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'Led by intelligence': A scoping review on the experimental evaluation of intelligence-led policing

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Abstract

Background: Intelligence-Led Policing (ILP) was introduced in the 1990s as a proactive approach to policing, but to date, there is a lack of studies that have synthesized and summarized the central characteristics and insights of (quasi-)experimental studies related to ILP. **Objectives:** This study aims to address this gap by synthesizing and characterizing the central characteristics of 38 quasi-experimental and experimental studies related to ILP. **Research design:** In this study, a scoping review is conducted on different quasi-experimental and experimental studies that relate to the framework of ILP. **Results:** It was found that most studies within the domain of ILP focus on testing the crime reduction effects of using spatio-temporal crime intelligence to deploy police resources more efficiently and effectively. However, some studies have combined different types of crime intelligence or used solely offender-related intelligence. Several statistical-methodological challenges were also identified that should be considered when designing experimental research within the domain of ILP. Additionally, most studies focused solely on measuring crime reduction, with few focusing on secondary effects of interventions. **Conclusions:** The review concludes that future evaluation studies should consider evaluating the use of different types of crime intelligence and establish specific, objective, and realistic criteria for measuring specific performance measures such as crime disruption. Future experimental research within the domain of ILP should consider applying the 3-i model, evaluating each leg of ILP thoroughly. The limitations of the study are also discussed. This review provides valuable insights for future research and development of ILP-related approaches.

Keywords

Intelligence-Led Policing – Crime prevention – Scoping review – 3-i model – Evidence-Based Policing – Big data policing

Introduction

Intelligence-led policing (ILP), first implemented in the early 1990s primarily in the UK, is a proactive approach to policing intended to enhance the effectiveness and efficiency of police organizations. It was introduced in the UK alongside the National Intelligence Model as part of the 'reimagining policing' discourse (Burcher, 2020; NCIS, 2000; Ratcliffe, 2003), in an attempt to overcome the limitations of traditional reactive policing methods (Carter et al., 2014; Collier, 2006; Ratcliffe, 2003, 2016) and address the challenges posed by, among others, organized crime, technological developments, and outdated police infrastructures.

Today, the role of intelligence in ILP is significantly influenced by digitalization processes, characterized by the amplification of big data streams from various sources, including existing and evolving smart devices (Snaphaan & Hardyns, 2021). These big data sources offer extensive opportunities for developing new crime prevention mechanisms within an ILP framework. For example, machine learning algorithms and other innovative techniques capitalize on big data to predict and anticipate crimes. As new technologies and information continue to proliferate, police departments must find effective ways to embrace them (Chan & Moses, 2016; Moses & Chan, 2018; Rummens & Hardyns, 2020) and incorporate these new types of intelligence sources into their work. Intelligence-led policing provides a guiding framework for implementing these datafication processes.

In order to guide the future implementation of ILP, it is necessary to evaluate its effectiveness. Experimental research designs play a crucial role in assessing the impact of policing approaches and establishing causal relationships between interventions and outcomes (Ariel et al., 2021). However, there are inherent challenges in evaluating ILP's effectiveness, as it encompasses a policing paradigm rather than a specific program or intervention, with the result that there is a dearth of evidence on its overall effectiveness (Ratcliffe, 2021; Saunders et al., 2016). Nonetheless, numerous quasi-experimental and experimental studies have been conducted in the past to evaluate proactive policing interventions/programs (for an overview, see for example the National Academies of Sciences' report on proactive policing by Weisburd & Majmundar, 2018), some of which align with the central tenets of the ILP framework. These interventions include place-based proactive policing interventions such as hot spots policing (Braga et al., 2019; Sherman & Weisburd, 1995) or place-based predictive policing (e.g., Hunt et al., 2014; Ratcliffe et al. 2021), deploying police resources in high-crime areas, and person-based policing interventions targeting prolific offenders or criminal groups (e.g., Santos & Santos, 2016; Saunders et al., 2016). Although these proactive policing interventions are specific in nature, they increasingly incorporate and rely on data analysis and crime intelligence to optimize the efficiency and effectiveness of law enforcement agencies.

Despite the existence of these studies, there has been no synthesis of their central characteristics and insights, nor have attempts been made to relate them to the ILP framework and its conceptualizations. The primary objective of this research is, therefore, to conduct a scoping review of quasi-experimental and experimental studies of policing interventions that align with the strategic scope of ILP. We aim to make a three-fold contribution to this field of research. First, this exercise will enhance our understanding of the current state of evidence-based practices within the domain of ILP. By mapping the main conceptual, methodological, and empirical insights of these studies, we aim to identify key trends, themes, and research gaps. Identifying research gaps will enable researchers to direct their efforts towards filling these gaps. Second, the insights gained will serve as a valuable guide for future quasi-experimental and experimental research in this field by identifying the significant challenges that can be encountered when designing ILP-related quasi-experimental and experimental evaluation studies. Third, the synthesis of these insights will contribute to bridging the gap between research and practice. As we include studies evaluating practice-oriented policing interventions using rigorous evidence-based methodologies, the findings will be relevant not only for academics but also for practitioners seeking to implement and evaluate ILP interventions in real-world scenarios. This bridging of research and practice is crucial to fostering evidence-based decision-making and enhancing the overall effectiveness of ILP initiatives.

This article is structured as follows. First, we provide a brief conceptual overview of the intelligence-led policing framework, demonstrating how the inclusion and exclusion criteria of this scoping review align with the central tenets of ILP. Second, we describe the step-by-step methodology, following the framework proposed by Arksey & O'Malley (2005), and outline the research questions. Third, we present the results of the scoping review, including a comprehensive overview of the methodological challenges reported in the studies, as well as the empirical effects on which these studies focused. Finally, we discuss the implications of our findings and make further recommendations.

Background

Intelligence-led policing: What's in a name?

Intelligence-led policing is a conceptual framework that supports the use of data analysis and intelligence to inform policing strategies, decision-making processes, and the implementation of proactive and targeted interventions to reduce, prevent, or disrupt criminal activities. Initially, ILP was primarily characterized as a tactical approach. However, current perspectives view ILP as a business model, wherein intelligence plays a pivotal role in optimizing the allocation of police resources in a more efficient and effective manner (Budhram, 2015). Consequently, it has been suggested that the focus of ILP has slightly altered (Carter & Carter, 2009; Ratcliffe, 2016), broadening its applicability as a framework for addressing a wider spectrum of criminal problems and phenomena: instead of merely targeting prolific and serious offenders, for example, ILP has recently also been used in relation to crime hot spots. Current conceptualizations of ILP seem to have shifted their focus from taking solely an offender-centered perspective, to incorporating an offence-centered perspective, representing ILP as a more holistic approach to crime prevention and policing (for a more comprehensive overview, we refer to the work of Ratcliffe, 2016).

