Journal of Quantitative Criminology
https://doi.org/10.1007/s10940-025-09643-5

ORIGINAL PAPER

The Effect of Police Deployment Strategy on Emergency Response Times

An Agent-Based Modelling Investigation

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Received: 3 March 2025 / Accepted: 27 October 2025

Abstract

Objectives This study investigates the impact of three police deployment strategies on emergency response times using agent-based modelling (ABM). Specifically, it evaluates the effectiveness of *random patrol*, *stationary deployment* (optimal spreading), and *last location deployment* (idling at last incident location). It further examines how key variables – urbanisation, call volume, and police capacity – moderate these effects.

Methods A detailed ABM was developed using NetLogo, integrating real-world data: historical calls-for-service (CFS), jurisdiction shapefiles, and street network data from the Netherlands. The model simulated police travel and response dynamics across 120 scenarios, varying deployment strategies, urbanisation levels, call volumes, and police capacity levels. Outputs were analysed to assess response times, fast response rates (< 3 minutes), and late response rates (>13 minutes). Methods were pre-registered at https://osf.io/yrwdp/.

Results On average, stationary deployment reduced response times by 35% (SD ±14%), increased fast responses by 74% (SD ±40%), and decreased late responses by 66% (SD ±33%) compared to random patrol. Last location deployment also outperformed random patrol, reducing response times by 13% (SD ±9%), increasing fast responses by 22% (SD ±14%), and reducing late responses by 42% (SD ±36%). The advantages of stationary and last location deployment were most pronounced in rural areas and at lower police capacity levels. Urbanisation reduced the performance gap between strategies, while higher call volumes modestly diminished the relative benefits of stationary deployment.

Conclusions This study highlights the significant impact of police deployment strategies on response times and rapid interventions. These findings underscore the need for further research on rapid response. The modular ABM framework offers a valuable tool for adapting investigations to different policing contexts, enhancing external validity.

Keywords Rapid response · Police response times · Agent-Based Modelling (ABM) · Police deployment strategies · Emergency response

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Introduction

The Standard Model of Policing consists of two core activities for police officers on the street: *rapid response* and *random patrol* (Frydl and Skogan 2004). While many different models of policing have been proposed and implemented in law enforcement agencies worldwide, these two activities still remain central to most departments. Nevertheless, their effectiveness has long been subject to scrutiny, particularly since the 1970s, when a series of landmark studies questioned the effectiveness of both of these core activities.

First, the Kansas City Preventive Patrol Experiment (Kelling et al. 1974) cast doubt on the effectiveness of random patrol, concluding that it had minimal impact on crime or citizen perceptions of safety. Soon after, the Kansas City Response Time Analysis Study (Bieck 1977) and its subsequent replication study in four more cities (Spelman and Brown 1981) challenged the utility of rapid response, asserting that most crimes are either discovered long after the perpetrator has fled or are not reported quickly enough by citizens for a rapid police response to be effective at increasing the chance of apprehension.

While both pillars of the Standard Model faced substantial critique, the academic response varied widely. The Kansas City Preventive Patrol Experiment spurred a robust debate see, (Farrington, 1983; Fienberg et al., 1976; Larson, 1975; Larson, 1982; Pate et al., 1975; Risman, 1980; Sherman and Weisburd, 1995; Weisburd et al., 2023; Zimring, 1978), leading to the development of innovative strategies like hot spots policing (Sherman and Weisburd 1995) and numerous follow-up studies evaluating its deterrent effects see, (Braga et al., 2019). Conversely, the critique of rapid response spurred very little debate and led to a strong dismissal of rapid response and its potential benefits in the influential *Preventing Crime: What Works, What Doesn't, What's Promising* report – commonly referred to as the *Maryland Report* (Sherman et al. 1997). The report argued that rapid response does not have an effect on arrest rates and, by extension, crime levels and that response times are hard to improve as: "Cutting police travel time for such crime from 5 to 2.5 minutes could require a doubling of the police force" (Sherman et al. 1997, Chapter 8, p. 11). Moreover, further experimental investigation into the effects of rapid response was discouraged as: "… there is neither empirical nor theoretical justification for such expensive test… further tests of this theory seem to be a waste of tax dollars." (Sherman et al. 1997, Chapter 8, p. 11).

As a result, experimental or quasi-experimental research into the rapid response strategy has never materialised. Some correlational studies have explored the predictors of response time for an overview, see, (Verlaan and Ruiter, 2023) and its effect on arrest likelihood, especially for in-progress burglaries e.g.,, (Coupe and Blake, 2005; Cihan et al., 2012). More recently, several studies in the economics literature have used methods from econometrics – such as instrumental variable (IV) designs – to estimate the causal effect of faster response on crime outcomes (Blanes i Vidal and Kirchmaier 2018; Weisburd 2021; Mastrobuoni 2019). Although these studies generally report positive effects, their findings have not sparked significant follow-up work within criminology with the exception of, (Rief and Huff, 2023).

However, an essay in the (recently published) doctoral dissertation by the first author argues that this neglect is unjustified, and that the prevailing view of rapid response is both overly simplistic and outdated (Verlaan, 2025). The essay reviews historical evidence showing that the effectiveness of rapid response is highly conditional, with substantial benefits observed for fast responses (i.e., under three minutes). Moreover, the essay highlighted that the (historically small) proportion of crimes amenable to rapid response has likely increased due to declines in property crime rates (known as *the crime drop*), and might now even constitute the majority of crime calls. Lastly, it argues that recent advancements in communication technologies have mitigated many of the primary reasons for citizen reporting delays (such as: *finding a payphone* or *asking permission to use someone's landline*), further enhancing the potential impact of rapid response. These insights underscore the need for renewed empirical investigation.

Nevertheless, large-scale experimental research to explore police response times remains impractical due to high costs, logistical complexities, and ethical concerns. Additionally, lingering doubts persist about whether police agencies can meaningfully improve response times, further complicating the justification for such resource-intensive studies. Before embarking on large-scale experiments, it is vital to address these doubts and explore the dynamics underpinning police agency in improving response times.

To this end, computational methods provide a powerful alternative for studying emergency response times, allowing for controlled experimentation without real-world risks or costs. Over the years, various modelling approaches have been applied to different aspects of police operations, including vehicle selection (Dunnett et al. 2019); patrol beat design (Curtin et al. 2010; Kwak and Leavitt 1984; Larson 1974; Mitchell 1972; Sacks 2000; Zhang and Brown 2012); patrol route design (Leigh et al. 2019); police station location optimisation (Aly and Litwhiler 1979; Chow et al. 2015; Larson 1974); police staffing (Taylor and Huxley 1989); and patrol deployment distribution over beats (Chenevoy 20220. However, with the exception of some research into ambulance response times (Jagtenberg et al. 2015, 2017; van Barneveld et al. 2016, 2018), no computational investigation has been done into the effect of *deployment strategies* on emergency response times – while this is identified as the primary variable under police control to improve police travel time (Verlaan and Ruiter 2023).

Moreover, with the exception of Chenevoy (2022), these studies relied on equation-based models, which, while effective for optimisation problems, often require high levels of abstraction that limit their ability to capture real-world variability. More flexible computational methods, specifically agent-based modelling (ABM), allow for greater realism by explicitly simulating individual police units, emergency calls, and their interactions within a spatially explicit environment. Unlike equation-based models, ABMs can capture real-life complexity and heterogeneity as they incorporate feedback loops, non-linearity, and path dependency.

