

Factors associated with the decision to grade missing people as high risk

A report by the MPS Strategic Insight Unit, May 2023

Executive Summary

The MPS's Strategic Insight Unit (SIU) conducted analyses to explore factors influencing whether missing people are graded as high risk, how this corresponds to the actual risk of harm, and how this varies by ethnicity. Our main findings are as follows:

1. Around 11% of White missing people were rated as High risk, compared to only 6% of Black missing persons. This suggests that White missing persons were 80% more likely to be rated as High risk, compared with Black missing persons. However, these figures do not take contextual factors into account that may be associated with ethnicity.
2. Using multivariate logistic regression analyses – which allow for controlling contextual factors – we find that risk gradings are far more influenced by aspects such as age and previous missing episodes, than ethnicity.
3. After accounting for various other contextual factors that may influence a missing person's risk grading, we found that the odds of a Black missing person being graded high risk were 0.85 that of a White missing person. This approximately translates to a 15% reduction in the chances of being graded high risk for black persons relative to white persons. However, Black persons were also less likely to come to harm, as their odds of being found deceased or hospitalised were 0.75 and 0.83 times the odds of White people, respectively (25% and 17% decrease in the odds for Black relative to White people).
4. Generally, MPS risk assessments were predictive of real risk. Compared to low risk persons, high and medium risk persons were 2.35 times (135% higher odds) and 1.31 (31% higher odds) more likely to be found deceased, respectively.
5. We identified some risk factors (such as individual risk questions) where perceived risk and actual risk (based on outcomes) strongly diverged. Training or improved decision making tools could be applied based on this work to improve risk forecasts.

1. Introduction

The policing response to any missing person (misper) investigation is determined by its risk grading. This officer-assessed grading can range from the lowest perceived risk, “absent” – where the individual is not formally considered ‘missing’ and a report is not required (from June 2020 no longer used as a category within MPS) – to high-risk, where “the risk of serious harm to the subject or the public is assessed as very likely”. This highest grading would then justify the immediate deployment of a wide range of policing resources (see full definition in Annex A).

Following a number of high-profile missing person cases, the MPS has received scrutiny over its approach to grading missing people. Specifically, critics have suggested that Black subjects may be consistently given a lower risk grading than subjects of other ethnicities, resulting in such cases receiving fewer police resources and less management oversight.¹

The Strategic Insight Unit (SIU) was asked to assess whether the risk gradings assigned by the MPS matched the actual risks those missing persons reported to the police were facing, and to what extent ethnicity and other factors influenced the risk grading decision process. This paper provides a brief overview of our analyses and findings – more detailed outputs are included in the Annex.

2. Data

For the purpose of this analysis, we used data from Merlin (a database for children and reported missing persons) for a total of 391,535 missing persons records between 2014 and early 2021. Of these, 37,765 were graded ‘absent’ rather than missing, and so were removed from our analysis as they are not subject to the same initial risk grading. We also removed those reports that were shown missing from somewhere other than an identified address within London (since we would not be able to link these records to demographic data²). Our final analysis included data from 300,411 records.

For each record, we extracted the first confirmed risk assessment that was conducted by a local officer at Inspector rank, and this risk grading served as the focus of our analysis. We are aware that some complaints about police risk assessments³ have focused on the speed at which risk gradings are increased as time elapses; however, information about decisions to change risk gradings are recorded in free text fields, which would take considerable resource to categorise and analyse. Decisions to change risk gradings over time must therefore fall outside the scope of this analysis.

¹ www.theguardian.com/uk-news/2021/oct/26/missing-black-people-mother-richard-okorogheye-public-inquiry

² Each subject was coded to LSOA level, and demographic data added using the [MOPAC LSOA Atlas](#). There is no comparable dataset for areas outside London, and as such we cannot control for these factors with the remainder of our dataset.

³E.g. <https://www.missingpeople.org.uk/discrimination-in-the-response-when-someone-is-reported-missing>

The ethnicity categories used in this analysis are necessarily limited to the pre-set categories on the Merlin reporting system. For the purposes of our analysis, we focus on White, Black and (South) Asian, noting that on Merlin, White is listed as “White – North European” and Black is termed “Afro Caribbean”. To be clear, there is no other Black category offered on the Merlin system so we can be confident that this includes all Black subjects, including those who are not in fact “Afro Caribbean”. Note that the ethnicity of the missing person was recorded by the reporting officer based on information available at the time. Typically this value is simply the description of the subject given by the person reporting them missing.