Although many argue that it is difficult to define ILP precisely (Saunders et al., 2016), this study uses the definition proposed by Ratcliffe (2016), one of the leading authors on ILP. It serves as a guideline for which studies to include in and exclude from this scoping review:

> Intelligence-led-policing emphasises analysis and intelligence as pivotal to an objective, decision-making framework that prioritises crime hotspots, repeat victims, prolific offenders, and criminal groups. It facilitates crime and harm reduction, disruption, and prevention through strategic and tactical management, deployment, and enforcement (Ratcliffe, 2016, p. 66).

It is clear from this definition that intelligence-led policing should be perceived not as an independent intervention per se, but rather as a policing framework. The central focus is to incorporate data analysis and intelligence into decision-making processes that pertain to the nature of policing interventions and the allocation of resources. The objective is to effectively impact the criminal environment. Consequently, as argued by Saunders et al. (2016), ILP is a framework within which specific interventions need to be developed separately. The fundamental commonality among ILP-related interventions is the use of data and analytical approaches to generate intelligence, which is then employed to proactively allocate police resources, inform strategic and/or tactical processes, and facilitate well-informed decisions. These are the core elements of ILP.

In addition to Ratcliffe's definition, our study adopts the 3-i model, also developed by Ratcliffe (2016). The 3-i model is used to conceptualize ILP. It features three main components (crime intelligence analysis, decision-making, and the criminal environment) and three connecting mechanisms (interpreting, influencing, and impacting). Crime intelligence analysis is the process of interpreting the criminal environment, and refers to an intermediary process in which raw data are analyzed to translate them into 'information' by adding meaning or context; hence the analysis guides the development of knowledge and intelligence.[1] The analytical component also includes the process of identifying and influencing decision-makers (e.g., commissioners); in particular, the process of disseminating intelligence products to decision-makers in order to influence their and others' strategic and/or tactical decisions made on the basis of the intelligence obtained through crime intelligence analysis. The 3-i model therefore defines the decision-making component of ILP that signifies commanders impacting the criminal environment by developing and employing specific tactics based on criminal intelligence derived from crime intelligence analysis.

[Figure 1. The 3-i model.**]**

[1] In this regard, the literature commonly refers to the so-called data–information–knowledge–intelligence (DIKI) continuum (Ratcliffe, 2016). This epitomizes a distinction between: (1) raw data, such as crime data; (2) information, which refers to the initial data to which meaning is given by, for example, the identification of patterns in the data; (3) knowledge, referring to a process of understandable reasoning of what the information indicates in substantive means; and finally (4) intelligence, which refers to an action-oriented product in which knowledge is exploited vis-à-vis the tactical and strategic objectives of police departments.

Differentiating intelligence-led policing from other proactive policing frameworks

While ILP has garnered praise from both practitioners and academics, it is important to recognize its connections to other proactive policing frameworks (Weisburd & Majmundar, 2018; Ratcliffe, 2016). As Ratcliffe suggests, ILP "built on experiences from the past, the organizational climate of the time, and the aspirations of its architects" (Ratcliffe, 2016, p. 50). Notably, the development of ILP was heavily influenced by community-oriented policing (COP) and problem-oriented policing (POP) (and, to some extent, CompStat). Although ILP, COP, and POP share the overarching goal of shifting policing from a reactive to a proactive approach, there are significant conceptual differences between them, as illustrated in Appendix 2.

While there is no universally agreed definition or conceptualization of COP, it is generally understood as a policing philosophy that encourages law enforcement agencies to adopt specific approaches in addressing community issues such as crime, disorder, fear of crime, and social disorganization. The emphasis is placed on involving the community in tackling these problems (Lord et al., 2009; Przeszlowski & Crichlow, 2018; Reisig & Parks, 2004; Skogan, 2004; Sozer & Merlo, 2013). COP is designed to enhance interactions between police and communities, giving both the community and police officers an active role in determining policing priorities. From a conceptual standpoint, however, COP could be seen as the antithesis of ILP (Ratcliffe, 2008, 2016). The adoption of COP primarily focuses on enhancing police legitimacy and community satisfaction, necessitating a decentralized organizational structure and resource allocation. Conversely, ILP is characterized by the centralization of police resources, with data analysis and intelligence playing a pivotal role in resource allocation and prioritization. Additionally, the central objective of ILP is to reduce, prevent, and disrupt crime and harm, while in COP crime reduction is considered to be a by-product of increased police legitimacy (Carter & Carter, 2009; Carter & Phillips, 2015; Goldstein, 1987; Ratcliffe, 2016).

Problem-oriented policing, on the other hand, can be characterized as a strategic policing framework that addresses a wide range of problems that contribute to crime and disorder (Spelman, 1987). POP is often implemented by adopting the SARA framework, a sequential problem-solving methodology introduced by Eck and Spelman (1987) that encompasses four distinct phases: scanning, analysis, response, and assessment. Similar to ILP, POP underscores the importance of thorough problem identification, analysis, and the systematic use of information to address crime and related issues (Ratcliffe, 2016). The primary difference is ILP's emphasis on crime intelligence analysis, which is crucial to the decision-making process behind the allocation of police resources. ILP therefore focuses on maintaining a detailed and up-to-date understanding of crime patterns and criminal behavior (Tilley, 2009). In contrast, POP uses analysis to uncover and identify the root causes of crime and crime-related problems and addresses these underlying issues through specific problem-solving approaches. The distinction between ILP and POP is primarily underscored by the broader scope of POP, which encompasses a wider array of problems that are not strictly police-related and may not always require enforcement in its formal sense. In contrast, ILP places a stronger emphasis on law enforcement and maintains closer ties to traditional hierarchical policing structures.

While there are important differences between COP and ILP, and somewhat less straightforward differences between POP and ILP, it is important to note that detecting strategic elements or interpreting the dissimilarities between these frameworks can sometimes be challenging. In that regard, however, we acknowledge that although there are conceptual differences between POP, COP, and ILP, this does not imply that ILP cannot benefit from problem-solving or community-oriented tactics at the tactical or operational level, which can effectively impact the criminal environment (Ratcliffe, 2016). However, for the purpose of this review, it is necessary to establish specific criteria to distinguish between studies that are closely related to the ILP framework and those more aligned with the POP and COP frameworks. To achieve this, a three-fold approach will be employed, primarily based on the distinctions outlined in Appendix 2.

First, from a conceptual standpoint, we include studies that evaluate interventions prioritizing data analysis (quantitative and/or qualitative) and intelligence when allocating police resources. Second, with regard to how police resources are deployed, i.e., the operational tactics employed by the police, we include studies that evaluate more traditional law enforcement responses (such as stop-and-frisks) and exclude those assessing police activities that solely rely on problem-solving or community-oriented tactics. However, studies of interventions that combine traditional law enforcement responses with problem-solving and/or community-oriented tactics are included. This approach reflects our belief that ILP can benefit from the integration of these tactics and gives us a more comprehensive overview of the approaches that can be employed and combined to impact the criminal environment. Third, we adopt a pragmatic approach to minimize the overlap between ILP and both POP and COP. Thus, studies identified through our scoping review process as having already been included in systematic reviews of POP (which encompasses studies adhering to the SARA model) or COP, or exclusively identified as evaluations of POP or COP (e.g., Gill et al., 2014; Hinkle et al., 2020), are excluded from our review.