Use of ABM in Simulating Crime and Police Response Dynamics

ABMs have been used to investigate a wide range of crime problems and policing responses. Many of these studies are primarily theory-driven, using ABMs to test the generative sufficiency of mechanisms proposed by criminological theory. For example, Birks et al. (2012, 2014) demonstrate how routine activity theory, rational choice theory, and crime pattern theory can jointly explain the emergence of core empirical regularities such as repeat victimisation, spatial clustering, and journey-to-crime patterns. Birks and Davies (2017) similarly test competing hypotheses about the influence of street network structure on crime risk. Groff (2007, 2008) employs ABMs to assess how spatial and temporal constraints on offender movement shape robbery opportunities, while Brantingham and Tita (2008) and Bosse and Gerritsen (2008) examine the formation and displacement of crime hot spots.

Other studies demonstrate how ABMs can be used to simulate crime prevention strategies under hypothetical or artificial conditions. For instance, Groff and Birks (2008) explores the potential of simulation to evaluate alternative crime prevention interventions, while Malleson (2012) models property crime risks in the context of urban regeneration. More recently, Weisburd et al. (2017) and Wooditch (2023) have used agent-based simulations to model the area-wide effects of hot spots policing and the potential gains of reallocating officers' uncommitted time to high-crime areas.

Despite this breadth, most ABM studies remain primarily exploratory or theoretical. To assess the potential for police agencies to meaningfully reduce response times, a more decision-support oriented approach is required – one that links simulation outcomes to actionable organisational choices under realistic operational constraints. The primary state-of-the-art example of such an approach is the work of Chenevoy (2022), who developed a simulation-based optimisation framework combining an agent-based model of patrol activities with a genetic algorithm to improve both response efficiency and crime deterrence. Her model is designed to support strategic decision-making by identifying effective configurations in complex urban environments.

While Chenevoy's work represents a significant advance, it primarily addresses the strategic (long-term) allocation of police resources. The present study complements this by focusing on the tactical implications of deployment strategy – such as coverage schemes and dispatch protocols – at finer temporal and spatial scales. Rather than optimising configurations, it provides a flexible, empirically grounded simulation environment for evaluating the performance of alternative deployment strategies.

The Present Study and its use of ABM

Specifically, the present study employs a highly detailed ABM to investigate the effects of police *deployment strategies* – the primary variable under police influence – on emergency response times, while also considering the moderating roles of key variables. The methodology expands on the chapter "Agent-based decision-support systems for crime scientists" by Birks and Townsley (2018), who demonstrated how ABMs can simulate police response dynamics, test the impact of various interventions and provide simulated counterfactuals inaccessible to empirical methods – as real-world methods cannot compare the two deployment strategies directly on the same incidents. While their approach relied on a simplified representation (i.e., imaginary geographic context and simulated crime data), the present study enhances the realism and granularity of the simulation by integrating real historical emergency calls-for-service (CFS) data, and detailed geospatial data that enable realistic modelling of street networks and current police jurisdictions. Additionally, it incorporates observed dispatch dynamics derived from ethnographic research, all within the NetLogo framework (Wilensky 1999).

In the Netherlands, as in many other parts of the world, deployment mostly takes the form of motorised patrol carried out by a one- or two-officer team. Motorised patrol ranges from undirected (often called *random*) to fully directed, and may even include optimally timed stops in hot spots (Koper 1995). However, sometimes more stationary forms of deployment are also used, an example is the use of temporary mobile police units in hot spots or near the house of a repeat-victim.

As such, this paper evaluates the impact of three distinct police deployment strategies – *random patrol deployment* (i.e., randomly, and consecutively, selecting target nodes to travel towards), *stationary deployment* (i.e., continuously returning to a predetermined, optimally central, node in the network), *last location deployment* (i.e., remaining at the node of the last CFS) – on police response times through simulation. In the random patrol strategy, police units sequentially and randomly select nodes within their jurisdiction's street network, travel to these nodes via the shortest path, and idle for 15 minutes before repeating the process unless dispatched to an emergency call. The stationary deployment strategy involves clustering nodes within a jurisdiction and assigning each police unit to the most central node in its cluster; when not responding to incidents, the units return to and remain at their designated (optimally distributed) stations. The last location deployment strategy positions police units at the location of their most recently handled emergency call. This approach assumes that recent incidents serve as a reasonable predictor for future calls, as crime and emergency events often exhibit spatio-temporal patterns.

Besides the effect of these three different police deployment strategies, we also investigate the effect of three variables suggested by Verlaan and Ruiter (2023) to moderate the effect between these police deployment strategies and police response time. These moderating variables are: *police capacity*, *call volume* and *degree of urbanisation of the front line team*, the lowest level geographical unit of the Dutch police with a police station; analogous to the US *precinct*. This leads to the following research questions:

1. What is the impact of police deployment strategies on emergency response times?

    a. How do urbanisation, call volume, and police capacity moderate these effects?

To systematically address these questions, we have developed six falsifiable hypotheses. The rationale behind these hypotheses is straightforward. Stationary and last location deployment are expected to outperform random patrol deployment because the former relies on the principle of optimal coverage and the latter on the principle that calls for service tend to cluster in space and time. We expect the influence of the coverage principle to be stronger than that of the clustering principle. Likewise, the moderating variables follow intuitive mechanisms: higher police capacity and lower call volume are expected to reduce queueing time; higher levels of urbanisation are expected to produce more spatially clustered calls for service and thus shorter travel distances. Therefore, the hypotheses are as follows:

1. *Stationary deployment* yields better response times than *random patrol deployment* operationalised as lower average response time, higher percentage fast responses (*i.e.* < *3 minutes*) and lower percentage late responses (*i.e.* >*13 minutes*).
2. *Last location deployment* yields better response times than *random patrol deployment* operationalised as lower average response time, higher percentage fast responses (*i.e.* < *3 minutes*) and lower percentage late responses (*i.e.* >*13 minutes*).
3. *Stationary deployment* yields better response times than *last location deployment* operationalised as lower average response time, higher percentage fast responses (*i.e.* < *3 minutes*) and lower percentage late responses (*i.e.* >*13 minutes*).

4. As *police capacity* increases, operationalised as the number of virtual police response units serving each front line team, the relative effect on *average response time*, percentages of *fast responses* and percentages late responses within *stationary* -, *last location* -, and *random patrol deployment* decreases.
5. As the *urbanisation* of the front line teams increase, operationalised based on its street length in metres per square kilometres, the relative difference in *average response time*, percentages *fast responses* and percentages *late responses* within *stationary* -, *last location* -, and *random patrol deployment* decreases.
6. As *call volume* increases, operationalised as high call volume shift or normal call volume shift, the relative difference in *average response time*, percentages of *fast responses* and percentages *late responses* within *stationary* -, *last location* -, and *random patrol deployment* decreases.

In answering these questions and testing these hypotheses, this research aims to provide actionable insights for both academic and practical contexts. By leveraging real-world data, including historical priority 1 CFS, jurisdictional shapefiles, and detailed street network data, the study seeks to bridge the gap between theoretical exploration and practical application. Furthermore, it aligns with recent calls to revisit long-standing assumptions about rapid response and its role in modern policing.