Multiple ethnicities were stated for approximately 2.5% of all missing persons in the dataset. For these cases, the reported ethnicities were sorted in alphabetical order (i.e., Afro Caribbean, Arab, Asian, Dark European, Oriental, Unknown, White European), and the first ethnicity in the list of reported ethnicities was used to represent the missing person’s ethnicity for statistical analysis. As a result of this procedure, missing persons with multiple ethnicities were more likely to be associated with the Black ethnic group than any other ethnic group, and they were never coded as White persons. Although this assignment procedure seems somewhat arbitrary, its impact on statistical outcomes should be negligible due to the low proportion of cases with multiple ethnicities attached.

In addition to age, sex, and time of last sighting, we extracted the following information:

- Addresses stated in the field “Missing From” on Merlin were geo-located and linked with census and demographic data from the Office for National Statistics.
- Free text responses to any of the 24 Risk Assessment Questions on Merlin (see Annex D) were converted to binary Yes/No responses. Any textual statement was recorded as a Yes response, whereas empty fields or statements that only contained the word “no” were coded as No response.⁴
- Total count of previous missing episodes recorded by the MPS at the time persons were reported missing.

When a missing person report is located, the case’s status changes to “cancelled”, indicating that no further investigation should take place, and a “cancellation code” that specifies the case’s outcome is entered into the system. There are 27 cancellation codes (e.g., “Misper - Found Dead - Blvd. Natural”; “Hosper - Friend/relation informed”). For our analyses, these codes were aggregated into four categories:

- Returned safely of own accord
- Returned by Police
- Found in hospital
- Found deceased

⁴ As the feature extraction procedures used for the Risk Assessment questions were fairly basic, results referring to these items (e.g., in Tables 5 and 6) should be interpreted with some caution. To explore the relevance of these questions in more detail, future work could employ more sophisticated pattern matching approaches.

3. Analysis

3.1 Descriptive statistics: overall counts and risk ratings

Figure 1 shows how the total count of missing records has shifted over time, and, notably, that the numbers of gradings have remained broadly consistent. Medium gradings comprise the vast majority, accounting for around three quarters of all records.

