal opportunities. The theoretical explanation of spatially-patterned behavior comes from early urban designers (Jacobs, 1961; and Newman, 1972) and from the work of Brantingham and Brantingham (1981; 1982; 1993; 1995; 1999). The first one is called *defensible space theory* and the latter is called as *offender search theory* in crime prevention literature.

Defensible space theory explains criminal opportunity with the lack of physical/housing design. The theory posits that poor housing design of an area gives less
surveillance to its residents that eventually impede neighborhood watch and cohesion against crime (Jacobs, 1961; Newman, 1972; Taylor, 1992; Taylor & Harrell, 1996). The theory contends that housing design, circulation patterns, and internal boundaries of an area can make individuals vulnerable to victimization. The main assumption of defensible space theory is that features that offer better surveillance, demarcation between public and private places, areas that are closed to well-used places, and places that are less permeable are less likely to provide opportunity for criminal victimization. Studies show that the volume of traffic (Brantingham & Brantingham, 1982; Donnelly and Kimble, 1997; Mathews 1993), permeability of places (White, 1990), and housing design (Greenberg, Rohe, & Williams, 1982; Newman, 1995) are significant predictors of the non-randomness of crime and criminal opportunity.

Later crime prevention studies also incorporated social context of places into physical features of places in order to stress how both physical features and social context of places influence spatial concentration of crime (Taylor & Harrell, 1996). In this context, Brantingham and Brantingham (1981) posit that crime occurs when an individual with some readiness to commit crime comes together with a target that offers sufficient opportunity for a crime. In their various studies, Brantingham and Brantingham tie offender motivation and perception to environmental factors to explain crime (1981; 1993, 1995, 1999). They posit that target selection is a multistage process from neighborhood to street to site selection. Characteristics of an environment emit many cues and signals in terms of its physical, social, economic, cultural, and legal features. These cues, cue signals and cue clusters are identified and learned by offenders. Once these cues are learned, they become fixed and reinforce individuals (also known as crime
template) to commit crime. Offenders seek similar opportunities or opportunity patterns to commit crime.

Brantingham and Brantingham (1981, 1999) explain crime concentration or crime patterns with five concepts: nodes, paths, edges, crime generators, and crime attractors. Nodes are centers of daily routine activities, such as home, school, work, and restaurants. Paths are defined as routes that connect different nodes. Edges are natural boundaries that serve to break down an area into homogenic places. For instance, if an area is bordered with commercial places, it is expected that that place suffers more crime. Crime generators are places where people generally go for their daily activities (i.e., shopping malls) independent from criminal activity. Crime attractors are places where people go to take advantage of known criminal opportunities.

In this context, Brantingham and Brantingham posit that individual and aggregate crimes concentrate or accumulate around major nodes and along paths because people know these places due to their daily routine activities. In other words, awareness of action brings awareness of places for criminal activities. The traffic flow of paths is also important because if paths provide higher traffic patterns, the awareness of place of individuals increase as a result of awareness of action. Eck (1993) proposes that crime concentration or crime patterns decrease as the familiarity of offenders for nodes and paths decay. Empirical studies found that a city’s major nodes, traffic patterns, differential land use (in terms of edge effects), such as bars, liquor stores, playgrounds, and schools, significantly increase crime concentration or crime patterns in an area (Brantingham & Brantingham, 1982; Donnelly & Kimble, 1997; Kurtz, Koons, & Taylor,
Based on this discussion, these theories suggest that optimal crime reduction can be accomplished through strategically allocating limited resources to the places that show spatial and temporal patterns of crime (Becker, 1968). Specifically, strategically directing ALPR mobile units to hot spot areas or placing stationary ALPR units along particular paths may bring more success in terms of crime reduction.

Criminal vehicles, however, are a different unit of analysis for crime prevention theory. They are neither individuals nor places. No empirical study has tested whether criminal vehicles (i.e., a vehicle utilized by a criminal offender) are more likely to hover in certain places that display characteristics favorable to criminal opportunities. On the other hand, existing literature suggests that offenders specifically seek out criminal opportunities based on the characteristics of environment (Brantingham & Brantingham, 1982; White, 1990). In this context, there is a close connection between crime prevention theory (i.e., offender search theory, crime pattern theory) and ALPR mobile units since the driver of the vehicles can be offenders searching for criminal opportunities. If this is the case, it is expected that ALPR mobile units would be most likely to hit criminal vehicles in the types of places described in the crime prevention theories reviewed above.

Upon discovering this possible pattern, ALPR mobile and fixed units can be more optimally allocated for maximum crime reduction.

In conclusion, crime prevention theory may help police departments to identify where ALPR movable units most likely encounter with hit vehicles. This possible identification can increase the effectiveness of intelligence-led policing through
allocating scarce resources to prioritized places where public safety is at the maximum need. In addition to crime prevention theory, integration of separate databases may also enhance crime prevention efforts by building more sensitive databases to future threats.
CHAPTER IV
RESEARCH QUESTIONS, DATA, AND METHODS

As noted in the literature reviews in Chapters 2 and 3, the move toward intelligence-led policing is becoming commonplace in police agencies across the United States. Technological innovations that support this approach are also increasing in popularity as police departments seek out effective ways to increase their data-driven policing capabilities. The use of Automatic License Plate Readers is one such promising technological innovation. Unfortunately, the effectiveness of the ALPR in reducing and preventing crime, and as a tool for intelligence-led policing, has been neglected in empirical research, particularly in examinations of its use in the United States. The goal of the current research is to empirically examine the use of ALPR by the CPD and evaluate its effectiveness in reducing crime and utility as a tool to support police departments interested in implementing an intelligence-led policing approach. The remainder of this chapter first lays out the research questions and hypotheses to be explored, and then describes the data and analytical plan that will be employed to examine these questions and hypotheses. Finally, descriptive statistics and preliminary results of these proposed analyses are presented.

Research Questions and Related Hypotheses

Given this context, this study aims to systematically answer two questions regarding the effectiveness and use of ALPR systems to assess whether this data-driven approach is promising for law enforcement efforts at reducing and preventing crime. The first research question is designed in order to evaluate whether ALPR systems increase the effectiveness of the Cincinnati Police Department in terms of making more arrests while ensuring less cost. The second research question seeks an answer to whether
ALPR systems can be more strategically deployed to increase the current effectiveness of ALPR mobile units.

**Research Question 1:**

The first research question to be explored is determining whether ALPR technology is an effective data-driven tool over traditional policing in terms of making more follow-up arrests (reported crime arrests). The following are three specific hypotheses to be tested based on this research question:

*Research Question 1, Hypothesis 1: Arrests.* It is expected that ALPR mobile units increased the number of follow-up arrests in the City of Cincinnati compared to the number of follow-up arrests in previous years.

*Research Question 1, Hypothesis 2: Manpower.* Examinations of manpower will establish that the percentage of follow-up arrests for officers working for ALPR units will be higher than the percentage of follow-up arrests for officers working for non-ALPR units.

*Research Question 1, Hypothesis 3: Costs.* Officers with ALPR units will make more proactive arrests compared to non-ALPR units while ensuring less cost to the Cincinnati Police Department.

**Research Question 2:**

The second research question examines how ALPR units can be most effectively deployed and explores whether ALPR-equipped vehicles are more likely to encounter criminal vehicles in the types of places predicted by crime prevention theories. Also to be considered is if ALPR vehicles can be more strategically deployed based on findings
that demonstrate any patterns for hit (criminal) vehicles\textsuperscript{10}? Based on the principles of various crime prevention theories reviewed in Chapter 3, this study proposed the following three hypotheses:

\textit{Research Question 2, Hypothesis 1a:} Streets compositions (i.e., high crime) increase the detection of criminal vehicles, controlling the effects of neighborhood covariates (i.e., concentrated disadvantage).

\textit{Research Question 2, Hypothesis 1b:} ALPR equipped vehicles will more likely identify criminal vehicles on city major nodes\textsuperscript{11} compared to non-major city nodes, controlling for neighborhood characteristics.

\textit{Research Question 2, Hypothesis 2:} ALPR equipped vehicles will more likely identify criminal vehicles in places/streets where recorded crime level is high compared to streets with lower crime levels. In addition, the impact of recorded crime levels on the identification of criminal vehicles will not be negated by neighborhood covariates.

\textit{Research Question 2, Hypothesis 3:} ALPR equipped vehicles will more likely identify criminal vehicles in places that are close to residences of identified criminal vehicle drivers compared to non-resident locations. In addition, this relationship will not be negated by neighborhood covariates.

\textbf{Data}

The current study proposes to use multiple databases provided by the Cincinnati Police Department to examine the research questions posited above. Prior to describing these data, a brief description of the CPD’s implementation of ALPR is provided below.

Thereafter, the specific data to be used will be described.

\footnote{Hit/criminal vehicles refer to vehicles with registered owners or drivers who are involved in any crime and are being sought by the police.}

\footnote{City major nodes emphasize high volume of traffic on a street.}
Cincinnati Police Department’s Implementation of ALPR

The Cincinnati Police Department (CPD) implemented ALPR in April 2008. Currently, the department has 13 police patrol vehicles equipped with ALPR. Of those, eight ALPR patrol vehicles are specifically deployed in different Cincinnati Districts, four are used in Hamilton County (outside of CPD jurisdiction), and one is used in Green Township. The long term goal of the CPD is to increase the number of ALPR patrol vehicles from 13 to over 40. Specifically CPD is seeking funding and is planning to purchase 42-62 units as it becomes fiscally possible. In addition to mobile ALPR vehicles, the CPD has future plans to implement 26 site cameras (fixed cameras) in certain locations (i.e., bridges) to increase the scope of the ALPR technology in the city.

In the city of Cincinnati, ALPR mobile units identified roughly 2.0% of total hotlist vehicles\textsuperscript{12} within a one-year study period. This internal review demonstrated that over 1,000 misdemeanor arrests and 103 felony arrests have been made with the help of ALPR within this period and 137 stolen vehicles were recovered. Moreover, anecdotal accounts from the Cincinnati Police Department suggest that the use of ALPR technology has been an invaluable resource to provide information necessary for gang and other law enforcement efforts. It is unclear, however, whether traditional policing efforts could have produced similar arrest rates in the absence of ALPR capability. Further, an empirical cost-benefit analysis of this technology has not been conducted.

\textsuperscript{12}“Hotlist” vehicles are the identified vehicles that are sought by the police because of some type of criminal involvement of their drivers.
ALPR and Other Data Sources

This study utilizes one year of ALPR data collected by the CPD from July 16, 2008 to July 15, 2009.¹³ For the current study, only data collected by the eight ALPR patrol vehicles deployed in the City of Cincinnati are utilized. ALPR units deployed in Hamilton County and Green Township are under the direction of different police agencies, and these geographic areas do not have city shape files available, which are necessary for ArcGIS mapping software. Therefore, this study includes 2,823,944 scanned license plate numbers, based on only the ALPR data provided by vehicles serving the City of Cincinnati from July 2008- July 2009.

The ALPR database contains entries for the following data fields: ALPR scan date and time, officer login name, geographic coordinates, control numbers for identified criminals, the scanned vehicle’s driver involved crime type, demographic characteristics of the scanned vehicle’s driver (e.g., date of birth, height, weight, eye color, and hair color), reason for ALPR stop, and police action as a result of traffic stop (i.e., felony arrest, issuing a ticket).

Incident Data: Incident-level crime data is also provided by the CPD. The incident-level crime database includes information related to Part 1 and Part 2 crimes. In addition, the database indicates whether the police classify the incident as “closed” (i.e., an arrest has been made) or whether the investigation is still pending (i.e., identification or investigation of perpetrators is still ongoing).

Arrest Data: Arrest data, provided by the CPD, include 2008 and 2009 Part 1 and Part 2 criminal arrests. The database provides detailed information about arrestees, such as:

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¹³ Although, as noted, the CPD began using ALPR in April 2008, in the initial months of its implementation there were some errors associated with data collection. These were resolved beginning in July 2008.
as race, gender, home address, control number for identification purposes, incident number, incident address, incident date, and time.

Closure by Arrest Data: The CPD also provided its closure by arrest database, which differs from the other arrest database in that it only contains follow-up arrestees (i.e., arrests resulting from incidents classified as “investigation pending”). When the perpetrator of an incident still under investigation is arrested by the police, this type of incident is marked as “closed by follow-up arrest.” This database includes follow-up arrest records from 2006 to 2009 and includes incident number, incident type, race, gender, and clearance/closure type (i.e., arrest adult, warrant issued).

Neighborhood Covariates: Census block information is derived from the 2000 U.S. Census and the CPD, which contain social and economic covariates at the block group level such as number of crime, number of liquor stores, percent non-white, median age, median income, percent female headed households, and percent vacant houses.

METHODS

Proposed Analyses for Research Question 1:

The first research question aims to systematically evaluate the impact of ALPR system in three different steps to discover whether this data-driven approach is promising for policing and crime prevention. In this context, there are three different hypotheses for Research Question 1. First, in order to test the impact of ALPR systems on the number of follow-up arrests made by the CPD, a comparison will be made between the number of monthly follow-up arrests\textsuperscript{14} before and after the CPD’s implementations of ALPR

\textsuperscript{14} Follow up arrests, available in the “closure by arrest” database described above are used for this comparison instead of regular arrest data because ALPR technology only alerts to license plate numbers that are included as suspicious or wanted in conjunction with still pending, rather than closed, investigations.
technology in July 2008. Because the unit of analysis is time for this test (e.g., months), interrupted time series analysis will be used. Specifically, the time-series analysis will compare the number of arrests per month for a three year period prior to the implementation of ALPR (2006-2008) with the last year’s number of arrests (2008-2009) to examine whether statistically significant differences in the number of arrests are evident. Regression analysis for time series is not an appropriate model because time points that are close to each other are generally highly correlated. For this reason error terms cannot be assumed as random which is a clear violation of regression models. To overcome this correlated error problem, different time series analyses were developed to clean correlated error and leave the random component of error terms (Box and Jenkins, 1976). Auto Regressive Integrated Moving Averages (ARIMA) models, available in SPSS 17, are one of these time series analyses that are generally used to predict the effectiveness of an intervention time point.