Importantly, this study focuses specifically on how deployment strategy and moderating variables influence outcomes in reactive policing, while acknowledging that officers on the street engage in a range of other activities, including proactive patrol – an area that has received comparatively greater empirical attention in recent years (Braga et al. 2019). We argue that the simulation approach used here is particularly well suited to studying reactive policing, as empirical experimentation in this area would require direct manipulation of police responses to real incidents, presenting significant practical and ethical challenges. Moreover, a key strength of the simulation method is its ability to isolate reactive policing from other core activities, something that would also be exceptionally difficult using traditional empirical approaches. Future research could of course apply similar approaches to explore proactive policing strategies and further models could combine simulation of additional police activities to better understand the relative opportunity cost impacts of each on the others. For instance, integrating models of proactive patrol, community engagement, or investigative work could provide a more holistic view of how police resources are allocated and the trade-offs involved.

Methodology

This study follows a data-driven simulation approach, integrating real-world police data, geographical information, and agent-based modelling to assess the impact of deployment strategies on response times. The ABM developed simulates daily police incidents and responses in the District Oost-Utrecht over a full year, operating on a second-by-second basis. Using real-world police data on incident timing, location, and recorded response actions, the model replicates observed response patterns while systematically varying police deployment strategy and capacity. To ensure the behavioural realism of the model, the development process was informed not only by administrative data but also by extensive fieldwork, including systematic observation in dispatch centres, ride-alongs with patrol units, and follow-up interviews with dispatchers and officers. By grounding the simulation in both data and practice, the model generates synthetic counterfactuals that allow for a structured evaluation of different strategies under controlled conditions. This approach enables direct comparisons of response effectiveness across key performance metrics, such as average response time and the proportion of rapid responses.

The methodology first describes the primary data sources, including police incident and dispatch records alongside geographical data used to simulate police movement. Next, it details the ABM environment, specifying agent behaviour, deployment strategies, and dispatch dynamics. The simulation design is then outlined, including variations in police capacity and strategy. Finally, the data extraction and analysis section explains how response time metrics are generated within the ABM, extracted, and analysed using descriptive statistics and regression models.

Primary Data

The GMS data used in the ABM is obtained from the Netherlands Police and covers the whole of District Oost-Utrecht for the year 2019. The data are spread over two databases. The first database contains information about the incident, the second contains information about the police dispatches to these incidents; one incident can have multiple units dispatched to it. Tables 5 and 6 in Appendix A represent the relevant pseudonymised variables which are used from each database.

In addition to police records, geographical data were incorporated to ensure realistic simulation of police movement and response times. Jurisdiction shapefiles were used to define the boundaries of each front line team, while street network data were retrieved from OpenStreetMap (OSM) via OSMnx (Boeing 2017). The road network was filtered to include only drivable roads, with travel speeds and road restrictions applied accordingly. Table 7 details the characteristics of the street network data.

Primary Data Pre-Processing

The pre-processing code is openly available on the OSF repository. Here, we provide a short summary of the pre-processing. We begin with a number of filtering steps in order to obtain a representative sample of incidents, and all individual dispatches to these various incidents. First, we exclude incidents that were initiated by the police (as this constitutes proactive policing). Second, we remove incidents which did not receive a physical dispatch, but were, for example, handled over the phone or considered *false alarm*. Third, we remove dispatches to incidents by non-standard response units, e.g. helicopter, military police units etcetera. These steps leave 34,593 incidents and 50,694 individual dispatches to model in the ABM. However, there are a few more filtering steps needed to ensure data quality and representativeness: Fourth, we exclude dispatches that contain timestamp logs in the hour in which, in the Netherlands, the clock is set to daylight-saving hours: *2019-10-27 02:00:00* until *03:00:00*. Fifth, we exclude dispatches for which *no cleared* timestamp is present in the data. Sixth, we exclude dispatches for which the duration between being dispatched to a call and clearing a call is less than five minutes, as these are often false alarms, resolved before police arrival, or otherwise erroneous. Seventh, we exclude dispatches which last longer than the duration of a shift; eight hours. Eighth, we exclude dispatches which arrive within one minute of being dispatched to a call. Lastly, we exclude calls for which the duration between arrival and clearing is less than one minute. After these last filtering steps, we are left with 30,380 (88%) incidents and 38,893 (77%) individual dispatches to these incidents. Table 8 in Appendix B summarises these steps, together with the reason behind each filtering step and its effect on the size of the database. Lastly, we took steps to infer missing data in the arrived timestamp, see the open code for details.

Agent-Based Model Development

This section describes the development of the ABM, including the model environment, agent behaviour, deployment strategies, dispatch dynamics, and experimental setup.

Model Environment

The agent-based model is built in NetLogo 6.2.2 (Wilensky 1999) and simulates traversable street networks for the four front line teams within District Oost Utrecht. Shapefiles of police districts and front line teams were sourced from the Netherlands Police, while street network data was retrieved from OpenStreetMap using OSMnx (Boeing 2017). The network was constructed with the "drive" specification, ensuring only drivable roads and paths were included. Each road segment in the network is characterised by parameters such as average travel speed for cars, directional flow, and true length in metres. For the Netherlands, these parameters in OSM are highly accurate and complete. The temporal dimension of the simulation is structured in ticks, where each tick corresponds to one real-world second. A graphical representation of the model is shown in Fig. 1.

Agents: Calls-For-Service

The model incorporates real historical calls-for-service (CFS) data from the year 2019 within the jurisdiction of District Oost-Utrecht, which includes the four *front line teams*. These calls provide the foundation for simulating police response dynamics and are preprocessed to ensure representativeness and compatibility with the ABM framework. The details of the CFS data are summarised in Table 1.

Each CFS is assigned a pseudonymised incident ID, enabling linkage with the original data while ensuring privacy. Incidents are also categorised by their priority level as assigned at the time of the call. To simplify the simulation, calls with lower priority levels (3, 4, and 5) are re-coded as priority level 2 due to their low frequency in the dataset. This adjustment maintains model efficiency without compromising realism.

CFS timestamps, indicating when the call was received by the dispatch centre, are operationalised as seconds elapsed since the start of 2019. This conversion aligns the data with the temporal structure of the ABM, where each tick corresponds to one second in real-world time.

The model further integrates operational details to accurately simulate resource allocation. This includes the number of police units deployed to each incident (*reactive_supply*) and a list of on-scene durations (*on_scene_times*), capturing the time each unit remains engaged with the incident. Additionally, spatial precision is ensured by mapping each inci-

