Investigating Disproportionality in Stop and Search in London.

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Key backdrop to the analytics...

Stop and Search is an intrusive tactic considered by police to be operationally important, but one which is often divisive for London's communities, particularly for Black Londoners, given concerns about the disproportionality of this police power.

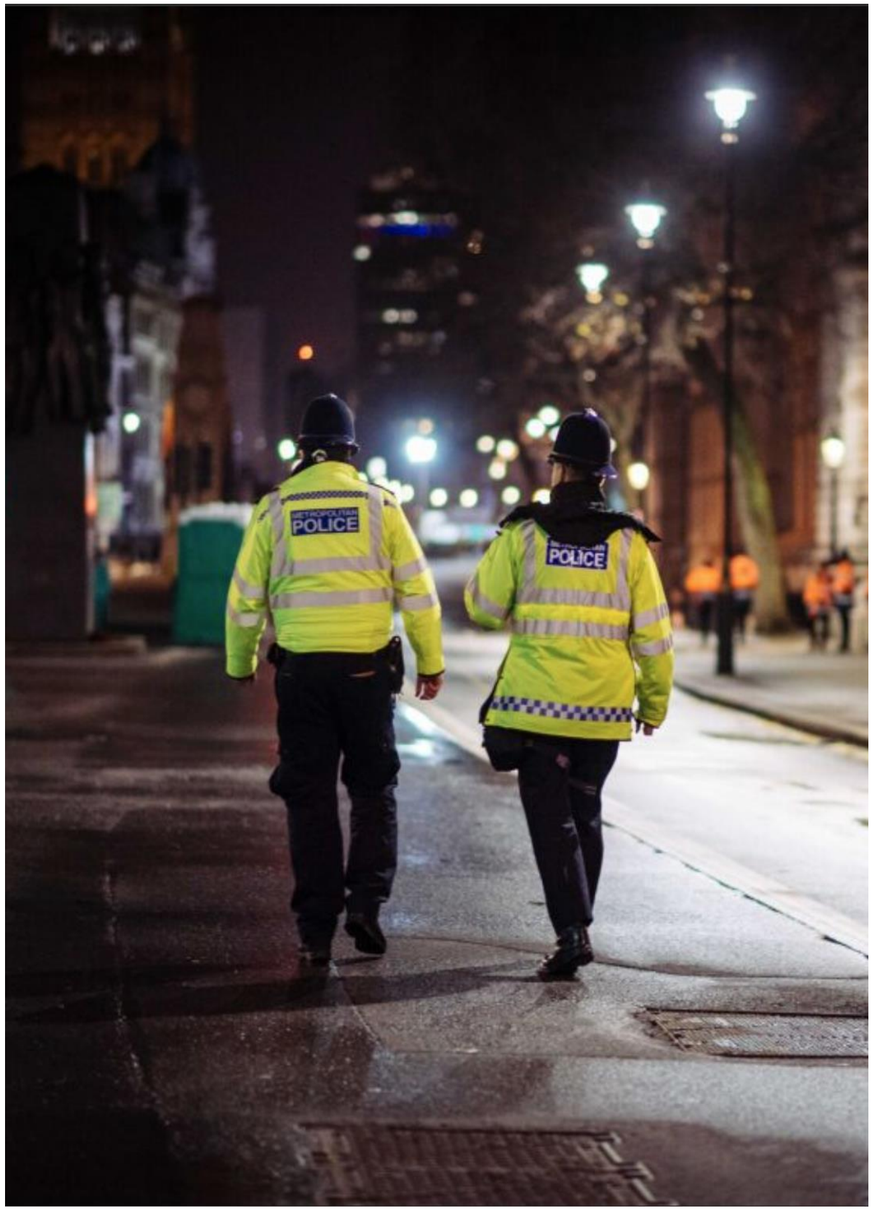
This disproportionality has remained largely consistent for many years, and there is no clear explanation as to why it exists. Outside of disproportionality, prior studies, albeit on a small scale (i.e., IOPC, 2022; HMICFRS, 2021; Shiner *et al*, 2018) have reported that Black Londoners are more likely to receive vague and subjective grounds when officers document their reasons for suspicion.

Looking more broadly, research on the efficacy of Stop and Search for crime reduction is mixed. Stronger evidence comes from American studies, with weaker findings from England & Wales. Yet many would argue to only focus on 'crime' misses the key story.

There is a growing awareness of the role Stop and Search can play within the social fabric between the public and police. Effective engagement, fair treatment, trust, confidence, legitimacy, and cooperation with the police can all be undermined by perceived unfairness or discrimination in the power.

This project delivers groundbreaking peer-reviewed analytics on a scale and depth not seen before on the topic. Leveraging police data on volume, public perceptions, and 152,000 officer-recorded Grounds, alongside broader MOPAC-commissioned analytics, which together seek to explore the Quality of Grounds, as well as modelling to understand the drivers and levels of disproportionality at a London, borough and local level looking to move beyond the flawed 'resident population' measure of disproportionality.

The aim is to deliver a package of original and operational insights in this crucial area for evidence-based oversight and scrutiny.



IOPC, 2022
OFFICIAL IOPC National stop and search learning report 20 April 2022_0.pdf

Shiner et al, 2018
201810__The_Colour_of_Injustice__full_report.pdf

HMICFRS, 2021 https://www.justiceinspectorates.gov.uk/hmicfrs/wp-content/uploads/disproportionate-use-of-police-powers-spotlight-on-stop-search-and-use-of-force.pdf

Key insights from the research

Existing data and analytics from the report show:

- A long-term decline in the use of Stop and Search.
- Disproportionality within Stop and Search is a long-standing concern.
- Public Voice data enables a different lens – a declining public support for the power.
- Black and disabled Londoners are more likely to report negative impacts of the encounter.
- The overall Quality of the Stop encounter is paramount with wider links to Trust and Confidence.

The core project involved hand-coding of 600 Grounds text, which was used to train machine learning models to replicate the coding for 152,000 Stops in 2023 (encompassing nearly 17 million words).

This is groundbreaking work and the largest research of its type to date.

Our key question: Are there differences in the nature of the Grounds between Black and White Londoners? Yes.

Black Londoners were significantly more likely to receive vaguer, more subjective documented Grounds; White more evidential.

Black Londoners see significantly lower Quality of Grounds overall driven by certain stops (i.e., Stolen Property, Weapons, Point and Blades, and Fireworks).

There is a clear association between Quality and time of day/volume of stops, with the highest quality coinciding with the lowest volume. Quality for Black Londoners sees a marked dip as volume increases, which is not seen for White.

There is a clear correlation to public perceptions – the better the Grounds quality, the more positive the perception on the power being used fairly in the MOPAC Public Attitude Survey.

Elsewhere, there were no significant differences between Black and White in Grounds word count or spelling errors, but the term ‘violence’ appeared significantly more with Black than White Londoners – even considering the same type of Stop.

Results indicate that improving the Quality of the Grounds could reduce overall disproportionality by between 11-19% but would not eliminate it.

Additional work commissioned to King’s College London explored the nature of disproportionality. Over 200 variables were used to develop a statistical model, of which eight were most strongly associated with disproportionality.

Disproportionality against Black Londoners was higher in:

- Areas with more residents employed as managers,
- Areas with more retired residents,
- Areas with a higher proportion of health conditions.

The strength differs across boroughs – there is no one size fits all solution. Some link to prosperity, others to vulnerability – this is not contradictory but reflects different dimensions of disadvantage and wider systemic challenges in London's geography that contribute in their own way.

Certain wards were identified by the model that hugely stood out in terms of disproportionality.

The model estimates a x3.49 level of disproportionality towards Black Londoners compared to the actual level of x3.82, indicating current levels are 9% higher compared to the model (i.e., amounting to 4361 more Black searches).

The model also explored the disproportionality for Asian Londoners. Here the model (x0.91) and actual levels (x0.90) were almost identical.

Recommendations and next steps

Improving the Quality of Stop and Search Grounds

- It remains unclear as to what explains the current findings on the greater likelihood of vague Grounds for Black Londoners. Explanations could cover everything from training gaps, wider operational pressures, or racial profiling/bias when documenting the grounds. New research/ analysis would be welcome – incorporating more officer detail (i.e., length of service) as well as officers' and other groups' views and experiences. The research has developed a new tool that enables any Grounds text to be assessed for quality – a real innovation in evidence based oversight.

- The MPS should set out clearly a developed plan as to how they will improve the Quality of Grounds and address the current findings.

- The MPS should publish new data on the detail of the Grounds split by ethnicity, enabling transparency as well as continued monitoring.

- Wider strategic conversations with the College of Policing, APCC, NPCC to explore wider policy or training support in this area.

The topic of disproportionality is not resolved

- Stop and search disproportionality is a long-standing national issue with no clear reason fully explaining it. The current research presents two projects that both suggest disproportionality towards Black Londoners should be lower than observed levels. Some will be in the police's control (i.e., quality of written Grounds for Black Londoners); others will not (i.e., poor health). This suggests a wider lens and systemic approach is required.

- Analytics highlighted different variables wielded a different influence across boroughs and that a more granular focus may be more beneficial. Certain wards were identified as being hugely disproportionate – the MPS should look at the top identified wards (n=24) and enhance oversight in these areas.

Technological innovation moving forward

- The analytics – in particular the machine learning merging human coding and natural language processing – is groundbreaking and should set the scene for future analytic innovation. New technologies can interrogate data at a scale not previously seen and this should set the analytic direction.

- Equally, new technology opens new opportunities. Data science techniques could be used in many ways – for example to review searches or Body Worn Video, or to generate automated feedback on the quality of the written Grounds and so on. These could be practical uses of the research technology.

- The current analytics on both Grounds and big-data modelling were run on 2023 data. Going forward, MOPAC will look to make improvements on the analytics and modelling, publishing updates annually with a view to hold the MPS to account on progress.

Next Steps - MPS response

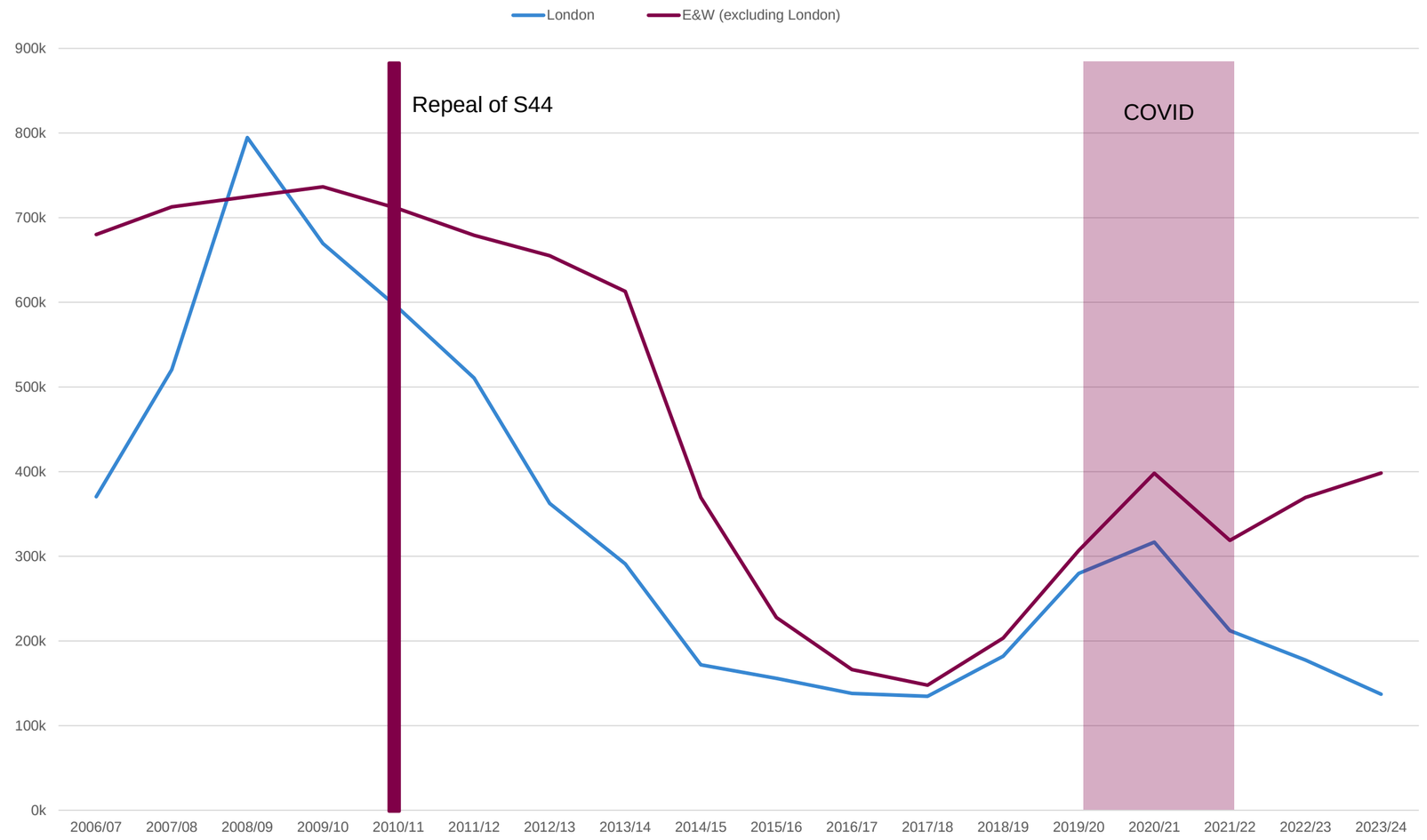
The MPS has committed to using the findings to inform how Stop and Search is understood, monitored, and improved. In particular, the MPS will:

- Use the findings to deepen their understanding of officer decision-making, continuing work with MOPAC to explore how the quality of recorded Grounds varies across groups and contexts to identify potential improvements.
- Integrate MOPAC's findings with internal MPS analysis to build a more rounded evidence base on the drivers of disproportionality and seek to communicate this with officers.
- Look to incorporate the insights into their *Quality of Encounter Supervision Tool* (QuEST) – which aims to improve the quality of all aspects of Stop and Search conducted by the MPS, including a question focused on the quality of Grounds. This tool enables targeted feedback to officers via supervision where recording of Grounds falls short.
- Apply learning at a local level – the research identifies notable variation in disproportionality across wards, complementing other ongoing MPS analysis. Together, this will inform locally tailored oversight.
- Improve scrutiny of Stop and Search encounters - strengthening supervisory and analytical focus on Stop and Search encounters - working with MOPAC on the Stop and Search BWV project.

Setting the scene

Setting the Scene: A long-term decline in the use of Stop and Search

London long term trend - MPS Stop and Search volumes (Financial Year 2006/07 to 2024/25)



Source: London Datastore, Crime, justice and the law gov.uk/

The use of Stop and Search peaked in 2008/09 and has seen a general decline since then, with a slight blip post-COVID, but since then the decline has continued.

Much of the decline is due to the repeal of Section 44 of the Terrorism Act, which was stopped after July 2010.

Illustrating the longer-term reduction, the volume in the year ending March 2025 was 84.5% below the peak in the year ending March 2009.

The majority of Stop and Search encounters are for drugs, accounting for 57% of all searches between March 2024 and February 2025.

The MPS has the highest number of searches in England and Wales (with 122k during 24/25).

In terms of rate per 1,000 population, the MPS are the 4th highest rate (below Greater Manchester, Cumbria and Merseyside).

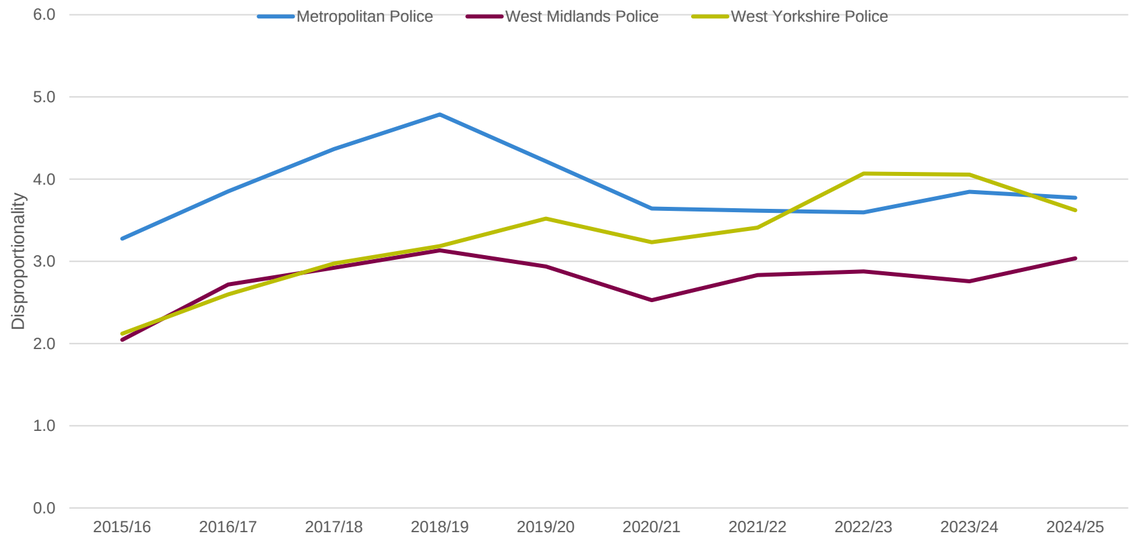
Disproportionality within Stop and Search is a longstanding concern

Nationally, Black individuals are 4 times more likely to be stopped and searched than White individuals. This figure is comparable to London (x3.7), as well as the MPS's Most Similar Forces.