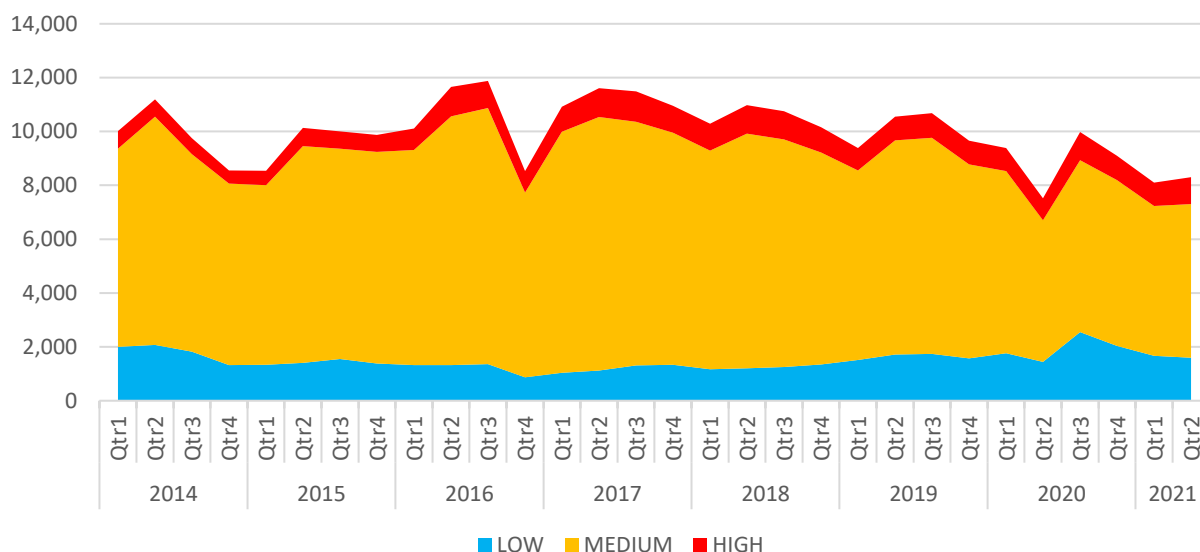


Figure 1: Monthly Missing Records per Quarter and Risk Rating

3.2 Descriptive statistics: comparisons by ethnicity

Table 1 includes the number and proportion of missing persons that were graded high risk by ethnicity across all missing person records considered. Notably, 10.8% of White missing people were rated as High risk, in contrast to 6.0% of Black subjects.

Table 1: Total Missing and Proportion Graded "High", by Ethnicity

Ethnicity	Missing Person Count	High Risk	Proportion Graded High
White	128,391	13,835	10.8%
Black	110,169	6,606	6.0%
Asian	28,705	2,467	8.6%
Dark European	14,218	1,134	8.0%
Unknown	9,171	942	10.3%
Arab	7,430	511	6.9%
Oriental	2,327	250	10.7%

Figure 2 shows the mean age and average number of times subjects were previously reported missing, calculated for the three largest ethnic groups – Asian, White and Black. **Compared**

to Asian and White missing persons, Black missing people were, on average, younger and were reported missing previously.

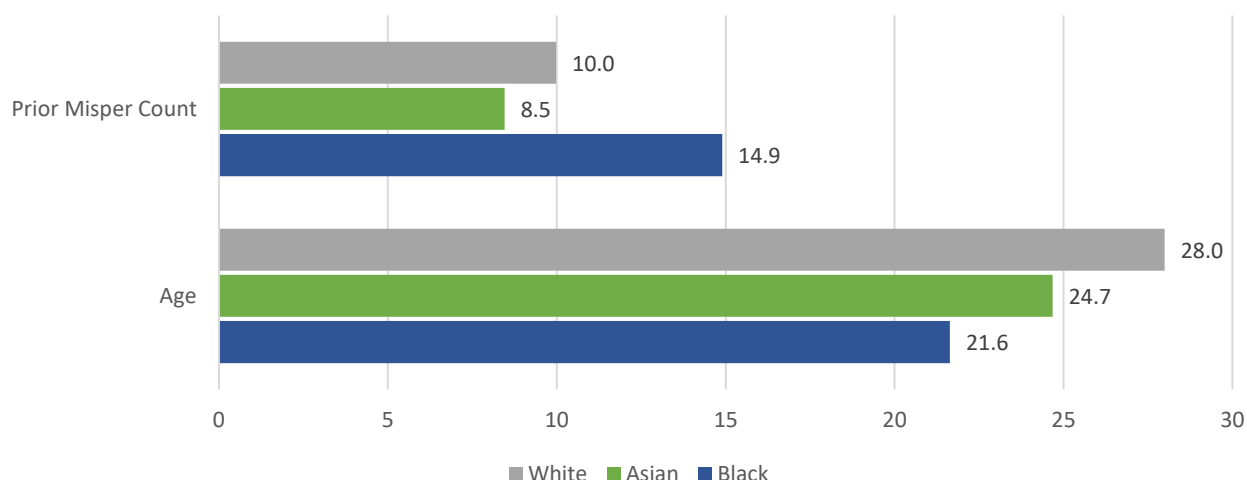


Figure 2: Prior Missing Reports (frequency) and Mean Age (in years) by Ethnicity

Figure 3 shows the proportion of missing persons who were graded high risk for Black, White and Asian missing persons as a function of age. We see broadly similar patterns for the three groups under the age of 18, and greater variation during adulthood. This would suggest that adultification of black children is not present when risk grading missing episodes. **Black missing persons between the ages of 18 and 60 were consistently the least likely to be graded high risk, whereas elderly Black subjects were more likely to receive high risk gradings than either White or Asian. The risk ratings for those under 18 were consistent across ethnicities.**