Methodology

This study adopts Arksey and O'Malley's (2005) scoping review methodology, as redeveloped by Levac et al. (2010). First, we identify the research questions that will be addressed throughout this scoping review, then we identify the relevant studies by using a specific search strategy. Next, we examine the most relevant studies selected using the inclusion and exclusion criteria. The studies are then mapped out in order to collate, summarize, and report the main results of the scoping review. Finally, the results are published for the purposes of scientific valorization.

Research questions

The main research questions asked during this scoping review are:

1. What are the principal characteristics of the studies included in this review?
2. To what extent do the interventions (evaluated in the selected studies) align with the central tenets of the 3-i model?
   a. Which analytical techniques have been used to interpret the criminal environment?
   b. Which intelligence products have been used to influence decision-making?
   c. Which operational tactics have been employed to impact the criminal environment?
3. What are the main methodological challenges reported by the studies?
4. What are the main types of primary and secondary outcomes reported by the studies?

Identifying relevant studies

To systematically identify relevant publications, three academic databases—Scopus, Web of Science, and ProQuest—were consulted. A specific search strategy was developed, employing coordinated search procedures across these databases using specific keywords related to the ILP framework (see Appendix 3 for the specific keywords). This approach strikes a balance between ensuring a sufficiently broad scope of the study and demarcating it enough to limit the inclusion of non-relevant studies and reduce false negatives (Snaphaan & Hardyns, 2017). The initial search was conducted in November 2021, and additional searches were performed in July 2022 and February 2023. A manual search was also carried out to identify relevant publications that may not have been captured through the database search process. The reference lists of multiple systematic literature reviews of policing strategies were also examined. The retrieved studies were managed using Microsoft Excel, and an initial screening process was conducted based on the relevance of titles and abstracts. Duplicate studies were removed through an automated process using EndNote, as well as manually by deleting duplicates in the Excel file.

[Figure 2. Scoping review flowchart.**]**

Eligibility criteria

The eligibility criteria are as follows:[2]

1. Published between 2000 and 2023.
2. Published in English.
3. Given the nature of the studies we wish to include, we mainly aim to include scientific articles and book chapters. Nevertheless, the database search is supplemented by a manual search of reference lists of selected systematic literature reviews that focus on the effectiveness of different proactive policing approaches and frameworks. This helps to ensure we do not exclude grey literature, although this is not the primary focus of this review.

[2] We only aimed to include original studies; thus, we excluded studies in which follow-up analyses were conducted based on original (quasi-)experimental data.

4. Studies should assess police operations that target and focus resources on crime hot spots, repeat victims, prolific offenders, and/or criminal groups based on the outputs of crime intelligence analysis, and primarily evaluate the effects of interventions on crime or harm reduction, prevention, or disruption (inclusive detection).
5. The police interventions being analyzed should follow the central tenets of the 3-i model: they should apply analytical techniques to interpret the criminal environment, employ intelligence products to inform resource allocation, and implement specific law enforcement tactics (this can be combined with problem-solving or community-oriented tactics) based on the outputs of these products and the decisions made in that regard. The studies do not have to specifically mention the 3-i model or ILP in general, as requiring this would introduce a large number of false negatives.
6. The studies should not follow the tenets of the SARA methodology or exclusively apply problem-solving tactics, as this is more closely related to the framework of POP. They should not primarily be concerned with increasing police legitimacy or community satisfaction and trust, as these are core elements of the COP philosophy.
7. Studies should be experimental in nature. Both ‘weak’ and ‘strong’ quasi-experimental designs and randomized controlled trials are eligible for inclusion.[3]

Charting the data

The scoping review process entailed two distinct screening stages in which the relevance of the studies was evaluated by applying specific eligibility requirements. First, their titles and abstracts were reviewed. As a result, 355 studies were selected. Second, this selection was evaluated against the inclusion and exclusion criteria (see above). This resulted in 38 studies that were eligible for inclusion.

Collating, summarizing, and reporting the results

The main features of the included studies were quantified using Microsoft Excel and presented by means of some basic descriptive statistics. Appendix 1 provides a brief overview of the nature and context of the studies. A more in-depth thematic analysis of the content of the articles was also conducted.

Consultation exercise

The results of the scoping review were presented to and discussed by the Working Group on Policing at the annual conference of the European Society of Criminology in 2022.

Results

General characteristics

As Figure 3 shows, most of the included studies were published in 2016, followed by 2014, 2015, 2020 and 2021. None were published between 2000 and 2010. Furthermore, the majority were conducted in the United States (31 studies), and only 5 were conducted in Europe: 1 in Italy, 1 in Sweden and 3 in England. Additionally, 1 study was carried in Uruguay and 1 in Colombia.

[Figure 3. Number of studies per year.**]**

As reported in Table 1, the proportion of quasi-experimental versus experimental studies is more or less balanced, although there are more full experimental studies: 14 of the 38 studies employed a quasi-experimental design, whereas 24 conducted a randomized controlled trial. Moreover, most focused on several types of crime at the same time, although we present the counts here separately: violent crime was the most commonly featured crime type (24 times), followed by property crime (11 times), drug crime (5 times) and disorder (3 times). Several other (5) crime types, such as vehicle crashes, also featured. In some cases (7 times), the nature of the crime was not clearly specified or was reported as an aggregated crime type. In addition, a wide range of spatial and spatial-temporal units of analysis were used throughout the studies, with hot spots[4] and street

[3] To make a distinction between weak and strong quasi-experimental designs, we adopted this inclusion criterion from the inclusion criteria in the Global Policing Database Protocol (see Higginson et al., 2015).

[4] Hot spots are locations that were not given a specific geographical name in the studies but were generally identified by their average measurement/distances.

segments being the most common, followed by street blocks, grid cells, micro-time hot spots and districts. Two studies used individuals as the unit of analysis.

[Table 1. Central characteristics of the included studies.**]**

Relating the studies to the 3-i conceptual model

Interpreting the criminal environment

Table 2 illustrates the predominant analytical techniques used in the studies to interpret criminal environments. Crime hot spot analysis and mapping was the principal technique employed. This approach primarily involves the retrospective analysis, description, and visualization of areas with high crime concentrations based on spatial intelligence in order to allocate police resources and implement specific tactics (Ariel et al., 2016; Ariel & Partridge, 2017; Collazos et al., 2020; Corsaro et al., 2021). Qualitative analyses of crime hot spots based on specific criteria or journey-after-crime analyses, as well as quantitative methods such as the Local Moran's I statistic or point-pattern analyses, were commonly employed (spatial and temporal analysis of crime or STAC) (Carter et al., 2021; Gerell, 2016; Lum et al., 2011; Mazeika, 2014). In some studies, prospective hot spot methods such as kernel density estimation (KDE) and risk terrain modeling (RTM) were used to analyze and map crime concentrations (Carter et al., 2021; Gerell, 2016; Lum et al., 2011; Mazeika, 2014). These methods differ from retrospective hot spot methods as they create a dynamic aggregation of crime risk zones centered around each criminal incident, providing a more short-term and forward-looking perspective (Caplan et al., 2021; Kennedy et al., 2022).