The overall London level of disproportionality has remained relatively stable over time, though there is clear borough variation.

In London, two-thirds (65.9%) of Stop and Search encounters result in No Further Action (NFA), and 17.4% lead to an arrest. Few differences exist here by ethnicity (i.e., 17.7% Black, 18% White arrest percentage).

London Stop and Search disproportionality rate over the last decade



Disproportionality Rate by Borough (Mar 24 to Feb 25):

	S&S volume per Borough	Disproportionality Rate			Positive Outcome Rate
		Asian	Black	Other	
Barking and Dagenham	2,854	0.6	1.0	0.7	37.0%
Barnet	1,837	0.7	4.0	2.8	36.7%
Bexley	2,312	0.6	2.0	1.4	33.2%
Brent	4,622	0.6	3.3	2.2	35.3%
Bromley	2,527	0.8	3.1	2.5	38.3%
Camden	4,318	1.0	6.6	1.8	31.2%
Croydon	4,072	0.6	2.4	4.3	35.2%
Ealing	3,673	1.8	4.7	2.2	29.6%
Enfield	3,781	0.5	1.7	0.6	34.5%
Greenwich	5,632	0.6	2.0	1.4	33.3%
Hackney	4,512	1.8	4.5	1.8	38.2%
Hammersmith and Fulham	3,056	1.2	5.5	2.9	38.4%
Haringey	3,898	0.8	3.4	1.6	34.0%
Harrow	1,869	0.5	2.7	2.6	33.2%
Havering	3,190	1.5	3.3	1.6	31.5%
Hillingdon	2,737	0.9	3.2	1.5	35.7%
Hounslow	2,223	0.7	4.3	1.7	39.7%
Islington	3,351	1.1	4.8	2.8	35.3%
Kensington and Chelsea	2,775	1.0	15.0	3.2	34.2%
Kingston upon Thames	1,370	0.6	4.7	1.8	**39.9%**
Lambeth	5,665	1.5	6.8	3.4	31.6%
Lewisham	4,969	0.7	3.0	1.0	33.8%
Merton	1,593	1.0	5.5	3.3	36.0%
Newham	5,436	0.4	1.3	0.4	33.6%
Redbridge	3,180	0.9	2.5	1.1	33.5%
Richmond upon Thames	748	1.2	9.3	2.5	31.8%
Southwark	6,870	0.8	4.0	1.7	30.2%
Sutton	1,404	0.6	4.0	1.1	33.8%
Tower Hamlets	6,147	1.6	3.8	1.0	34.1%
Waltham Forest	3,746	1.1	2.4	0.6	32.8%
Wandsworth	3,379	1.4	6.2	3.3	**29.2%**
Westminster	9,593	1.2	8.7	2.0	33.7%
MPS Total	117,339	0.9	3.7	2.0	33.9%

Public voice data enables a different lens – declining public support

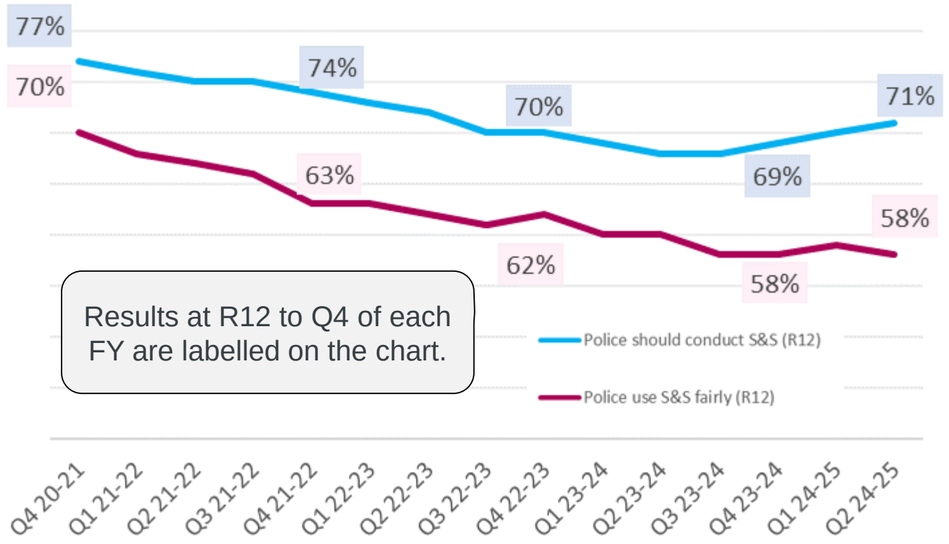
MOPAC conducts the Public Attitude Survey (PAS), which sees a representative sample of 19,200 Londoners be interviewed face to face each year. In R12 to Q2 24-25…

71% of Londoners believe the police should conduct Stop and Search.

58% feel the police use their Stop and Search powers fairly.

Public support for Stop and Search has declined since 20-21.

However, this has seen a recent upturn in overall support. Perceptions on whether the police use the power fairly remain on a slow downward trend.



Results at R12 to Q4 of each FY are labelled on the chart.

Some demographic groups are less likely to support police use of Stop and Search.

This includes LGBT+, Black and Mixed Ethnicity Londoners, and younger age groups.

*Table shows pp. gap from MPS result**		Police should S&S	Police use S&S fairly
MPS		71%	58%
Sex	Male	1%	3%
	Female	-1%	-2%
Age	16-24	-13%	-6%
	25-34	-8%	-4%
	35-64	3%	1%
	65+	10%	10%
Ethnicity	White British	3%	1%
	White Other	3%	6%
	Mixed	-18%	-19%
	Asian	5%	9%
	Black	-14%	-17%
	Other	4%	3%
LGBT+	Not LGBT+	1%	1%
	LGBT+	-20%	-21%
Disability	Disability	2%	1%
	No Disability	0%	0%

Support for Stop and Search varies across London – with lowest results in Haringey, Lewisham and Hackney.

	Police should use S&S	Police use S&S fairly
Harrow	87%	72%
Hillingdon	86%	75%
Hounslow	81%	65%
Richmond Upon Thames	80%	76%
Brent	80%	63%
Ealing	80%	58%
Havering	79%	72%
Merton	79%	66%
Sutton	78%	65%
Kensington & Chelsea	76%	67%
Hammersmith & Fulham	75%	61%
Barnet	75%	54%
Bexley	74%	72%
Kingston upon Thames	74%	71%
Bromley	74%	64%
Croydon	74%	58%
Barking & Dagenham	73%	56%
Westminster	71%	68%
Wandsworth	71%	61%
Redbridge	70%	53%
Enfield	70%	50%
Greenwich	67%	59%
Newham	67%	58%
Tower Hamlets	65%	54%
Camden	63%	53%
Lambeth	63%	51%
Southwark	62%	48%
Waltham Forest	62%	45%
Islington	59%	47%
Haringey	59%	38%
Lewisham	57%	46%
Hackney	49%	38%

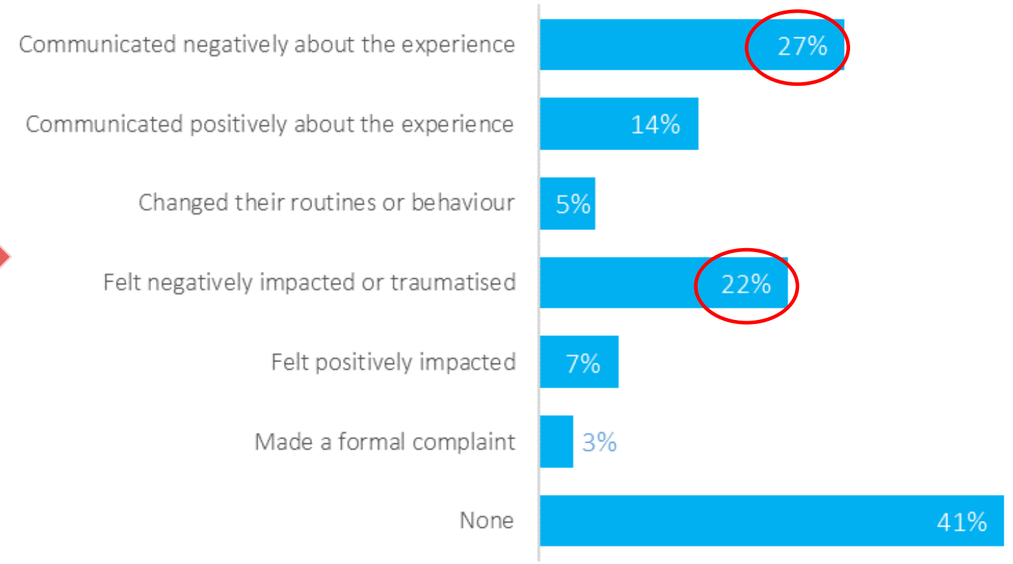
Black and disabled Londoners are more likely to report negative impacts

8%

…of Londoners interviewed by the PAS during R12 to Q2 24-25 said they had ever been stopped and searched by the police in London.

Just under a quarter of these Londoners report to be traumatised by the encounter.

The impact of Stop and Search on Londoners has remained relatively stable over time*.



Disabled Londoners were more likely to say they had been negatively impacted or traumatised by their perception of the encounter.

Black Londoners were more likely to say they had been negatively impacted or traumatised, and that they had communicated negatively to friends and family.

Different groups of Londoners are impacted differently by their perceptions of Stop and Search*.

	MPS	Sex		Disability		Ethnicity			
		Male	Female	Disability	No Disability	White British	White Other	Asian	Black
Communicated negatively about the experience	27%	-1%	5%	-2%	0%	-10%	-9%	-2%	14%
Communicated positively about the experience	14%	0%	4%	-3%	1%	4%	5%	7%	-5%
Changed their routines or behaviour	5%	-1%	0%	2%	-1%	0%	-1%	-2%	-1%
Felt negatively impacted or traumatised	22%	-1%	2%	12%	-2%	-8%	-5%	-4%	13%
Felt positively impacted	7%	0%	-2%	-3%	0%	1%	0%	3%	-5%
Made a formal complaint	3%	0%	-1%	1%	0%	0%	-2%	0%	0%

Table shows pp. gap from MPS result for demographic groups, with gaps of 5pp. or more highlighted.
*Note that no gaps of 5pp+ were seen by age. LGBT+, 'mixed' and 'other' ethnicity groups not show due to low base sizes.

Source: PAS, R12 to Q2 24-25

The perceived quality of the Stop encounter varies between groups

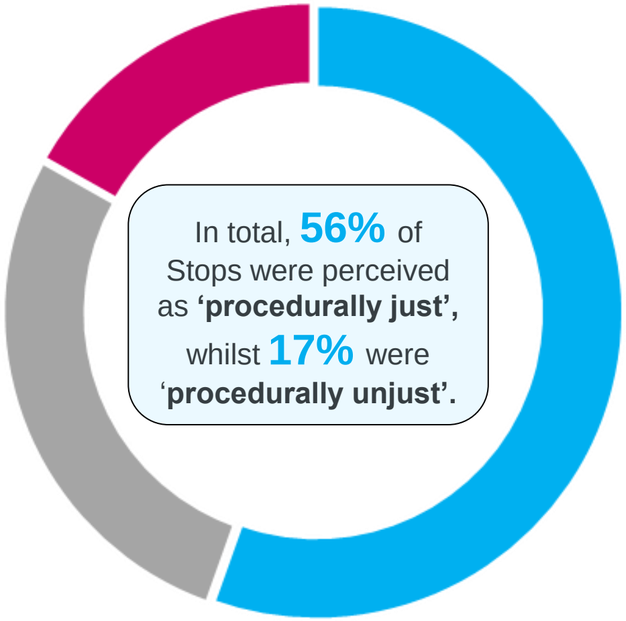
When asked about their Stop and Search interaction with the police…

62% …perceived the police were polite.

64% … perceived the police treated them with respect.

77% … perceived the police explained why they had been stopped.

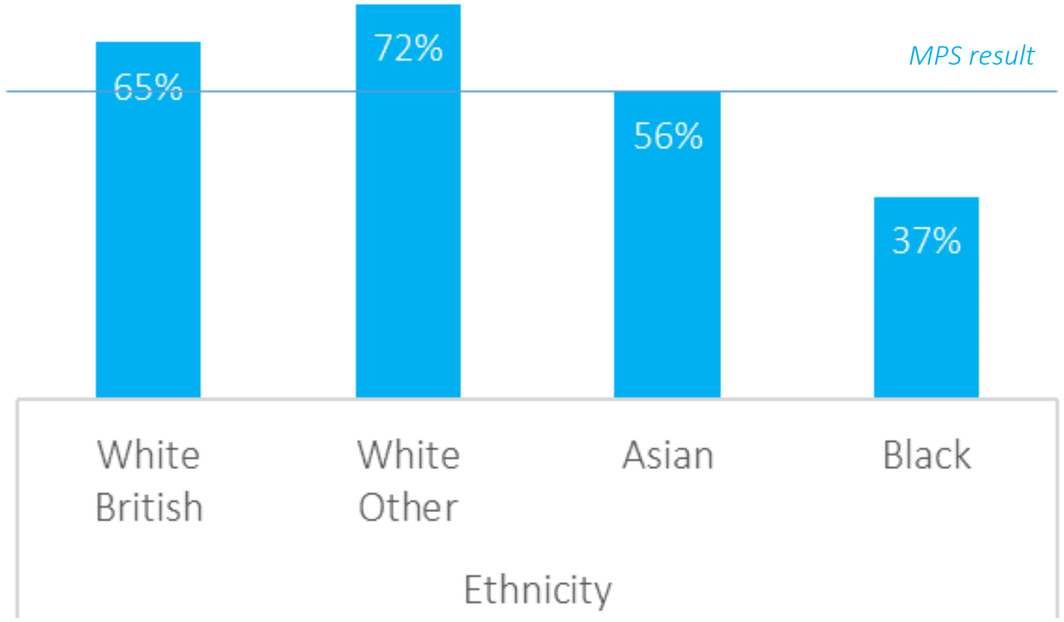
Some groups of Londoners were less likely to perceive their Stop as 'procedurally just' – particularly those from Black ethnic backgrounds* (37%).