For the second and third hypotheses of Research Question 1, simple comparison techniques, such as two sample t-test, will be used. These hypotheses compare manpower and cost effectiveness of ALPR technology over traditional policing.

**Variable Measures for Research Question 1**

As described above, the impact of ALPR technology over traditional policing can be examined in three different analyses, including: 1) a comparison of the number of follow-up arrests between ALPR and traditional policing, 2) a comparison of manpower between ALPR and traditional policing, and 3) a comparison of cost effectiveness between ALPR and traditional policing.

*Dependent Variable-1*
There are two dependent variables of interest for this study. For the first comparison, the dependent variable is the “number of follow-up arrests per month.” Follow-up arrests from “arrest by closure database” are utilized for this comparison with ALPR data rather than regular arrest data because ALPR vehicles randomly scan license plate numbers and conduct arrests to randomly encountered criminal vehicles. On the other hand, traditional policing generally makes arrests during an incident (i.e., domestic violence). In order to compare the number of ALPR arrests with traditional policing arrests, similar arrest types should be compared with each other. As noted in the previous chapter, ALPR mobile units randomly patrol in the city and seek for pre-identified criminal vehicles. In other words, ALPR mobile units look for criminal drivers who were not arrested during an incident and sought by the police after the incident. Likewise, the Cincinnati Police Department has a database that contains follow-up arrestees who were not arrested during the incident but arrested after conducting follow-up investigations. For instance, the suspect of a domestic violence call may not be present at the time of incident, but detectives might have arrested that person after conducting a follow-up investigation. Since follow-up arrest procedure is very similar to the arrest process of ALPR systems, we selected the number of follow-up arrests as the dependent variable to obtain a fair comparison tool for the number of ALPR hits.

In this context, the monthly number of follow-up arrests beginning from January 2006 to July 2009 were included for this analysis (N=42 months). Because the ALPR technology was fully implemented in July 2008, monthly follow-up arrests from July 2008 to July 2009 reflect the sum of ALPR follow-up arrests and traditional policing follow-up arrests. Figure 1 depicts the monthly number of arrests before and after the
implementation of ALPR. Figure 1 suggests a clear seasonal effect on follow-up arrests. At the beginning of each year, follow-up arrests are very rare, and through the end of year, follow-up arrests visibly increase. There may be two reasons for this: 1) follow-up arrests accumulate starting from the first month (January) of the year; and 2) since follow-up arrests take a certain amount of time to finalize, high follow-up arrest accumulations occur towards the end of each year. Alternatively, the intervention time point (July 2008) in Figure 1 suggests that follow-up arrests tangibly increased compared to previous months.

**Figure 1. Number of Follow-up Arrests from January 2006 - July 2009**

![Graph showing number of follow-up arrests from January 2006 to July 2009 with ALPR intervention point marked.]

*Independent Variables*

The first independent variable for the comparison of the number of follow-up arrests before and after the implementation of ALPR technology is a dichotomous variable (the number of follow-up arrests done by *ALPR units* = 1) and (the number of follow-up arrests by *non-ALPR units* = 0). With the term of time series analysis, (1) describes intervention time points and (0) represents the others. The second independent
variable is the number of pending investigations for 2006 – 2009. As previously discussed, follow-up arrests occur when the police arrest the suspects of ongoing investigations. Therefore, the number of pending investigations must be added in the interrupted time series’ equation in order to control for the number of pending investigations per year.

Dependent Variable-2

The second dependent variable, which is related to the second and third comparisons, is the average number of follow-up arrests before and after the implementation of ALPR technology in the Cincinnati Police Department. In this context, the average number of follow-up arrest for the periods of January 1, 2006 – December 31, 2008 made by traditional policing units will be compared with the number of ALPR arrests for the period of July 16, 2008 – July 15, 2009 made by ALPR units. Using a three-year average will also minimize random fluctuations in monthly follow-up arrests. Table 2 displays the monthly averages of traditional follow-up arrests and the monthly number of ALPR follow-up arrests. Table 2 indicates that ALPR mobile units conducted 3.46 times more follow-up arrests than traditional policing (242 compared to 844).
Table 2. Number of Follow-up Arrests

<table>
<thead>
<tr>
<th></th>
<th>Traditional Policing</th>
<th>ALPR Technology</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Average Arrest</strong></td>
<td><strong># of Arrest</strong></td>
<td><strong># of Arrest</strong></td>
</tr>
<tr>
<td>January</td>
<td>4</td>
<td>49</td>
</tr>
<tr>
<td>February</td>
<td>3</td>
<td>76</td>
</tr>
<tr>
<td>March</td>
<td>5</td>
<td>59</td>
</tr>
<tr>
<td>April</td>
<td>6</td>
<td>74</td>
</tr>
<tr>
<td>May</td>
<td>5</td>
<td>80</td>
</tr>
<tr>
<td>June</td>
<td>11</td>
<td>47</td>
</tr>
<tr>
<td>July</td>
<td>17</td>
<td>13</td>
</tr>
<tr>
<td>August</td>
<td>17</td>
<td>88</td>
</tr>
<tr>
<td>September</td>
<td>21</td>
<td>29</td>
</tr>
<tr>
<td>October</td>
<td>31</td>
<td>63</td>
</tr>
<tr>
<td>November</td>
<td>45</td>
<td>109</td>
</tr>
<tr>
<td>December</td>
<td>78</td>
<td>157</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>242</td>
<td>844</td>
</tr>
</tbody>
</table>

Independent Variables for the Second Comparison – Manpower

As discussed above, the second comparison addressing the first research was the comparison of manpower between ALPR technology and traditional policing. In other words, traditional policing and ALPR arrests are compared based on the number of police officers assigned to the shifts. Because there are eight mobile ALPR units in the city of Cincinnati, 75 to 100 police officers were assigned to these vehicles and units. In contrast, traditional police arrests can be standardized based on the number of police officers assigned to line duties. After standardization, this study will identify any significant difference between ALPR and traditional policing units on the number of follow-up arrests made per officer as a measure of efficiency.

Given this context, the “number of police officers assigned to ALPR units” and “number of police officers assigned to traditional policing” will be employed as two
independent variables. In this way, ALPR technology and traditional policing can be compared in terms of their manpower efficiency for follow-up arrests.

Table 3 shows a raw comparison between ALPR technology and traditional policing in terms of the number of arrests and number of assigned police officers. The monthly average number of assigned police officers for traditional policing was obtained from “arrest by closure data.” All follow-up arrests were categorized yearly and monthly. The number of different assigned police officer names was counted in order to determine the number of officers assigned for unclosed/pending investigations per month for each year between 2006 and 2008. Monthly numbers for assigned officers were then divided by three in order to acquire the three years’ monthly average number of assigned police officers. As noted above, this procedure eliminates random fluctuations in the number of assigned police officers for a month. Similarly, the number of assigned ALPR officers was obtained by counting each different police officer name for the specific months during the July 16, 2008 – July 15, 2009 time period.

As presented in Table 3, based on monthly averages, 30 police officers were assigned to ALPR mobile units and conducted 844 total follow-up arrests during a one-year period. In contrast, an average of 111 police officers per month was assigned to follow-up arrests in the traditional policing system. These 111 police officers conducted 242 total follow-up arrests for the three years’ average. In addition, Table 3 indicates the number of arrests and the number of assigned police officers per month. In this context, while one officer assigned to an ALPR unit conducted 2.5 follow-up arrests per

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15 For traditional policing, the average number of assigned police officers was measured as a three year average of assigned police officers to follow-up arrests in order to control random fluctuations between years.
year, one officer assigned to a traditional policing unit conducted only 0.17 follow-up arrests per year.

Table 3. Comparison of Number of Follow-up Arrest by Manpower

<table>
<thead>
<tr>
<th></th>
<th>Traditional Policing</th>
<th>ALPR technology</th>
</tr>
</thead>
<tbody>
<tr>
<td># of Arrest</td>
<td># of Assigned Officers</td>
<td># of Arrests per Officer</td>
</tr>
<tr>
<td>January</td>
<td>4</td>
<td>24</td>
</tr>
<tr>
<td>February</td>
<td>3</td>
<td>24</td>
</tr>
<tr>
<td>March</td>
<td>5</td>
<td>28</td>
</tr>
<tr>
<td>April</td>
<td>6</td>
<td>34</td>
</tr>
<tr>
<td>May</td>
<td>5</td>
<td>50</td>
</tr>
<tr>
<td>June</td>
<td>11</td>
<td>54</td>
</tr>
<tr>
<td>July</td>
<td>17</td>
<td>80</td>
</tr>
<tr>
<td>August</td>
<td>17</td>
<td>97</td>
</tr>
<tr>
<td>September</td>
<td>21</td>
<td>115</td>
</tr>
<tr>
<td>October</td>
<td>31</td>
<td>180</td>
</tr>
<tr>
<td>November</td>
<td>45</td>
<td>255</td>
</tr>
<tr>
<td>December</td>
<td>78</td>
<td>390</td>
</tr>
<tr>
<td>Total and Averages</td>
<td>242</td>
<td>111 (Avg)</td>
</tr>
</tbody>
</table>

Table 4 gives a more detailed manpower comparison by crime type. This analysis includes follow-up arrests according to crime types (Part 1 and Part 2) and the number of assigned police officers. Part 1 crimes include more serious crimes (i.e., homicides, burglary, assault), while Part 2 crimes contain less serious crimes, such as domestic violence and burglary. As the table depicts, traditional policing follow-up arrests overwhelmingly include Part 1 crimes compared to ALPR technology. In contrast, ALPR movable units generally result in follow-up arrests for Part 2 crimes.

Table 4 also indicates the number of arrests per officer for both ALPR technology and traditional policing. For Part 1 crimes, the difference between traditional policing and ALPR technology is low. The monthly average for Part 1 arrests for a traditional
policing unit is 0.17 per officer, compared to 0.21 for ALPR units. For Part 2 crimes, however, the difference is more tangible. As Table 4 reports, on average one police officer using traditional policing make no Part 2 arrests per month, while one police officer using ALPR technology makes an average of 2.30 Part 2 arrests per month.
<table>
<thead>
<tr>
<th>Month</th>
<th>Average # of P1 Crime Arrest</th>
<th>Average # of P1 Arrests per Officer</th>
<th>Average # of P2 Crime Arrest</th>
<th>Average # of P2 Arrests per Officer</th>
<th>Average # of Assigned Police Officers</th>
</tr>
</thead>
<tbody>
<tr>
<td>July</td>
<td>4.00</td>
<td>0.16</td>
<td>0.00</td>
<td>0.00</td>
<td>24</td>
</tr>
<tr>
<td>August</td>
<td>3.00</td>
<td>0.13</td>
<td>0.00</td>
<td>0.00</td>
<td>24</td>
</tr>
<tr>
<td>September</td>
<td>5.33</td>
<td>0.19</td>
<td>0.00</td>
<td>0.00</td>
<td>28</td>
</tr>
<tr>
<td>October</td>
<td>5.67</td>
<td>0.17</td>
<td>0.00</td>
<td>0.00</td>
<td>34</td>
</tr>
<tr>
<td>November</td>
<td>5.00</td>
<td>0.10</td>
<td>0.00</td>
<td>0.00</td>
<td>50</td>
</tr>
<tr>
<td>December</td>
<td>11.33</td>
<td>0.21</td>
<td>0.00</td>
<td>0.00</td>
<td>54</td>
</tr>
<tr>
<td>January</td>
<td>15.67</td>
<td>0.20</td>
<td>1.00</td>
<td>0.01</td>
<td>80</td>
</tr>
<tr>
<td>February</td>
<td>16.67</td>
<td>0.17</td>
<td>0.00</td>
<td>0.00</td>
<td>97</td>
</tr>
<tr>
<td>March</td>
<td>21.00</td>
<td>0.18</td>
<td>0.00</td>
<td>0.00</td>
<td>115</td>
</tr>
<tr>
<td>April</td>
<td>30.33</td>
<td>0.17</td>
<td>0.33</td>
<td>0.00</td>
<td>180</td>
</tr>
<tr>
<td>May</td>
<td>45.33</td>
<td>0.18</td>
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<td>0.00</td>
<td>255</td>
</tr>
<tr>
<td>June</td>
<td>77.67</td>
<td>0.20</td>
<td>0.00</td>
<td>0.00</td>
<td>390</td>
</tr>
<tr>
<td>Averages</td>
<td>20.08</td>
<td>0.17</td>
<td>0.11</td>
<td>0</td>
<td>111</td>
</tr>
</tbody>
</table>

**Traditional Policing**

(1 Jan 2006 / 31 Dec 2008)

**ALPR technology**

(16 July 2008 / 15 July 2009)

<table>
<thead>
<tr>
<th># of P1 Crime Arrest</th>
<th>Average # of P1 Arrests per Officer</th>
<th># of P2 Crime Arrest</th>
<th>Average # of P2 Arrests per Officer</th>
<th># of Assigned Police Officers</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>0.58</td>
<td>44</td>
<td>3.67</td>
<td>12</td>
</tr>
<tr>
<td>4</td>
<td>0.11</td>
<td>72</td>
<td>2.00</td>
<td>36</td>
</tr>
<tr>
<td>3</td>
<td>0.11</td>
<td>56</td>
<td>2.07</td>
<td>27</td>
</tr>
<tr>
<td>4</td>
<td>0.15</td>
<td>70</td>
<td>2.59</td>
<td>27</td>
</tr>
<tr>
<td>1</td>
<td>0.02</td>
<td>79</td>
<td>1.88</td>
<td>42</td>
</tr>
<tr>
<td>2</td>
<td>0.07</td>
<td>45</td>
<td>1.67</td>
<td>27</td>
</tr>
<tr>
<td>0</td>
<td>0.00</td>
<td>13</td>
<td>0.48</td>
<td>27</td>
</tr>
<tr>
<td>5</td>
<td>0.16</td>
<td>83</td>
<td>2.68</td>
<td>31</td>
</tr>
<tr>
<td>1</td>
<td>0.04</td>
<td>28</td>
<td>1.00</td>
<td>28</td>
</tr>
<tr>
<td>6</td>
<td>0.15</td>
<td>57</td>
<td>1.46</td>
<td>39</td>
</tr>
<tr>
<td>7</td>
<td>0.22</td>
<td>102</td>
<td>3.19</td>
<td>32</td>
</tr>
<tr>
<td>25</td>
<td>0.93</td>
<td>134</td>
<td>4.96</td>
<td>27</td>
</tr>
</tbody>
</table>

**Averages**

20.08  0.17  0.11  0  111  5.42  0.21  65.25  2.30  30
**Proposed Analysis for the Third Comparison – Cost Effectiveness**

Finally, the cost effectiveness of ALPR is examined. For this analysis, a specific formula is used to compare the approximate $20,000 cost of a single ALPR unit to the overall savings (in manpower) per arrest. As noted previously, this formula is based on the difference in arrests between the ALPR units and traditional policing units. For example, if one mobile ALPR unit arrests 10 times more criminals than a traditional policing unit, then, the cost effectiveness of ALPR vehicle would be:

\[
\text{Cost per ALPR patrol vehicle} + \text{sum of } n \text{ number of ALPR police officers' wages} - \left( \text{sum of } i \text{ number of police officers' wages from trad. policing} \right) \times 10
\]

That is, assuming that an ALPR police vehicle operated by three police officers for different shifts arrested 10 times more criminals than \( n \) number of police officers from traditional policing, the cost effectiveness of ALPR would be the sum of the cost of the ALPR vehicle and the wages of three police officers minus 10 times \( n \) number of police officers’ wages from traditional policing. The result will then be compared to the initial costs of the systems, with an overall projection established of how long it will take for the ALPR units to become a cost savings to the CPD.