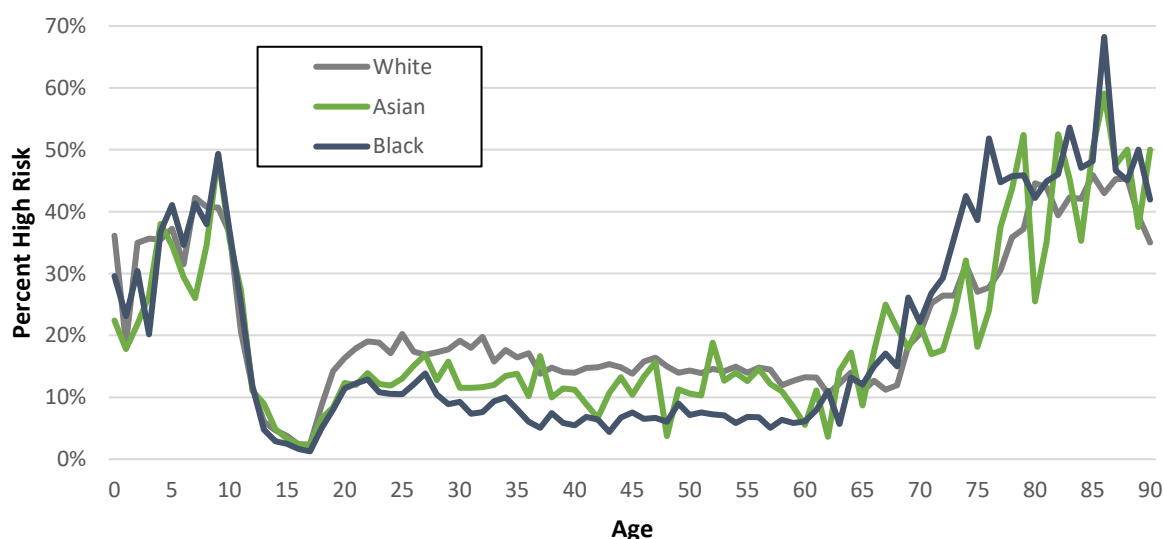


Figure 3: Proportion Graded High Risk by Age and Ethnicity

Table 2 details who reported the missing person, and when the report was made, for Asian, White and Black missing persons. **Missing person reports for Black subjects were slightly**

more likely to be made at night, and were more likely to be reported by a carer or social worker.

Table 2: Breakdown of informants that reported a person missing, and the shift during which the person was reported, by Ethnicity

Ethnic Appearance	Informant						Shift Reported		
	Carer	Social Worker	Partner	Friend	Medical	Family	Early	Late	Night
Black	32.4%	16.0%	1.7%	0.7%	6.6%	32.0%	18.4%	30.1%	51.4%
Asian	23.4%	11.3%	5.2%	1.5%	7.2%	39.8%	17.6%	34.6%	47.8%
White	27.2%	15.4%	5.4%	2.6%	9.7%	26.7%	18.0%	34.0%	47.9%

Across all ethnicities, **the apparent risk of serious harm is minute**. As shown in Table 3, less than 1% of all subjects were found in hospital or deceased. More than half returned of their own accord, and a third returned within a day of reporting. **White persons were more likely to be found hospitalised or deceased (0.37% and 0.43% respectively) than Asian (0.23% and 0.31%) or Black persons (0.22% and 0.16%).**

Table 3 - Distribution of Outcomes by Ethnicity

Ethnic Appearance	Own Accord	Own Accord (24 hrs)	Police	Hospital	Deceased
White	54.41%	31.24%	26.40%	0.37%	0.43%
Black	63.44%	34.12%	19.36%	0.22%	0.16%
Asian	56.30%	32.96%	24.53%	0.23%	0.31%
Dark European	57.76%	31.02%	21.85%	0.37%	0.38%
Unknown	56.30%	31.85%	21.88%	0.37%	0.26%
Arab	56.62%	30.31%	23.20%	0.34%	0.31%
Oriental	44.48%	27.37%	25.18%	0.56%	0.73%

To summarise, descriptive analysis suggests that both **the chance of receiving a high risk grade and the risk of suffering severe or fatal harm varies across different ethnicities**. The next section outlines approaches that allow for assessing the statistical reliability of risk factors while controlling for variables that are associated with the ethnicity of missing persons.