Procedurally just Stop (i.e., 'yes' to all three)

Mixed Stop

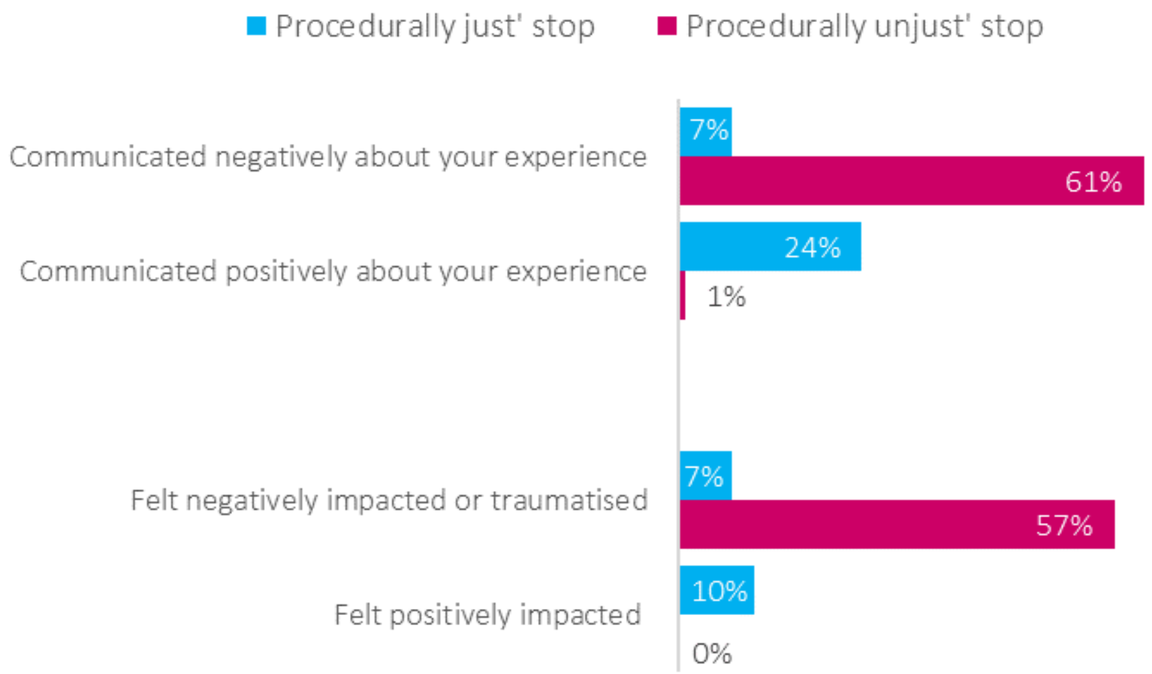
Procedurally unjust Stop (i.e., 'no' to all three)



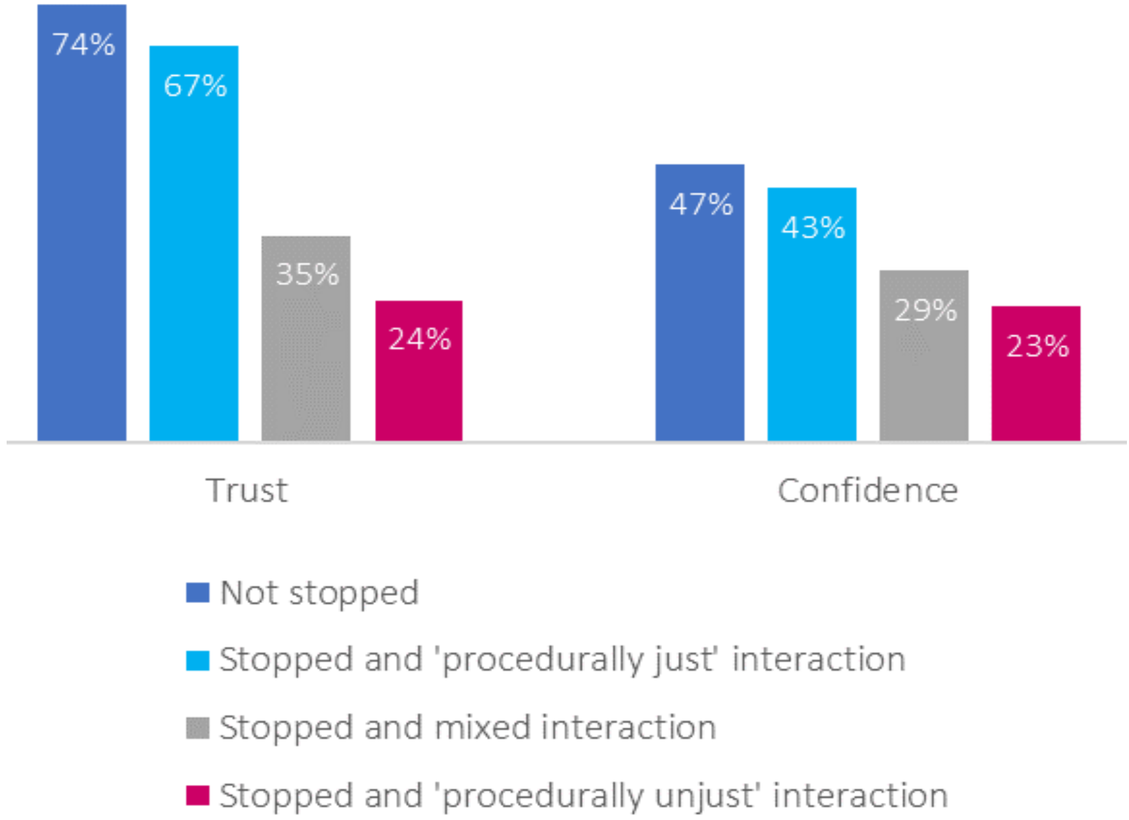
Source: PAS, R12 to Q2 24-25

The perceived quality is paramount to trust and confidence

Those who perceived a ‘procedurally unjust’ stop were far more likely to have communicated negatively (61%) or to have felt traumatised by it (57%).



Amongst those who perceived their Stop and Search as ‘procedurally just’, trust and confidence remain broadly in line with those never stopped. Mixed and ‘unjust’ see far lower levels.



Source: PAS, R12 to Q2 24-25

Exploring officers' documented Grounds for Stop and Search - are there differences between Black and White Londoners?

Combining qualitative expertise and data science to understand disproportionality in recorded Grounds

MOPAC Disproportionality Board External Reference Group Coding:

Data was obtained from all Stop and Search encounters in London in 2023, covering virtually all† recorded stop and searches, with 152k records containing a recorded Ground.

1

The MOPAC Disproportionality Board External Reference Group (ERG) manually coded a sample* of these (600 cases) using a bespoke MOPAC-designed framework.

They reviewed the text of each Ground and tagged/coded relevant phrases – for example, noting when 'smell of cannabis' was written and so on. This allowed the research to document the content and decision-making of the written Grounds. Each record was also assigned a Strength of Grounds score, indicating how strong the justification appeared for conducting the search.

Apply coding on full sample:

2

Using the ERG's expert-coded sample as training data, 18 bespoke natural language processing (NLP) models were developed. These models were used to apply the same coding framework to all 152,000 search records, scaling up the manual process to span the entirety of the sample. Tests showed the models were all able to detect significant differences. The method and code developed was peer-reviewed by three experts.

Analyse fully coded sample:

3

With every record coded, the data could be analysed. By adding detail such as borough, type of search, and search outcomes, we were able to identify patterns and disparities that would have been impossible to spot manually, and at a scale not seen previously in the literature. This analysis encompassed nearly 17 million words.

Using these factors we also calculated a composite Strength of Grounds metric (using the coders' measure as a sense check) to understand how this varies across demographics and geographies.

Coding themes - each of these had a range of behaviours within to code into
Intelligence or Information (i.e., part of an operation, specific report).
Police presence (i.e., mobile, uniform, plain clothes).
Subject Context (i.e., smell of cannabis, seen with associates/group).
Subject behaviour (i.e., seen committing offence, seen to hide object).
Vehicle specific (i.e., erratic driving, failure to stop).
Police contact (i.e., knife arch, drug dog).
Subject demeanour during police contact (i.e., nervous, aggressive, evasive).
Subject appearance (i.e., matched description, concealing clothing).
Grounds Summary (i.e., clear what was being searched for, overall rank of Grounds).

* N.B. The sample size is a limitation of the study. A stratified sample was taken from 3 boroughs. The assumption is that the specific grounds and language used should not vary significantly per borough.
† 254 searches had no Grounds information recorded.

The text of the Grounds provide genuine insights into officer decision making

Examples of Grounds full text are below.

“ Whilst dealing with an incident on The Strand, subject has walked past and given me a furtive glance and immediately looked away which I felt was a deviation from the baseline. I have walked after the male and started to interact with him.

I asked him to account for himself, where he was going and what he was doing etc. When I asked if he had any drugs, knives or weapons on his person he replied "no".

However, I did not believe this as he patted his right jeans pocket with his right hand which was an involuntary action. I could not see any lump or bulge in his pocket so I suspected he may be in possession of drugs which are easily concealed. I also noticed, he appeared rather padded on his upper half.”

“...at approximately 1650hrs my colleagues and I were requested to attend on an urgent assistance by the dog unit. Upon attending groups of people were all gathered around. One male had been stabbed in the leg and one other male had a head injury. Upon attending I was relayed the information that the group of delivery drivers were involved and a knife was potentially seen with them. None of the drivers had been searched at the time.

Due to the intelligence and the knowledge that a knife was used in an altercation that led to a male being stabbed and another sustaining a head injury, I proceeded in detained the driver under section 1 of PACE. I relayed the information to him and then informed him that the object of the search was a knife. The search was satisfactory and the details were obtained. I arrested the male for ABH and GBH. “

N.B. Examples show exactly the words recorded. Spellings and typos have not been corrected.

What 17 million words reveal about Stop and Search Grounds

The recorded grounds varied from a single word (i.e., "Awaits") to 596 words. The average Ground had 111 words for each search.

Overall, there were no real differences in word count between Positive Outcomes (on average, 108 words recorded) and No Further Action (on average 110 words).

1.47% of words (250k words in the sample) were misspelt.

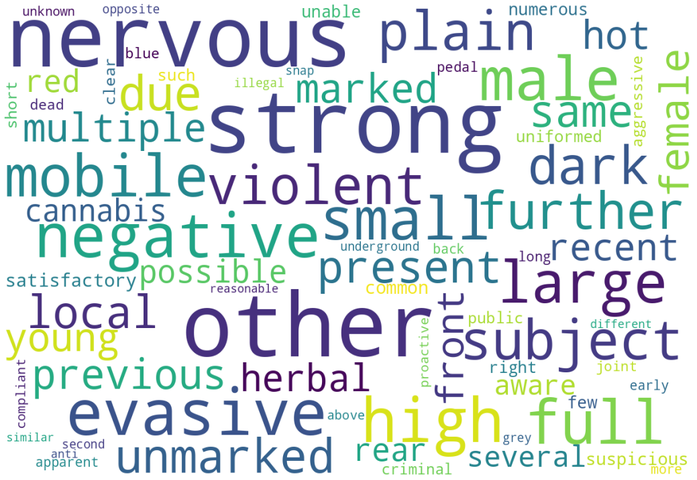
There was geographic variation in word count. Bexley had the highest average (134), and Barking and Dagenham the lowest (87).

There were no meaningful word count differences comparing Black and White (i.e., Black on average received 4 more words in the Ground). There were no significant differences in misspellings by ethnicity or gender.

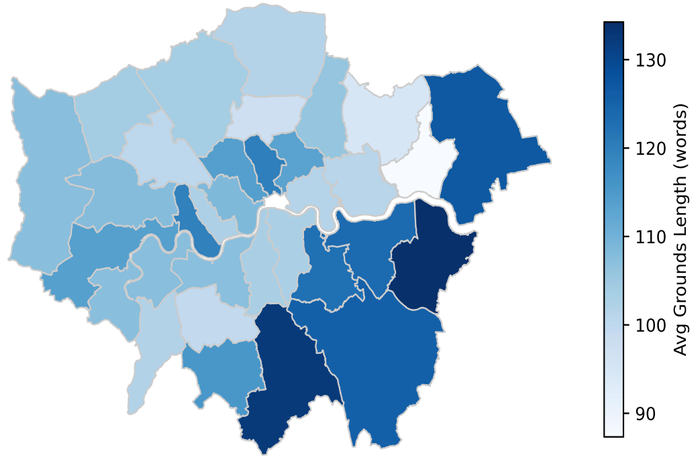
There were no significant differences when looking at the wider sentiment captured in the Grounds. However, the word "violent" appeared significantly more often for Black than White Londoners – even when looking at the same type of stops (i.e., within weapon stops for Black Londoners versus for White Londoners). Further details are provided in the Appendix.

Category	Total	Reason for stop		
		Drugs	Weapons, Point & Blades	Stolen Property
Stop and Searches	152k	86k (56%)	27k (18%)	26k (17%)
Positive outcomes (%)	44k (29%)	27k (31%)	8k (30%)	6k (23%)
Recorded words	Avg: 109 Max: 596 Min: 1	Avg: 108	Avg: 114	Avg: 110
Misspelling rate (%)	1.47	1.45	1.42	1.46

Overall Word Cloud

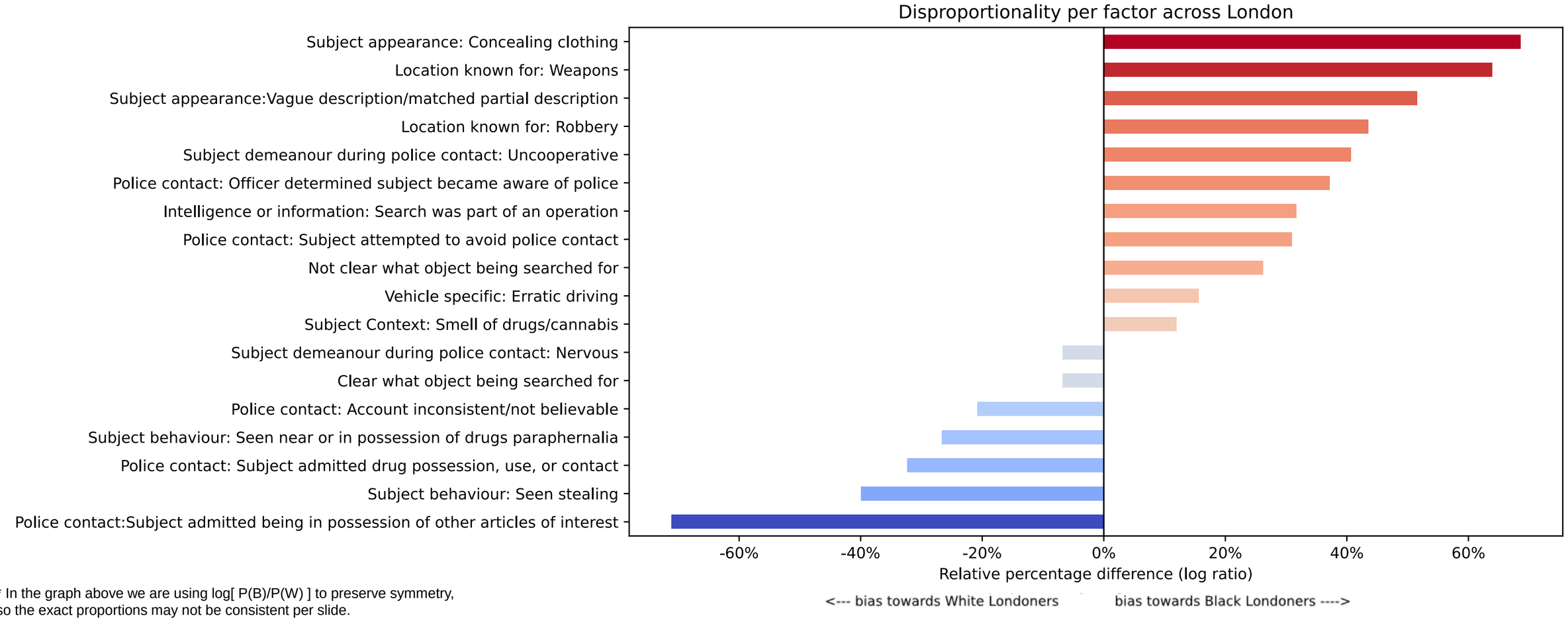


Average Number of Words Recorded



Clear evidential differences in Grounds between Black and White Londoners

- Black Londoners were significantly more likely to receive vaguer, more subjective documented Grounds, White Londoners more evidential.
- Percentages below represent relative difference, e.g., 60% would mean that the variable is 60% more likely to apply to Black Londoners than White Londoners (and vice versa). To illustrate, we would see “Concealing clothing” apply to 10% of White Londoners but 16% of Black Londoners.
- All below differences are statistically significant.



* In the graph above we are using log[P(B)/P(W)] to preserve symmetry, so the exact proportions may not be consistent per slide.

The Quality of Grounds varies across London and aligns with perceptions of Stop and Search being used fairly

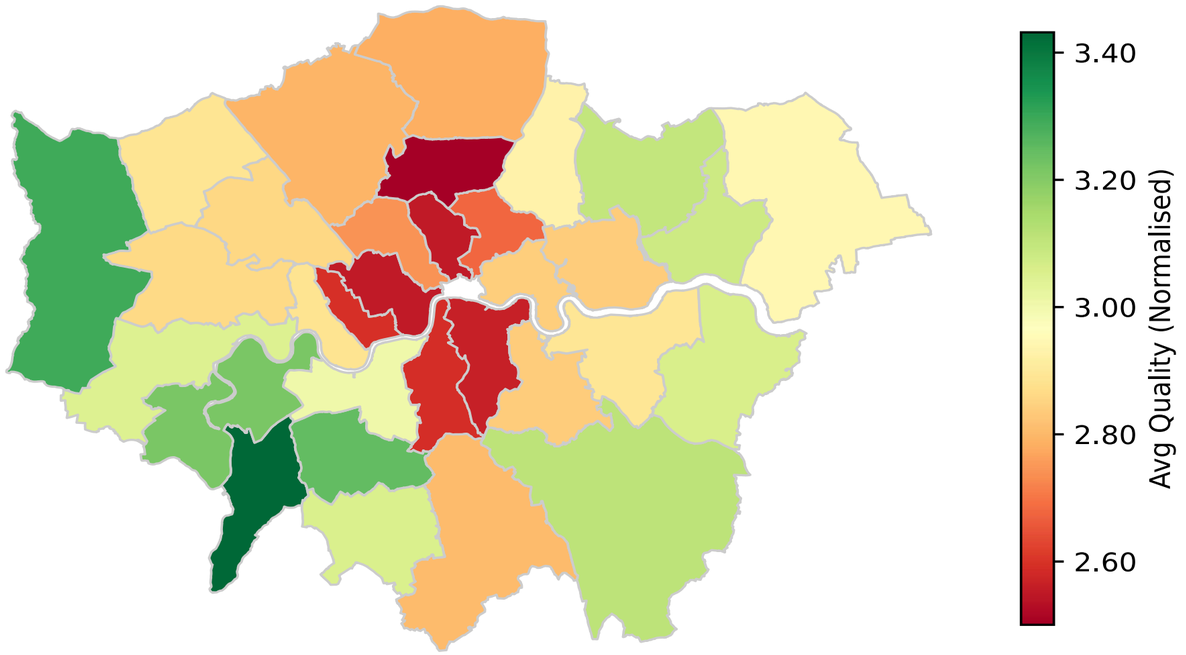
We used the coded data to construct an overall Quality of Grounds measure based on the statistical likelihood of a reaching a positive outcome. Put simply, the higher the quality score, the greater likelihood of receiving a positive outcome, with a lower quality score associated to the greater likelihood of no further action. More detail is in the appendix.