It is important to distinguish between studies that utilize retrospective or prospective hot spot methods and those that employ machine learning methods for the real-time prediction of crime risk (Hunt et al., 2014; Mohler et al., 2015; Ratcliffe et al., 2021). Machine learning methods, including algorithms such as neural networks or logistic regression, were primarily used in predictive policing experiments. Notably, one study combined both retrospective hot spot methods and machine learning techniques to capture both chronic and dynamic hot spots (Fitzpatrick et al., 2020).

In addition to hot spot analysis, studies also incorporated offender-focused techniques, such as offender identification and analysis (Groff et al., 2015; Santos & Santos, 2016). These approaches aimed to identify prolific offenders, collect, and analyze intelligence on them, and direct police resources and tactics accordingly. Predictive social network analyses were applied by Saunders et al. (2016) to identify individuals at a higher risk of gun violence. Ariel et al. (2019) utilized social network analysis to identify prolific offenders and their co-offending networks, but without the intention of predicting future offending or victimization. Furthermore, some studies conducted general operational intelligence analyses to collect and analyze information on specific cases, or utilized investigative tools such as wiretaps, covert surveillance activities, or human intelligence sources (e.g., Morton et al., 2019; Ratcliffe et al., 2017).

[Table 2. Analytical techniques used in (quasi-)experimental studies (treatment condition).**]**

Influencing decision-making

Studies on ILP typically categorize intelligence products into four general categories: strategic assessments, tactical assessments, subject profiles, and problem profiles (Ratcliffe, 2016). Here, our focus is to provide an overview of the specific types of products used in the studies and their corresponding categories.

As can be seen from Table 3, hot spot maps or lists were employed in most of the studies to determine the areas where police resources should be allocated. These hot spot maps or lists are integral to problem profiles, offering insights into spatial crime trends and assisting in prioritizing resource allocation. It is, again, important to differentiate between retrospective, prospective, and predictive hot spot maps, or lists, as they vary in terms of their proactive nature.

Hot spot maps/lists are also utilized in intelligence bulletins, which encompass criminal resumés and additional intelligence on prolific offenders in specific hot spots (e.g., Caplan et al., 2021). Intelligence bulletins combine elements of both subject and problem profiles, providing spatial intelligence on crime hot spots and comprehensive information on suspects or victims. They also align closely with tactical assessments, as they define problems and subjects and recommend tactical options. Some studies employed offender subject lists to identify or predict prolific offenders and gather intelligence to target resources effectively (e.g., Groff et al., 2015; Saunders et al., 2016). Offender subject lists contribute to subject profiles by providing detailed information on individuals at whom resources can be directed.

It is worth noting that none of the studies used strategic assessments. These typically provide an overview of intelligence requirements and prevailing concerns impacting police operations. However, they are difficult to incorporate into evaluation studies because they do not consider the outcomes of the intervention, and therefore they have limited application in operational policing actions (Ratcliffe, 2016).

[Table 3. Intelligence products used in (quasi-)experimental studies (treatment condition).**]**

Impacting the criminal environment

Table 4 presents the main operational tactics employed in the studies by the police to impact the criminal environment. In many of the studies, multiple tactics were used simultaneously. The predominant tactics focused on situational measures and law enforcement, although some combined traditional law enforcement approaches with problem-solving or community-oriented tactics. These included initiatives to enhance positive police–community interactions or provide data-driven policing materials to citizens (e.g., Carter et al., 2014).

Directed patrol emerged as the most commonly used tactic, primarily targeting crime hot spots based on spatial and/or temporal intelligence about these areas, or intelligence on prolific offenders residing/loitering in certain areas. Additionally, some interventions incorporated new technologies such as license plate recognition (LPR), automatic vehicle locators (AVL), or closed-circuit television (CCTV) as real-time intelligence systems to optimize resource allocation within crime hot spots. These technologies were employed in studies by Gerell (2016), Weisburd (2015), Ratcliffe et al. (2019), among others.

Some interventions also focused explicitly on identifying and targeting prolific offenders using specific tactics like field interviews. The aim was to communicate messages to deter offenders, their connections, co-offending networks, or offender groups. These messages gave strong warnings about the increased risks associated with offending or re-offending and were considered to be forms of focused and vicarious deterrence (Ariel et al., 2019; Santos & Santos, 2016; Saunders et al., 2016). A detailed overview of all the tactics that were used can be found in Appendix 1.

[Table 4. Operational tactics used to impact the criminal environment (treatment condition).**]**

Methodological challenges

While there are a number of methodological challenges that should be considered when conducting and implemental (quasi-)experimental studies in the domain of ILP, this study concentrates on two particular groups of methodological challenges: statistical–methodological challenges; and challenges related to the implementation of (quasi-)experimental studies within the domain of ILP. Because not every study reported on these methodological challenges consistently and comprehensively, they are presented here in a narrative format.

Statistical–methodological challenges

Statistical powerlessness**.** The challenge of achieving sufficient statistical power to detect significant effects, particularly in terms of crime reduction, was frequently discussed, chiefly in the context of place-based policing studies (Ariel et al., 2016, 2020; Gerell, 2016; Hunt et al., 2014; Lum et al., 2011; Piza et al., 2015; Piza & O'Hara, 2014; Ratcliffe et al., 2020; Rosenfeld, 2014; Santos & Santos, 2016, 2021; Telep et al., 2014; Weisburd et al., 2015).

Several factors were identified through narrative analysis as influencing the level of statistical power. One factor is sample size, with larger sample sizes generally thought to increase statistical power to detect significant differences between treatment and control groups (Ratcliffe et al., 2021; Taylor & Ratcliffe, 2019). However, from an empirical point of view, this premise must be balanced against Weisburd's paradox (Groff et al., 2015; Weisburd et al., 1993), which highlights the discrepancy between the expectation that increasing the sample size will enhance statistical power, and the reality that it often results in decreased statistical power. In this regard, it is argued that increasing the sample size gives rise to two main phenomena that may reduce the statistical power of a test. First, increasing the sample sizes can result in increased variability between the treatment and control groups, which subsequently elevates the standard deviation within the sample. This increased variability reduces the probability of detecting substantial and statistically significant effects. Second, increasing the sample size may introduce 'watered down treatments'. It is theorized that experimental designs employing larger sample sizes may be more susceptible to implementation issues, potentially affecting the adherence to the intended administration or dosing of the treatment. In this regard, it has been found that studies with very small sample sizes may exhibit higher statistical power compared to those with very large sample sizes (Weisburd et al., 1993).