3.3 Multivariate analyses

To understand which factors predict the risk of harm to missing persons, we used logistic regression to attempt to isolate the effect of any one factor if *all other factors were held equal*. We then built two final models, examining both:

- Predicted risk, measured as whether or not a subject is graded High Risk; and
- Real risk, measured as whether or not a subject has experienced severe harm.

The final regression model includes the following factors:

- Risk factor presence, as suggested by a positive response to a risk question.
 - Age when missing
 - Subject ethnicity (as reported to police)
 - Sex
 - Nationality (i.e. if British)
 - Time report created
 - Time since last seen
 - Time elapsed between last sighting and report
 - Number of previous incidents when the individual was reported missing
 - Whether the subject was previously graded high risk
 - Informant (e.g., family, carer, friend, etc)
 - MPS Borough
 - Total number of missing persons in the preceding 8 hours for that borough
- (The full list of features and ratios is available in Annex E).*

Our final logistic regression model that examined the association between the input variables and the chance of missing persons being found deceased fit the data reasonably well (MacFadden's pseudo- $R^2 = 0.173$). An excellent fit was obtained with the logistic regression model that assessed the link between the input variables and the MPS risk grading (i.e., "predicted risk", pseudo- $R^2 = 0.238$).

We furthermore validated the results of the logistic regression models using a random forest algorithm (see Annex B). The main advantage of random forests over logistic regressions is that they do not assume a linear relation between the input variables and the predicted target variable. This is particularly interesting for variables that may have a u-shaped relation with the target variable. For example, as shown in Figure 3, very young and very old missing persons are most likely to receive a high risk grade, whereas risk grades tend to be lower for average aged persons. Although the results of random forest models are less straightforward to test for statistical significance than those obtained with a logistic regression, they provide a more nuanced understanding of the impact of continuous variables (e.g., age or prior missing person reports).

3.4 Factors influencing predicted risk (MPS Risk Grading)

Table 4 provides the odds ratios for each of the three largest ethnic groups. These figures indicate the relative likelihood of being graded high risk in comparison to the reference group (i.e., White persons). For example, the odds ratio of 0.85 for Black persons means that – after accounting for all of the other factors listed above – they were 0.85 times as likely to be rated high risk as White missing persons. Hence, their odds of being graded high risk were 15%⁵

⁵ Throughout this report we state odds ratios (ORs) and also percentage scores indicating the relative difference in odds for the relevant event taking place (e.g., being graded high risk) as compared with the reference group. These percentages are calculated by subtracting 1 from the respective OR before multiplying the result with 100%. For example, a resident from abroad who has gone missing in the UK (see Table 6) has an OR of 0.59 for being graded high risk relative to the reference group (i.e., a UK misper who does not reside abroad). For the former persons, the odds of being graded high risk are thus reduced by 41% $[(0.59 - 1) * 100\%]$ relative to the

lower than for White people. This suggests that ethnicity is a relevant factor that influences the likelihood that a missing person will receive a particular risk grading.

Table 4: Significant Odds Ratios for Ethnicity

Ethnicity	Odds Ratio
Black	0.85
Asian	0.87
White (reference)	1.00

Age is also an important factor influencing the risk grading decision-process. According to our logistic regression model, the odds of being graded high risk increase by 1.02 (+2%) for every additional year of difference from age 18. However, rather than assuming a linear relation between age and graded risk, the random forests model used to create the partial dependence plot⁶ in Figure 4 suggests that this relation is better described as being u-shaped. As shown in Figure 4, the probability of being graded high risk drops to the lowest level around age 16 and remains stable until around age 70, after which the probability of being graded high risk increases sharply. This pattern was found broadly consistent across all ethnicities.