We find a large variation in quality across London. Kingston upon Thames has the highest average quality (~3.4) while Haringey the lowest (~2.5).

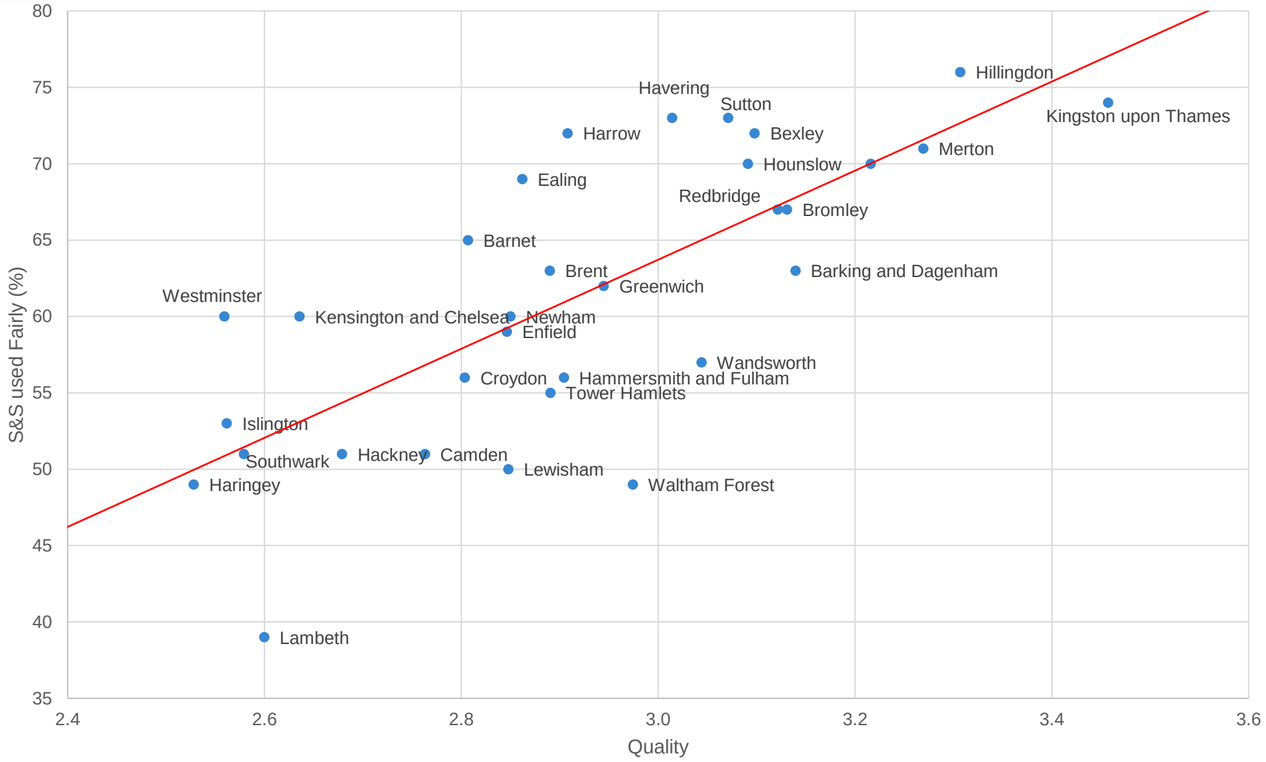
Quality is significantly lower on searches involving individuals aged under 18 and for Black Londoners, and higher for females.

There is also a clear correlation to public perceptions – the higher the Quality of Grounds, the more positive the perception on the power being used fairly in the MOPAC Public Attitude Survey*.

Average Quality per Borough



Quality vs PAS (S&S Used Fairly)

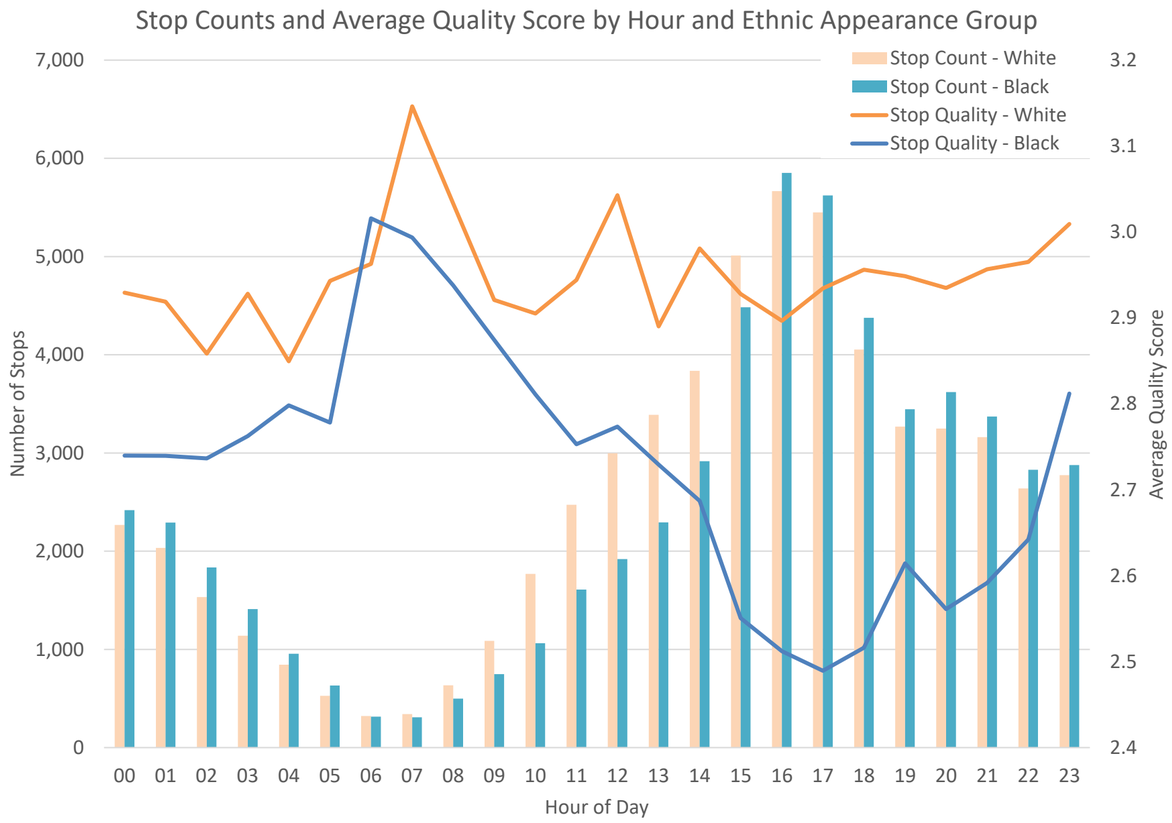


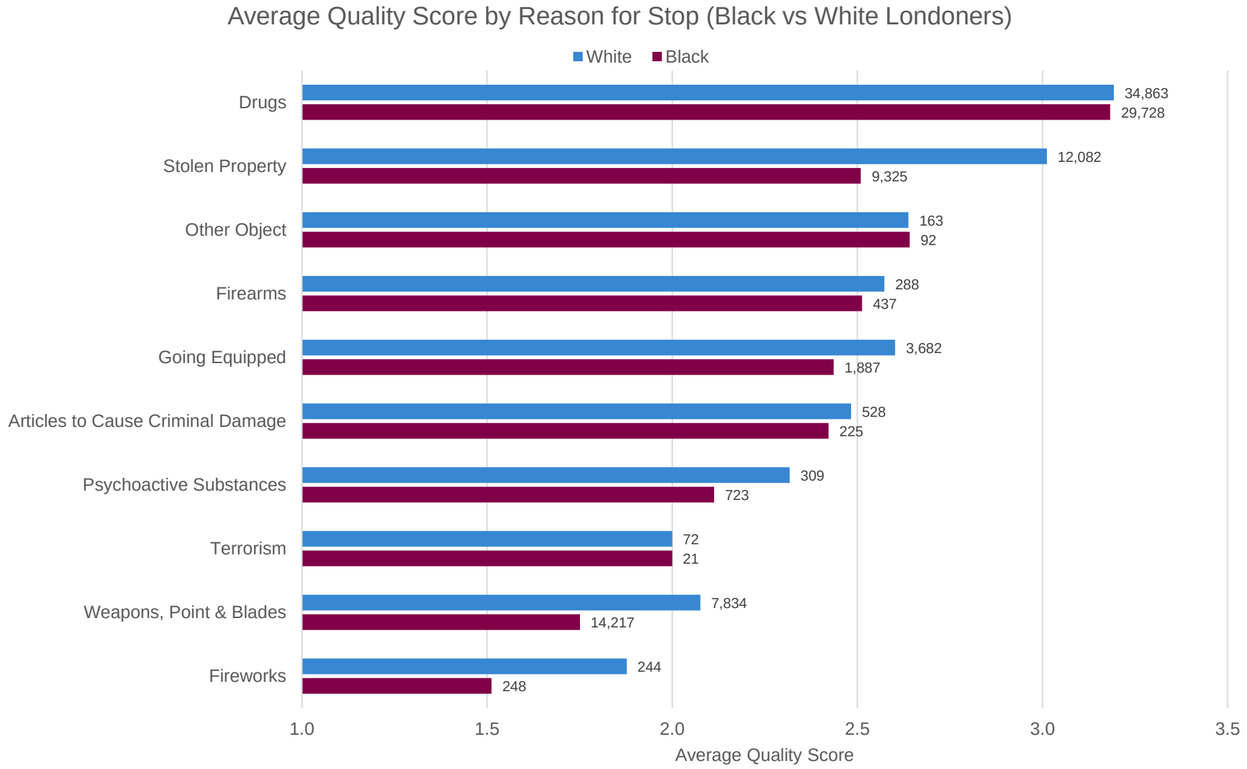
* PAS Borough R12 Q3 22-23

Quality also varies across types of Stop and time of day with links to volume

There is a clear association between Quality and time of day/volume of Stops, with the highest quality coinciding with the lowest volume.

Quality for Black Londoners sees a marked dip as volume increases, which is not seen for White Londoners.





Black Londoners see significantly lower Quality of Grounds across Stolen Property, Psychoactive Substances, Weapons, Point and Blades, Going Equipped, and Fireworks.

There were no significant differences in terms of drug searches.

Improving the Quality of Grounds could reduce overall disproportionality by between 11-19%

The Quality of the Grounds can also link to wider disproportionality.

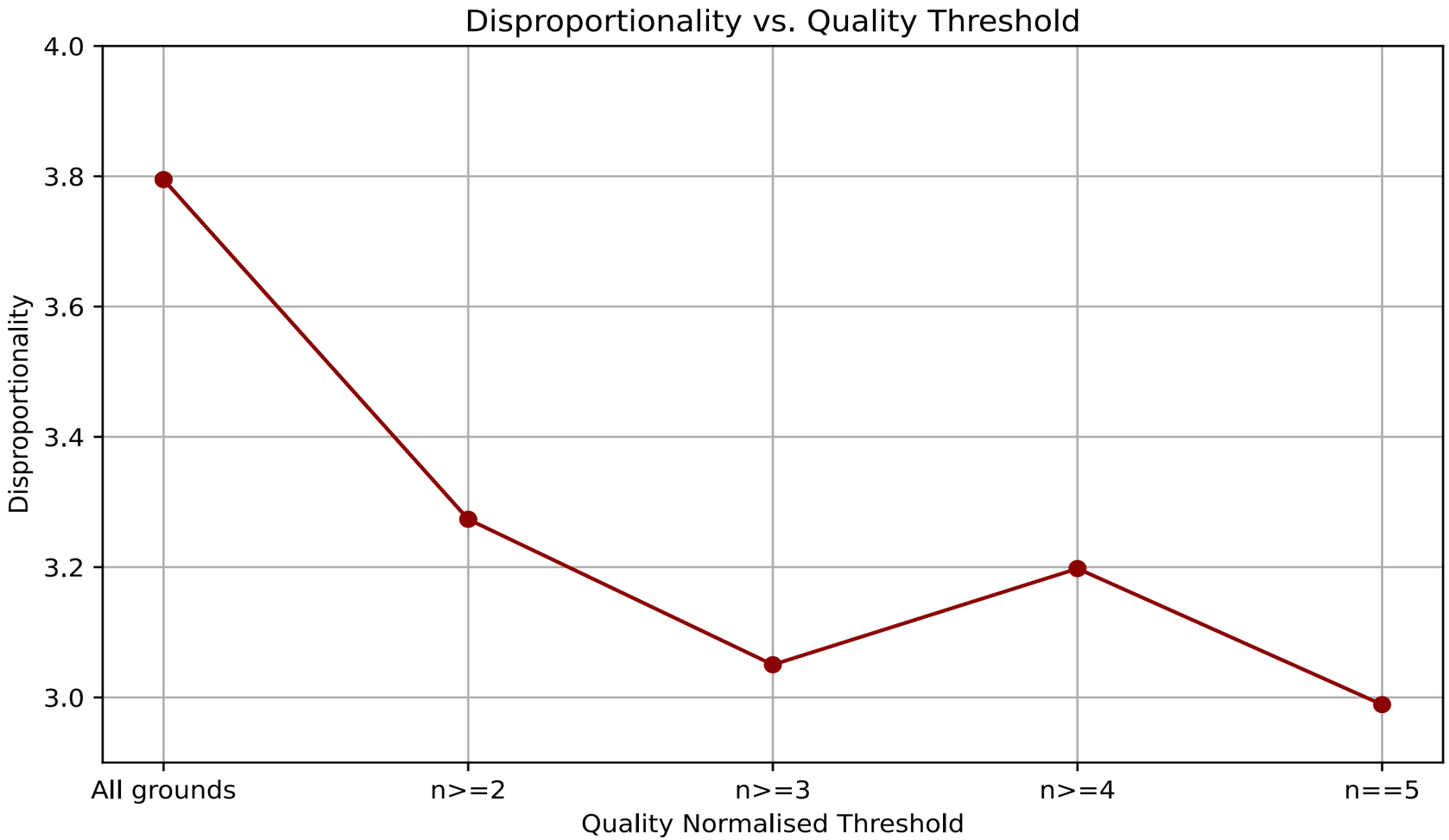
Removing the lowest Quality recorded Grounds (i.e., those with a score of 1, ~32k) reduces overall Stop and Search disproportionality from 3.7 to 3.3, an 11% decrease.

Conversely, retaining only the strongest Grounds (i.e., those with a score of 5) would see the rate fall from 3.8 to 3.0, a fall of approximately 19%.

Both these would lower, although not eliminate, disproportionality.

Some boroughs are more impacted than others.

For example, Kensington and Chelsea decreases by 39% by eliminating the lowest 40% of Grounds and decreases by 51% when only keeping the top 20%. Similar large reductions are seen in Westminster and Haringey.



Understanding the factors behind different levels of disproportionality

Grounds contribute, but can we understand more about what drives disproportionality?

The evidence base and wider analysis so far demonstrate clear disparities in the overall disproportionality of Stop and Search, as well as within the reasons and Quality of recorded Grounds.

Black Londoners were more likely to receive vague or subjective justifications, and this contributed to overall disproportionality - but only explaining part of it.

Historically, disproportionality within Stop and Search has been measured by comparing who is stopped versus the Census resident population. This measure is too simplistic.

In this way, a complementary project was commissioned from King's College London* to further explore the factors contributing to disproportionality in London and to better understand its extent and bring additional nuance to the discussion. As far as we know, this is the first time such work has been attempted, and MOPAC will look to refine the model in the future.

A Data Science Methodology

Linear regression on 2023 data to examine the factors which influence disproportionality in Stop and Search across the boroughs and wards of London.

Analysed over 200 demographic factors such as age, socio-economic factors such as deprivation and health, and environmental factors such as green space and commercial services as well as crime and policing factors.

*The interdisciplinary research team included project leads Dr Yijing Li, Professor Robert Haining, academic advisors Dr Odinaldo Rodrigues, Dr Yu Luo, across departments and disciplines, as well as dedicated research students Ms Sijie Tan, Mr Matthew Palmer, Mr Vishal Hall, Miss Alshahad Baasem, and Mr Umair Qureshi, from Department of Informatics.

A model to understand the wider factors influencing disproportionality

A statistical model identified eight variables associated with disproportionality.

The strongest five are outlined here. Disproportionality against Black Londoners is higher in areas:

- with more residents employed in managerial positions.
- with more retired residents.
- with a higher proportion of full-time workers.
- with fewer disabled residents.
- with a higher prevalence of health conditions.

The strength of these associations differs across boroughs – there is no one-size-fits-all solution.

Some variables link to prosperity, others to vulnerability – this is not contradictory but reflects different dimensions of disadvantage and wider systemic challenges in London's geography that each contribute in their own way.

For example, disproportionality within Richmond upon Thames is influenced more by the proportions of ‘managers’, and ‘retirees’ and far less by ‘bad health’. This contrasts to Hackney, which is more driven by ‘bad health’ and less by the other factors.