**Proposed Analyses for Research Question 2**

The second research question seeks an answer to the question of whether crime prevention theory can increase the effectiveness of ALPR systems by predicting relevant patterns (i.e., spatial) for hit (criminal) vehicles. As discussed earlier, crime prevention theory explains the criminal opportunity at both the micro and macro-levels. For this reason, the unit of analysis is multi-level. At the individual level, Cincinnati streets are
the unit of analysis. At the contextual level (aggregate level), social and economic covariates of census block groups is the unit of analysis.

When considering multi-level data, HLM 6 is the preferred statistical analysis tool compared to SPSS because it minimizes the threat of correlated error. Specifically, correlated error can occur when individuals that are sampled from the same neighborhoods because they share similar characteristics and therefore would not have independent error terms (Raudenbush & Bryk, 2002; Raudenbush, Bryk, Cheong, & Congdon, 2004). Although correlated error can be handled in SPSS with specific methods, SPSS does not allow for an examination of how street level variables16 (i.e., total crime in each street) interact with macro-level covariates (block group median income) (Wilcox, Land, & Miethe, 1994). For example, the adverse effect of city major nodes (street level variable) can be mediated or negated by block group covariates such as median income. In this way, HLM analyses allow researchers to explore how compositional (street level variables) and macro-level covariates (block group covariates) together explain an interested phenomenon, such as identifying criminal vehicles. Therefore, HLM specifically reports how the slope of identifying criminal vehicles for each street varies within block groups characterized by different covariates such as low income versus high income level. HLM analysis also gives interaction effects for between compositional and macro level variables. Based on this capability of HLM, it is used to examine whether crime prevention theory helps to increase the effectiveness of ALPR technology by more strategically allocating resources.

This analysis requires merging ALPR data, incident data, normal arrest data, and Census data. The new comprehensive database can analyze where ALPR mobile units

16 Street level variables are considered as level-1 variables.
stopped criminal vehicles (ALPR data), the residential addresses of hit (criminal) vehicles (arrest data), the number of crimes per city block groups (incident data), and social and economic covariates for each block group (census data). If the analysis reveals that there is a pattern between opportunities and capturing criminal vehicles, then ALPR mobile units can be strategically deployed to optimally prevent crime.

**Measures of variables for the optimal allocation of ALPR mobile units**

*Dependent Variable*

The dependent variable for the optimal allocation of ALPR mobile units is the “number of hits/criminal vehicles” for the streets of Cincinnati. Within the one year period of examination (July 16, 2008 – July 15, 2009), ALPR mobile units scanned and stored 2,823,944 license plate numbers on 2,706 different Cincinnati streets. However, ALPR mobile units only encountered hit vehicles (i.e., criminal vehicles) on 1,902 streets. For this reason, as summarized in Table 5, the number of streets of the key dependent variable (hit vehicles) is reduced from 2,706 streets to 1,902 streets. On these 1,902 streets, ALPR mobile units hit 57,767 criminal vehicles (2.05% of all scanned vehicles).

It is important to note that this dependent variable (e.g., number of ALPR hits) includes many duplicate license plate numbers. Specifically, of the 57,767 hits, there are 23,455 unique license plate numbers in the ALPR data and 34,312 cases that represent instances where a duplicate license plate number appeared at a different time and place. Nonetheless, these cases are not exactly alike. That is, although the same license plate number may appear more than once, the time and location of each scan is different. Given that these cases represent unique ALPR scans, albeit with duplicate license plate
numbers, all cases remain in the data. Independent variables were created to control for the effects of duplicate cases within the analysis. This is described in more detail in a forthcoming section. Furthermore, it is important to include all ALPR scans, including those with duplicate license plate numbers, in order to explore whether an ALPR hit occurred near the home address of the vehicle’s driver. Multiple scans of the same license plate numbers allow the opportunity to examine how many multiple ALPR hits occurred near the residence of the vehicle’s driver.

**Independent Variables**

*City major nodes/permeability:* According to crime prevention theory, the volume of traffic (Brantingham & Brantingham, 1982; Donnelly & Kimble, 1997; Mathews, 1993) and permeability of places (White, 1990) significantly explain non-randomness of crime and criminal opportunity. Based on this theoretical notion and retrospective empirical findings, city major nodes were created as independent variables. Specifically, city major nodes were measured by counting the intersections of each street through the use of ArcMap software (Geographic Information System software). Then, these intersections were aggregated to street level in order to find out the number of intersections per street. In order to determine whether a street is a city major node compared to the others, the z-score test is used. Streets that are 1.65 standard scores away from the mean of the distribution for the number of intersections are coded as city major nodes (city major nodes=1; non-city major nodes=0).

*Number of crimes per street:* Crime pattern theory predicts that the spatial distribution of crime is non-random (Sherman et al., 1989). As discussed above, a non-random distribution of crime depends on both individual and contextual level variables
that give opportunity for crime. An indirect interpretation of this finding is that places with a high level of crime provide more opportunity for crime. Hence, the “number of crimes per street” is employed as an indirect indicator of criminal opportunity. “Number of crimes” variable is created by taking the three years’ average (2006, 2007, and 2008) of Part-1 crimes of each street.

**Standardized ALPR Scans by the Strength Length:** As previously noted, the dependent variable for the second analysis is the “number of hits per street,” which can be affected by certain factors. For instance, ALPR mobile units might disproportionately scan vehicles on certain streets. In this case, ALPR mobile units are more likely to encounter criminal vehicles on streets in which ALPR mobile units generally patrol. Alternatively, street lengths can also disproportionately affect the number of hit vehicles. For instance, it is more likely that ALPR mobile units encounter criminal vehicles on certain streets that are longer compared to shorter streets. Given this context, disproportionate ALPR hits should be controlled by taking into account each street’s length and the total number of ALPR scans (including ALPR hits and non-ALPR hits) per street.

For this purpose, a new independent variable (standardized ALPR scans by the street length) was created by dividing the number of all scans by the street length. As noted above, the purpose of this variable is to standardize/control ALPR hits by taking into account both street length and all ALPR scans. In this sense, when the “standardized ALPR scans by the street length” variable is introduced to the equation, the risk of disproportionate ALPR patrols and street length is controlled. In addition, the volume of traffic is also controlled by this variable because ALPR patrol vehicles continuously scan
all vehicles’ license plate numbers (including hits and non-hits vehicles). The “standardized ALPR scans by the street length” variable was created with the help of ArcGIS software. Each street length was obtained from the Cincinnati shapefiles of ArcGIS software. Then, the total number of ALPR scans (including hits and non-hits) of each street was divided by its corresponding street length. Since ArcGIS software uses feet as a measurement tool for street lengths; this new variable can be read as the proportion of scanned vehicles for each foot of a street. In order to obtain this information in a more readable format, this proportion was multiplied by 100 to get the number of vehicles scanned in each 100 feet of a street.

<table>
<thead>
<tr>
<th>City of Cincinnati Street Summaries</th>
<th>Streets (N)</th>
<th>Range</th>
<th>Mean</th>
<th>s.d.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of ALPR Scans</td>
<td>2706</td>
<td>1 – 95848</td>
<td>1010.83</td>
<td>3679.22</td>
</tr>
<tr>
<td>Street Length (in feet)</td>
<td>2706</td>
<td>52 – 21224</td>
<td>1324.86</td>
<td>1517.07</td>
</tr>
<tr>
<td>City Major Nodes</td>
<td>2706</td>
<td>0 – 1</td>
<td>0.11</td>
<td>0.31</td>
</tr>
<tr>
<td>Crime per Street</td>
<td>2706</td>
<td>0 – 1033</td>
<td>24.73</td>
<td>60.34</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hit Summaries</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Hits per Street</td>
<td>2706</td>
<td>1 – 1182</td>
<td>20.61</td>
<td>69.75</td>
</tr>
<tr>
<td>Standardized Scans per Street in 100 feet</td>
<td>1902</td>
<td>0 – 66.77</td>
<td>1.35</td>
<td>3.72</td>
</tr>
<tr>
<td>Same Vehicle Hits within the Same Street</td>
<td>1902</td>
<td>1 – 749</td>
<td>22.25</td>
<td>81.51</td>
</tr>
</tbody>
</table>

The distance between criminals’ resident addresses to ALPR hit place: According to offender search theory, criminals are more likely to commit crimes in places that are close to their residential places. Brantingham and Brantingham (2003) and Eck (1993) explain this relationship with the term of “familiarity decay.” The authors posit that criminals are more likely to know the criminal opportunities in close proximity to their residential places. In this context, we employed the distance between criminals’ residents to the location of ALPR hits based on this prediction.
In order to calculate distances from hit (criminal) vehicles’ driver home addresses to ALPR hitting points, a number of different procedures were followed. Normally, ALPR data only provides information about hit vehicles’ license plate number, control number of drivers\(^{17}\), the geographic coordinates of hit place, date, time, crime type, and a short description (i.e., whether the car is parked, driver is arrested). There is no field that shows the home addresses of hit vehicles in ALPR data. Even though the ALPR database does not provide any detailed information for hit vehicles, it provides a unique control number for the drivers of hit vehicles. Therefore, home addresses of individuals related to specific license plate numbers are ascertained from other databases by matching the control numbers of ALPR hit vehicles with other databases’ control numbers. When the other CPD databases were explored, one was found that includes arrestees from January 1, 2008 to September 1, 2009 that provides both the control number and home addresses of arrested persons. When this database was merged with ALPR data, the home addresses of certain individuals linked to “hit vehicles” were obtained. In the ALPR database, 21,623 out of 57,767 records had associated criminal suspect control numbers. As noted above, not all records in the ALPR database have unique license plate numbers. For this reason, only 6,601 out of 21,623 vehicles have unique control numbers. In addition, a unique control number can have more than one license plate number, since one person can own more than one vehicle. In this context, unique license plate numbers with duplicate control numbers represent 10,660 cases in ALPR data set. Table 6 summarizes the above explanations.

\(^{17}\) Control numbers are the unique identification numbers given by the Cincinnati Police Department to individuals involved in any criminal activity.
Table 6. Case Classifications

<table>
<thead>
<tr>
<th>Case Classification</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Hits</td>
<td>57,767</td>
</tr>
<tr>
<td>Duplicate License Plate Numbers</td>
<td>34,312</td>
</tr>
<tr>
<td>Unique License Plate Numbers</td>
<td>23,455</td>
</tr>
<tr>
<td>License Plate Numbers (LPNs) that have Control Numbers (including duplicate LPNs and duplicate control numbers)</td>
<td>21,623</td>
</tr>
<tr>
<td>Unique Control Numbers</td>
<td>6,601</td>
</tr>
<tr>
<td>License Plate Numbers with Unique Control Numbers (including duplicate control numbers)</td>
<td>10,660</td>
</tr>
</tbody>
</table>

Taken together, 21,623 hits associated with 6,601 unique control numbers can be potentially matched with the arrest database in order to find the home addresses of those 21,623 hits. When the ALPR data and arrest database were merged, 2,568 out of 6,601 unique control numbers match. Those 2,568 matched control numbers enabled the identification of 7,743 home addresses in ALPR data, which account for 36% of 21,623 cases. After this process, matched home addresses were uploaded to ArcGIS, mapping software, in order to calculate the point distances from home addresses of hit vehicles to the ALPR hit points. However, when the home addresses were geo-coded, it was discovered that only 5,774 hit vehicles’ drivers reside within the City of Cincinnati and have addresses that can be geo-coded by ArcGIS to determine the distances between the home address and ALPR hit location.

To calculate distances from ALPR hit points to identified hit vehicles’ home addresses, the “point distance” feature of ArcGIS was used. With this feature, ArcGIS compares each hit vehicle’s point distance with the distance of the identified home address and reports the distance between these two points. In other words, ArcGIS reports $10,660 \times 5,774$ point distance, which is equivalent to 61,550,840 different
calculations. Then, these point distances were classified with an ordinal scale ranging from 1000 meters to 5000 meters. If a hit vehicle falls into 1,000 meter away from its home address, that vehicle is counted in that category. When all the calculations were completed for the 61,550,840 iterations, the categories were aggregated to street level. Table 7 summarized this aggregation process.