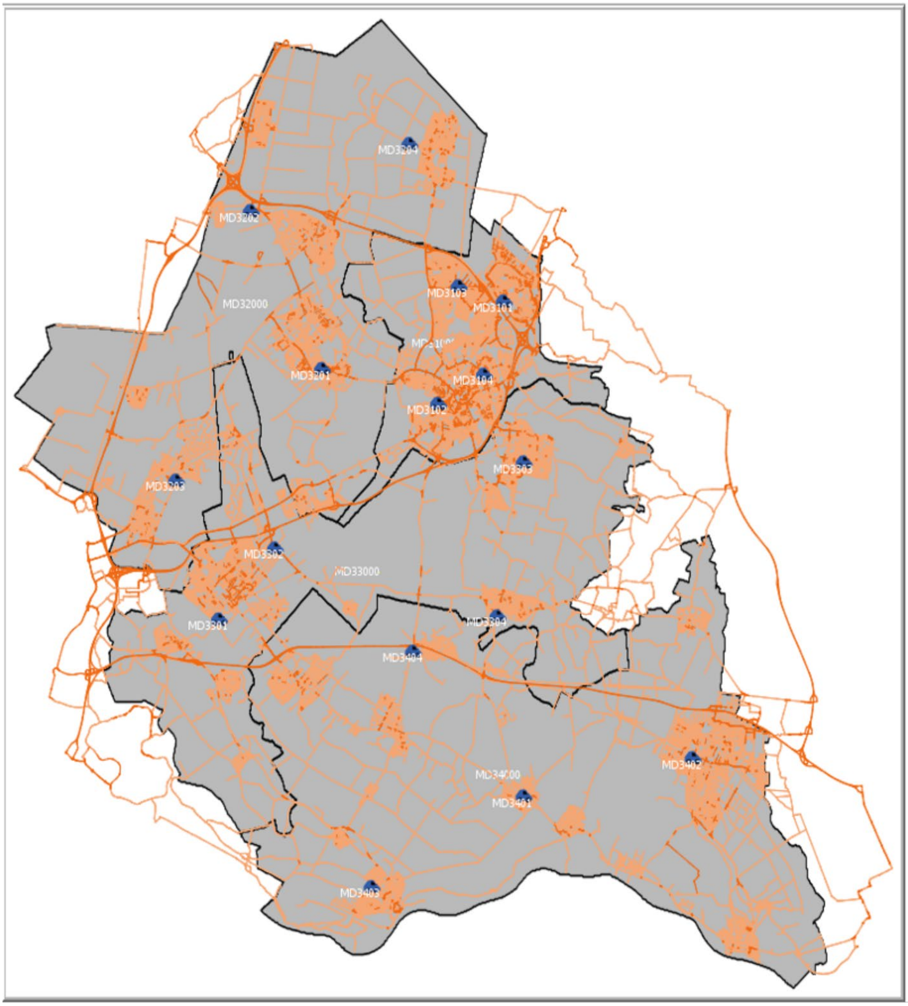

Fig. 1 Graphical representation of the ABM model - instantiated with police capacity = 4

dent to specific x and y coordinates (*Xcor* and *Ycor*) within the NetLogo world, aligning the incidents with the simulated street network.

Agents: Virtual Police Response Units

The agent-based model simulates a population of virtual police response units to represent the operational capabilities of law enforcement within each front line team. These agents act as individual police units, dynamically responding to CFS and interacting with the simulated environment in real time.

The number of virtual police units per front line team varies between 1 and 10, depending on the instantiation of the simulation run. This variation allows for an exploration of the moderating effects of differing police capacity levels on the relationship between police

Table 1 Pre-processed CFS data input in the ABM

Variable name	Description
Incident_id	Unique incident identifier
Priority_level	Priority level of the incident
Start_incident	Timestamp of incident recorded by dispatch centre, operationalised as seconds since start of the year 2019
Reactive_supply	Number of virtual police units to respond to the incident
On_scene_times	List of on-scene times (*arrived_cleared*)
Xcor	Integer representing the x coordinate of the incident on the street network, in the format of the NetLogo world
Ycor	Integer representing the y coordinate of the incident on the street network, in the format of the NetLogo world

strategy and response times. At the start of the simulation (tick = 0), all agents are instantiated and deployed within the street network of their respective front line team jurisdictions.

For simplicity and to focus on response dynamics, the model does not include mechanisms for returning police units to their stations at the end of shifts. Additionally, the size of the police force remains constant throughout the simulation, irrespective of typical fluctuations in staffing levels during day and night shifts. While these simplifications may reduce fidelity in certain contexts, they allow for a controlled examination of deployment strategies and response outcomes without the added complexity of shift-based staffing adjustments.

Each virtual police unit is equipped with a set of behavioural rules that govern their movement, response to dispatches, and idle behaviour. These rules vary depending on the active deployment strategy, ensuring the agents accurately represent the operational logic of different patrol methods. By incorporating individual decision-making processes and interactions with the environment, the agents are capable of capturing emergent patterns in response times and resource allocation under various scenarios.

Model Dynamics: Call and Agent Behaviour

Call Behaviour

The behaviour of CFS is driven by real-world historical data. Each call becomes active at the simulation tick corresponding to its *start_incident* timestamp, representing the time the call was received by the dispatch centre.

When a call becomes active, the model assesses the availability of the required number of police units (*reactive_supply*) within the front line team. If units are available, they are dispatched to the incident. When fewer units are available than required, the maximum number of available units is dispatched, and the remaining demand is added to a dispatch queue. Calls in the queue are prioritised by urgency (priority level), with waiting time determining the order of dispatch for calls of the same priority. This queuing system follows a first-in, first-out strategy for calls of equal priority.

Once dispatched, police units travel along the shortest path to the incident location, observing road speed limits (always travelling at the maximum travel speed of a road section) and restrictions. Upon arrival of the first unit, the response time is recorded as the elapsed time since *start_incident*. The units then remain on scene for the duration specified in the call data (*on_scene_times*), during which they are unavailable to respond to other calls. However, units can be redirected mid-response to handle higher-priority incidents. In such cases, the interrupted call re-enters the dispatch queue, and the interrupted on-scene time is preserved for completion in the future.

Agent Behaviour

The actions of virtual police response units are divided into two phases: their behaviour during response to active calls and their behaviour during idle periods.

When responding to a call, agents traverse the street network to reach the incident location via the shortest possible route, calculated based on road speed and travel time. Upon arrival, agents remain at the scene for the allocated time before becoming available for new assignments. During this response phase, agents can be dynamically reallocated if a higher-priority call arises. This ensures that police response prioritises the most urgent incidents.

During idle periods, the behaviour of agents is determined by the deployment strategy assigned in the simulation. Under the *random* deployment strategy, agents sequentially and randomly select nodes within their front line team jurisdiction and travel to these nodes, idling at each location for 15 minutes before repeating the process. This pattern mimics undirected patrol operations commonly observed in real-world policing.

The *stationary deployment* strategy assigns agents to optimally distributed locations within their front line team. Street network nodes are divided into n clusters (n being equal to the number of initialised virtual response units in the particular simulation run) using k-means clustering, and agents are stationed at the node with the highest closeness centrality within each cluster. When not responding to incidents, agents return to their designated stations via the shortest path and remain there until dispatched to another call. This strategy reflects a more structured and centralised approach to resource deployment.

Under the *last location deployment* strategy agents remain idle at the location of their most recently handled call for service. This approach seeks to leverage the temporal and spatial clustering of incidents by assuming that recent call locations serve as effective predictors for future demand, and provides an alternative to centralised or random patrol patterns.

Model Robustness

The ABM presented in this study is deliberately designed to be straightforward and transparent (apart from the open code, a visual representation of the model – in the form of a flow diagram – is available on OSF). The model relies heavily on real data and operational mechanisms observed and documented during extensive fieldwork.

The only substantive model parameter that requires an assumption is vehicle speed. We model this using road-specific speed limits from OpenStreetMap (OSM), which is known to be highly accurate in the Netherlands. Agents follow the maximum allowed speed for each road segment. We chose not to perform formal sensitivity analysis on this parameter, as we consider it the most defensible and realistic approximation available and the value most central to the phenomenon being modelled.