Further details can be found in the Appendix.

The table shows the relative strength of the main variables. The more squares, the stronger the influence in the borough.

Region	Borough	Managers	Retirees	Full Time Workers	No Disabled People	Very Bad Health
Central	Kensington and Chelsea	■■■■■	■■■■	■■	■■■■	■■■
	Westminster	■■■■	■■■■	■■■	■■■	■■■■■
	Camden	■■■■	■■■■	■■	■■	■■■■
	Islington	■■■	■■■	■■■■	■	■■■■■
	Lambeth	■■■	■■	■■■■	■■■	■■■
	Southwark	■■■	■■	■■■■	■■■	■■■
East	Tower Hamlets	■■■	■	■■■	■■■■	■■■■
	Havering	■■	■■■■■	■■	■■	■■■
	Redbridge	■■	■■■■	■	■■■■■	■■■
	Waltham Forest	■■	■■■	■■	■■■	■■■
	Hackney	■■■	■■	■■■	■■■	■■■■■
	Newham	■	■■	■■	■■■■■	■■■■
	Lewisham	■■	■■■	■■■	■■	■■■
	Greenwich	■■■	■■■	■■■	■■	■■■
	Bexley	■■	■■■■■	■■■	■■	■■■
	Barking and Dagenham	■	■■	■	■■■	■■■■
North	Barnet	■■■	■■■■	■■	■■■■	■■■
	Haringey	■■	■■■	■■	■■■	■■■■
	Enfield	■■	■■■■	■	■■■	■■■■
South	Kingston upon Thames	■■■	■■■■	■■■	■■■■	■■
	Wandsworth	■■■■	■■■	■■■■■	■■■■■	■
	Sutton	■■■	■■■■	■■■	■■■	■■
	Bromley	■■■	■■■■■	■■■	■■■	■■
	Merton	■■■	■■■■	■■■	■■■■	■■
	Croydon	■■	■■■■	■■■	■■■	■■■
West	Richmond upon Thames	■■■■■	■■■■■	■■■	■■■■	■
	Harrow	■■■	■■■■	■■	■■■■■	■■
	Hammersmith and Fulham	■■■■	■■■	■■■■	■■■■	■■■
	Hounslow	■■	■■■■	■■■	■■■■	■■■
	Hillingdon	■■	■■■■	■■	■■■■	■■
	Ealing	■■■	■■■■	■■	■■■■	■■■
	Brent	■■	■■■	■■	■■■■	■■■

Understanding the context within Stop and Search across London's diverse landscape

The topic of Stop and Search disproportionality is a heavily contested and passionate debate and there is, relatively speaking, little empirical work to understand this disproportionality. The current analytics represent the first large-scale attempt to explore a new direction.

We know the current measurement of disproportionality which compares who is stopped versus the resident population is flawed. We also know that policing works downstream from a wider range of social ills, and that crime and many socio-economic disadvantages do not fall equally across Londoners.

These issues are clearly seen in the variables identified by the King's College London model.

Black Londoners are less likely to live in the top areas for Managers (5%) or Retirees (6%), and more likely to live in the top areas of Very Bad Health (18%) and Disability (17%).

The model is stating that Black Londoners are being disadvantaged at both ends of the spectrum – being more likely to be stopped in the high affluence markers (i.e., top % for Managers or Retirees) even though they form a smaller population, and more likely to be stopped in the lower affluence markers (i.e., top areas for Very Bad Health) where they form a greater population.

In attempting to estimate the levels of disproportionality within Stop and Search, the model is limited to and largely reflecting the current systemic challenges that London faces.

	London 2011*	London 2021*	Stop & Search (2023)
Male	49%	48%	**90%**
Female	51%	52%	10%
White	60%	54%	43%
Black	13%	14%	**32%**
Asian	18%	21%	15%
Under 18	23%	22%	19%
18-29	19%	18%	**45%**
30-39	18%	17%	18%
40-49	14%	14%	11%
50-59	10%	12%	4%
60+	15%	17%	2%

	White %	Black %
Top 20% areas for Managers	70%	5%
Bottom 20% areas for Managers	36%	20%
Top 20% areas for Retirees	70%	6%
Bottom 20% areas for Retirees	47%	18%
Top 20% areas for Very Bad Health	49%	18%
Bottom 20% areas for Very Bad Health	65%	8%
Top 20% areas for Disabled	58%	17%
Bottom 20% areas for Disabled	51%	8%
Top 20% areas for Full Time Workers	63%	13%
Bottom 20% areas for Full Time Workers	38%	16%

Census Estimates for London Wards (LDS) ONS Ward-level population estimates

Can we statistically estimate the levels of disproportionality (if at all) for Black Londoners?

Methodology

By examining the demographic, socio-economic, and environmental factors the model can statistically estimate levels of disproportionality at both the London and borough level.

To note – as far as we are aware, this is the first time such analytics has been conducted in this manner. This is the first iteration of the model.

Insights

- Overall, across London, the model estimates a x3.49 level of disproportionality towards Black Londoners, compared to the actual level of x3.82. This indicates that current levels are 9% higher compared to the model (i.e., amounting to 4,361 more Black searches).
- Most boroughs show levels of disproportionality broadly in line with modelled expectations (e.g., Newham, Barnet, and Waltham Forest).
- Some boroughs record higher disproportionality than predicted, including Richmond, Kingston, and Lambeth.
- Others fall below modelled levels, such as Bromley and Greenwich.
- However, given the earlier findings that there is no one-size-fits-all solution, is this borough-level focus too blunt an approach?

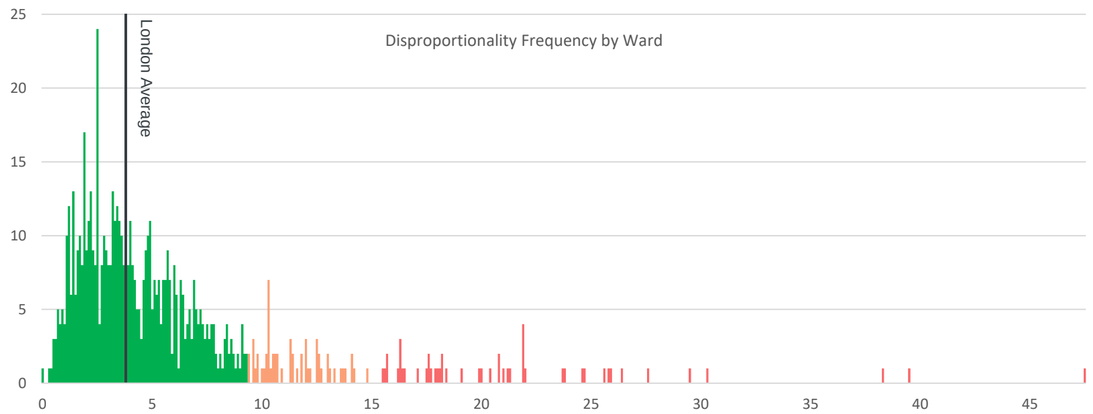
Borough	Stop and Search in 2023*	Actual Disproportionality	Modelled Disproportionality	Difference (Actual – Modelled)
Richmond upon Thames	0.8k	14.41	9.82	4.59
Kensington and Chelsea	3.1k	11.10	10.34	0.76
Wandsworth	3.2k	8.86	8.29	0.57
Kingston upon Thames	1.9k	8.11	6.55	1.56
Hammersmith and Fulham	3.5k	6.74	7.32	-0.58
Westminster	13.2k	6.47	7.11	-0.64
Lambeth	5.7k	6.33	5.17	1.16
Barnet	2.5k	5.88	5.73	0.15
Camden	6.0k	5.39	4.64	0.75
Ealing	4.6k	5.14	4.51	0.63
Islington	5.1k	4.95	5.38	-0.43
Sutton	1.3k	4.65	4.28	0.37
Bromley	3.9k	4.49	5.74	-1.25
Hillingdon	2.6k	4.39	3.51	0.88
Merton	1.7k	4.02	3.86	0.16
Hackney	3.7k	3.96	4.90	-0.94
Southwark	6.9k	3.78	4.27	-0.49
Hounslow	2.5k	3.70	3.38	0.32
Tower Hamlets	7.0k	3.64	2.89	0.75
Haringey	5.6k	3.52	2.84	0.68
Harrow	1.9k	3.49	3.90	-0.41
Waltham Forest	4.2k	3.47	3.46	0.01
Havering	4.5k	3.44	3.84	-0.40
Brent	4.1k	3.22	3.06	0.16
Redbridge	3.9k	3.14	4.17	-1.03
Croydon	6.0k	3.05	3.56	-0.51
Lewisham	4.2k	2.68	3.93	-1.25
Greenwich	5.2k	1.99	3.66	-1.67
Bexley	2.3k	1.83	3.02	-1.19
Newham	5.8k	1.80	1.78	0.02
Enfield	2.7k	1.72	2.53	-0.81
Barking and Dagenham	4.7k	1.32	1.49	-0.17
London	**134.1k**	**3.82**	**3.49**	**0.33**

* Data sourced from https://data.police.uk/data/ and matched to 2021 Ward boundaries. Stop and Search without Long/Lat excluded from numbers.

Lower than modelled
Within 1 standard deviation of modelled
Over 1 standard deviation of modelled
Beyond 2 standard deviation of modelled

Looking at the hyper-local may be more fruitful in tackling disproportionality

Stop and Search disproportionality for Black Londoners varies across London wards

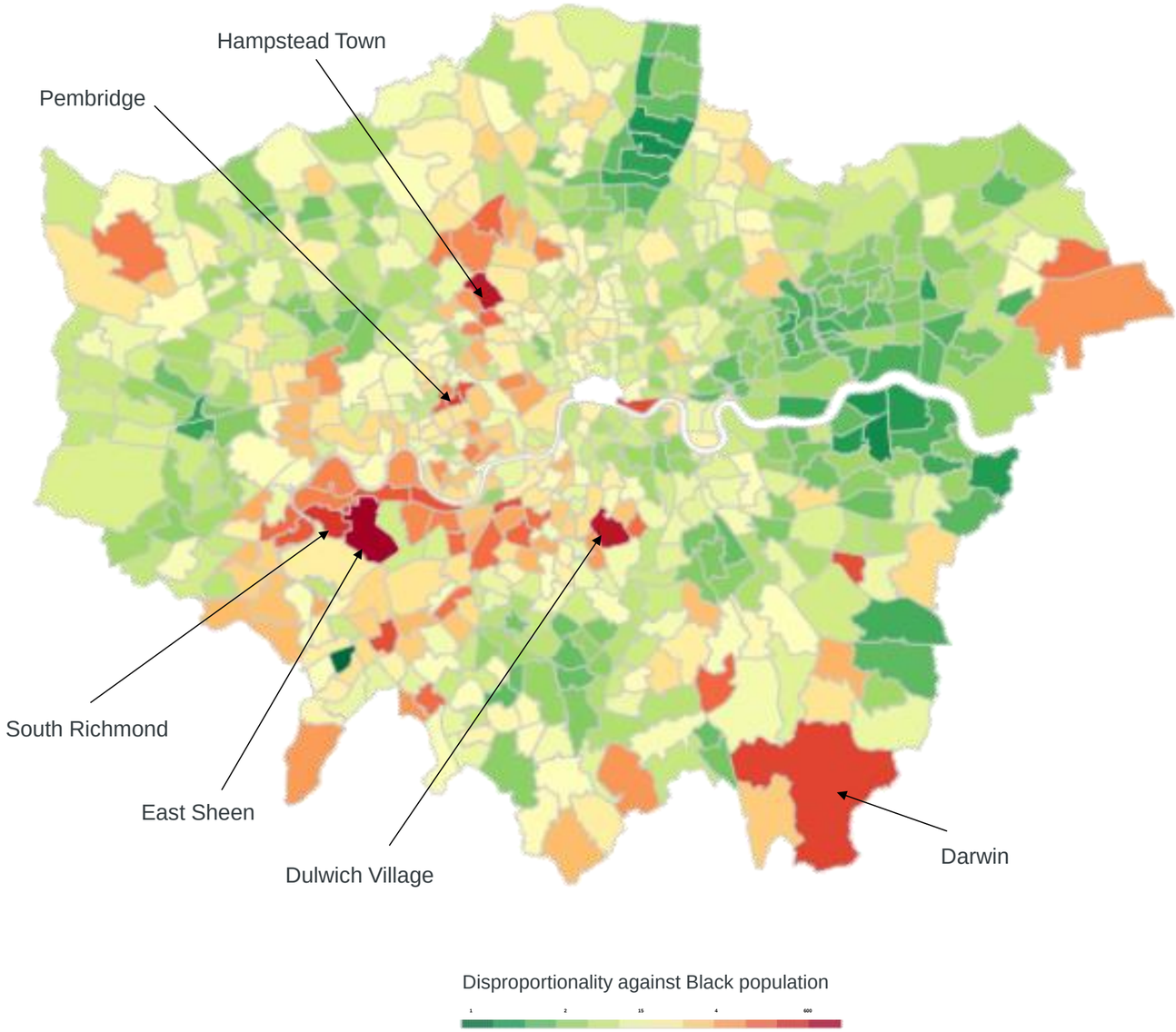


- **106/680** wards (16%) have disproportionality more than 1 standard deviation from the London Average.
- **24** (4%) are 2 standard deviations from the London average.

Top 10 Wards	Actual Disproportionality	What the model expects...
East Sheen	x48	x14
Dulwich Village	x40	x11
Hampstead Town	x38	x13
South Richmond	x30	x14
Pembridge	x30	x17
Darwin	x28	x8
St Katharine's & Wapping	x26	x9
Lavender	x26	x12
New Malden Village	x26	x6
Longlands	x26	x5

We see overall proportionate boroughs with disproportionate areas and vice versa. Targeted activities in these wards would have a disproportionate impact on the overall picture in London.

Highest levels of disproportionality across London are focussed in a selection of wards



We can also estimate the levels of disproportionality (if at all) for Asian Londoners

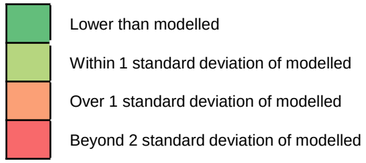
Methodology

Repeating the methodology with disproportionality against Asian Londoners, the model can statistically estimate the modelled level of London and borough level disproportionality.

Disproportionality against Asian Londoners stands at 0.90 meaning that Asian people are underrepresented in Stop and Search overall.

Insights

- The model places the actual level of disproportionality for this group in London almost exactly at what the model expects.
- Disproportionality in Ealing, Hackney and Hillingdon have a higher level than the model suggests.
- Some boroughs are lower than modelled (i.e., Lewisham and Bromley).



Borough	Stop and Search in 2023*	Actual Disproportionality	Modelled Disproportionality	Difference (Actual – Modelled)
Hackney	3.7k	1.82	1.54	0.28
Wandsworth	3.2k	1.70	1.76	-0.06
Ealing	4.6k	1.56	0.91	0.66
Richmond upon Thames	0.8k	1.51	1.70	-0.19
Waltham Forest	4.2k	1.40	1.44	-0.04
Merton	1.7k	1.28	1.20	0.08
Kensington and Chelsea	3.1k	1.24	1.20	0.04
Islington	5.1k	1.24	1.46	-0.22
Lambeth	5.7k	1.19	1.18	0.01
Tower Hamlets	7.0k	1.18	1.23	-0.05
Hammersmith and Fulham	3.5k	1.15	1.53	-0.37
Havering	4.5k	1.11	1.06	0.06
Hillingdon	2.6k	1.07	0.80	0.27
Southwark	6.9k	0.97	0.83	0.14
Redbridge	3.9k	0.95	1.07	-0.12
Westminster	13.2k	0.88	0.80	0.09
Kingston upon Thames	1.9k	0.86	0.86	0.00
Haringey	5.6k	0.78	0.81	-0.03
Croydon	6.0k	0.75	0.73	0.02
Lewisham	4.2k	0.72	1.15	-0.43
Greenwich	5.2k	0.67	0.96	-0.29
Barnet	2.5k	0.66	0.95	-0.29
Barking and Dagenham	4.7k	0.65	0.54	0.11
Camden	6.0k	0.63	0.90	-0.27
Bexley	2.3k	0.59	0.59	0.00
Hounslow	2.5k	0.58	0.68	-0.10
Sutton	1.3k	0.57	0.80	-0.23
Bromley	3.9k	0.56	0.93	-0.38
Brent	4.1k	0.55	0.35	0.20
Newham	5.8k	0.53	0.68	-0.14
Enfield	2.7k	0.53	0.74	-0.21
Harrow	1.9k	0.41	0.43	-0.02
London	**134.1k**	**0.90**	**0.91**	**-0.01**

* Data sourced from https://data.police.uk/data/ and matched to 2021 Ward boundaries. S&S without Long/Lat excluded from numbers.

* Data sourced from https://data.police.uk/data/ and matched to 2021 Ward boundaries. S&S without Long/Lat excluded from numbers

Appendix

All aspects of the work have been Peer Reviewed to provide assurances of quality

This work has undergone a significant amount of peer review absorbing valuable feedback from a range of experts across policing, Stop and Search policy as well from a technical/data science perspective.