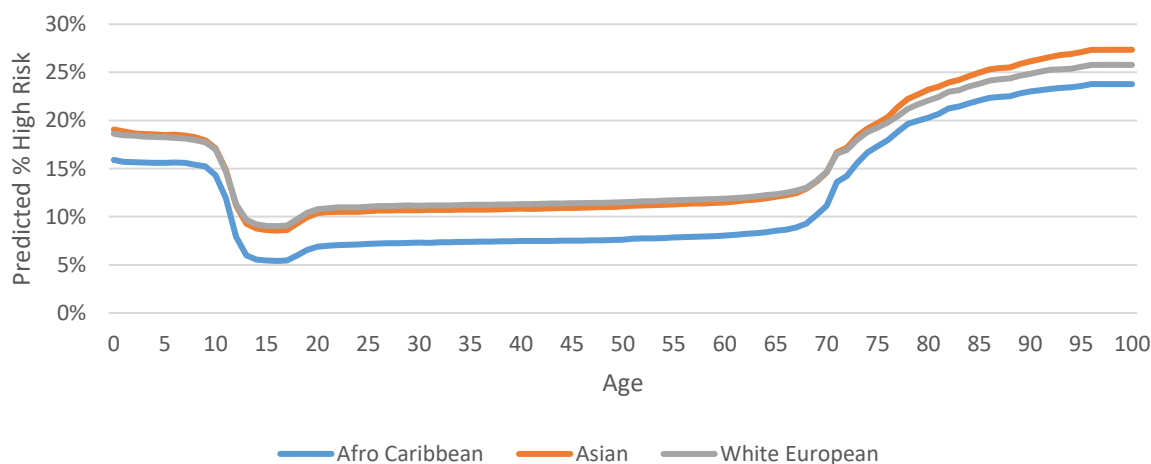


Figure 4: Partial Dependence Plot of High Risk as a Factor of Age and Ethnic Appearance

The following tables show odds ratios for a range of factors that strongly affect the probability of receiving a high risk grading. As we would expect, the answers to the standardised risk

reference group. Crucially, while any changes in odds are linked with changes in the probability of events, odds and probabilities are not identical concepts and cannot be used interchangeably. For example, Table 6 indicates that the odds of being deceased increase by 270% when suicide is suspected. However, this does not imply that suspected suicide increases the probability of death by this same percentage, or that the death toll is 270% higher for this group of mispers relative to mispers that are not suspected to commit suicide.

⁶ Partial dependence plots (PDPs) illustrate the influence of a variable of interest (such as age) on the target variable, while collapsing across all other variables that were included in a model. Hence, PDPs reflect the expected response in the target variable as a function of the input variable, independent of other variables.

assessment questions are especially predictive of a high risk grading, with suspicion of suicide or self-harm presenting the largest odds ratio among these items. **A missing person who is suspected to be at risk of suicide or self-harm has 3.7 times (+270%) the odds of receiving a high-risk rating compared with someone who is not. On the other hand, being reported by a social worker or carer reduces the chances of receiving a high risk rating (compared with those who are not reported by a social worker/carer).**

Table 5: Factors that reduce the probability of a high risk rating (left), and factors that increase the probability of a high risk rating (right)

Feature	Odds Ratio	Feature	Odds Ratio
Informant is social worker	0.36	High in last six months	4.36
Child Criminal Exploitation	0.41	Unknown Gender	4.00
Informant is a carer	0.43	Suspected suicide/s-harm	3.69
Prior missing person reports	0.44	Possible critical incident	3.13
From residential care home	0.56	Domestic incident	2.99

Among the answers to the risk assessment questions, positive responses to the questions on suspected suicide / self-harm and possible critical incidents are the strongest predictors of a high risk grade.

Table 6: Largest and smallest odds ratios, responses to 'risk questions'

Feature	Odds Ratio	Feature	Odds Ratio
Suspected suicide/s-harm	3.70	School/college problems	0.73
Possible critical incident	3.13	Drug dependency	0.67
Inability to interact safely with others	1.84	UK resident travelled abroad	0.67
Other unlisted factors which officer/supv feels relevant	1.42	Resident abroad, missing in UK	0.59
Mental illness	1.37	Community concerns	0.56

The frequency of prior missing episodes also influences risk grading decisions, but the relation between these variables is not linear, as confirmed by our random forests model. As shown in Figure 5, persons who have been reported missing for the first time are more likely to receive a high risk grading than persons who have been missing on several occasions. After a few dozens of missing episodes, there is a slow rebound, and chances to receive a high risk grading increase progressively. **In simple words, being a regular missing person reduces the risk grade, but being an extreme case increases it. This pattern of results was generally consistent across all ethnicities.**