Experimental Setup

Each experiment simulates the same calls-for-service within District Oost-Utrecht for the exact same 365 days (in 2019) on a second-by-second basis. The simulation experiments

Table 2 Simulation parameters

Simulation parameters	Description	Operationalisation
Policedeployment strategy	A navigation strategy for police units not currently responding to a call	random patrol deployment; stationary deployment; last location deployment
Police capacity	The number of virtual police response units per front line team in the simulation	1–10 (increment: 1)

Table 3 Structure of ABM dispatch level output data

Call sign	Incident ID	Dispatch ID	Timestamp	Status
Police call sign	Unique ID	Unique ID	In ticks (seconds since start 2019)	Levels = dispatched, arrived, cleared, cancelled

systematically vary the key independent variables: *police deployment strategy* and *police capacity*. Each experiment is run under a combination of these conditions, allowing for a structured assessment of their effects on response times. Police deployment strategy has three levels: random patrol, stationary deployment, and last location deployment. Police capacity varies from one to ten units per front line team. The range of 1 to 10 units per front line team was selected to capture both typical and extreme staffing scenarios. Empirical data (see Fig. 6) show that most front line teams operate with three to seven active units per shift. Including values outside this range enables the model to explore the impact of under- and over-capacity conditions on response outcomes, which may be relevant for resource planning or stress testing deployment strategies.

These two parameters result in thirty unique simulation scenarios. The full set of simulation parameters is summarised in Table 2. The *last location* and *stationary* deployment models are fully deterministic, and the *random* deployment model is highly deterministic with only minor influences of stochasticity. Hence, multiple random seed reruns of the models were found to be unnecessary.

Model Outputs and Data Analysis

Model Output Data

Each simulation run generates a dataset capturing all dispatch-level events, structured similarly to the original police dispatch input data (see Table 6). These generated data include a record of each dispatch event, capturing the police unit involved, the corresponding incident, a unique dispatch and key time stamps. This results in 30 output datasets, each corresponding to one of the unique simulation runs. Table 3 details these output data.

Data Analysis Approach

The analysis focuses on quantifying response times and evaluating the effects of different deployment strategies under varying conditions. Following Verlaan and Ruiter (2023), response time is operationalised as the elapsed time (in seconds) between the dispatch timestamp and the arrival of the first unit on the scene. To test the hypotheses, response times are analysed using descriptive statistics and visualised per front line team and police capacity level. As preregistered, falsification of the hypotheses is attempted based on mean and median response times, as well as distributions of fast responses (under three minutes) and late responses (over 13 minutes). The results are compared across deployment strategies, while controlling for urbanisation level, call volume, and police capacity. The variables included in the analysis and their sources are detailed in Table 4.

Hypothesis Testing and Exploratory Analysis

The results section systematically attempts falsification of the hypotheses using descriptive plots, regression and statistical summaries. The analysis first examines response time distributions for each strategy per front line team and police capacity level. Following Verlaan and Ruiter (2023), and in order to ensure comparability, findings are only interpreted for priority 1 calls, where all independent variables can be considered limiting factors.

Falsification of hypotheses 1–3 is conducted under all conditions of police capacity and per front line team but only within the "normal" call volume condition. Hypothesis 4 is tested across all deployment strategies and front line teams but again restricted to normal call volumes. Hypothesis 5 is evaluated across all strategies and police capacity levels, while hypothesis 6 is tested under all strategy and front line team conditions. Since different scenarios may yield different results, hypotheses may be falsified under some conditions but not others.

All simulation code, pre-processing scripts, and output visualisations will be made openly available on the project's OSF repository.

Results

The results presented below are based on Figs. 2, 3 and 4. These figures provide insights into the outcome metrics of mean response time, percentage of fast responses (< 3 minutes), and percentage of late responses (>13 minutes) for each of the scenarios (combination of jurisdiction and initialised police capacity level). More specifically, Fig. 2 shows the response time distribution for each scenario, Fig. 3 details the mean response time, percentage fast

Table 4 Dependent and independent variables

Variables	Operationalisation	Source
Response time	(s)	ABM
Deployment strategy	Random; Stationary; Last location	ABM
Urbanisation rank	standardised (0–100) front line team rank: *metres of streets/km*^{2}	GIS
Police capacity	Police units/shift	ABM
Call volume	Calls-for-service/shift	GMS

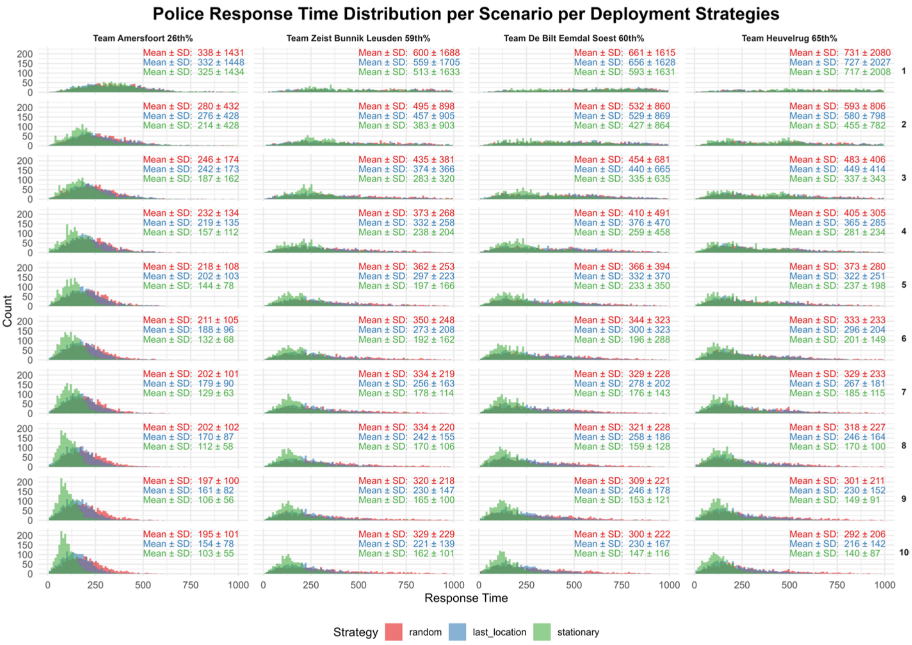

Fig. 2 Police response time distribution per deployment strategy per front line team per capacity level