The following questions were asked:

1. Methodological Soundness – Are the analytical methods, modelling choices, and data-processing approaches appropriate, sound, and well-justified for the research aims?

2. Fairness in Comparison – Are the included or excluded variables (e.g., demographic or ethnicity variables) appropriate, and do they support a fair, unbiased analysis? Are there alternative comparison methods or benchmarks that you think should be considered?

3. Interpretation of Results – Are the conclusions drawn from the analysis reasonable and appropriately cautious? Do they reflect what the data supports?

4. Assumptions and Limitations – Are the potential sources of bias or error, such as ambiguity in free-text interpretation, adequately addressed? Are the model's assumptions well-supported, and have potential confounding factors been sufficiently addressed?

5. Ethical and Social Implications – Does the research appropriately consider the wider implications of these findings, particularly in relation to public trust, operational practice, and oversight?

The feedback provided supported the techniques used and aided in the refinement of the analyses and helped contribute to the ongoing discourse surrounding disproportionality in Stop and Search practices.

Grounds for Stop and Search

"I really enjoyed reading the slides and getting into the detail. You tell a fascinating and important story, and am impressed by what you have achieved."

"The results are clearly presented, and you've done a good job of explaining the technicalities of what you've done."

"The results are presented transparently, and the statistical limitations are clearly acknowledged. The analysis is very thorough, with multiple interpretative angles thoughtfully explored."

Drivers of Disproportionality

"The research questions and aims of the analysis are clear. Factors used all look like sensible choice …. Linear regression is an appropriate method given you are predicting the drivers of disproportionality and dealing with a continuous variable as the outcome. …. Using a stepwise reduction approach is a good and logical approach"

"First, good job on what is clearly a big, lengthy and robust analysis!

*Many of your variables are proxies for how young or how poor a ward is. A smaller set of core demographic and economic metrics may get close to the same R^2, and would be less prone to variation over time**"*

***** In response to this feedback, we refined our model to use 8 primary metrics. It delivered comparable predictive power and was tested on 2024 data with similar results.

Grounds for Stop and Search

Appendix

Details of the coding framework

A framework was developed based on academic work, as well as using a grounded approach to incorporate elements from a sample of cases.

Coding captures a range of recorded factors as well as an overall summary assessment.

1. Only code information preceding the search itself i.e., prior information, observed behaviour, stop & account, etc – only anything that formed suspicion.

2. Code as many factors as apply to the grounds as possible.

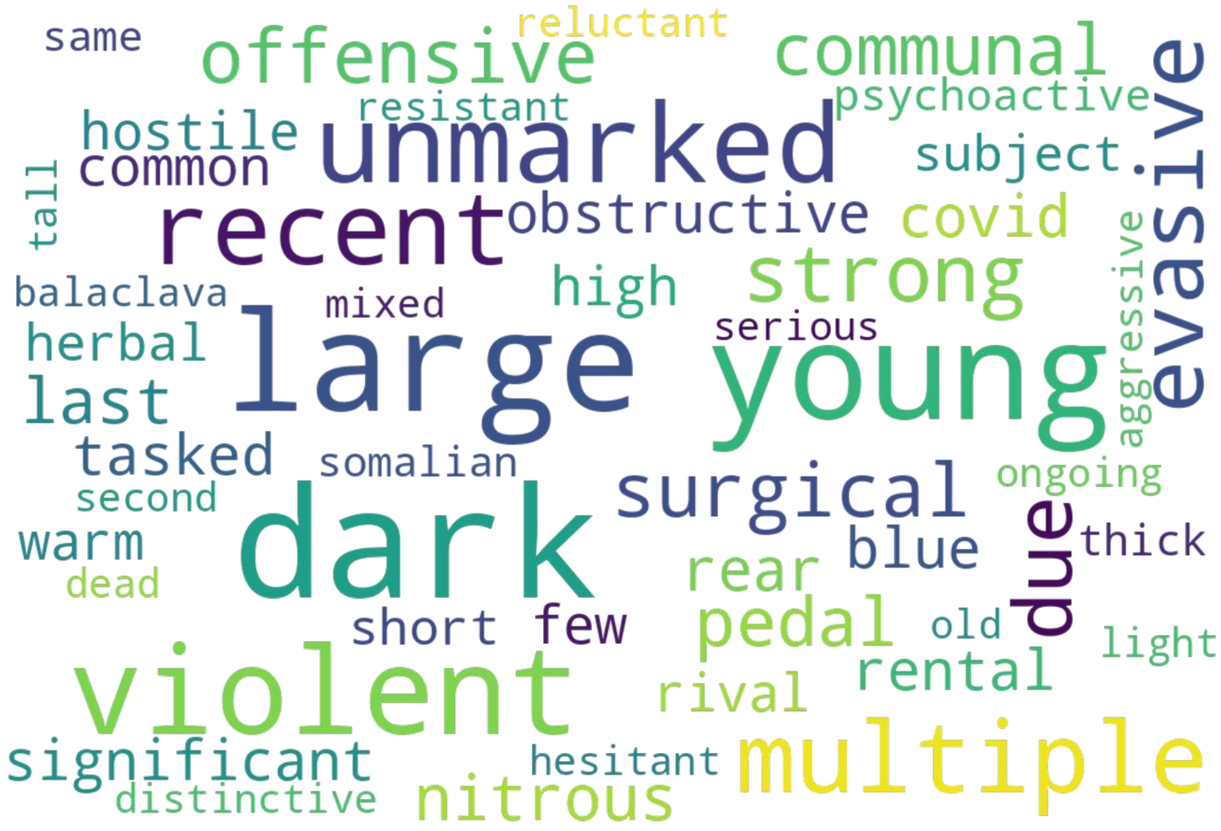
Theme		Factor	Additional info
Intelligence or information		Search was part of an operation	
		Section 60 in place	
		Responding to specific report/incident/CAD	
		Subject was known to police	
		Subject previously arrested / convicted	
		Seen in vague location/area known for:	
		Seen in specific location/area known for:	select all that apply:
		Seen in specific location/area with recent/specific intel re:	
			crime
			ASB
			drug use
			drug supply
			violence
			robbery
			weapons
			gangs
Police presence		Mobile patrol	
		Foot patrol	
		Marked car	
		Unmarked car	
		Uniform	
		Plain clothes	
		TSG/Specialist Unit	
		Deployed to area from elsewhere	
reported / third party / prior information AND / OR observed by officer	Context	Seen in or near a vehicle	
		Seen on or near bike/e-bike/scooter	
		Seen with an associate or group	
		Seen 'late at night'	
		Seen in a secluded public space	
		Seen in a restricted place	
		Seen in residential area/property they don't live in	
		Smell of drugs / cannabis	
		Seen near criminal damage / damaged property	
	Subject behaviour	Seen to hide, swallow, discard or store object	
		Seen or suspected to be intoxicated	
		Heard to talk about items of interest	
		Seen or heard threatening others	
		Seen 'loitering'	
		Seen scoping	
		Seen or suspected to be targeting	
		Seen in possession of weapon	
		Seen in possession of other items	
		Seen stealing	
		Seen committing other offence	
		Seen using, near or in possession of balloons / NOS / laughing gas	
		Seen smoking, near or in possession of suspected drugs	
		Seen near or in possession of drugs paraphernalia	select all that apply:
		Seen / suspected drug dealing	
			cannabis
			cocaine
			crack cocaine
			(crystal) meth
			heroin
			ketamine
			MDMA
			mephedrone
			white powder
			pills
			psychoactive
			prescription

Vehicle specific	Traffic offences/involved in an RTC	
	Erratic driving	
	Failure To Stop (FTS)	
	Suspected stolen vehicle	
	Vehicle recently flagged/linked to drug supply	
	Vehicle recently flagged/linked to other crime	
	Travelling as a group	
	Damage to vehicle	
	Tinted windows	
	Sped up	
Police contact	Drug-dog indication	
	Subject attempted to avoid knife arch	
	Knife arch triggered	
	Subject identified by victim/witness present	
	Object found on associate	
	Stolen phone location tracked	
	Stolen car location tracked	
	Subject unable to account for presence/behaviour	
	Account inconsistent/not believable	
	Subject admitted drug possession, use, or contact	
	Subject admitted being in possession of other articles of interest	
	Subject attempted to avoid police contact	
	Officer determined subject became aware of police	
	General suspicion	
	Behaviour perceived to match known MO	
Subject demeanour during police contact	Nervous	
	Evasive	
	Uncooperative	
	Confrontational	
	Aggressive	
	Denial of observed behaviour	
	Physically unsettled	
Subject appearance	Matched specific physical description	
	Vague description / matched partial description	
	Clothing inconsistent with weather/location	
	Concealing clothing	
	Hands in pockets, waistband	
	Suspected drug user	
Grounds summary	inconsistent grounds with object being searched for	
	non-specific eg. to specific individual within a group	
	clear what object being searched for	
	not clear what object being searched for	
	highly subjective interpretation of subject behaviour	
	overall, rank the grounds for suspicion on a scale of 1 to 5:	1 very weak
		2 weak
		3 acceptable
		4 strong
		5 very strong

Some differences emerge when looking at the basic words used...

Words most prevalent in searches of White Londoners

Words most prevalent in searches of Black Londoners



Examples of ‘violent’ and ‘violence’ used in recorded Grounds

- As outlined, the word "**violent**" appeared significantly more with Black than White Londoners – even when looking at the same type of stops.
- In most cases, the use of ‘violent’ or ‘violence’ refers not to the encounter itself but to previous activity in the area. All examples except the one outlined are of Black individuals.

officers responded to a call on CAD 6954 and reports of an ic1 male in light blue jeans and a orange top and dark trainers who had assualted someone on [REDACTED NAME] [REDACTED ADDRESS] and as officers got to [REDACTED NAME] highstreet outside dominoes. we saw the male who matched that description and has made off from officers. so we have pursed in a footchase of the suspect [REDACTED ADDRESS] and as we were approaching the male he was making hand movements in to his waist band so he was detained under s1 of pace and placed in handcuffs in a prone rear stack position and full GOWISELY was given and nothing was found but the male was arressted for common assualt. the suspect was extremley intoxicated and very aggressive and violent towards officers.

We were tasked to North West (NW) due to the increase in violence on the ground. There have been several incidents involving stabbings and firearm discharges. Gang members are carrying weapons to protect themselves from rival members. Our unit was tasked to QA when our attention was drawn to vehicle which tried to avoid being stopped by police. This vehicle was known to our CAD system for violent offences, potentially suspect for a GBH inside the vehicle.

Whilst on proactive mobile patrols of CROYDON TOWN CENTRE, an area with disproportionate levels of drug related crime, an vehicle came to officers attention on [REDACTED ADDRESS]. The vehicle had two (2) occupants, a young IC6 male in his 20s and an older IC3 male. There was a recent violent altercation between IC3 and IC6 males in WEST CROYDON whereby a male recieved GBH injuries sustained from a large knife. The IC6 male got out of the vehicle and joined a large group of other IC6 males. The driver continued on. WEST CROYDON is a well known drugs hot spot with regular intelligence of drug dealing. As the vehicle was stopped, there was a strong and distinct smell of cannabis orginating from within the vehicle. Also the males story in answering police questions was not making sense, stating that he did not know who was in the vehicle with him. He stated that he was a cannabis user

Male seen wearing a dark knee length puffer jacket and walking with a straightened left leg, indicative of someone concealing a large article down the trouser leg. This was seen in an area with frequent and recent incidents of violent offences involving large bladed articles. Also wearing a balaclava, often used to conceal identity. When seen by police, froze, and immediately changed direction walking away from police at a faster pace than before. When stopped attempted to break free and run away requiring to be detained on the floor. Handcuffed and detained for a search under s1 PACE.

Male was with two other males with faces covered. the group were walking back and forth outside west croydon br and approaching peple, the subject would reach into his hoody pouch pocket regularly and hold something inside, leading me to suspect he may be concealing a weapon. when challeneged they could not give any reasonable explaination for their behaviour or presence at the location which is an area that suffers a large ammount of robberies and knife enabled violent crime.

Officers were conducting patrols under Operation Nightingale tackling violence. The male was seen by officers walking along and he has spotted officers and ran into the shop he was beside. He was then observed hiding in the shop trying to peak out and see where officers were. When officers drove into a car park opposite the male has exited the shop and looked up both ends of [REDACTED ADDRESS] before heading in the direction he was orginally seen to be going in. When officers stopped the male appeared surprised and instantly became verabally agressive. The area he was in has in the past 36 hours had an increase in violent crime involving gangs where knives have been used. The male was known to officers as being violent and previously has attempted to run officers over to evade them.

N.B. Quotes show exactly the words recorded. Spellings and typos have not been corrected.

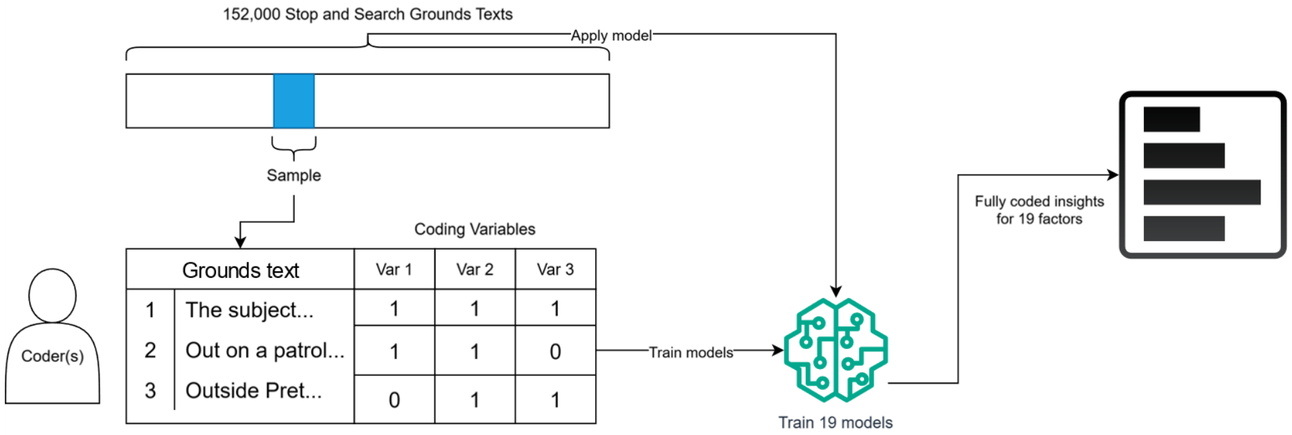
Model overview

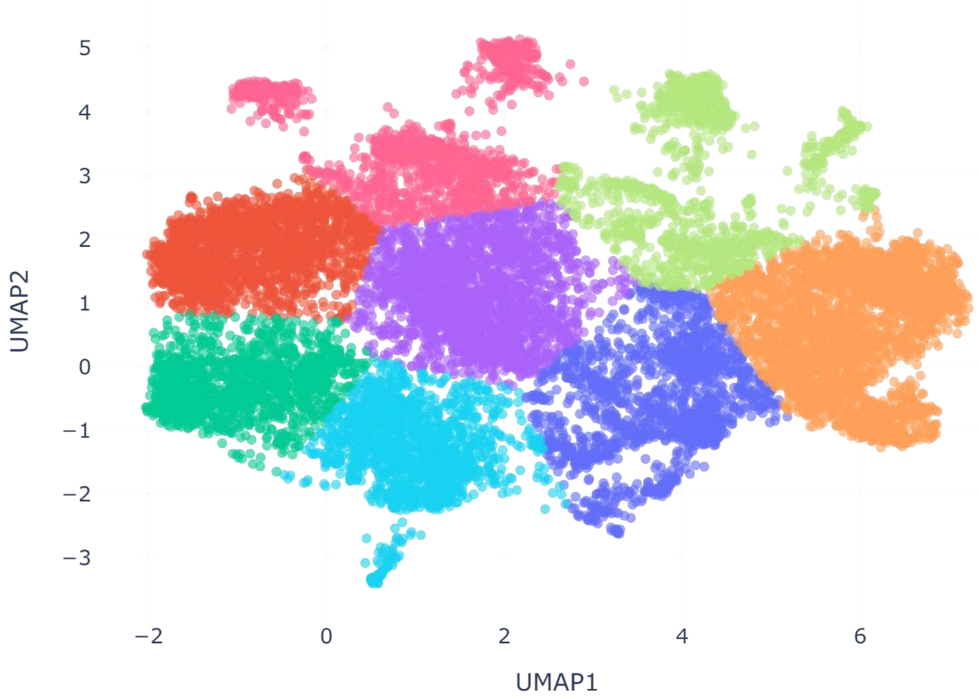
Our approach uses **neural networks** to classify **text embeddings** (generated via “intfloat/e5-large-v2”) into binary outcomes. The architecture incorporates:

- Multi-head attention (3 heads) with feedforward layers and L1 regularisation
- Focal Loss (α=0.25, γ=2) and balanced sampling (≥25% positives per batch) for class imbalance
- Data augmentation through noise injection for minority class samples
- AdamW optimisation with learning rate scheduling and early stopping on F1

We trained an ensemble of 5 models with different random seeds, evaluating performance through ROC curves, F1-optimised thresholds, and attention weight analysis. The human-annotated data was divided into training (80%) and testing (20%) sets.