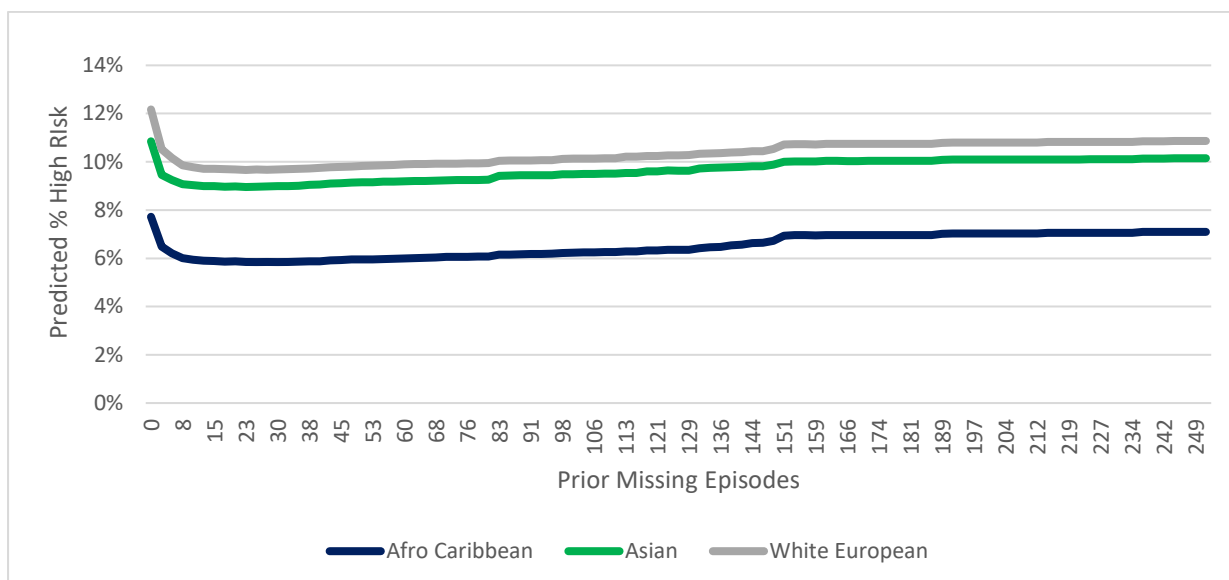


Figure 5: Predicted likelihood of high risk grading, by number of previous reports

To summarise, our analyses have highlighted the wide range of factors affecting a risk grading, with past behaviour of the individual, as well as social, demographic, and geographic factors playing a role. While **there are a number of variables that impact the risk grade assigned by the MPS more strongly than ethnicity (e.g., age, gender, suicidal tendencies, mental health crises, and the role of the informant reporting the missing person)**, our results confirm that **ethnicity of the missing person does influence risk grading decisions within the MPS**. Members of both Black and Asian minorities are less likely to receive a high risk grading than White persons, even when other variables that may affect the risk grading decision have been controlled for.

3.5 Real risk: Different definitions

In the previous section, we have used machine learning to examine which variables are significantly associated with the risk gradings assigned by the MPS to missing persons (i.e., “predicted risk”). For this section, we employed a similar approach to explore which variables are linked with the possibility that a missing person suffers serious harm (i.e., “real risk”).

What outcome qualifies as serious harm? Death is clearly the most harmful outcome; the prevalence of this outcome is very low, ranging from 0.16% for Asians to 0.43% for White missing persons (see Table 3). Hospitalisation could also be interpreted as an outcome indicating severe harm, however, this interpretation is based on a conjecture, as the cancellation code recorded on Merlin does not inform about the specific reason why a missing person had been admitted to hospital. Hospitalisation may have been the direct consequence of harmful events that occurred during the missing episode, but it could also have been linked with pre-existing conditions (e.g., mental vulnerabilities, physical ailments, age-related need for medical attention, etc.), or even police actions that were taken to retrieve the missing person.