Parked Vehicles: In order to control for the potential impact of parked/unoccupied vehicles to the point distance between residential places of hit vehicles and ALPR hit location, the number of parked vehicles (parked within 100 meter distance from home addresses of criminal vehicles’ drivers), is subtracted from the 1,000 meter point distance. For instance, a hit vehicle that was coded within the distance of 1,000 meters to the ALPR hit location could be a vehicle that was parked in front of criminal driver’s home address. Since the interest of this study is to determine whether criminals usually hover near their residential places to seek out criminal opportunities, parked vehicles have to be controlled in the analysis18.

There are 8,661 parked vehicles that were identified as criminal vehicles by ALPR mobile units. However, not all parked vehicles on the streets are the vehicles that have control numbers, home addresses, and geo-coded home addresses at the same time. Recall that these characteristics are important to calculate point distances of each vehicle. Therefore, only 1,803 out of 8,661 parked vehicles have the above listed characteristics (control numbers, home addresses, and geo-coded home addresses) at the same time. In this vein, if parked vehicles contain these characteristics at the same time, those vehicles

---

18 If the potential effect of parked vehicles was not taken into account, the magnitude of the point distance slope might be artificially increased because parked vehicles that were generally parked in front of criminal home addresses would automatically increase the number of detection of criminal vehicles that were already parked by their owners. In order to mitigate this potential bias, the effect of parked vehicles was removed by subtracting them from total number of distances (i.e., 1000 meters, 2000 meters).
are subtracted from total number of point distance variable ranging from 1,000 to 5,000 meters. Based on this notion, the potential impact of parked vehicles from point distances was removed to measure the net effect of point distances on the dependent variables (number of ALPR hits).

<table>
<thead>
<tr>
<th>Table 7. Hit Distances and the Impact of Parked Vehicles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hit Distances to Home Addresses</td>
</tr>
<tr>
<td>1000 meters (0.62 mile)</td>
</tr>
<tr>
<td>2000 meters (1.24 mile)</td>
</tr>
<tr>
<td>3000 meters (1.86 mile)</td>
</tr>
<tr>
<td>4000 meters (2.49 mile)</td>
</tr>
<tr>
<td>5000 meters (3.11 mile)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hit Distances to Home Addresses After Removing the Effect of Parked Vehicles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Streets (N)</td>
</tr>
<tr>
<td>1000 meters (0.62 mile)</td>
</tr>
<tr>
<td>2000 meters (1.24 mile)</td>
</tr>
<tr>
<td>3000 meters (1.86 mile)</td>
</tr>
<tr>
<td>4000 meters (2.49 mile)</td>
</tr>
<tr>
<td>5000 meters (3.11 mile)</td>
</tr>
</tbody>
</table>

*Hit Vehicles’ Demographics:* Hit vehicles’ demographics were also obtained by matching control numbers of the ALPR hit vehicles with the control numbers of arrest database. In this manner, over 3,500 hit vehicles’ demographics were found and aggregated to the street level to measure street level demographics. Table 8 summarizes the demographic characteristics of hit vehicles; this information is presented strictly for descriptive purposes. No hypothesis testing is conducted using these demographic characteristics.
Table 8. Hit Vehicle Drivers’ Demographics

<table>
<thead>
<tr>
<th>Streets (N)</th>
<th>Range</th>
<th>Mean</th>
<th>s.d.</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Black Drivers</td>
<td>1032</td>
<td>0 – 158</td>
<td>6.02</td>
<td>13.15</td>
</tr>
<tr>
<td>Number of White Drivers</td>
<td>1035</td>
<td>0 – 87</td>
<td>1.20</td>
<td>4.27</td>
</tr>
<tr>
<td>Number of Female Drivers</td>
<td>1032</td>
<td>0 – 39</td>
<td>1.18</td>
<td>3.09</td>
</tr>
<tr>
<td>Number of Male Drivers</td>
<td>1037</td>
<td>0 – 143</td>
<td>6.02</td>
<td>13.21</td>
</tr>
<tr>
<td>Median Age of Drivers</td>
<td>1199</td>
<td>19 – 79</td>
<td>32.56</td>
<td>7.50</td>
</tr>
</tbody>
</table>

*Neighborhood Covariates:* With the exception of the “average number of crimes” and “total ALPR scans,” all of the other neighborhood covariates were obtained from the 2000 Census data. Average number of crimes, came from the CPD database system and was obtained in the same manner as the street-level number of crime variable. Three years’ (2006, 2007, and 2008) Part-1 crimes were aggregated to the neighborhood level and then divided by three to get the average numbers in case of any random fluctuations. The “neighborhood-level total ALPR scans” variable was created by aggregating all street level ALPR scans (including hits and non-hits) to neighborhood-level with the help of ArcGIS software. All the other neighborhood-level covariates (median household income, percent Black, and percent vacant) came from Census 2000 tract. Table 9 provides descriptive statistics for neighborhood-level covariates, including median household income, percent Black, percent vacant, total ALPR scans, and percent crime.

Table 9. Descriptive Statistics for Neighborhood Covariates

<table>
<thead>
<tr>
<th>N</th>
<th>Range</th>
<th>Mean</th>
<th>s.d.</th>
</tr>
</thead>
<tbody>
<tr>
<td>53</td>
<td>91956 - 104494</td>
<td>32346.27</td>
<td>15605.65</td>
</tr>
<tr>
<td>53</td>
<td>0.10 - 95.00</td>
<td>42.32</td>
<td>30.40</td>
</tr>
<tr>
<td>53</td>
<td>3.21 - 36.68</td>
<td>11.84</td>
<td>6.85</td>
</tr>
<tr>
<td>53</td>
<td>1763 - 288953</td>
<td>51666.38</td>
<td>59791.15</td>
</tr>
<tr>
<td>53</td>
<td>3.38 - 101.97</td>
<td>23.63</td>
<td>20.47</td>
</tr>
</tbody>
</table>

19 Shapefiles of ArcGIS software report both street names and neighborhoods.
Strengths and Limitations

There are few studies that examine the effectiveness of ALPR systems as it relates to crime reduction. The results of the current study will provide critical information to other law enforcement agencies performing cost/benefit analyses prior to purchasing ALPR systems. This study is also the first known to apply the principles of crime prevention theory to ALPR mobile units with substantial details on both individual level variables and block group covariates. Finally, this study will broadly discuss data management strategies in policing to obtain maximum crime prevention in a given region. Such studies are rare in the literature.

Nevertheless, the current study has certain limitations that should be considered. First, census block covariates are derived from 2000 Census data, which are nearly a decade old comparison to the 2008 and 2009 ALPR data. It is possible that the Census block covariates utilized at the aggregate level in this study may have changed since the 2000 Census was conducted. Using the 2000 Census data was the only option available given that the 2010 Census is not yet available. The findings reported within this study should later be compared to analyses conducted using the 2010 Census data.

Second, there are issues with the completeness of the ALPR data. As described above, the ALPR database includes information regarding the ALPR scan (date, time, location, officer identification), reason for ALPR stop, control numbers of criminals, demographic characteristics of driver of scanned vehicle, and police action as a result of the traffic stop. Missing data for these fields of interest, however, is an important limitation. For example, only 21,623 of 57,767 (37.4%) hit vehicles have control numbers of drivers and associated detailed information. Furthermore, since other
relevant details such as home addresses of hit vehicles are not provided by the ALPR data, additional matching processes had to be conducted in order to obtain other relevant variables. During this matching process, a considerable number of cases do not match with other databases due to missing data for control numbers. In the current study, however, this issue was not as severe because all hit (criminal) vehicles were aggregated to 1,881 streets of Cincinnati. Due to this aggregation process, individual non-matched control numbers did not severely affect the street summaries. When the matched cases were aggregated to the street level from individual hit vehicles, a raw representation was obtained from existing matched cases. Nevertheless, the amount of missing data for the control number data field is still a concern that must be addressed within this study.

Despite these limitations, the current study provides unique information about ALPR systems; this is especially critical because of the lack of empirical information available regarding their use and effectiveness. In addition, this study will provide new insights to police departments by illuminating the importance of data management strategies.
CHAPTER V
RESULTS

This chapter presents the results of data analyses outlined in Chapter IV. In the first set of analyses, the impact of ALPR technology will be assessed with the mixed methods including time series analysis and independent sample t-test. In the second set of analyses, hierarchical linear model (HLM) is used to evaluate whether the deployment patterns of ALPR technology can be improved by using the tenets of crime prevention theory. Implications are discussed in the following chapter.

The Impact of ALPR Technology on Policing

The first hypothesis of Research Question 1 is designed to evaluate whether ALPR mobile units increased the number of follow-up arrests in the City of Cincinnati after the implementation of ALPR mobile systems. The appropriate analysis for this hypothesis is interrupted time series analysis, which is also known as auto regressive integrated moving average (ARIMA) (McDowall, McCleary, Meidinger, & Hay, 1980). When using time series data\(^\text{20}\), the potential problem is that adjacent time points or error terms can be correlated with each other, which in turn lead to biased standard errors and biased test results (i.e., t statistics). For this reason, correlated error terms, also known as the “noise component,” should be cleaned or whitened from the data in order to leave stationary / homoscedastic error terms for impact analysis (McDowall et al., 1980).

Given this context, the first procedure in ARIMA is to find an appropriate model that ensures independent error terms with a mean of zero and a constant variance. This process is called “pre-whitening” procedure in ARIMA language (Granger & Newbold, 1986). An appropriate ARIMA model can be a combination of non-seasonal and

\(^{20}\) Time series data is a set of ordered observations that interest variable(s) are watched over time.
seasonal models, which is modeled in ARIMA(p,d,q) (P,D,Q); where p is the number of autoregressive terms/orders, d is the number of non-seasonal differences, and q is the number of moving average orders in the model. Capital P, D, and Q stands for seasonality with the same explanations for p, d, and q (Pridemore & Chamlin, 2006).

Figure 2 presents a time series graphic for the first hypothesis of Research Question 1. The continuous line represents the observed number of follow-up arrests. The dotted line reflects whether the selected ARIMA models fit the observed data. As the figure suggests, the ARIMA (1,0,0)(1,1,0) model is a good fit to observed data. The non-seasonal part of the ARIMA model (1,0,0) indicates only autoregressive orders. An indication of autoregressive orders is that previous time point predicts the current values. Yet the differencing process cleans pulses and ensures that the data are stationary. The moving average orders determine whether deviations from the series mean for preceding values are used to predict current values. However, Figure 2 visually suggests that no indication for pulse function and moving average orders. Figure 2 also clearly shows seasonal correlated error problems for two reasons. First, the prior season’s arrest patterns predict the current season’s arrest patterns (seasonal autocorrelation). In other words, as the figure suggests, toward the end of each year, follow-up arrest increases. Second, seasonal differencing occurs because the figure shows obvious seasonal pulse function. After these identifications, the ARIMA (1,0,0)(1,1,0) model appears to be the most appropriate model for the data.
In addition to this visual identification, a number of different goodness-of-fit test should be used to figure out whether the selected model is the appropriate one. For this purpose, the most used goodness of fit tests for time series data are stationary R-squared value and Ljung-Box Q statistic (Box, Jenkins, and Reinsel, 1994). The stationary R-squared value provides how the model explained the total variation in the series. As in Ordinary Least Squares (OLS) regression, values that are close to 1 indicate better fits (1 is the maximum). In Table 10, the stationary R-squared value is 0.958, which suggests a better fit for the model of ARIMA (1,0,0)(1,1,0). Alternatively, the Ljung-Box Q statistic should be a non-significant value (less than 0.05). Finding non-significant values suggest that there is no systematic variation/structure left in the series. As presented in Table 10, the Ljung-Box Q statistic is much larger than 0.05, and suggests that the ARIMA model is correctly specified.
After the model fit process, the data are ready for hypothesis testing because with the appropriate ARIMA model, it ensures that the error terms are independent with a mean of zero and have a constant variance. Table 11 presents the test results for the hypothesis of whether ALPR technology increased the number of follow-up arrest in the City of Cincinnati after its implementation. The results in Table 11 indicate that ALPR technology substantially increased the number of follow-up arrest after its implementation (as of July 15, 2008). In order to account for the adverse affect of the number of crimes\textsuperscript{21}, the number of crime occurring each year are controlled in the model. The number of crimes, however, was not significantly associated with follow-up arrests and therefore, did not mediate or negate the impact of ALPR technology.

<table>
<thead>
<tr>
<th>Table 11. ALPR Technology and Follow-up Arrests</th>
<th>t-value</th>
<th>s.e.</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALPR Technology</td>
<td>9.11</td>
<td>6.59</td>
<td>.00</td>
</tr>
<tr>
<td>Number of Crime</td>
<td>.110</td>
<td>.019</td>
<td>.91</td>
</tr>
</tbody>
</table>

Given this context, the findings support the hypothesis that ALPR technology increased follow-up arrests in the City of Cincinnati. In this analysis, however, the time series analysis provided a macro examination for the impact of ALPR technology. For this reason, further analyses (reported below) are needed to better evaluate the impact of ALPR technology on policing.