This complexity developed due to the imbalanced nature of the data; most Grounds texts only had a handful of variables identified, combined with the relatively small training set. In this setting, overfitting is less problematic as we’re more interested in consistent detection of text patterns than in abstract generalisability.





Embedding models take text and output a series of numbers. We can plot these numbers in 2 dimensions (using *Uniform Manifold Approximation and Projection*); each dot above is a single Grounds text. We can group similar dots together, and close dots are stops with similar language in the Grounds text, which could be equivalent reasons for stop, or possibly stops in similar areas. These “embeddings” are the data we use to train the models, as it captures the *semantic* information in the Grounds text.

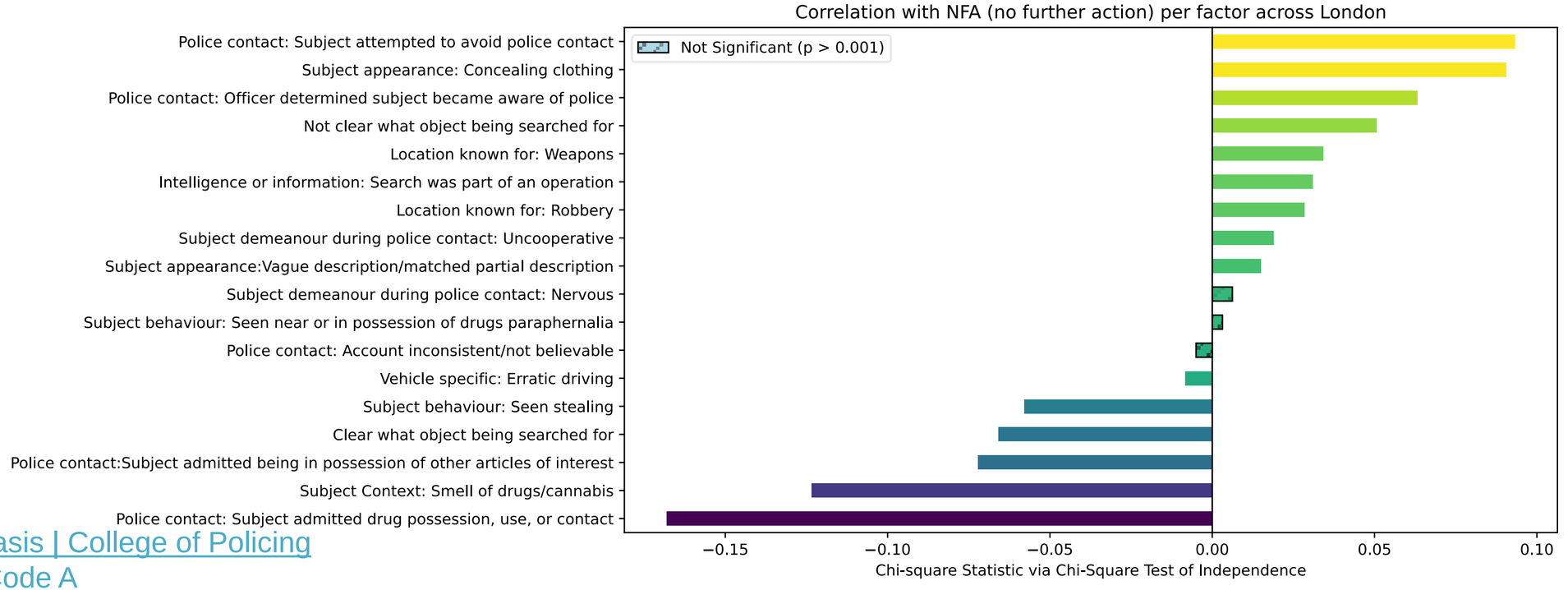
Development of a Quality of Grounds metric

*"**PACE Code A states that reasonable grounds for suspicion must relate to the likelihood that the object in question will be found.** It also says that, in the absence of specific intelligence or information, reasonable grounds may exist on the basis of someone's behaviour, and that searches are more likely to be effective and legitimate when their Grounds are based on multiple objective factors." [1, 2]*

Given the above we can outline a method of measuring the **Quality** of a given Grounds text. If we have decomposed our Grounds text into our isolated factors, we can measure the quality as follows:

$$\sum_{F} C_{F_i} \cdot F_i$$

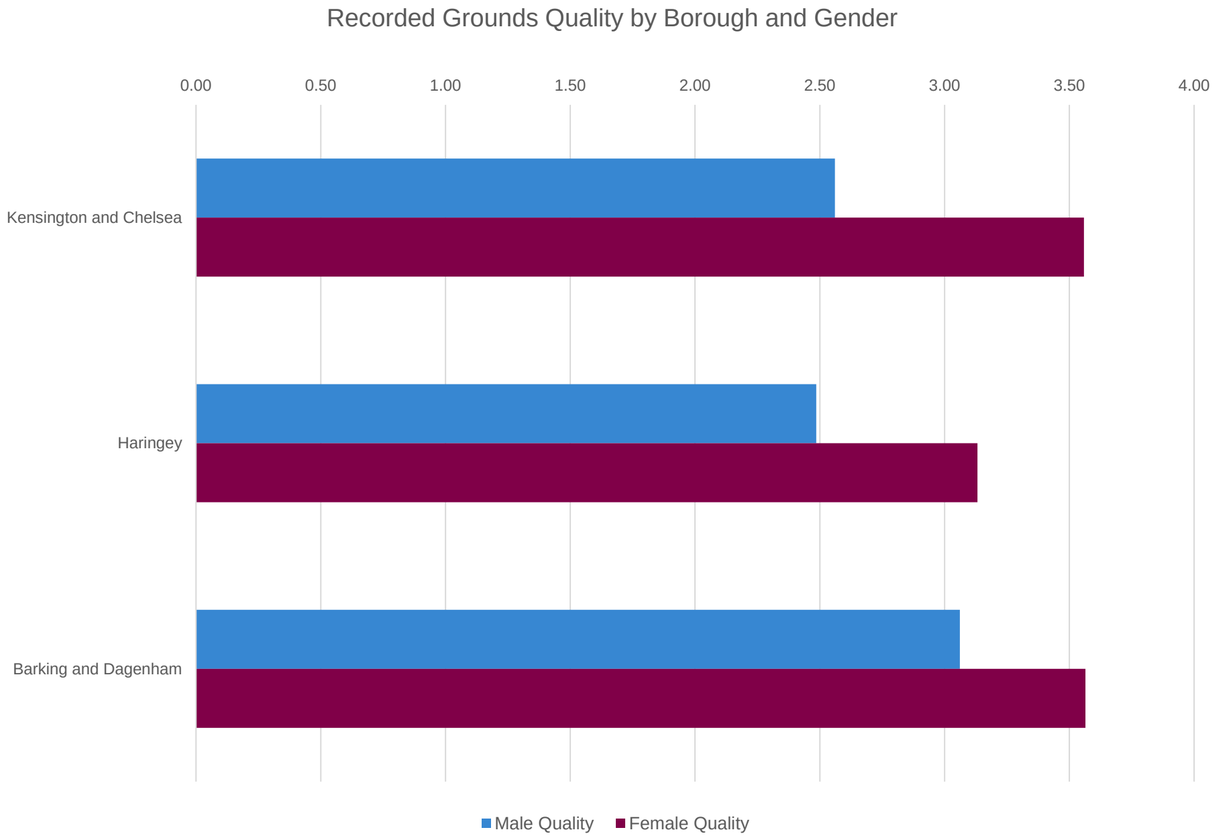
In other words, we just add together all the correlations with NFA, for each factor (contributing 0 if the factor isn't mentioned in the Grounds). We then normalise this to be one of [1, 2, 3, 4, 5].



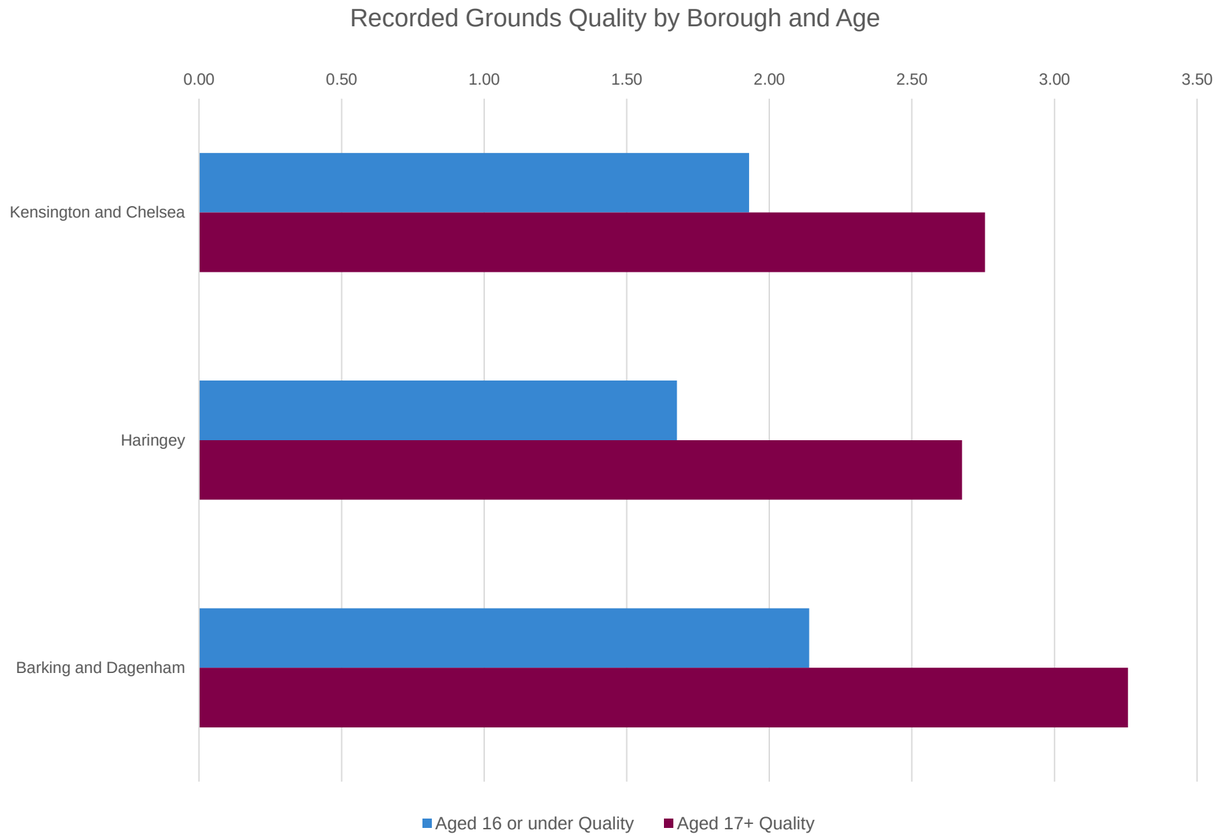
[1] Legal basis | College of Policing
[2] PACE Code A

Quality by Age and Gender

The chart shows the Quality of recorded Grounds by gender in Kensington and Chelsea, Haringey, and Barking and Dagenham. In each borough, male Stop and Searches have lower Quality scores than female searches, with the largest gap in Kensington and Chelsea.



The chart shows the Quality of recorded Grounds by age in Kensington and Chelsea, Haringey, and Barking and Dagenham. In each borough, stop and searches of people aged 16 and under have lower Quality scores than those of older individuals, with the largest gap in Barking and Dagenham.

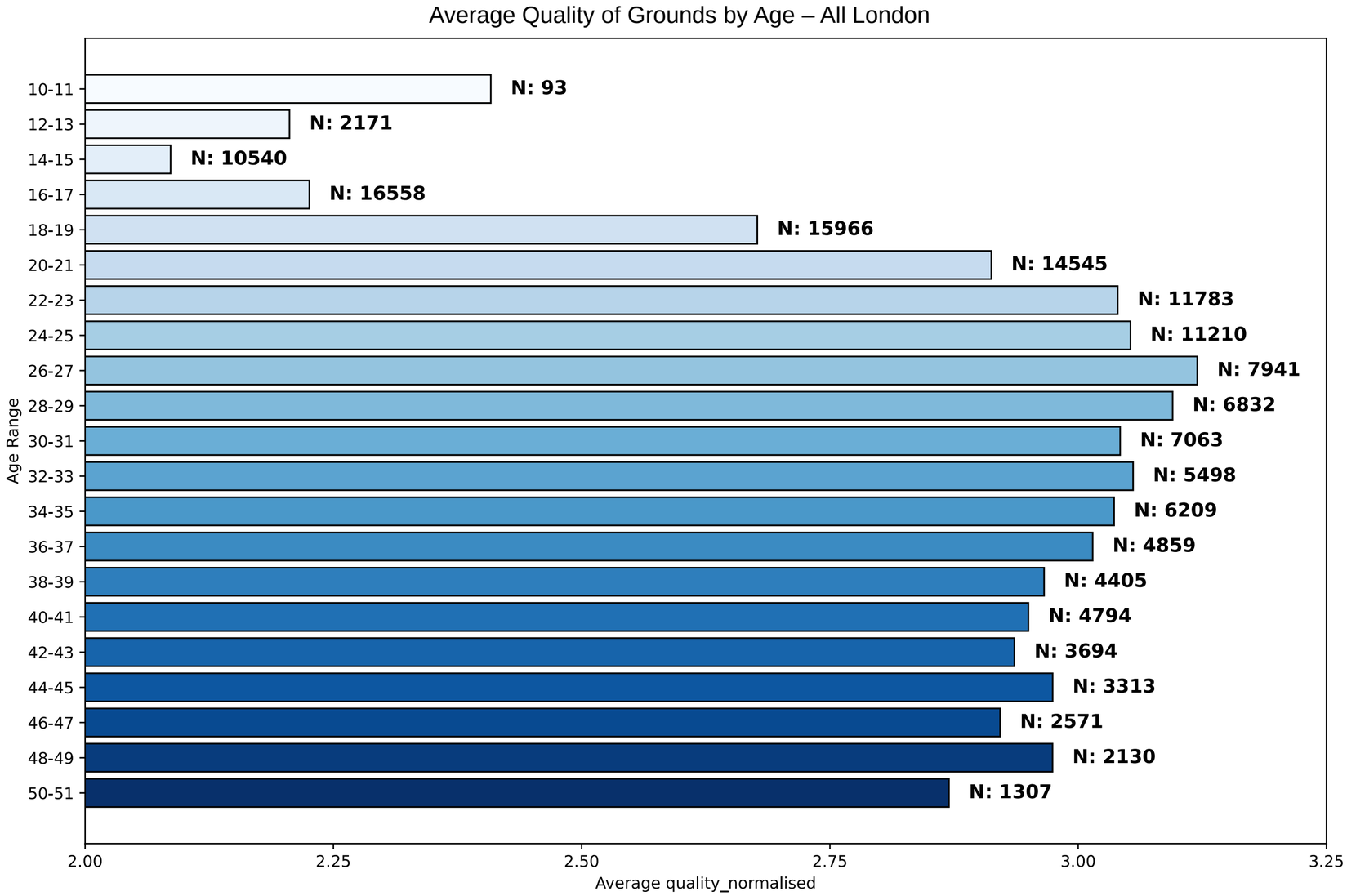


Data shown for three boroughs that have been identified as areas of focus by ERG

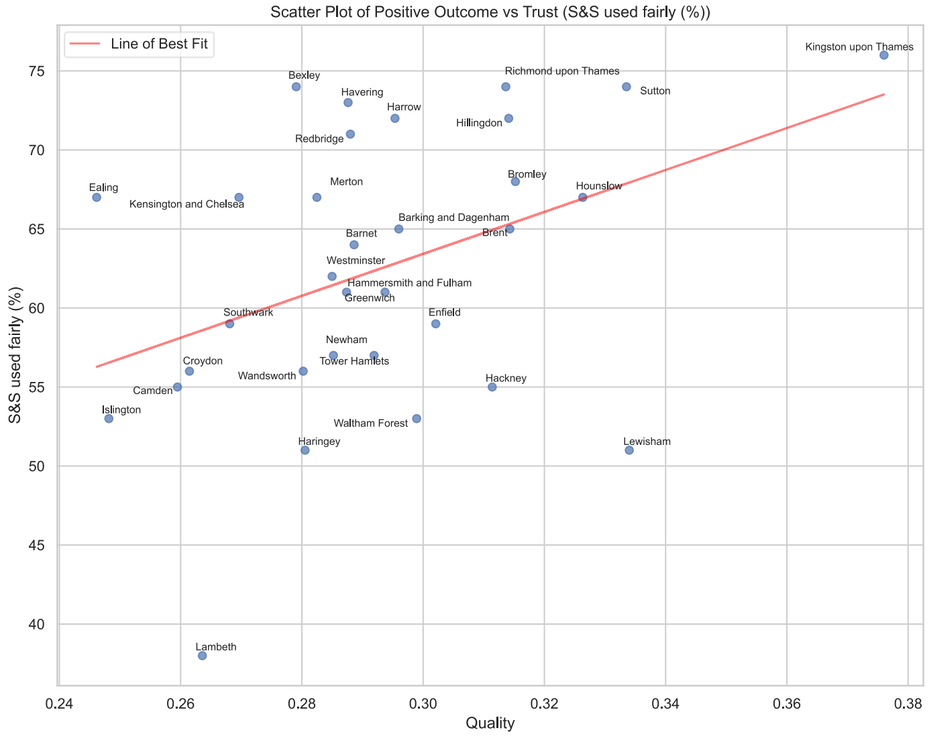
Overall Quality of Grounds is lower for younger age groups

Quality of Grounds reaches a minimum in the age group 14-15, reaching a maximum at 26-27 then decreasing again.