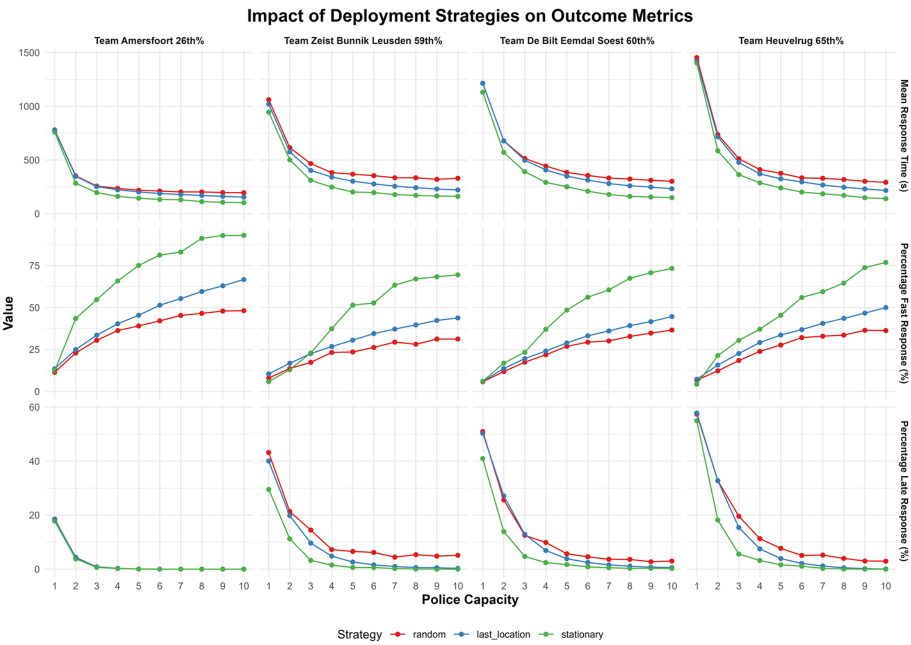

Fig. 3 Impact of deployment strategies on outcome metrics per front line team.

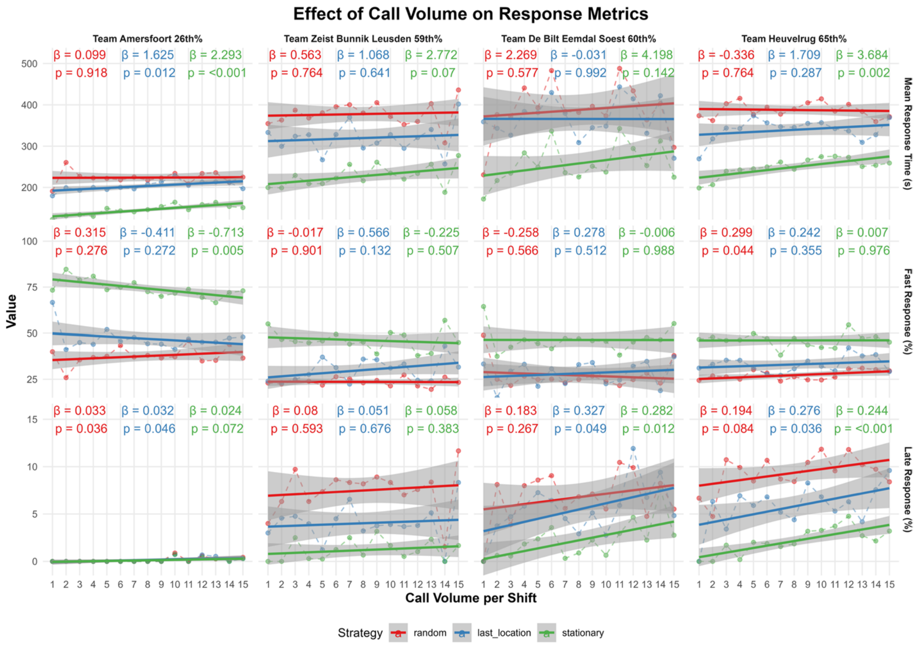

Fig. 4 Impact of call volume per front line team per deployment strategy (for police capacity 3 - 7)

responses, and percentage late responses per scenario, and Fig. 4 investigates the relative impact of incremental increases in call volume.

To provide context to these results, we first examine the empirical distribution of priority 1 call volume per shift and police capacity per shift for each real-world front line team, as presented in Figs. 5 and 6 (in Appendix C). A substantial proportion of shifts – approximately a quarter to a third – receive no priority 1 calls. Among shifts that do, most shifts receiving around six calls per shift (SD = 5). Meanwhile, police capacity per shift shows less variation within each front line team, with most shifts operating at five police units (SD = 2). These distributions inform the conditions under which different deployment strategies are evaluated in the subsequent analyses.

Average Effect of Deployment Strategies

Across all scenarios, stationary deployment consistently outperformed both last location and random patrol strategies in terms of mean response time, percentage of fast responses (< 3 minutes), and percentage of late responses (>13 minutes). As detailed in Fig. 2, on average among the 40 different scenarios (4 front line teams × 10 capacity levels), stationary deployment reduced mean response times by 35% (± 14%) compared to random patrol. Similarly, it achieved substantially higher rates of fast responses (74% ± 40%) and reduced late responses by 66% (± 33%). Last location deployment also exhibited substantial improvements over random patrol, particularly in scenarios with higher police capacity. Mean response times were reduced by 13% (± 9%), with fast response rates increasing by 22% (± 14%) and late response rates decreasing by 42% (± 36%).

Figure 3 illustrates the potential of stationary deployment in absolute terms: in the urban context of front line team Amersfoort, under the average capacity of 5 police units, *stationary* deployment enables police to (theoretically) respond to 75% of all priority 1 calls in under 3 minutes – approximately twice as many as under *last location* deployment (38%) or random patrol (32%). Even with police capacity doubled to 10 units, *last location* deployment would barely be able to respond to 65%, and *random* patrol would still fail to reach 50% of such calls within the same time frame.

Moderating Effect of Police Capacity

As police capacity increased, mean response time and the percentage of fast and late responses improved in absolute terms across all deployment strategies. However, in line with hypothesis 4, both the relative as well as the absolute marginal improvement per additional police unit diminished. Nevertheless, as is evident from Fig. 3, the marginal benefit of each additional police unit is larger under *stationary* deployment than under *last location* and *random* deployment for all three measures.

For *percentage of late response*, we observe saturation (meaning all calls are serviced with the time frame of 13 minutes) across all front line teams within the currently tested levels of police capacity. For *percentage of fast response*, this saturation does not yet take place, although it is close for front line team Amersfoort under stationary deployment. In contrast, for *random patrol*, it is not clear whether it will ever reach saturation, as the curve appears to asymptote below the 50% line.

Ultimately, across virtually all scenarios and metrics, stationary deployment with a police capacity of four outperforms last location and random with a police capacity of ten.

Moderating Effect of Urbanisation

Across the board, it is evident that the more rural a jurisdiction is (all else being equal), the higher the response times and higher the percentage of late responses. However, this is mainly due to having a higher baseline, the marginal effects per additional police capacity does not appear to vary per front line team over any of the strategies. It is noteworthy that we do not witness the same dynamic for fast response. In fact, while we do observe substantially higher percentages of fast response in the urban jurisdiction of front line team Amersfoort, there is no observable difference between the other more rural jurisdictions for similar police capacity levels.

Moderating Effect of Call Volume

Figure 4 details the effect of (the empirical fluctuation of) call volume on the three outcome metrics. The effect of call volume on response metrics is not strictly monotonic across strategies and jurisdictions. While mean response time and late response rates show some discernible increases as call volume rises, the relationship is less clear for fast responses. The impact is also more pronounced under stationary deployment, likely because its efficiency depends on pre-positioning, which becomes less relevant when calls accumulate, forcing units into a queue. As queueing increases and units have reduced idling time, deployment strategy plays a diminishing role in performance, effectively eroding the advantage of better strategies.

As such, at higher call volumes, the differences between deployment strategies diminish.