\textsuperscript{21} As the number of crime increases, follow-up arrests also increase. For this reason, we introduced number of crime as a control variable to the equation.
Manpower Comparison Results

The second hypothesis of Research Question 1 was whether the standardized number of police officers\textsuperscript{22} working for ALPR units makes more follow-up arrests compared to the assigned police officers working in traditional policing. Table 13 presents different aspects of manpower comparison by providing bivariate hypothesis tests (t-tests). The first bivariate test compares number of monthly ALPR follow-up arrests with the number of monthly traditional policing follow-up arrests. As the results suggest, ALPR units conducted an average of 70.33 follow-up arrests per month. By comparison, traditional policing units only produced an average of 20.19 follow-up per month. The result of independent sample t-test suggests that the difference between the ALPR units and traditional policing units is statistically significant.

\begin{table}[h]
\centering
\begin{tabular}{lccccc}
\hline
 & \textbf{ALPR Technology} & & & \textbf{Traditional Policing} & \\ & mean & s.d & & mean & s.d & \textbf{t-value} \\
\hline
Total Follow-up Arrest & 70.33 & 37.70 & & 20.19 & 22.09 & 4.36* \\
Assigned Police Officers & 29.58 & 7.61 & & 110.94 & 111.32 & -4.35* \\
P1 Crime Arrest & 5.42 & 6.60 & & 20.08 & 22.08 & -3.54* \\
P2 Crime Arrest & 65.25 & 32.73 & & 0.11 & 0.52 & 6.89* \\
\hline
\end{tabular}
\caption{Manpower Comparison}
\end{table}

The second bivariate test compares the number of monthly assigned police officers for the ALPR units with the number of monthly assigned police officers for the traditional policing units.\textsuperscript{23} As Table 12 suggests, on average 29.58 police officers were assigned to ALPR units per month, compared to an average of 111.32 police officers assigned to traditional policing per month. In other words, there were 3.8 times fewer

\textsuperscript{22} The number of assigned police officers is divided by the number of follow-up arrests.

\textsuperscript{23} Police officers in traditional policing are assigned to “investigation pending” incidents in order to finalize or close the ongoing investigation. The number of ongoing investigations directly impacts the number of assigned police officers to finalize the “investigation pending” incidents. The number of assigned ALPR police officers reflects the number of police officers that worked in ALPR units for a given/specific month.
police officers assigned to ALPR units per month compared to traditional policing. This difference is significantly associated with any known critical regions in statistics \( t = -4.35 \). The last two bivariate tests give more details in terms of follow-up arrest type. As noted earlier, Part 1 arrests include serious crimes, and Part 2 arrests include less serious crime. In this context, the results in Table 12 demonstrate that while ALPR police officers made less Part 1 follow-up arrests, they conducted more Part 2 follow-up arrests compared to traditional policing (5.42 compared to 20.08; and 65.25 compared to 0.11, respectively).

Even though bivariate hypothesis test results suggest that police officers working in traditional policing units made more Part 1 follow-up arrests compared to ALPR assigned police officers, multivariate hypothesis testing will determine if this bivariate relationship remains statistically significant while controlling for other relevant factors. Recall that the number of police officers assigned to traditional policing was 3.8 times higher than ALPR police officers. When the number of assigned police officers is controlled in the multivariate equation, the number of Part 1 follow-up arrests for traditional policing units is 5.28 rather than 20.08 (20.08 divided by 3.8). Making this adjustment demonstrates that police officers working in traditional policing units did not conduct more Part 1 follow-up arrests compared to police officers assigned to ALPR units.

In summary, the various aspects of the manpower hypothesis tests confirm that ALPR mobile units make more follow-up arrests with less manpower. Even though bivariate tests of Part 1 arrests demonstrate fewer Part 1 arrests for ALPR units, further adjustments based on the number of assigned police officers for each unit (traditional vs.
ALPR) indicated that there is no statistically significant difference for Part 1 follow-up arrests between ALPR units and traditional policing.

**Cost Comparison Results**

The third and final hypothesis of Research Question 1 considers whether ALPR units make more follow-up arrests compared to non-ALPR units while ensuring less cost to the CPD. In recent years police departments around the world have been increasingly investing their scarce resources to technological advancements. In this vein, ALPR technology is one of the most coveted technological advancements in policing.

According to CPD officials, patrol cars are equipped with ALPR technology for an additional cost of $21,500 per unit. As noted earlier, the CPD has eight ALPR mobile units for the City of Cincinnati. Therefore, the CPD has spent $172,000 for its current ALPR mobile units.

Personnel costs also represent an enormous portion of police departments’ budgets. For the CPD in 2009, the average hourly rate for police officers and specialists assigned to patrol duties is $31.57. This translates to an average monthly salary of $5,051 (average of 8 hours per day X 20 days per month). Recall that the average monthly number of assigned police officers to ALPR vehicles is 30, compared to 111 for traditional policing. By using this existing information, ALPR follow-up arrests and non-ALPR follow-up arrests can be compared for their cost effectiveness. The below formula is designed for this purpose:

$$\frac{(\text{Cost of ALPR patrol vehicles} + \text{Sum of ALPR police officers' salaries})}{\text{Sum of police officers' salaries working in traditional policing system}} \times \frac{\text{Rate of ALPR efficacy}}{}$$
Cost of per ALPR patrol vehicles= $21,500 X 8 = $172,000
Sum of ALPR police officers’ salaries= $5,051 X 30
Sum of police officers’ salaries working in traditional policing system= $5,051 X 111
Rate of ALPR efficacy over traditional policing for follow-up arrests\textsuperscript{24} = 3.48

Therefore:

\[ \left[ \left( \$172,000 + \$151,530 \right) - \left( \$560,661 \right) \right] \times 3.48 \]

\[ = -1,627,570 \text{ US dollars} \]

Based on these monthly averages (i.e., the average number of assigned police officers per month, and the average number of follow-up arrests), the above results can be interpreted as the monthly cost difference between ALPR and non-ALPR units for follow-up arrests. It might be expected that ALPR mobile units will cost more money to police departments for a given month; however, when the efficacy rate of ALPR technology is taken into account, ALPR technology is cost effective as presented in the above comparison.

In addition to this cost effectiveness, the cost difference between ALPR and traditional policing is noticeably large, which means that ALPR technology amortizes itself in a very short time. In this case for instance, officers using ALPR technology produce the same outcomes (in terms of follow-up arrests) for $1,627,570 less in a given month, compared to traditional policing. When the total cost of ALPR technology is taken into account ($172,000 per unit x 8 ALPR mobile units = 1,376,000) the ALPR mobile units amortized themselves in shorter than \textit{four days}.

\textsuperscript{24} This rate is based on the manpower comparison (monthly average of ALPR follow-up arrests / monthly average of traditional policing follow-up arrests = 70.33 / 20.19 = 3.48).
In contrast, it could be argued that there is not much difference between ALPR technology and traditional policing in terms of arresting Part 1 crime suspects for ongoing investigations. In this scenario, the rate of ALPR technology to traditional policing would be one that reflects no efficacy rate. However, since traditional policing assigns more police officers for the same job (follow-up arrests) compared to ALPR units, the ALPR technology would amortize itself in slightly longer period. If we apply Part 1 follow-up arrests to the above formula, the ALPR units would do the same job for $237,131 less each month. Therefore, considering only Part 1 follow-up arrests, the ALPR technology amortizes itself in less than one month.

Another previously unconsidered aspect of the cost effectiveness of ALPR technology is that ALPR mobile units have high capability for the detection of stolen vehicles and identification of those delinquent on fines or otherwise failing to pay their legal obligations (i.e., traffic ticket). For instance, ALPR mobile units identified and recovered 147 stolen vehicles and released them to their owners within a one year period. The CPD has also reported that ALPR mobile units detected over 2,600 vehicles with delinquent citations (Combs et al., 2009). Considering these functions of ALPR technology along with the identification of criminals, ALPR technology amortizes itself even more quickly.

Summary of Findings for Research Question 1

The results of first research question suggest that the number of follow-up arrests tangibly increased after the implementation of ALPR technology in the City of Cincinnati. In addition, manpower comparisons showed that ALPR mobile units make more follow-up arrests using fewer police officers during the same time period. Finally,
the cost analysis of ALPR technology revealed that ALPR technology is cost effective and capable to amortize itself within a very short time.

**Results for Optimal Allocation of ALPR Technology – Research Question 2**

The second research question examines how ALPR units can be most effectively deployed and explores whether ALPR-equipped vehicles are more likely to encounter criminal vehicles in the types of places predicted by crime prevention theory. The first hypothesis of Research Question 2 considers whether ALPR equipped vehicles are more likely to identify criminal vehicles on major city nodes compared to non-major city nodes.

Given that crime prevention theory is multilevel, analyses of Research Question 2 will include both micro and macro levels (i.e., Cincinnati streets and neighborhoods). The key point of a multilevel approach is that criminal opportunities that lead to higher crime rates vary in both micro level (i.e., streets) and macro level (i.e., neighborhoods) units based on their characteristics. All of the analyses reported below are based on the use of Hierarchical Linear Modeling (HLM) 6.06 software.

Because crime prevention theory proposes that criminal opportunity varies across the categories of macro unit based on their characteristics (i.e., income level), the first analysis should target whether the number of ALPR hits varies across the neighborhoods of Cincinnati as the crime prevention theory predicts. This step is crucial because if the number of ALPR hits does not significantly vary across Cincinnati neighborhoods, then, it is not necessary to include neighborhood covariates for statistical analyses. Given this context, the first step is to examine whether the number of ALPR hits on the streets of Cincinnati significantly vary across the neighborhoods of the city.

---

25 ALPR hits: Identifying/encountering criminal vehicles on a street.
In HLM, this step is called the “unconditional model.” Before presenting results for the unconditional model, the characteristics of the dependent variable (i.e., the number of ALPR hits on the streets of Cincinnati) will be detailed because the first hypothesis of Research Question 2 has two different predictions. The first hypothesis (Hypothesis 1a) predicts that street characteristics (city major nodes) and neighborhood characteristics are significantly associated with a high number of ALPR hits. Hypothesis 1b predicts that ALPR hits are more likely to occur in city major nodes and in certain neighborhoods (i.e., low income neighborhoods) based on their characteristics.

While Hypothesis 1a of Research Question 2 includes cases even though no ALPR hits occurred, Hypothesis 1b only considers streets that at least one ALPR hits occurred. For this reason, the sample size of the Hypothesis 1a is all Cincinnati streets (N=2,706). In contrast, the sample size of Hypothesis 1b is 1,902 streets, which includes only the streets that have at least one ALPR hit on a criminal vehicle.

Because Hypothesis 1a includes streets with and without ALPR hits, the dependent variable (ALPR hits) has many zeros (N=804), which in turn lead to highly skewed distribution toward the right side of the scale. For this reason, the dependent variable is logged, using the natural log function to fit the data to OLS regression. Nevertheless, the logged dependent variable (transformed to obtain a normal/smooter distribution) still does not have the desired distribution for OLS regression. As presented in Table 13, the standard deviation was nearly the same with the mean of the dependent variable, and this violates the normality assumption of OLS regression.

| Table 13. Dependent Variable Distribution Hypothesis 1a. |
|-----------|-------------|---------|---------|
|           | N           | Range   | Mean    | s.d.    |
| Number of ALPR Hits | 2706         | 0 – 1182 | 16.22   | 62.42   |
| Number of ALPR Hits (Logged) | 2706         | 0 – 7.08 | 1.51    | 1.53    |
The distribution of the logged dependent variable is appropriate, however, for Poisson regression, which is designed to handle slightly skewed distributions (Osgood, 2000). Hence, Poisson regression is used for Hypothesis 1a of Research Question 2. Alternatively, for Hypothesis 1b, when the dependent variable was logged, there was no violation for the normality assumption of OLS regression such as that observed for the sample including all streets. Table 14 presents the original metric and logged function of the dependent variable for Hypothesis 1b.

<table>
<thead>
<tr>
<th>Dependent Variable Distribution for Hypothesis 1b.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of ALPR Hits</td>
</tr>
<tr>
<td>N</td>
</tr>
<tr>
<td>1902</td>
</tr>
<tr>
<td>Number of ALPR Hits (Logged)</td>
</tr>
<tr>
<td>N</td>
</tr>
<tr>
<td>1902</td>
</tr>
</tbody>
</table>

In addition to skewed distribution of the some dependent variables, the independent variables were also highly positively skewed. For this reason, we also transformed independent variables (with natural log) to better fit the data to regression analyses. Table 15 reveals descriptive statistics before and after the transformations of independent variables for Hypothesis 1a, Hypothesis 1b and Hypothesis 2. As presented in Table 15, the transformed independent variables better fit the assumptions of regression analyses because the standard deviations and mean values of the logged independent variables provide smoother distribution for OLS regression.
Table 15. Descriptive Statistics

<table>
<thead>
<tr>
<th>Descriptive Statistics for Hypothesis 1a</th>
<th>Original Metric Variables</th>
<th>Logged Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Crime per Street</td>
<td>N</td>
<td>Range</td>
</tr>
<tr>
<td></td>
<td>2706</td>
<td>0-1033</td>
</tr>
<tr>
<td>Standardized ALPR Scans</td>
<td>2706</td>
<td>0-66.8</td>
</tr>
<tr>
<td>Number of Same Vehicles Per Street</td>
<td>2706</td>
<td>0-749</td>
</tr>
</tbody>
</table>

Desc. Statistics for Hypothesis 1b & 2

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Range</th>
<th>Mean</th>
<th>s.d.</th>
<th>Range</th>
<th>Mean</th>
<th>s.d.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Crime per Street</td>
<td>1902</td>
<td>0-1033</td>
<td>33.06</td>
<td>70.18</td>
<td>0-6.94</td>
<td>2.38</td>
<td>1.58</td>
</tr>
<tr>
<td>Standardized ALPR Scans</td>
<td>1902</td>
<td>0.02-66.8</td>
<td>1.92</td>
<td>4.31</td>
<td>0.02 - 4.2</td>
<td>.72</td>
<td>.70</td>
</tr>
<tr>
<td>Number of Same Vehicles Per Street</td>
<td>1902</td>
<td>0-749</td>
<td>22.25</td>
<td>81.51</td>
<td>0-6.62</td>
<td>1.10</td>
<td>1.68</td>
</tr>
<tr>
<td>Distance within 1000 meters</td>
<td>890</td>
<td>0-65</td>
<td>1.25</td>
<td>4.31</td>
<td>0-4.19</td>
<td>.41</td>
<td>.69</td>
</tr>
<tr>
<td>Distance within 2000 meters</td>
<td>890</td>
<td>0-67</td>
<td>1.83</td>
<td>5.09</td>
<td>0-4.22</td>
<td>.58</td>
<td>.78</td>
</tr>
<tr>
<td>Distance within 3000 meters</td>
<td>890</td>
<td>0-72</td>
<td>2.36</td>
<td>5.97</td>
<td>0-4.29</td>
<td>.71</td>
<td>.83</td>
</tr>
<tr>
<td>Distance within 4000 meters</td>
<td>890</td>
<td>0-77</td>
<td>2.91</td>
<td>6.86</td>
<td>0-4.36</td>
<td>.84</td>
<td>.86</td>
</tr>
<tr>
<td>Distance within 5000 meters</td>
<td>890</td>
<td>0-89</td>
<td>3.51</td>
<td>8.18</td>
<td>0-4.50</td>
<td>.95</td>
<td>.89</td>
</tr>
</tbody>
</table>