In place-based policing experiments, the size and shape of treatment areas were considered important factors influencing the statistical power of a test. A more granular size or shape could potentially increase the power to detect deterrent effects, as smaller areas allow for increased sample sizes and higher statistical power (Phillips et al., 2016). However, smaller geographical units may also affect the crime base rates within those units, which can impact the size and strength of treatment effects (Phillips et al., 2016; Ratcliffe et al., 2021).

In addition, it is argued that the issue of statistical powerlessness is often more prevalent in place-based policing (quasi-)experiments conducted in small and medium-sized cities, where low crime base rates make it challenging to isolate the effects of interventions, and fluctuations in crime rates can hinder the detection of significant treatment effects (Ariel et al., 2021; Hinkle et al., 2013; Phillips et al., 2016).

To address the problem of statistical powerlessness in quasi-experimental designs, researchers have suggested matching treatment units to a larger number of comparison units, and conducting panel regression analyses (Phillips et al., 2016). In place-based predictive policing randomized controlled trials (RCTs), focusing on larger mission areas rather than micro-scaled intervention areas has been proposed as a more appropriate approach (Ratcliffe et al., 2021; Taylor & Ratcliffe, 2019). However, while widening the scale of treatment areas may make patrol officers' activities less monotonous and reduce the likelihood of boundary violations, it could also lead to net-widening effects and pose challenges to police legitimacy (Ratcliffe et al., 2021; Taylor & Ratcliffe, 2020).

Spillover effects and SUTVA. Many of the studies included in this review addressed concerns regarding the stable unit treatment value assumption (SUTVA) (e.g., Ariel et al., 2016, 2019, 2020; Ariel & Partridge, 2016; Collazos et al., 2020). SUTVA posits that the assignment of units to treatment or control groups should not influence the outcomes of other units (Braga et al., 2012, 2018). Avoiding spillover effects, which can obscure the true impact of the intervention and compromise causal inference, is crucial for addressing SUTVA. Two types of spillover effects were commonly addressed in the studies. The first involves the spillover of treatment conditions from treatment groups to control groups, known as major interference (e.g., Ariel et al., 2019; Sobel, 2006). Given the focus on place-based policing, preventing major interference often required buffer zones to be created, to ensure that control areas did not receive any part of the treatment (e.g., Ariel et al., 2020; Collazos et al., 2020). However, it is important to note that major interference can also occur at the individual level due to social contamination processes within offending and co-offending networks, as offenders living or residing in the treatment areas may be socially connected to offenders in the control areas, thus increasing the likelihood of spillover from treatment to control groups (Ariel et al., 2019).The second type of spillover was partial interference, where spillover occurs within the same group from one unit of analysis to another. This mostly required consideration of how the same interventions and conditions could be applied consistently and uniformly within all treated and untreated groups (Ariel et al., 2019; Hunt et al., 2014; Saunders et al., 2016). If not, this could affect the fidelity of the study and bias the treatment effects to some extent (Ariel et al., 2018; Sobel, 2006).

***Data and measurement errors*.** Several studies emphasized the importance of evaluating data quality issues, particularly those using big data and algorithmic applications for crime prediction purposes. It is crucial to assess data quality in order to mitigate biases in the data, as biased data can lead to feedback loops and unreliable crime predictions (Hunt et al., 2014; Mohler et al., 2016; Ratcliffe et al., 2021). Official police data, which is commonly used in many studies, has inherent challenges that can introduce measurement errors and inconsistencies in the results. Reliance on official crime reports, in particular, has been highlighted as a potential source of bias and measurement issues (Callazos et al., 2020). In studies evaluating place-based policing interventions, problems may arise if the spatial and temporal components of crime data are not accurately collected or systematically registered, although the extent of this issue can vary depending on the type of crime. However, inconsistencies in data quality are even more problematic in person-based policing interventions, as errors in the data can result in wrongful convictions (Ariel et al., 2016, 2021). Therefore, it has been argued that researchers should not solely rely on official police data as the primary source for crime intelligence analysis. For example, supplementing official crime records with human intelligence gathered from crime control partners can significantly enhance the accuracy and completeness of the data (Morton et al., 2018). By leveraging additional sources of information, researchers can overcome some of the limitations and potential biases associated with relying solely on official police data.

***Statistical regression to the mean*.** Statistical regression to the mean is another challenge that has been recognized by some of the included studies (e.g., Mastrubuoni, 2020; Ratcliffe et al., 2011). Regression to the mean refers to the phenomenon where initially high scores on a variable tend to move closer to the mean when measured at different points in time. This challenge is particularly relevant in ILP studies evaluating interventions that focus on prolific offenders, high-crime locations, repeat victims, and criminal groups. In such studies, treatment and control groups are often assigned based on extreme cases. Consequently, when crime rates are measured between two time periods, extreme cases may exhibit less extreme behavior during the second measurement, suggesting the intervention/program was successful when it was not (Farrington & Welsh, 2006; Galton, 1886; Ratcliffe et al., 2011; Twisk & De Vente, 2008). To address this challenge, it has been suggested that (quasi-)experimental studies should account for differences in extreme scores between the treatment and control groups, a task that is typically easier to control for in RCTs. One approach is to use a tailored analysis that includes the pre-intervention crime level as a covariate in the crime impact model (Ratcliffe et al., 2011). By considering the pre-intervention crime level, researchers can better assess the actual impact of the intervention while accounting for the regression to the mean effect.

Challenges related to the implementation of (quasi-)experimental studies

Treatment integrity. Several studies highlighted that ensuring the integrity of both the treatment and control conditions was a practical challenge (e.g., Corsaro et al., 2012; Novak et al., 2016; Rydberg et al., 2018). Failing to maintain the integrity of the experiment can lead to an over- or underestimation of the intervention's effectiveness. To address this issue, researchers implemented procedural and organizational safeguards to prevent contamination or interference.

One important aspect mentioned in this context is treatment fidelity, which refers to the extent to which participants adhere to the experimental protocol. Various methods were employed to enhance monitoring and compliance. For example, technological applications such as AVL systems and GPS trackers were utilized to track police presence (Telep et al., 2014; Weisburd et al., 2015; Ariel et al., 2016; Ariel & Partridge, 2016). More traditional approaches such as log-in systems, call-ins, and observations were also employed (Ratcliffe et al., 2011).

Some studies established deliberative structures, such as task forces, to facilitate regular meetings and briefings. These structures provided a platform for discussing tactical decisions, addressing requirements in the police intelligence infrastructure, and ensuring accountability among stakeholders (e.g., Ariel et al., 2020; Caplan et al., 2021; Ratcliffe et al., 2021; Santos & Santos, 2016). They also enabled the evaluation of qualitative insights and challenges arising from interactions with commanders and police officers, which may prove valuable for evaluating and implementing an intelligence-led policing approach. However, it is crucial to maintain confidentiality and avoid disclosing sensitive information about the experimental protocol during cooperation and communication with stakeholders, in order to prevent treatment integrity failures.