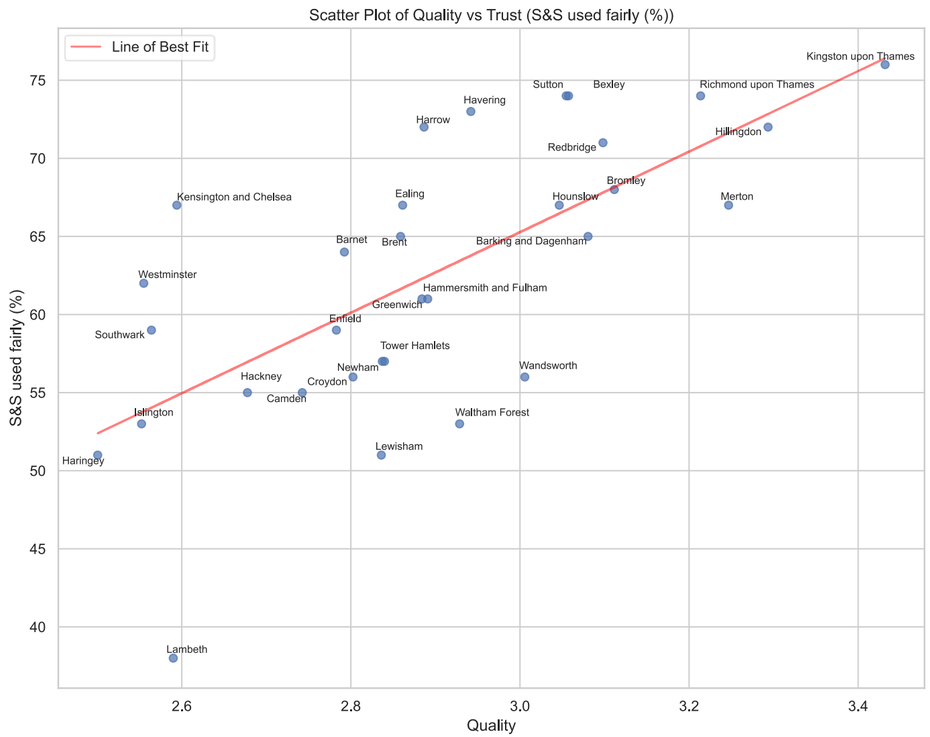
This is based on the officer's calculated estimate of the individual's age. While this measure is valuable, it may include a margin of error.



Quality of Grounds vs Survey & Positive Outcome vs Survey



R-squared: 0.1676
P-value: 0.01998



R-squared: 0.4658
P-value: 1.687e-05

Similarly, we see a weak positive correlation (left) between the rate of positive outcomes (reverse of NFA) and PAS R12 to Q2 24-25.

We can perform the same scatter plot (right) with our new Quality measure, and we see a stronger positive correlation with a much higher statistical significance.

Using Linear Regression to understand factors behind Quality of Grounds

Summary

Results have shown that Black Londoners were more likely to receive lower Quality recorded Grounds for Stop and Search than other ethnic groups. Linear regression analysis was conducted to understand how ethnicity as well as other relevant factors explained the Quality metric.

The significant variables in the model are in the below table. Black ethnicity was negatively associated with Quality of Grounds, remaining a significant predictor even when holding all other variables constant. Other factors linked to lower quality scores were Weapon, Point and Blades, young ages (10-19), MO7 Taskforce, and male gender. In contrast, drug related stops were associated with higher Quality scores.

Method

Because quality varies by Reason for Stop, we analysed how a broader set of factors relate to recording Quality. The coders — and the models based on their assessments — did not have access to these additional features, reducing the risk of circular reasoning.

We converted each factor into a simple yes/no variable and used Elastic Net regression to estimate their independent contributions, while adjusting for sample imbalance and overlap between variables.

In this model:

- A **positive contribution** indicates association with higher-Quality.
- A **negative contribution** indicates association with lower-Quality.
- A **zero contribution** means the factor did not remain after regularisation, due to small effects, limited sample size, or strong correlation with other variables.

This allows us to identify which characteristics are independently linked to recording quality.

Input variables

Variable	Examples
Reason for Stop	Drugs (s.23 Drugs Misuse Act), Weapons, Point & Blades (s.1 PACE, s.139 CJ Act)
Ethnic Appearance Group	White, Black, Other, Asian
Calculated Age	Any integer between 0 and 100, but grouped in to brackets of 10
Gender	Male, Female
Officer OCU	MO7 – Taskforce, Central West

Results

Variable	Correlation
Reason for Stop: Drugs (s.23 Drugs Misuse Act)	0.36
Reason for Stop: Weapons, Point & Blades (s.1 PACE, s.139 CJ Act)	-0.30
Age: 10-19	-0.19
Officer OCU: MO7 – Taskforce	-0.15
Gender: Male	-0.08
Ethnic Appearance Group: Black	-0.08
Age: 20-29	0.07
Gender: Female	0.06
Officer OCU: MO8 – Roads and Transport Policing Command	0.02
Ethnic Appearance Group: Asian	0.00
All Other Variables	0.00

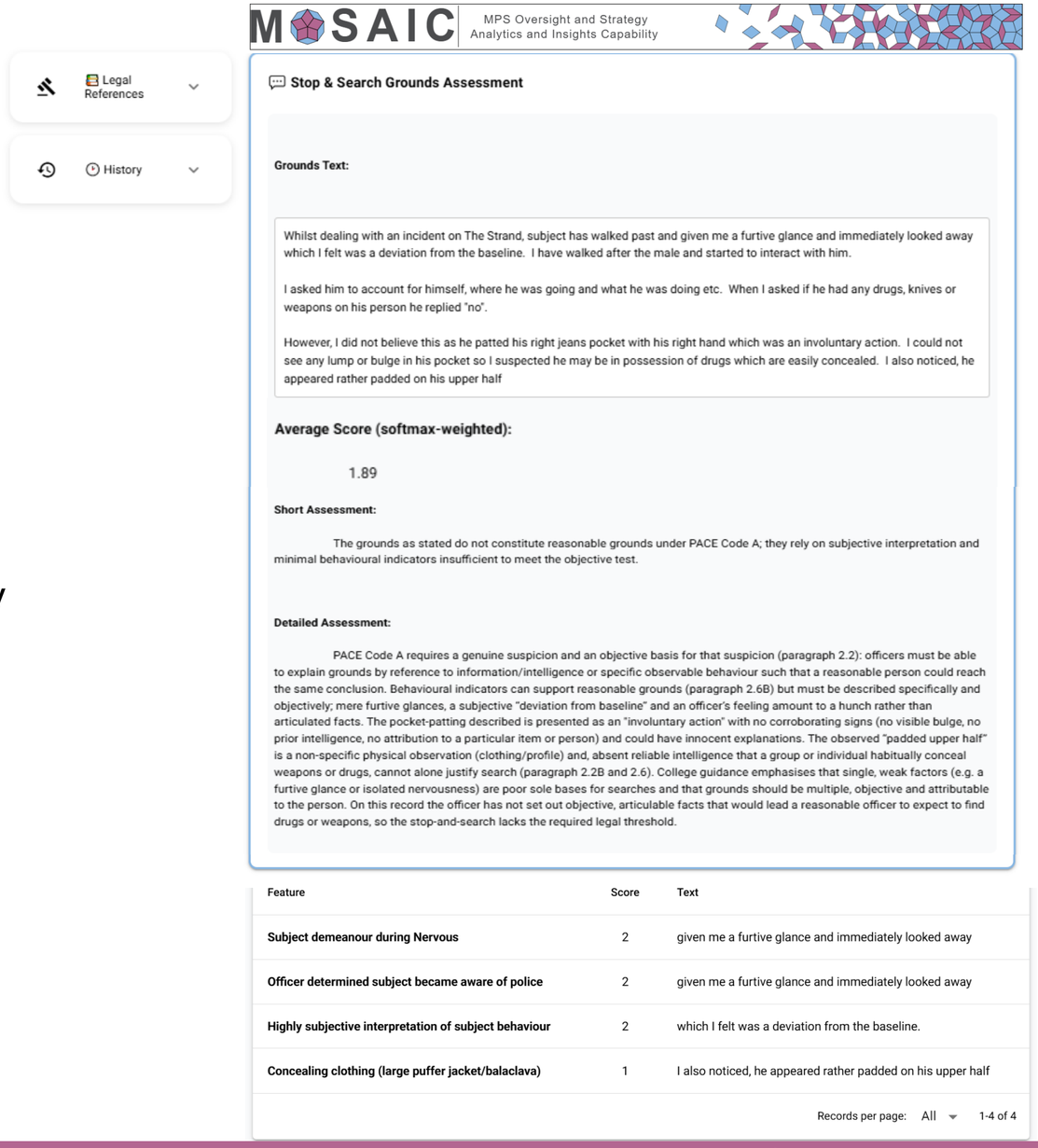
Creating a tool to assess the Quality of Grounds

Building on this research, the MOPAC Data Science team have developed a prototype tool, nicknamed “the Groundskeeper”, that allows users to input any recorded Grounds text for a Stop and Search.

The tool then generates a Quality of Grounds score between 1-5 based on the methodology used in this analysis.

Additionally, the tool mirrors of the College of Policing’s *“AI enhanced supervision of stop and search”* approach, whereby written Grounds are assessed against relevant reference materials (such as PACE Code A).

This enables an immediate evidence based rating of the Grounds – of real value for supervisors, auditors, community and scrutiny groups.



Drivers of Disproportionality

Appendix

Methodological Approach: Kings College London

Purpose

To understand what factors best explain why some areas of London show higher levels of disproportionality in Stop and Search than others.

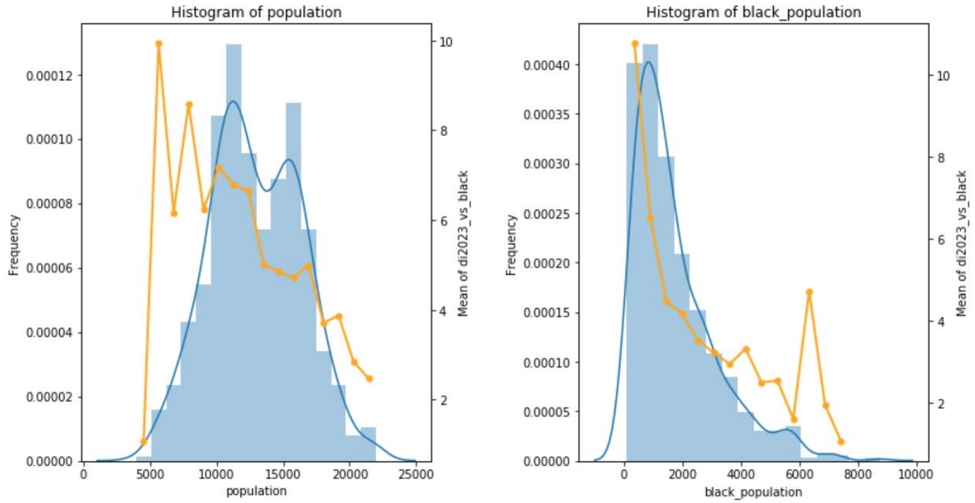
Approach:
We built a statistical model using over 200 potential explanatory factors drawn from crime data, census information, and local characteristics.
Each factor was tested to see how well it helps predict the *Disproportionality Index:*

$$\textit{Disproportionality Index} = \frac{\textit{Black People Stop \& Searched}}{\textit{Resident Black Population}} \Big/ \frac{\textit{White People Stop \& Searched}}{\textit{Resident White Population}}$$

Data Refinement

- Removed factors with too many missing values.
- Filled small data gaps where appropriate.
- Removed variables acting as proxies for ethnicity – e.g., religion.
- Much of the data was not normally distributed and so log, square root, reciprocal, rank and logit transformations were tested and assessed by Anderson-Darling statistic to determine the best.
- The target variable was log transformed.
- Variables with where the best transformation resulted in an Anderson-Darling score > 5 were removed (159 variables remain).
- Variables were scaled with a MinMaxScaler – so that they all range between 0 and 1. This ensures the coefficients of the model are all relative to each other.

Factor Type	Number of Variables	Examples
Population	29	Household Composition
Crime	58	Total Offences; Offences flagged as Knife Enabled
Nationality	18	Born in the UK
House Type	9	Terraced
Health	8	Disabled
Occupation	20	Full Time; Managers
Commercial Properties	22	Pubs
Deprivation	21	Indices of Deprivation
Parks & Open Spaces	10	Local Parks
Age Group	18	Young Adults
Other	6	Median Income; Unauthorised school absence



Model Selection: Kings College London

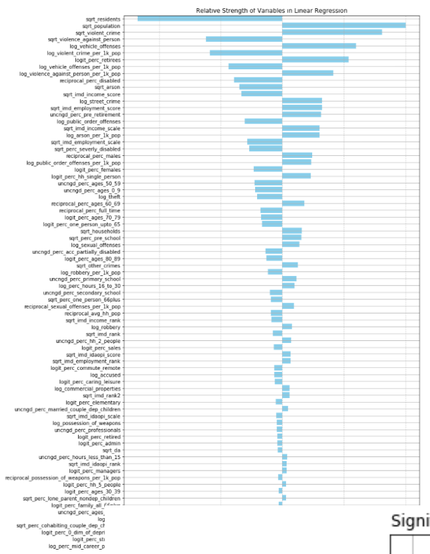
Methodology: Linear Regression

A linear regression model estimates how changes in each factor affect disproportionality. Each factor receives a weight showing how strongly it relates to disproportionality. The model also measures how much of the disproportionality it cannot explain – the “unexplained” element.

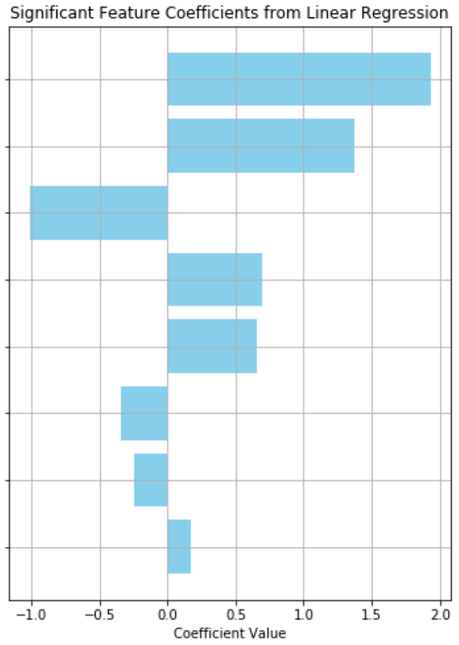
Initial Model Performance

Accuracy (R^2): 0.61 – meaning the model explains around 60% of the variation in disproportionality between areas.

This indicates a strong and meaningful relationship between area characteristics and disproportionality levels.



Final Model

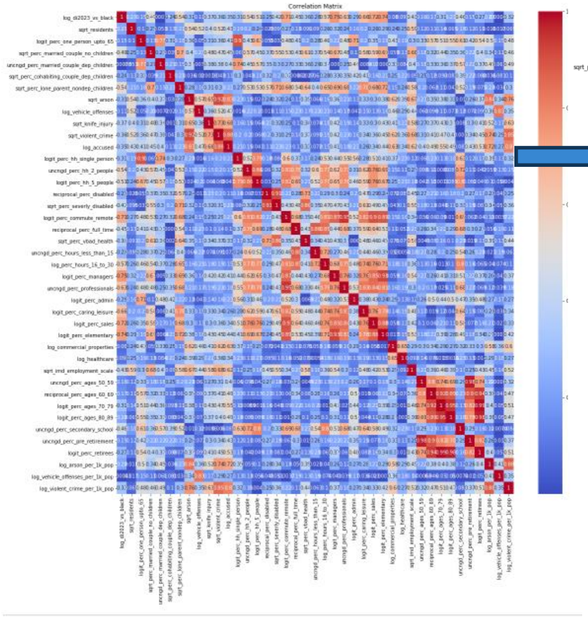


Refining the Model

With over 200 factors, many were overlapping or highly correlated.
We applied stepwise reduction and multicollinearity checks to keep only the most independent and explanatory factors.

1.Reduce to ~20 strongest predictors - R^2 = 0.76
2.Remove variables with multicollinearity or are hard to interpret.
3.Rebuild and test the final, lean model - R^2: 0.62

Reduced Model



Final Model