The last important issue before beginning to hypothesis tests using multiple regression is to analyze whether there is a multicollinearity problem among the independent variables. Multicollinearity occurs when more than two independent variables highly correlated with each other. If the correlation coefficient (Pearson r) of two variables is correlated at the 0.7 level or higher, it suggests that those variables are highly correlated because both variables explain their residuals for 0.49 percent. Putting these two variables into the multivariate equation results in a collinearity problem because regression analysis cannot differentiate which variable explains which of the dependent variables. For this reason, reporting zero order correlation coefficients are vital for any multivariate analysis. As presented in Table 16, none of the independent variables is correlated with each other at 0.7 or higher.
Table 16. Zero Order Correlations

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>--</td>
<td>.414*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>--</td>
<td></td>
<td>.545*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>.756*</td>
<td>.545*</td>
<td>--</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>.629*</td>
<td>.286*</td>
<td>.523*</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>.861*</td>
<td>.276*</td>
<td>.639*</td>
<td>.411*</td>
<td>--</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>.349*</td>
<td>.148*</td>
<td>.298*</td>
<td>.274*</td>
<td>.351*</td>
</tr>
</tbody>
</table>

1=Number of ALPR Hits; 2=City Major Nodes (yes); 3=Number of Same Vehicle per Street; 4=Number of Crime per Street; 5=Standardized ALPR Scans by Street Length; 6=Point Distance

*p<.05

Results for Hypothesis-1a of Research Question-2

After the identification of the appropriate regression analyses for the different Hypotheses of Research Question 2, the first step of an HLM analysis is to determine whether ALPR hits significantly vary across Cincinnati neighborhoods. This first step is called the “unconditional model.” The unconditional model of the first hypothesis revealed that the number of ALPR hits significantly varies across 53 Cincinnati neighborhoods (t ratio= 7.86, reliability estimate of ALPR hit coefficient= 0.778). The significance of the unconditional model emphasizes that the mean/intercept of the dependent variable significantly varies between the neighborhoods of Cincinnati. Figure 3 visually depicts how the means of the 15 randomly selected neighborhoods differ from each other. The X axis represents neighborhoods (N=15) and Y axis represents the dependent variable (mean level of ALPR hits). The plus sign on the graph indicates the mean of neighborhoods for the dependent variable (number of ALPR hits). As Figure 3 suggests, the neighborhood means visually differ from each other, and therefore the

26 There are 52 neighborhoods in Cincinnati; however, it is impossible to show all neighborhoods in one graph. For this reason, 15 neighborhoods were randomly selected for visual presentation.
unconditional model suggests that there is a significant variation between neighborhoods’
mean that can be explained with certain neighborhood characteristics (i.e. income level).

Figure 3. Box-Whisker Graph for ALPR Hits at the Neighborhood Level

After the identification of substantial variation at level-2 (neighborhood level), the
interclass correlation coefficient (ICC) is calculated. The ICC reports the amount of
variance that resides between neighborhoods and provides an estimate that can predict the
explanation strength\textsuperscript{27} of the neighborhood level variables on the dependent variable (i.e.,
mean level of ALPR hits). That is, the ICC is the amount of variance that can be
potentially explained by level-2 variables. It is calculated by dividing the level-2
variance (tau) by the sum of level-1 (sigma square) and level-2 variance. In this case, the
ICC is:

\textsuperscript{27} The amount of variation explained by level-2 (i.e. block groups, neighborhoods) variables.
ICC = τ / (τ + σ²)  
ICC = .10938 / (.10938 + 1.38503)  
ICC = .073

The ICC suggests that level-2 variables can explain 7.3% variance in addition to the explanation power of level-1 variables (i.e., street characteristics/compositions). The last step for substantial level-2 variance is to determine appropriate level-2 variables that can explain 7.3% neighborhood level variance suggested by unconditional model. Given this context, four neighborhood level variables, including the total ALPR scan, race (percent African American), median income, and percent vacant property, were determined as the best level-2 predictors. Note, however, that the percent African American, median income, and percent vacant property are highly correlated with one another. For this reason, a measure of “concentrated disadvantage” was created by merging these three variables with the function of factor analysis of SPSS 17. As presented in Table 17, merging these three variables under one factor is statistically confirmed by the results of the factor analysis. The acceptable value for Kaiser-Meyer-Olkin measure of sampling adequacy is 0.5, which is 0.661 in our newly created factor. In addition, the determinant should not be zero (0), otherwise the factor analysis cannot create a new factor. As seen in Table 17, the determinant value is 0.472 (greater than zero).

| Table 17. Factor Analysis: Concentrated Disadvantage |
|---------------------------------|---------|
| Median Income                   | -.868   |
| Percent Black                   | .813    |
| Percent Vacant                  | .770    |

Determinant = .472
KMO Measure of Sampling Adequacy = .661
In brief, two neighborhood level variables – concentrated disadvantage and total ALPR scans – were selected to explain neighborhood level substantial variance identified by the unconditional model. Table 18 shows the introduction of these two level-2 variables in the HLM equation. When these level-2 predictors are introduced to unconditional model, level-2’s (intercept, mean ALPR hits) variance component was substantially reduced.28

Table 18. Unconditional & Conditioned Model

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Unconditional Model</th>
<th>Conditioned Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b</td>
<td>se</td>
</tr>
<tr>
<td>Mean ALPR Hits (base)</td>
<td>.396</td>
<td>.050</td>
</tr>
<tr>
<td>Neighborhood-level Total Scan29</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Neighborhood-level Concentrated Disadvantage</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Random Effects</th>
<th>Variance Component</th>
<th>Variance Component</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level-2</td>
<td>.10938</td>
<td>.04056</td>
</tr>
<tr>
<td>Level-1</td>
<td>1.385</td>
<td>1.389</td>
</tr>
</tbody>
</table>

After the identification of the appropriate level-2 variables, the level-1 variables (street characteristics) and level-2 variables can be tested at the same time (i.e., the full model). Recall from the methodology section that certain street characteristics (e.g.,

\[ R^2 = \frac{(\tau_{\text{unconditional}} - \tau_{\text{conditioned}})}{\tau_{\text{unconditional}}} \]

With this formula, the amount of explained variance in tau can be subtracted from the unconditional model and then divided to the sum of unconditional and conditioned model variance components in order to find out explained variance for level-2. Therefore:

\[ R^2 = \frac{(1.0938 - .04123)}{1.0938} \]

\[ R^2 = .623 \]

This amount represents the explained variance for level-2 variance (tau). Recall that only 7.3 percent variance resides between neighborhoods. For this reason, when 7.3 percent variance is multiplied by the calculated \[ R^2 (.623) \] of level-2 variance, the actual amount of explained variance for level-2 is 4.55 percent.

29 Since ALPR total scan contain raw numbers, its slope is close to zero even though it is significant. In addition to this, we logged the dependent variable; therefore, the interpretation of coefficient is slightly different than original metric dependent variable. Because we logged the dependent variable and not logged the neighborhood level independent variable, we should interpret unit change in dependent variable as percent. In this vein, one unit increase in the independent variable corresponds .0002 percent increase in the dependent variable (mean level of ALPR hits).
ALPR point distance to home address of criminals) are not available for all streets because there must be at least one ALPR hit per street that is associated with a control number of a criminal driver to calculate the additional variables (i.e., the point distance).

For this reason, the test of the first hypothesis of Research Question 2 includes only three street covariates: city major nodes, standardized ALPR scans by the street length\textsuperscript{30}, and number of crime per street. Thus, level-1 variables are restricted to these variables. The full model of Hypothesis 1a of Research Question 2 is presented in Table 19.

Table 19. HLM Poisson Regression Model for City Major Node Hypothesis\textsuperscript{+}

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Model 1</th>
<th></th>
<th></th>
<th>Model 2</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean ALPR Hits (base)</td>
<td>.192</td>
<td>.061</td>
<td>.003</td>
<td>.108</td>
<td>.055</td>
<td>.054</td>
</tr>
<tr>
<td>Neighborhood Level Total Scan</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>.000001</td>
<td>.000</td>
<td>.005</td>
</tr>
<tr>
<td>Neighborhood-level Concentrated Disadvantage</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>.171</td>
<td>.036</td>
<td>.000</td>
</tr>
<tr>
<td>Alternative Neighborhood Level $R^2$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.040</td>
<td></td>
</tr>
<tr>
<td>City Major Node (Yes)</td>
<td>.169</td>
<td>.045</td>
<td>.000</td>
<td>.169</td>
<td>.042</td>
<td>.000</td>
</tr>
<tr>
<td>Number of Crime</td>
<td>.207</td>
<td>.024</td>
<td>.000</td>
<td>.206</td>
<td>.022</td>
<td>.000</td>
</tr>
<tr>
<td>Standardized Scans by the Street Length</td>
<td>.592</td>
<td>.045</td>
<td>.000</td>
<td>.591</td>
<td>.039</td>
<td>.000</td>
</tr>
<tr>
<td>Alternative Street Level $R^2$</td>
<td>.619</td>
<td></td>
<td></td>
<td>.619</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Random Effects

<table>
<thead>
<tr>
<th>Variance Component</th>
<th>Variance Component</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level-2</td>
<td>.08585</td>
</tr>
<tr>
<td>Level-1</td>
<td>.52766</td>
</tr>
</tbody>
</table>

\textsuperscript{+} Analysis is based on 2,706 streets and 53 neighborhoods

Model 1 of Table 19 includes only level-1 variables. As predicted in Hypothesis 1a, street compositions, city major nodes, number of crimes, and standardized ALPR scans by the street length, are significantly and positively associated with the mean level of ALPR hits. As a specific example, a one unit change in the city major node’s slope yields to 0.169 percent change in the dependent variable (ALPR hits). Since the ALPR

\textsuperscript{30} \text{(total scans/street length)}*100
scans and street length are employed with the “standardized ALPR scans by the street length” variable, it can be argued that the city major nodes increase the detection chance of ALPR hits compared to non-major city nodes and the number of crimes controlling for street length and total ALPR scans at the street level.

Model 2 of Table 19 contains both level-1 and level-2 variables. As Model 2 indicates, level-2 variables are significantly associated with the mean level of ALPR hits at the neighborhood level. Putting it differently, the average ALPR hits significantly increased in neighborhoods where ALPR mobile units were more likely patrolled and where concentrated disadvantage was higher. The street compositions (number of crimes, city major node, and standardized measure of ALPR scans) also remained significant predictor of the mean level of ALPR hits independent of neighborhood covariates.

Unlike SPSS outputs, HLM outputs do not report R square (explained variation by independent variables). Rather, HLM outputs report the variance component for level-1 and level-2. To determine the differences in the explained variance between the two models, the standardized difference (in percentage) between the first model and the second model must be calculated. Snijders and Bosker (1994; 1999) call this process an alternative R square. Since the hierarchical models have two levels (streets and neighborhoods) for one intercept, the HLM outputs report both level-2 variance (tau) and level-1 variance (sigma square). By comparing the differences (reduction in level-1 and level-2 variances) the alternative R square can be reported. Given this context, the unconditional model’s variance component was 1.385 for level-1 variance and .109 for the level-2 variance (see Table 18). For Table 19, the alternative R square can be
calculated for level-1 (sigma square, $\sigma^2$) and level-2 (tau, $\tau$). In this case, for level-1 the alternative R square:

$$R^2 = \frac{(\sigma^2_{\text{unconditional}} - \sigma^2_{\text{conditioned}})}{\sigma^2_{\text{unconditional}}}$$

$$R^2 = \frac{(1.385 - .528)}{1.385}$$

$$R^2 = .619$$

Level-2 predictors also explain level-2 variance for the intercept. In this case, the level-2 alternative R square is:

$$R^2 = \frac{(\tau_{\text{unconditional}} - \tau_{\text{conditioned}})}{\tau_{\text{unconditional}}}$$

$$R^2 = \frac{(.109 - .0497)}{.109}$$

$$R^2 = .544$$

This amount represents the explained variance for level-2 variance (tau). However, recall from the ICC value that only 0.073 (7.3%) variance reside between neighborhoods. For this reason, the above R square for level-2 only explains 54.4 percent of level-2 variance, which is 0.073 according to unconditional model. Therefore, multiplication of these two values (54.4 X .073) gives us alternative R square for level-2, which is almost 4%.