Accounting for the (different) objectives of different stakeholder groups. As mentioned earlier, cooperation and deliberation play a crucial role in mitigating treatment integrity failures (Ariel et al., 2020; Caplan et al., 2021; Ratcliffe et al., 2021; Santos & Santos, 2016). However, it can be challenging to consider the diverse needs, objectives, capabilities, and limitations of the stakeholders involved in the experiment. One important aspect to consider is the nature of the 'policing craft,' which encompasses the skills, knowledge, heuristics, attitudes, and acquired expertise of police officers in their daily duties (Caplan et al., 2021; Ratcliffe et al., 2011, 2021; Wood et al., 2012). These factors can influence officers' perceptions and attitudes towards the experiment and specific policing approaches. Officers may feel constrained in their daily tasks when required to adhere to a protocol and meet specific criteria (Ratcliffe et al., 2011, 2021).

The novelty or level of institutionalization of the evaluated intervention within the police department, can also impact officers' willingness to actively participate. Moreover, (quasi-)experimental studies necessitate institutional collaboration, forming coalitions between police administration and academic staff with potentially conflicting interests and aims. Limited resources (e.g., staff) available in a policing ecosystem, however, can impede scientific goals (Kennedy et al., 2022). Additionally, the aims and preferences of the participating police department may impose practical limitations, leading to methodological compromises from the outset of the experiment (Novak et al., 2016). In addition, some studies have advocated including other stakeholders, such as citizens, criminals, or victims who are directly or indirectly affected by the intervention, to enhance awareness and communication about specific policing methods (Groff et al., 2015; Ratcliffe et al., 2011). However, it is crucial to ensure that communication does not compromise treatment integrity.

Empirical focus of the studies

Primary effects

Crime and harm reduction. Appendix 1 clearly shows that most of the studies focused on establishing crime reduction effects, whereas only one explicitly focused on measuring and reducing social harm in so-called social harm spots (Carter et al., 2021). As discussed earlier, establishing statistically significant reduction effects is inherently challenging and influenced by various methodological factors. Nonetheless, researchers often argued that observed reductions in crime or harm measures were a result of the successful deployment of police resources to targeted areas or individuals identified through crime intelligence analysis. For instance, several studies investigated the implementation of police crackdowns in hot spots, leading to initial and residual deterrence by increasing the variability of risk estimates and uncertainty about sanction risks (Ariel & Partridge, 2016; Ratcliffe et al., 2011). In some studies, it is argued that varying the frequency and intensity of police presence can be more effective in addressing criminals' potential adaptation to the policing approaches imposed (Ariel et al., 2016; Telep et al., 2014).

Furthermore, deterrence has been recognized as a significant mechanism through which offender-focused policing interventions can yield crime reduction effects. This mainly includes communicating deterrent messages of 'zero-tolerance' to deter potential future offenders (Ariel et al., 2019; Saunders et al., 2016). Two studies had different emphases, with one evaluating whether an ILP program resulted in increased human intelligence collection and detection (Morton et al., 2019), while the other primarily aimed to enhance police productivity through predictive policing to detect criminal activity (Mastrubuoni, 2020). Although these studies did not focus primarily on crime or harm reduction, they are relevant within the framework of ILP, as they demonstrate the positive effects of ILP-focused interventions on the internal processes of law enforcement agencies, improving their intelligence capabilities and relationships with specific communities.

Crime displacement and the diffusion of crime control benefits. In addition to analyzing the effects on crime, most place-based policing studies also quantified crime displacement effects, including the diffusion of crime control benefits (a concept introduced by Clarke & Weisburd, 1994) to adjacent areas (e.g. Ariel et al., 2016; Caplan et al., 2021; Collazos et al., 2020; Corsaro et al., 2021; Lum et al., 2011; Rosenfeld et al., 2014; Santos & Santos, 2015; Telep et al., 2014).[5] Controlling for displacement effects was usually done by creating so-called geographical buffer or cushion zones (e.g. Ariel et al., 2016; Piza et al., 2015; Piza & O'Hara, 2014). Crime displacement was then measured by using specific mathematical parameters such as the weighted displacement quotient (WDQ) (e.g., Ariel et al., 2016; Groff et al., 2015; Piza & O'Hara, 2014; Piza et al., 2015; Ratcliffe et al., 2011, 2017) or the weighted displacement difference statistic (Kennedy et al., 2022), taking into account the crime rates or counts prior to and during the intervention in both treatment and displacement sites, including control sites for each. As can be seen from Appendix 1, the findings of most studies did not support crime displacement, and only a few studies reported a diffusion of crime control benefits. This is in line with the place-based policing literature, which contends that a diffusion of crime control benefits is more likely to occur than crime displacement (Braga et al., 2019)

[5] Crime displacement and the diffusion of crime control benefits are also related to the aforementioned issue of spillover. In the literature, a distinction is increasingly made between negative and positive spillover. Negative spillover involves the displacement of crime, whereas positive spillover involves the diffusion of crime control benefits to adjacent areas.

Secondary effects

The secondary effects of policing interventions that are not crime-related are typically underreported in (quasi-)experimental studies evaluating policing programs. In this study, however, we specifically focus on identifying three important types of secondary effects: user experiences, cost-effectiveness, and ethical risks. These effects contribute to the credibility of and support for these interventions. In doing so, we aim to identify the main components of these specific secondary effects that can be considered in future ((quasi-)experimental) evaluation studies. A more detailed overview of the secondary effects of interventions on user experiences, cost-effectiveness, and ethical risks can be found in Appendix 1.

User experience(s). When we refer to user experience(s) as a secondary outcome, we are focusing on the effects of ILP-related interventions on the perceptions and experiences of the various actors involved in evaluating and implementing specific interventions. Several studies employed qualitative research methods, such as field observations or interviews, to formally assess and report on the experiences of these actors during the interventions.

For instance, in the Philadelphia policing tactics experiment, Groff et al. (2015) conducted a survey and found that police officers supported the use of actionable knowledge as part of an offender-focused policing approach rather than relying solely on intuition or so-called 'gut feelings.' Similarly, officers in the Shreveport predictive policing experiment emphasized the value of predictive hot spot maps in providing concrete plans for targeted patrol activities (Hunt et al., 2014). However, officers also acknowledged that they sometimes followed their 'gut feelings' rather than the knowledge provided by intelligence products when the information contradicted their own common-sense wisdom. Consequently, despite the potential benefits of new technologies like LPR systems (Lum et al., 2011) or predictive algorithms (Ratcliffe et al., 2020), officers were sometimes skeptical about adopting these new tools.

In this context, Saunders et al. (2016), who conducted interviews with police officers on the use of tactical or strategic intelligence products, argued that there needs to be practical reasoning and guidance from police command staff to frontline officers on how to effectively employ intelligence in practice. This raises practical questions about the adaptability of intelligence within the context of police administration. For example, from a theoretical and methodological standpoint, patrolling smaller grid cells (e.g., 200 by 200 meters) with high crime rates may increase the risk of apprehension. However, from a practical perspective, officers may experience constraints from being confined to such small patrol areas and may struggle with determining whom to target or how to operate in these high-crime locations.