For realistic policing conditions – where front line teams typically operate with three to seven units per shift (see Fig. 6) and priority 1 call volumes rarely exceed fifteen per shift (see Fig. 5) – the overall effect of call volume is limited:

As call volume increases, mean response times also rise – by approximately 10–20 seconds under random patrol, 20–30 seconds under last location deployment, and up to 40 seconds under stationary deployment, where high demand begins to erode its advantage. In contrast, the proportion of fast responses declines by 10–15 percentage points under random patrol, 7–12 under last location, and 5–10 under stationary deployment and late responses increase by 3–5 points for random patrol, 2–4 for last location, and only 1–3 for stationary – reinforcing the stationary strategy's relative resilience even under pressure.

Crucially, stationary deployment at the highest observed call volumes still outperforms random and last location deployment at the lowest call volumes. Even when facing the most demanding conditions, stationary deployment achieves substantially lower response times, higher fast response rates, and fewer late responses than the other strategies under optimal conditions. This highlights that deployment strategy is a far greater determinant of performance than variations in call volume, reinforcing the importance of an effective positioning approach.

Summary

The findings strongly support hypotheses 1–3: stationary deployment consistently outperforms both last location and random patrol across all response metrics. Even under the highest call volumes, it achieves faster response times, more fast responses, and fewer late responses than last location and random patrol under optimal conditions.

Hypothesis 4 is also confirmed, as marginal gains from additional police capacity diminish across all strategies, though stationary deployment benefits most. Hypothesis 5 receives partial support – while urban areas see lower response times and fewer late responses, the effect on fast response rates is less clear.

The results for hypothesis 6 (call volume effects) are mixed. While response times and late responses increase with more calls, the effect remains relatively minor within realistic policing conditions. More importantly, as call volume rises, differences between strategies narrow, particularly for stationary deployment, where its effectiveness is increasingly nullified by workload saturation.

Ultimately, deployment strategy is the dominant factor in determining response times, outweighing the effects of urbanisation, call volume and police capacity.

Discussion

This study set out to investigate the impact of police deployment strategies – stationary deployment, last location deployment, and random patrol deployment – on emergency response times and to examine how these effects are moderated by police capacity, urbanisation, and call volume. By employing a detailed ABM that integrates real-world CFS data, geographical information, and dispatch dynamics, we have provided actionable insights into the dynamics of police response times under varying conditions.

The findings reveal that stationary deployment – whereby response vehicles relocate themselves to a central location within their respective jurisdiction after resolving each incident – consistently outperforms both last location deployment and random patrol across all key metrics of response time, percentage of fast responses (< 3 minutes), and percentage of late responses (>13 minutes). This superiority is particularly evident in fast responses, where it produces a large and decisive impact.

These findings contribute to the reinvigorated academic debate surrounding rapid response in modern policing. The results demonstrate a substantial potential for the police to reduce response times and increase fast responses through the selection of deployment strategies. This challenges Sherman's (1997, chapter 8, p. 11) conjecture that cutting response times in half may require doubling the police force. Instead, the choice of deployment strategy shows a much larger effect size, underscoring the agency that police departments have in improving response times without significant increases in resources. Coupled with rapid response literature on the effect of fast responses on on-scene arrests see, (Bieck, 1977; Blanes i Vidal and Kirchmaier, 2018; Cihan et al., 2012; Clawson and Chang, 1977; Isaacs, 1967; Spelman and Brown, 1981; Tarr, 1978), these findings indicate that police departments can substantially improve their arrest and clearance rates through their deployment strategy.

Beyond theoretical contributions, these findings also hold direct implications for practice. Stationary deployment is particularly effective for either increasing fast responses or limiting late responses, making it valuable in understaffed conditions where meeting on-time response quotas – such as the 90% threshold mandated in countries like the Netherlands – is critical.

From an academic perspective, the study underscores the potential of ABM as a decision-support tool for exploring complex policing dynamics. By explicitly simulating individual police units, CFS, and their interactions within a spatially explicit environment, the ABM provides a level of granularity and realism that is difficult to achieve with traditional equation-based models.

A final theoretical insight emerged from the performance of last location deployment – whereby officers remain at the location of the most recently resolved incident until they are required to respond to the next. While this deployment strategy performs poorly under low police capacity levels, it demonstrates increasing effectiveness as capacity rises. To us, this pattern suggests a fundamental misalignment between the cyclical nature of hotspots – where recent incidents predict future activity – and the sequential nature of police response. The assumption that the location of the last call serves as an effective predictor of the next call breaks down when intervening calls from other hotspots redirect police units. This sequential reality introduces delays that disrupt the predictive power of the strategy. However, as police capacity increases, this misalignment diminishes, as more units are available to simultaneously address calls from multiple hotspots.

Limitations

While this study provides valuable insights, several limitations should be acknowledged. First, like all models, the ABM's external validity is inherently constrained by the context of its design. The simulation focuses on Dutch front line teams, with specific geographic, demographic, and operational characteristics. While these findings may generalise to similar contexts, their applicability to other policing systems (e.g., in the US or UK) requires further exploration.

Second, the model incorporates several simplifying assumptions to enhance computational efficiency and isolate the effects of deployment strategies. For instance, the model does not account for shifts or the practice of returning police units to stations at the end of a shift. Similarly, non-reactive policing activities, such as proactive patrols or community engagement, are not simulated, potentially limiting the holistic applicability of the findings.

This focus on reactive policing means the model does not capture potential trade-offs or synergies between emergency response and other police functions, such as proactive patrol or community engagement. As such, the results should be interpreted as highlighting response time dynamics in isolation and ignorant of the proactive task of policing.

Future Research and Broader Implications

The demonstrated influence of deployment strategies on response times underscores the need for renewed empirical investigations into rapid response, a topic long side-lined in policing research. While randomised controlled trials (RCTs) may remain impractical due to cost and ethical concerns, quasi-experimental and observational studies offer viable alternatives to advance this line of inquiry.

Additionally, the modular nature of the ABM developed in this study allows for its adaptation to diverse policing contexts. Future applications in different geographical and operational settings, such as urban US precincts or rural UK constabularies, would enhance the external validity of the findings and identify context-specific dynamics. By extending the model's scope, we hope to support a broader understanding of rapid response and inform evidence-based strategies for improving public safety.

Further research could also explore the potential synergy between stationary deployment and hot spots policing. Rather than relocating units purely based on spatial centrality, future models could incorporate spatial and temporal crime and call-for-service patterns to identify optimal fixed node placements. This would allow agencies to evaluate whether positioning patrol units near chronic high-demand locations could achieve both efficient emergency response and increased deterrence. By integrating insights from spatial crime analysis with deployment strategy design, such models could bridge the gap between proactive and reactive policing priorities.

In conclusion, this study demonstrates the substantial potential for police agencies to influence response times through strategic deployment, challenging longstanding assumptions and providing a strong foundation for further research and policy development. The findings emphasise that renewed focus on rapid response is not only feasible but overdue, offering a clear opportunity to bridge the gap between theoretical insights and practical advancements in policing.