Finally, when we sum these level-1 and level-2 explained variances, we can find the total explained variance of intercept for any corresponding model. For instance, for Model 2 of Table 19, the total explained variance is .040 + .619 = .659. In other words, both level-1 and level-2 predictors together explain 65.9% variance of the dependent variable.31

Regarding the HLM analysis, another important issue is how to center the level-1 predictors for dependent variable because “the meaning of the intercept in the level-1 model depends on the location of the level-1 predictor variables” (Raudenbush & Bryk, 2002, p.31). In other words, since the level-1 predictors become outcome variables at level-2, the location of level-1 variables is very important for the interpretation of

---

31 Note that SPSS outputs also report nearly identical R square values for level-1 predictors.
dependent variable. In HLM analysis, there are two options for centering: group-mean centering and grand-mean centering. In the group-mean centering option, level-1 predictors are centered on their corresponding level-2 unit means. Specific to this study, the streets were centered on their corresponding neighborhood unit means. Alternatively, with grand-mean centering, level-1 predictors are centered on the average level-2 unit means. Based on this distinction, the interpretation of group mean centered level-1 predictors would be “the intercept (or mean level of ALPR hits) is the best estimate when level-1 predictors are set equal to their corresponding level-2 unit means. In addition, with group-mean centering, compositional effects (level-1 predictors effect) can be seen separately since level-1 predictors are centered on their corresponding level-2 unit means (Raudenbush & Bryk, 2002). Similarly, Hoffman and Gavin (1998) briefly explained group mean centering as the appropriate decision when the purpose is to detect separate effects of both levels' predictors. Paccagnella (2006, p.70) explains this issue as follows:

\[ \text{.....centering with respect to the group mean allows us to interpret the intercept as the expected outcome for a student in classroom } j \text{ whose covariate values are equal to the classroom's means (that is, the mean across all students in the classroom } j). \text{ This is done when the researcher is particularly interested in separating the between-group and the within-group components from the total variation to investigate how groups (contexts) affect student performances, explicitly accounting for the group structure into the model.} \]

Based on this rationale, group-mean centering was used in the analysis to separately examine both the effects of street level variables (compositional effects) and the effects of level-2 variables (contextual). More specifically, it was important to see whether the relative position of a street within in the group is more important than the

\[ ^{32} \text{Heterogeneity of slopes can be maintained with group-mean centering. For this reason, group-mean centering reflects unadjusted slopes for the intercept.} \]
absolute/total rating (Hox, 2002, Snijders & Boskers, 1999). In brief, based on the above rationale, group mean centering was used in all HLM analyses, and the mean level of ALPR hits (intercept) should be interpreted as the mean level of ALPR hits is the best estimate when level-1 predictors are set equal on their corresponding neighborhood unit means.

Results for Hypothesis 1b and Hypothesis 2

Hypothesis 1b and Hypothesis 2 differ from Hypothesis 1a because Hypothesis 1b only includes streets that have at least one ALPR hit. Because non-ALPR hit streets were excluded, the distribution of the logged dependent variables for Hypothesis 1b and Hypothesis 2 are normal and therefore meet the assumptions of OLS regression. The unconditional model and interclass correlation coefficient (ICC) of Hypothesis 1b suggests that 6.6% variance resides between neighborhoods and 68.9% of this variance is explained by selected level-2 variables (e.g., total ALPR scan and concentrated disadvantage). Table 20a presents full model of Hypothesis 1b.

Table 20a. Hierarchical Linear Model for Hypothesis 1b and Hypothesis 2

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>se</td>
</tr>
<tr>
<td>Mean ALPR Hits (base)</td>
<td>2.076</td>
<td>.057</td>
</tr>
<tr>
<td>Neighborhood-level Total Scan</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Concentrated Disadvantage</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Alternative Neighborhood Level $R^2$</td>
<td>.423</td>
<td>.049</td>
</tr>
<tr>
<td>City Major Node (base)</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Total Scan</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Concentrated Disadvantage</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Number of Same/Duplicate Vehicles</td>
<td>.131</td>
<td>.016</td>
</tr>
<tr>
<td>Number of Crimes</td>
<td>.286</td>
<td>.012</td>
</tr>
<tr>
<td>Standardized Scans by the Street Length</td>
<td>1.191</td>
<td>.053</td>
</tr>
<tr>
<td>Alternative Street Level $R^2$</td>
<td>.836</td>
<td>.836</td>
</tr>
<tr>
<td>Variance Component</td>
<td>.161</td>
<td>.084</td>
</tr>
</tbody>
</table>

*Analysis is based on 1902 streets and 53 neighborhoods*
Model 1 of Table 20a includes only level-1 variables (street compositions) that are centered around their corresponding neighborhood unit mean. The slope of “city major nodes” was specified as random to see its effect both at the street level and the neighborhood level. Unlike the Poisson regression model in Table 19, the “number of same vehicle” variable was included in order to control the adverse effects of duplicate hit vehicles on the same street. Model 1 suggests that the number of duplicate vehicles is significantly associated with the number of ALPR hits. More specifically, a one percent increase in the “number of same vehicle” leads to a 0.131 percent change in mean level of ALPR hits. All the other three variables – city major node, number of crimes, and standardized measure of number ALPR scans by the street length – are also significantly and positively related to the intercept (i.e., mean level of ALPR hits). As predicted in the Hypothesis 1b, if a street is characterized as a city major node, the mean level of ALPR

---

33 Notice that both the independent and dependent variables were logged; therefore the interpretation has to be “percent change” rather than “unit change.”
hits substantially increases on that street the independent of number of crimes, standardized (by street length) measure of ALPR scans, and number of same hit vehicles.

In Model 2 of Table 20a, the neighborhood covariates are included. Concentrated disadvantage and total ALPR scans are significantly and positively associated with the mean level of ALPR scans. Concentrated disadvantage significantly and negatively interacts with the random slope of city major nodes. As a caveat, the interpretation of interaction terms in HLM outputs is different than the SPSS outputs. A negative sign of neighborhood covariates suggests that the mean level of concentrated disadvantage and mean level of total ALPR scans at the neighborhood level have lessened or tempered the effect of street level percent city major node. The temperance effect of neighborhood level covariates, however, did not completely negate the compositional effect of city major nodes. That is, city major nodes remained as a significant predictor of mean level of ALPR hits.

Table 20b reports the results testing Hypothesis 2 of Research Question 2, which explores whether ALPR mobile units identify criminal vehicles in places/streets where the number of crimes is higher compared to other places. For this reason, in Table 20b, only the slope of “number of crimes” is specified as random. Model 2 of Table 20b reports similar findings to Model 2 reported in Table 20a. While neighborhood level covariates are significantly and positively correlated with the mean level of ALPR hits, only neighborhood level concentrated disadvantage is associated with the random slope of number of crimes. Results again suggested that contextual variables (in this case, concentrated disadvantage) temper the effect of the number of crimes to some extent;
however, they cannot completely negate the effect of the number of crimes on the mean level of ALPR hits.

**Results for Hypothesis 3, Research Question 2**

Research Question 2, Hypothesis 3 proposes that ALPR equipped vehicles will more likely identify criminal vehicles in places that are close to residences of identified criminal vehicles’ drivers compared to non-resident locations of criminals. In addition, Hypothesis 3 predicts that the adverse effects of structural covariates at the neighborhood level will affect the mean level of ALPR hits. For this reason, only point distance slopes are specified as random in the analyses.

As discussed in the methodology section, point distances (between ALPR hit place and criminals’ home addresses) cannot be calculated for all ALPR hits. An ALPR hit has to simultaneously have a control number, a matched arrest record from any CPD database, and a matched home addresses in ArcMap (Geographic Information System software) to calculate the point distance. For this reason, only 7,743 ALPR hits were aggregated to the street level, which included 890 streets for the individual level data. It was also necessary to control for the impact of parked vehicles for the point distance analysis because there were some vehicles parked in front of criminals’ residential addresses that potentially inflate (overestimate) the results for Hypothesis 3. Based on this concern, Hypothesis 3 was tested with and without the effect of parked vehicles. While it is necessary to control for the effect of parked vehicles in the HLM regression equation, the parked vehicles variable is highly correlated with the point distance calculations (presented in Table 21). Therefore, the number of parked vehicles was

---

34 Within 100 meters away from home addresses of criminal vehicles’ drivers.
subtracted from the total numbers of various distances (i.e., 1000 meters, 2000 meters) to overcome any possible multicollinearity problem. Given this context, the first set of analyses includes the effect of parked vehicles and the second set excludes the effect of parked vehicles.

Table 21. Zero order correlations between parked vehicles and distances

<table>
<thead>
<tr>
<th></th>
<th>X1</th>
<th>X2</th>
<th>X3</th>
<th>X4</th>
<th>X5</th>
<th>X6</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X2</td>
<td>0.908</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X3</td>
<td>0.845</td>
<td>0.958</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X4</td>
<td>0.766</td>
<td>0.883</td>
<td>0.951</td>
<td>--</td>
<td></td>
<td></td>
</tr>
<tr>
<td>X5</td>
<td>0.707</td>
<td>0.828</td>
<td>0.913</td>
<td>0.973</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>X6</td>
<td>0.667</td>
<td>0.778</td>
<td>0.875</td>
<td>0.938</td>
<td>0.972</td>
<td>--</td>
</tr>
</tbody>
</table>

1=Number of Parked Vehicles; 2=Distance within 1000 meters; 3=Distance within 2000 meters; 4=Distance within 3000 meters; 5=Distance within 4000 meters; 6=Distance within 5000 meters

Table 22 presents results for Hypothesis 3 without taking into account the effect of parked vehicles with five different models. Model 1 of Table 22 explores whether ALPR mobile units identifies criminal vehicles within 1,000 meters of their drivers’ residential addresses. Model 1 suggests that the relationship between a 1,000 meter point distance (from residential home address of criminal vehicles’ driver to ALPR hit points) and ALPR hit is significant in positive direction. That is, ALPR mobile units more likely encountered criminal vehicles in places that are close to the previously arrested people’s residential addresses. More specifically, a one percent change in the 1,000 meter point distance corresponds to a 0.181 percent change in the mean level of ALPR hits. The other possible explanation of this significant relationship could be that a small amount of people repeatedly commit crime; therefore, focusing on places that contain high offender populations compared to other places will experience more ALPR hits. The relationship between point distances and ALPR hits increases as the distance between criminal
vehicles’ drivers and ALPR hit point increases. Indeed, the increment difference (in terms of R square change) between Model 1 and Model 6 is moderate. If we compare alternative R squares of two models, we can discover the difference between Model 1 (1000 meters point distance) and Model 6 (5000 meters point distance). In this context, the difference is:

\[ \Delta R^2 = (.822 - .837) = -.015 \]

which means that 5000 meters point distance better explain mean level of ALPR hits for 1.5 percent than 1000 point distance.

Table 23 presents the full HLM model for the point distance analyses without the effect of parked vehicles. In any model of Table 23, the level-2 variables are significantly associated with the mean level of ALPR hits. In more detail, a one unit increase in neighborhood-level total ALPR scan corresponds with a 0.0004 percent average ALPR hits.\(^{35}\) However, both neighborhood level covariates did not interact with any random slopes of point distances. These results suggest that point distance has strictly compositional effect on the mean level of ALPR hits.

Table 24 is a replication of Table 23 with a distinction that these reported analyses take into account the effect of parked vehicles in the point distance analyses. According to the results, all point distances remained similar when the effect of parked vehicles was subtracted from the number of vehicles that fall into any corresponding point distance radius (i.e., 1000 meters, 2000 meters). In addition, the comparison of the variance component (in terms of alternative R square change) of Table 24 and Table 23 also

---

\(^{35}\) Recall that unlike the dependent variable, level-2 predictors were not logged. For this reason, the slope of neighborhood level total ALPR scan should be multiplied by 100 and the dependent variable has to be stated in percentage change rather than unit change.
suggests that the strength of point distance slope is similar with and without the effect of parked vehicles.
Table 22. Hierarchical Linear Model for Hypothesis 3 Excluding The Effect of Parked Vehicles+

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b</td>
<td>se</td>
<td>b</td>
<td>se</td>
<td>b</td>
</tr>
<tr>
<td>Mean ALPR Hits (base)</td>
<td>2.972*</td>
<td>.065</td>
<td>2.969*</td>
<td>.065</td>
<td>2.966*</td>
</tr>
<tr>
<td>Neighborhood-level Total Scan</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Concentrated Disadvantage</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Alternative Neighborhood Level $R^2$</td>
<td>.351*</td>
<td>.052</td>
<td>.338*</td>
<td>.053</td>
<td>.324*</td>
</tr>
<tr>
<td>City Major Node</td>
<td>.181*</td>
<td>.031</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Total Scan</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Concentrated Disadvantage</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>ALPR Hits within 1000 meters (base)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>.192*</td>
</tr>
<tr>
<td>Neighborhood-level Total Scan</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Concentrated Disadvantage</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>ALPR Hits within 2000 meters (base)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Total Scan</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Concentrated Disadvantage</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>ALPR Hits within 3000 meters (base)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Total Scan</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Concentrated Disadvantage</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>ALPR Hits within 4000 meters (base)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Total Scan</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Concentrated Disadvantage</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>ALPR Hits within 5000 meters (base)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Total Scan</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Neighborhood-level Concentrated Disadvantage</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Number of Crime</td>
<td>.279*</td>
<td>.017</td>
<td>.278*</td>
<td>.017</td>
<td>.273*</td>
</tr>
<tr>
<td>Standardized Scans by the Street Length</td>
<td>.944*</td>
<td>.055</td>
<td>.931*</td>
<td>.057</td>
<td>.912*</td>
</tr>
<tr>
<td></td>
<td>.133</td>
<td>.021</td>
<td>.131</td>
<td>.020</td>
<td>.125</td>
</tr>
<tr>
<td>Alternative Street Level $R^2$</td>
<td>.822</td>
<td>.824</td>
<td>.829</td>
<td>.831</td>
<td>.837</td>
</tr>
</tbody>
</table>

Random Effects

<table>
<thead>
<tr>
<th>Level-2</th>
<th>Variance Component</th>
</tr>
</thead>
<tbody>
<tr>
<td>.193</td>
<td>.194</td>
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<tr>
<td>City Major Node Slope</td>
<td>.004</td>
</tr>
<tr>
<td>Level-1</td>
<td>.319</td>
</tr>
</tbody>
</table>

(+ Analysis is based on 890 streets and 52 neighborhoods; *p<.05
Given the similar results between Tables 23 and 24, it is save to conclude for point
distance analyses that ALPR mobile units are more likely to identify criminal vehicles in
places that are close to residential places of previously arrested criminals, controlling the
effect of parked vehicles. Further, the addition of level-2 variables did not temper the
effect of the point distance variable on the mean level of ALPR hits.
Table 23. Hierarchical Linear Model for Hypothesis 3 Excluding The Effect of Parked Vehicles

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
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<tr>
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<td>--</td>
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<tr>
<td>Level-1</td>
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Analysis is based on 890 streets and 52 neighborhoods; *p<.05
Table 24. Hierarchical Linear Model for Hypothesis 3 Including The Effect of Parked Vehicles

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<th>Fixed Effects</th>
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<td>Point Distance Slopes</td>
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<td>Level-1</td>
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(+) Analysis is based on 890 streets and 52 neighborhoods; *p<.05
CHAPTER VI
DISCUSSION

This research explored the impact of Automatic License Plate Reader (ALPR) systems for the Cincinnati Police Department. The findings from the multiple research questions and related hypotheses provide new insights and implications for policing more generally. In this chapter, these research findings are discussed within a broader context by considering current policing approaches. Thereafter, the larger implications of this study will be detailed.