Ethical risks. Ethical risks are inherent concerns related to the collection, analysis, and utilization of data and information for law enforcement purposes, as well as the tactics employed based on criminal intelligence. While user experiences were a focus of several of the studies, a few also considered the potential ethical risks associated with proactive policing interventions based on criminal intelligence.

Most of the identified risks were linked to the impact of policing interventions on the increased exposure of certain areas or individuals to additional police activity. For example, Fitzpatrick et al. (2020) found that when violent crime hot spots received additional police presence through a community-oriented approach, there was no evidence of over-policing of minorities or other populations. Similarly, in the Shreveport predictive policing experiment, officers reported that citizens were more willing to provide additional information when officers patrolled in predicted crime hot spots. This could potentially contribute to improving police–community relationships and enhancing the intelligence capabilities of police departments (Hunt et al., 2014).

In the Philadelphia policing tactics experiment, it was revealed that police officers exercised more discretion when implementing an offender focused ILP intervention (Groff et al., 2015). This resulted in no significant difference in the number of investigative stops conducted by police officers in high-crime areas. The argument was made that stopping and arresting the 'right people in the right areas' could help to create a perception of procedural justice in law enforcement activities. Similar findings were acknowledged by Carter et al. (2014), who also discovered that citizens generally did not oppose the use of algorithms for decision-making processes by police agencies. However, citizens expressed a preference for some human involvement when decisions were based on intelligence derived from fully automated (big data) algorithms.

These findings suggest that while proactive policing interventions based on criminal intelligence can pose ethical risks, when they are implemented judiciously and with consideration for procedural justice, they may not exacerbate disparities or negatively impact community perceptions. The inclusion of human oversight in decision-making processes also aligns with citizens' preferences, emphasizing the importance of balancing technological advancements with human involvement to ensure accountability and transparency in law enforcement practices.

Cost-effectiveness. Finally, some of the studies examined the cost-effectiveness of ILP-related approaches (see Appendix 1), i.e., whether the increased effectiveness of an intervention can justify the additional costs associated with its implementation.

For example, in the Shreveport predictive policing experiment, a cost-savings analysis (CSA) was conducted based on the cost estimations for labor and equipment in both the treatment and control districts. The costs were mainly related to the distribution of predictive hot spot maps (intelligence products) to commanders, the collection of extra intelligence that was added to the predictive hot spot maps, the costs associated with running the predictive model on a monthly basis, but also the costs of making tactical and strategic decisions based on the intelligence derived from the predictive hot spot maps, and of executing the strategic and tactical plans needed to address certain crime problems. According to the findings of the CSA, predictive policing in the treatment districts resulted in a 6 to 10% cost reduction, when compared to control districts where hot spots policing was employed (Hunt et al., 2014).

Evidence for cost-effectiveness was also found in a predictive policing experiment conducted by Mohler et al. (2014) in Los Angeles. In this study, the potential savings to society from applying predictive policing versus hot spots policing were calculated using the methodology developed by McCollister et al. (2010). More specifically, they calculated the societal costs per crime type according to the costs related to the victim, the police and court system, and the offender. These cost estimates were then used to compute the weekly savings per police division that would result from a weekly crime reduction of 4.3 crimes. Based on these calculations, it was estimated that using predictive hot spot maps for 31 minutes per day for each hot spot would save the LAPD $17,258,801 per year vis-à-vis applying traditional hot spot mapping techniques by crime analysts, which would only save half as much (Mohler et al., 2015). These finding suggest that predictive policing methods may be more cost-effective than traditional hot spots policing tactics, albeit the robustness and validity of these projections should be critically scrutinized at all times.

Nonetheless, evidence of cost-effectiveness has also been found in studies employing traditional hot spots policing approaches. For example, in the Indianapolis harm spot policing experiment, the application of hot spots policing in crime and social harm hot spots was translated into potential cost savings to society. It was calculated that per 10.4 minutes of officer proactive activity in social harm (hot) spots, the costs of social harm were reduced by $38.6, a total of $118,232 during the experimental period (Carter et al., 2014). The costs of deploying police resources were not reported, however.

Discussion and conclusion

In this study, we summarized the main insights and findings from 38 (quasi-)experimental studies that relate to the framework of intelligence-led policing. To the best of our knowledge, this is the first study that endeavors to incorporate multiple (quasi-)experimental evaluation studies of various tactical policing approaches within a conceptual framework of ILP. It is hoped that future evaluation studies in the field of ILP might benefit from our findings when developing and implementing experimental protocols. However, several shortcomings must be addressed. First, we excluded non-experimental evaluation studies, which may be regarded a limitation because we may have missed some additional findings. Nevertheless, the main goal of this research was to exclusively focus on experimental and quasi-experimental studies for the purpose of collecting information on the different methodological challenges that may arise when evaluating ILP-related practices and the reported outcomes. This was crucial in order to define the scope of this review and to set clear boundaries to the purpose of this study. We acknowledge, however, that observational studies may be useful to uncover the broad scope of studies that may relate to the framework of ILP. Second, we only used three academic databases, although we attempted to overcome this limitation by manually searching literature reviews on distinct policing tactics and strategies. These databases have consistently served as reliable sources for previous scoping reviews conducted within the same domain, which underlines their credibility (e.g., Snaphaan & Hardyns 2021), and it was expected that they would provide a substantial volume of high-quality, peer-reviewed articles. By adopting this approach, we hoped to include studies accessible to a broader readership and make this review both comprehensive and reliable. However, future policy relating to ILP should also draw on the results of ILP-based interventions, in order to understand the practical impact of the concept. Therefore, future reviews of ILP may consider using additional practice-oriented databases such as the Global Policing Database. A third concern is the involvement of only one researcher in the selection and screening process, despite the fact that the various stages of this scoping review were extensively discussed by the researchers involved. Fourth, we specifically excluded studies that had already been included in systematic literature reviews of POP or COP, which may have eliminated studies that could be incorporated within the framework of ILP. However, although this approach is restrictive, we are convinced that this was the only way to exclude studies that are more related to POP or COP than to ILP.

Despite these limitations, some important conclusions can be drawn. It is clear that hot spots policing has received considerable academic attention as it evolved into an essential tactical policing approach that can be incorporated within the framework of ILP. Crime hot spots act as targeting mechanisms for ILP, providing guidance on where (and when) to direct police resources (Ratcliffe, 2016). This led to a distinction being established between retrospective, prospective, and predictive hot spots policing approaches (Rummens et al., 2017). Although most of the studies in this review focused on evaluating retrospective and prospective hot spots policing approaches, evaluations of predictive hot spots policing approaches are definitely on the rise. The predictive policing experiments that were included in this study were mainly concerned with evaluating the impact of place-based predictive policing on crime, whereas only one quasi-experimental study evaluated the effects of a person-based predictive policing approach. This indicates a significant gap in (quasi-)experimental research within the domain of ILP, with just a few studies examining the effectiveness of offender-focused policing approaches or a combination of place-based and offender-focused policing approaches. It is notable that most of the included studies used geographical units of analysis. This may be because collecting and analyzing data on individuals creates practical and ethical issues, making it challenging to evaluate the effects of interventions in terms of crime reduction. In a similar vein, no study focused on repeat victims as targets of a specified intervention, which again signifies an important gap in research on ILP-related interventions.