Appendix A Input Data

Table A1 GMS calls-for-service data

Variable name	Description
Incident ID	Unique identifier of each incident
Dispatch ID	Unique identifier of each dispatch
Call_sign	Unique identifier of police response unit vehicle
Incident_start_timestamp	Timestamp of when the call was received.
Incident_closure_type	Captures response to CFS, e.g., fake call or handled over phone
Incident_priority_level	Priority level of call – range: 5 Levels (1,2,3,4,5)
T_x_coord_aanrij	X coordinate of the location
T_y_coord_aanrij	Y coordinate of the location

Table A2 GMS dispatch data

Variable name	Description
Incident ID	Unique identifier of each incident
Dispatch ID	Unique identifier of each dispatch
Timestamp	Timestamp of status logging (Format: yyyy-mm-dd hh:mm:ss)
Status	Status logged by unit (4 Levels: dispatched, on-way, arrived, cleared)

Table A3 OSM "drive" street network data within District Oost-Utrecht

Variable name	Description
Road_ID	Unique identifier for each road segment within the network
Average_Speed	Average travel speed for cars on the road segment (km/h)
Directionality	Indicates whether the road is one-way or two-way
Length	True length of the road segment (metres)

Appendix B Data Preprocessing

Table B4 Pre-processing steps and their impacts on incidents and dispatches

Filter	Incidents	Dispatches	Rationale for filtering step
District Oost-Utrecht 2019	72,649 (100%)	113,959 (100%)	The dataset encompasses four front line teams, both rural and urban
Reactive calls	56,118 (77%)	90,695 (80%)	This ABM focuses exclusively on reactive policing, necessitating the exclusion of proactive or preventive calls
Received dispatch	38,457 (53%)	67,983 (60%)	Certain CFS are false alarms or are resolved without police dispatch
Received police response unit	34,593 (48%)	50,694 (44%)	Some CFS are handled by nonstandard units, such as Military Police, which fall outside the scope of this study
Summer-time	34,573 (48%)	50,664 (44%)	The transition from summer to wintertime results in clock adjustments that create timestamp inconsistencies; these cases were removed to prevent data integrity issues
“cleared” missing	33,664 (46%)	45,426 (40%)	Incidents lacking a *cleared* timestamp were excluded, as the duration of police presence at the scene could not be determined
"dispatched" to "cleared" >5 min	32,882 (45%)	43,687 (38%)	Calls with a very short duration often lack complete timestamps and are likely false alarms, resolved before police arrival, or otherwise erroneous
"dispatched" to “cleared" < 8 hrs	32,880 (45%)	43,682 (38%)	A police shift lasts eight hours, this step removes only a minimal number of cases (five dispatches and two incidents)
"dispatched" to "arrived" >1 min	32,099 (44%)	41,990 (37%)	These cases are likely instances of cars already at the scene or other unrepresentative events
"arrived" to "cleared" >1 min	30,380 (42%)	38,893 (34%)	These cases are likely the result of data entry errors or are otherwise unrepresentative of typical police responses

Appendix C Context

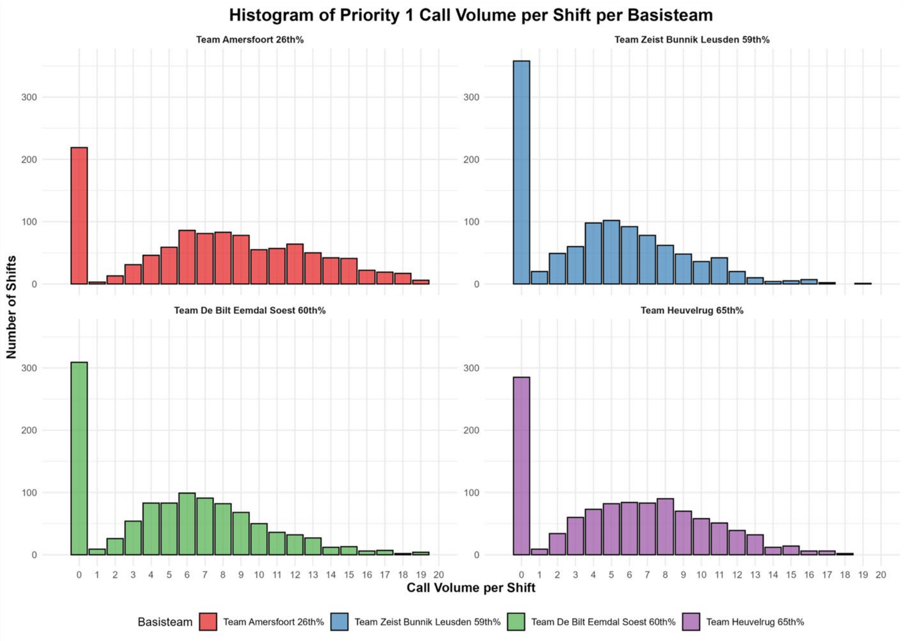

Fig. C1 Histogram of priority 1 call volume per shift per front line team

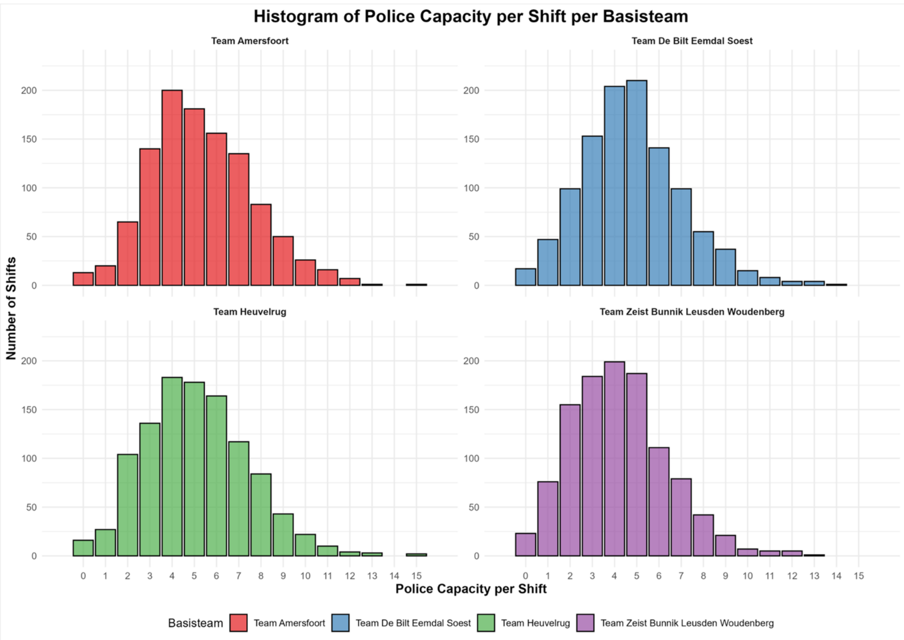

Fig. C2 Histogram of police capacity per shift per front line team (only including police units active within the shift)

Acknowledgements This work benefitted from conservations with and feedback from: Stijn Ruiter, Henk Elffers, Nick Malleson, and Samuel Langton. Daniel Birks gratefully acknowledges the support of the Economic and Social Research Council (Grant Reference: ES/W002248/1) and UK Research and Innovation (Grant Reference: UKRI1356).

Funding This research was carried out within the *What Works in Policing* research programme of the *Netherlands Institute for the Study of Crime and Law Enforcement* (NSCR) and funded by the *Netherlands Police*. The funder had no role in study design, data collection and analysis, decision to publish or preparation of the manuscript.

Data Availability Statement The empirical calls-for-service data is not openly available. All other data are made available on the OSF repository: https://osf.io/yrwdp/.

Declarations

Competing Interests The authors declare that they have no competing interests, financial or non-financial, related to this manuscript.

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