The Impact of ALPR Technology on Policing

There are few previous empirical studies regarding the impact of ALPR technology, and none that have addressed the specific hypotheses current posed; therefore, it is not possible to make comparisons between the current findings and previous studies. This study is one of the first to systematically evaluate the impact of ALPR technology on policing.

To assess the impact of ALPR technology on policing, various analytical techniques were used, including time series analysis, bivariate tests, and cost effective analyses. The interrupted time series model examining the impact of ALPR systems indicated that ALPR technology significantly increased follow-up arrests in the CPD compared to more traditional policing approaches. The impact of ALPR technology was also assessed by conducting manpower and cost effectiveness analyses. Comparative manpower analyses revealed that ALPR technology carried out more follow-up arrests by using less police officers compared to traditional policing.

In police departments, one of the concerns about adopting new technologies into daily police activities is financial cost. Like other organizations, police departments have
scarce sources to maintain public safety; therefore, to maximize effectiveness and efficiency in crime prevention efforts they must rely on new technologies. ALPR technology has significant front-end costs and represents a substantial financial investment of departmental resources. The cost analysis of ALPR technology for the CPD, however, revealed that ALPR technology is cost effective and amortizes itself within less than one week. More specifically, ALPR mobile units effectively do the same job (produce follow-up arrests) with less officers compared to traditional policing. In addition to the follow-up arrest measure of effectiveness, ALPR mobile units have high detection capability for stolen vehicles and identification of delinquents who did not pay their legal financial obligations (i.e., traffic ticket, insurance). Adding these additional superiorities of ALPR technology increases it cost effectiveness over traditional policing applications. From this perspective, ALPR technologies can be seen as a smart investment for police departments to optimally allocate scarce resources while effectively and efficiently enforcing the law and engaging in crime prevention.

**Crime Prevention Theories and ALPR Technology**

Conducting different analyses in the first research question revealed that ALPR technology is an effective and efficient tool for policing. The second research question of this study considered if the effectiveness of ALPR mobile units could be improved by employing the principles of crime prevention theory. Consistent with the main premise of crime prevention theory (non-random distribution of crime in time and space), the findings demonstrated that ALPR mobile units non-randomly identified criminal vehicles on certain streets of Cincinnati. In this context, the findings from the test of four specific hypotheses collectively explained this non-random identification of criminal vehicles by
ALPR mobile units. These explanations (further described below) include spatial analysis, city major nodes, recorded crimes, and point distance.

**Spatial Analysis:** Hypothesis 1a of Research Question-2 explored whether street compositions (i.e., high crime, city major nodes) increased the detection of criminal vehicles, controlling for neighborhood covariates. For this spatial analysis, all Cincinnati streets (including streets with and without ALPR hits) were included. The inclusion of all streets in the analysis provides a broader perspective to determine whether ALPR hits were concentrated on certain streets because of their street compositions (i.e., city major node, number of crime per street) and their corresponding neighborhood characteristics. Given this context, HLM analysis revealed that street compositions, city major nodes and number of crimes, significantly increased the identification of criminal vehicles controlling for other street characteristics (number of crime and standardized measure of ALPR scans by the street length) and neighborhood covariates (concentrated disadvantage and total ALPR scans per neighborhood).

**City Major Nodes:** In the crime prevention literature, various empirical studies found that city major nodes significantly increased non-random concentration of crime (Brantingham & Brantingham, 1982; Donnelly & Kimble, 1997; Mathews 1993; White, 1990). Additional theories proposed that offenders commit more property crimes along the facilities of city major nodes because offenders have more familiarity for those places for criminal opportunities (Brantingham & Brantingham, 1982; 2003; Eck, 1993). Based on this notion, it was hypothesized that city major nodes would increase the detection of criminal vehicles compared to non-city major nodes.
Unlike Hypothesis 1a, Hypothesis 1b only included streets that had at least one ALPR hit. As noted above, the reason of exclusion streets having no ALPR hits is that research questions were normally designed to see where ALPR mobile units more likely encountered with criminal vehicles. For this reason, streets having no ALPR hits are not the focus of the second research question. Concentrating on only streets with ALPR hits enables the use of additional variables by merging hit/criminal vehicle drivers’ control numbers (unique identifiers) with corresponding CPD databases. Given this context, the results revealed that city major nodes significantly increased the detection of criminal vehicles by controlling for other street compositions and neighborhood covariates.

In brief, the findings from tests of both hypotheses support the central propositions of crime prevention theory. These findings revealed that street compositions increased the identification of criminal vehicles, controlling for neighborhood covariates. Because the standardized measure of ALPR scans in the analyses was controlled, the threat of unequal ALPR patrol applications was controlled to some extent. For instance, ALPR mobile units might patrol in certain streets more frequently compared to others. In this case, detection of criminal vehicles would automatically increases on those streets. Similarly, longer streets may contain more vehicles compared to shorter ones, which may increase the detection of criminal vehicles. Due to these possibilities, the ALPR scans were standardized by introducing additional variables into equation in order to control for the possible adverse effects of non-random ALPR patrol applications and street length. As a result, city major nodes significantly increased the number of ALPR hits even after relevant control variables were added.
**Recorded Crime Level / Number of Crime:** According to crime prevention theory, places that have high number of crimes are somewhat vulnerable to subsequent criminal victimization (Sherman et al., 1989). Based on this notion, we hypothesized that ALPR hit vehicles were more likely to identify criminal vehicles on certain streets that have high number of crime compared to others. The results indicated that higher crime areas were significantly and positively associated with the number of ALPR hits at the individual level (street level). This relationship remained the same with the addition of neighborhood covariates to the equation.

**Point Distance:** The offender search theory within crime prevention theory suggests that criminals more likely to commit crime near their residential places because they are more familiar with those locations (Brantingham & Brantingham, 2003; Eck, 1993). This study shows support for this proposition. Specifically, this study demonstrated that ALPR mobile units were more likely to identify criminal vehicles near their residential addresses. To further explore the point distance analysis, different point distances were used that ranged from 1,000 meters to 5,000 meters. The results suggested that as the point distance increased, the identification of criminal vehicles also increased.

One concern about point distance analysis was that parked vehicles might lead to a spurious finding of a significant relationship between the point distance variable and the number of ALPR hits, when in fact there was no relationship. For this reason, two different point distance analyses were conducted. In the first examination (described previously), the HLM analysis was conducted without considering the effect of parked vehicles and found a significant positive relationship between the point distance variables
and the number of ALPR hits. In the second analysis, the equation was conducted by taking out the effect of parked vehicles from the point distance variable. The results indicated that the impact of parked vehicles on point distance was insignificant and did not change the original relationship between the point distance variable and the number of ALPR hits. In addition, this relationship still remained the same with the inclusion of neighborhood covariates.

**Street Compositions vs. Neighborhood Covariates**

The results of Research Question 2 also demonstrated the separate effects of street level compositions and neighborhood level covariates for the number of ALPR hits. Overall the findings suggest that the street compositions (number of crime, city major node, and point distance) explained 82% to 84% of variance. In contrast, the explanatory power of the neighborhood covariates, concentrated disadvantage and total ALPR scans, was weak and only explained 1.5% of the variance in the dependent variable (number of ALPR hits). Relying on these findings, it is clear that the street compositions (number of high crime, city major node, and point distance from criminal residences) are more important to predict the places where ALPR mobile units will most likely identify criminal vehicles.

**Summary**

Analyses conducted based on the principles of crime prevention theory indicated that ALPR vehicles were more likely identify criminal vehicles on certain streets of Cincinnati compared to others. The results revealed that streets characterized as city major node, with higher crime, and closer proximity to residential places of previously

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36 In HLM analysis, the correct usage of language for dependent variable is “mean level of ALPR hits” because dependent variable of the first level becomes the intercept of the second level. However, we interchangeably used number of ALPR hits and mean level of ALPR hits for ease understanding.
arrested people (i.e., point distance) increase the chance of detection of criminal vehicles. This non-random identification of criminal vehicles suggests important implications for current applications of policing, which will be discussed in the next section of this chapter.

Intelligence-Led Policing and ALPR Technology

Police scholars argue that intelligence-led policing is one of the field’s most promising new approaches (Kelling & Bratton, 2006; Maguire & John, 2006). Intelligence-led policing (ILP) enables police departments to more effectively enforce laws, optimally allocate scarce resources, and maximize crime prevention efforts (John & Maguire, 2004). Core themes of intelligence-led policing are to analyze all relevant crime data and to generate proactive strategies in light of effective crime prevention theories and best practices.

These research findings suggest that ALPR technology is an effective tool for intelligence-led policing in several directions. For instance, the findings revealed that ALPR mobile units non-randomly identified criminal vehicles on certain streets of Cincinnati. In addition, the street compositions (number of high crime, city major node, and point distance) almost completely explain this non-random identification of criminal vehicles (83% of the variance). These two major findings provide that police departments need to deploy ALPR mobile units more strategically to best met the principles of intelligence-led policing. In addition, the point distance analysis revealed that ALPR mobile units are more likely to identify criminal vehicles near residential addresses of previously arrested people/offenders. This finding indirectly provides further confirmation that a small group of people repeatedly commit crime and are
repeatedly being sought by the police. This information also enables police departments to generate more proactive strategies within the context of intelligence-led policing. As noted earlier, the Kent Police Department, UK, reduced crime for 25% by implementing this method (Clarke & Newman, 2007; Maguire & John, 2006).

Another aspect of ALPR technology is the collection of timely and accurate data about criminals and non-criminals. This feature of ALPR technology provides invaluable information for intelligence-led policing; with timely and accurate data, police departments can trace the movement of criminal vehicles from one place to another. Based on this, crime patterns of a city can be mapped, which in turn will enable police departments to implement prevention efforts.

In brief, intelligence-led policing is seen as the newest and most influential policing approach to tackle crime. In this context, technological enhancements like ALPR technology, are the main requisites of “intelligent” police departments because this technological enhancement both collects timely and accurate data, while identifying criminals/criminal vehicles much faster than any traditional method. These abilities enable police departments to implement more proactive policies against crime and criminals – this is the core principle of intelligence-led policing.

**Research Implications**

This study provides several implications for future research. As noted above, police departments using intelligence-led policing can integrate separate databases in order to detect future crime patterns. In traditional policing, each unit separately maintains databases; however, a specific crime can stem from the combination of several crimes. Separate databases are incapable of detecting these crime patterns.
ALPR systems are new technologies for police departments. Their main advantage over any other data collection systems is that they collect timely and valid for police departments. Future studies can try to integrate ALPR data to other police databases in order to figure out whether integration of ALPR database with other relevant databases can increase the prediction of future criminal patterns as suggested by intelligence-led policing.

Studies utilizing ALPR technology can also impact other studies of police behavior – including racial profiling studies (e.g., see Buerger & Farrell, 2002; Harris, 2002; 2006; Ramirez et al., 2000; Walker, 2001). ALPR data could serve as a comparison tool for racial profiling studies because researchers who want to study racial profiling can examine ALPR data and use it as a comparison with traditional traffic stops. Since ALPR data provide automated data, differences between ALPR traffic stops and traditional way of traffic stops may give new insights to racial profiling studies.

**Conclusion**

The purpose of this study was to examine whether the use of technological innovations like ALPR technology can help police departments to effectively enforce laws, optimally allocate scarce resources, and maximize crime prevention efforts. To determine the impact of ALPR technology on policing, two research questions were proposed. The first research question compared the effect of ALPR technology with traditional ways of policing by using follow-up arrests as a comparison tool. In addition, manpower comparisons and cost effectiveness comparisons were also conducted to assess the value of ALPR technology in policing. The results indicated that ALPR technology substantially increased follow-up arrests by employing fewer police officers. The cost
effectiveness analysis also revealed that ALPR technology is capable to amortize itself within less than one week.

The second research question utilized crime prevention theory and hypothesized that ALPR mobile units were most likely to identify hit vehicles in certain places that are predicted by crime prevention theory, such as city major nodes and high crime areas. It was expected that this possible identification, in turn, can increase the effectiveness of intelligence-led policing through allocating scarce resources to prioritized places where public safety is at the maximum need.

These expectations were supported through findings using hierarchical linear and hierarchical generalized linear models that indicated ALPR mobile units were more likely to identify criminal vehicles in places predicted by crime prevention theory. At the street level, city major modes, high crime areas, and places that are close to previously arrested offenders were found to increase the detection of criminal vehicles. At the neighborhood level, concentrated disadvantage and total ALPR scans were found as significant predictor for the identification of criminal vehicles.

Overall the results suggest that ALPR technology is an effective instrument for police departments. The cost effectiveness of ALPR mobile units over traditional policing also suggests that most patrol vehicles in the United States will be equipped with ALPR systems in near future. Finally, findings of crime prevention theory imply that ALPR mobile units can be more strategically deployed by analyzing crime patterns of a given city/region within the tenets of crime prevention theory. In this way, intelligence gathering and crime prevention can be merged to provide better foresights for the prediction of future crime patterns and the prevention of those crimes.
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