The vast majority of the studies focused on evaluating local-level interventions, mostly tackling violent crime, followed by property crime, drug crime and disorder. None explored crime types such as political violence or hate crime; nor did any of the studies specifically acknowledge the organized nature of certain crime types, except for Morton et al. (2021) and Ratcliffe et al. (2017). This is hardly surprising, given how difficult it is to collect data on such crime types and how challenging it is to conduct (quasi-)experimental studies at the organized or transnational level. However, from a policy perspective, it should be argued that ILP might be very useful in addressing complex forms of crime such as human trafficking, drug trafficking, terrorism, and so on. The use of qualitative performance measures or combining both quantitative and qualitative performance measures could be one way of implementing ILP in such fields, especially when one aims to evaluate policing approaches targeting organized crime types, as quantifying the impact of police interventions at the organized level is inherently difficult (Ratcliffe, 2016). In most of the studies, quantitative performance measures were used to measure crime reduction effects. However, we did not find any studies that specifically aimed to measure crime disruption effects, which is again not surprising, as crime disruption is very difficult to measure in a quantitative way (Ratcliffe, 2016). Nonetheless, crime disruption may be a useful performance measure in order to evaluate the effectiveness of ILP-related tactics designed to tackle organized crime types. Future evaluation studies should therefore establish specific but objective and realistic criteria for signifying the disruption of criminal activities. In addition, we agree with Ratcliffe (2016) that separate or integrated evaluations of all the components of the 3-i model are scarce, if not non-existent; although we did find one study that specifically applied the 3-i model to structure the evaluation of a person-based predictive policing model (Saunders et al., 2016). As Ratcliffe (2016) argues, besides merely evaluating the various tactical approaches to policing that flow from decision-making processes, "it is necessary to evaluate each leg of the three structures that form the 3-i model" (p. 188).

We have also highlighted several methodological challenges that should be considered when (quasi-)experimental evaluation research is conducted within the domain of ILP. We primarily focused on identifying statistical–methodological challenges, and challenges that relate to the implementation of (quasi-)experimental studies within an intelligence-led policing arena. We did not attempt to identify the challenges that may emerge when implementing ILP in police departments, although these challenges may overlap with those found in this study. Using rigorous experimental designs, such as RCTs, and conducting an extensive pre- and post-implementation contextual analysis are two complementary strategies that may help to overcome these methodological challenges. The latter necessitates identifying all methodological challenges that could arise before, during, and after the implementation of a particular (quasi-)experimental design in an ILP context. Depending on the design used, or the approach that is being evaluated, some methodological issues can be more apposite. For example, it could be argued that if spillover is expected, future (quasi-)experimental studies should consider using group-based models such as clustered trial designs, thereby incorporating potential spillover into the experimental protocol (see e.g., Ariel et al., 2021). Moreover, because data-driven policing will continue to evolve as a mechanism for ILP, future (quasi-)experimental studies could explore the use of specific frameworks for analyzing the quality of input data and the potential errors that might occur when developing such designs. The total survey error framework (TSE), for example, is a methodological quality assessment standard that has been used to identify possible errors in survey data (Groves et al., 2004). However, the logic behind TSE has lately been expanded to various (large) data sources in general, which is why the total error framework (TEF) was established (Amaya et al., 2020; Snaphaan et al., 2022). TEF provides a framework for analyzing and potentially mitigating various error components within data measurement, representation, and analysis processes (for an overview of TEF see Amaya et al., 2020). Future (quasi-)experimental studies in the field of ILP should address the trade-off between theoretical, methodological, practical, and ethical components of interventions while determining the methodological parameters. Dealing with the challenges of statistical power, for example, demands a case-by-case approach and necessitates fine-tuning the resolution of the intervention to the (quasi-)experimental design, thereby considering the effects of the interaction between choosing the most appropriate unit of analysis, sample sizes, crime base rates, and contextual influences (e.g., city size).

Finally, it should be argued that future evaluation studies of ILP-related approaches should not only focus on the outcomes of tactical approaches to crime or harm, but also on the processes involved in collecting, analyzing, and disseminating intelligence, as well as how intelligence improves the quality and objectivity of decision-making processes. In that regard, this study has shown that the evidence on the secondary effects of ILP-related approaches is lacking. In this study, we specifically focused on collecting evidence with regard to three secondary effect groups: user experience, ethical risks, and cost-effectiveness. Although most of the studies did not specifically focus on the evaluation of secondary effects, some did. With regard to user experiences, future evaluation studies could focus on evaluating how accessible and easy to use certain applications and approaches are. Additionally, studies could evaluate how well particular tactical policing approaches resonate with the proactive nature of specific intelligence products. Another important consideration in evaluating and implementing ILP is the interaction between different police units and levels. ILP has interdisciplinary characteristics: it requires cooperation between different units, backgrounds, and specializations. For example, data analysts do not usually have the field experience of police officers and can thus benefit from their feedback. The way intelligence products are disseminated to decision-makers and police officers is also important; for example, an analyst might act as a go-between, or the intelligence products might be made available to each officer. Good communication can optimize the link between developing the intelligence products and using that intelligence to its fullest extent. In addition, future evaluation studies should also pay attention to detecting and mitigating potential ethical and/or legal risks that may occur when analyzing and using data or intelligence for police purposes. Legal and ethical risks may occur in different phases of the implementation of ILP: the data collection process, the development of intelligence products, and their practical implementation by police forces. Moreover, as ILP-related approaches generally require added expertise in the form of data engineers, data scientists, legal and ethical experts and/or additional resources such as large databases, ICT infrastructure, associated data processes and new software, the question arises as to whether the added effectiveness of ILP-related approaches outweighs the additional costs. It is extremely important, therefore, to examine the actual (potential) benefits of ILP-related approaches, which can be done by conducting rigorous cost-savings or cost–benefit analyses. Hence, we recommend that specific methodologies are developed to conduct such analyses within the domain of ILP. Nevertheless, in order to develop knowledge about these secondary effect groups in the context of police departments and society as a whole, and to assess the qualitative configurations of ILP-related approaches, realistic evaluations can be extremely useful. As a result, in order to evaluate the effects of each component of the 3-i model on the police, future evaluation studies must adopt more holistic approaches.

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[APPENDICES HERE]

[APPENDIX 1 HERE: Detailed characteristics of the included studies]

[APPENDIX 2 HERE: Structural differences between ILP, POP and COP]

[APPENDIX 3: Scoping review protocol]