Broadening the definition by aggregating outcomes would increase the prevalence of a positive outcome (i.e., serious harm) in the dataset, but it may hamper classification if the aggregated events are associated with different patterns in the input variables.

An alternative strategy could be to focus on the complement of the outcome of interest, that is, outcomes that would not be considered as severely harmful to the missing person. These would include cases where the missing person had been returned by the Police or returned of their own accord (possibly, within a certain timeframe, such as 24h after having been reported missing).

It should be noted that due to system limitations if harm is disclosed after report closing this is not accounted for nor does merlin link to any subsequent criminal allegations that may include harm so this cannot be included within the data.

Table 7 shows the goodness-of-fit for statistical models that used the same input variables but different outcome measure. The best fit to the data – as indexed by pseudo R^2 scores – was provided by the model that tested whether the input variables were associated with the outcome that the missing person would be found deceased (pseudo $R^2 = 0.173$).

Table 7: Model fits for different outcome variables

Outcome	Pseudo R-Squared
Dead	0.1732
Found in Hospital	0.1165
Found Dead or In Hospital	0.1372
Returned by Police	0.0801
Returned of Own Accord	0.0918
Returned within 24 Hours	0.0355

Figure 6 shows the odds ratios for Asian and Black people for different outcomes, namely, to return of their own accord, to be returned by the Police, to be hospitalised, and to be found deceased. The ORs for these ethnicities were measured relative to White missing persons (which would therefore have an OR of 1). **Results indicate that both Asian and Black people are less likely to be found deceased or hospitalised than White people, and are more likely to return of their own accord. However, members of both Asian and Black minorities are less likely to be returned by the Police than White people.**

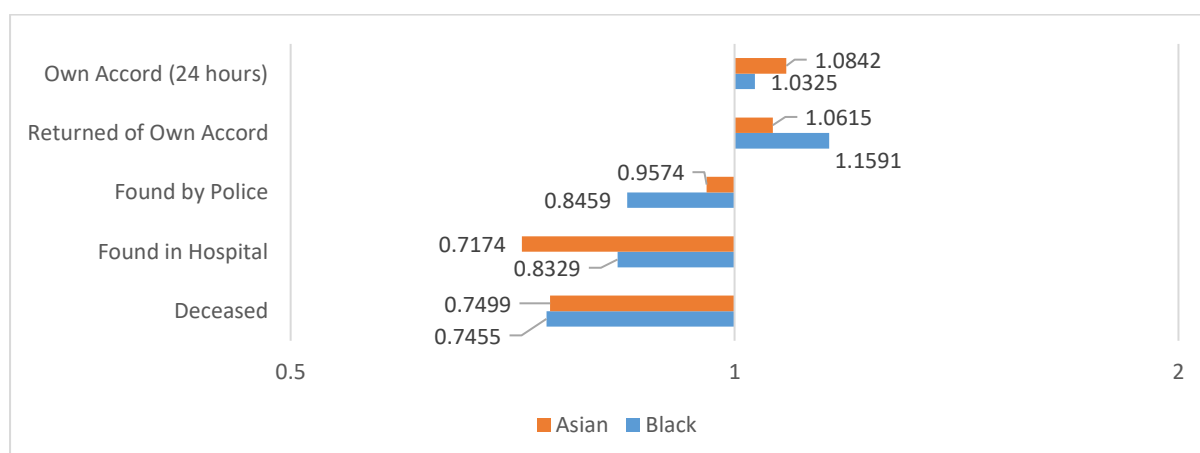


Figure 6: Odds Ratios for different Outcomes by Ethnicity (relative to White people)

3.6 Does Predicted Risk reflect Real Risk?

To explore whether MPS risk ratings were consistent with real risk, we initially included these MPS risk ratings as an input variable in our regression models that were used to predict different types of real risk. In these models, a low risk grade was used as reference category for estimating odds ratios for medium and high risk grades. As shown in Figure 7, **the MPS risk grades were indeed indicative of real risk, as the odds of being found deceased were 1.31 times (+31%) higher for missing persons that had been graded as medium risk rather than low risk. Further, the odds of being found dead were 2.35 times (+135%) higher for persons graded high risk relative to low risk.**

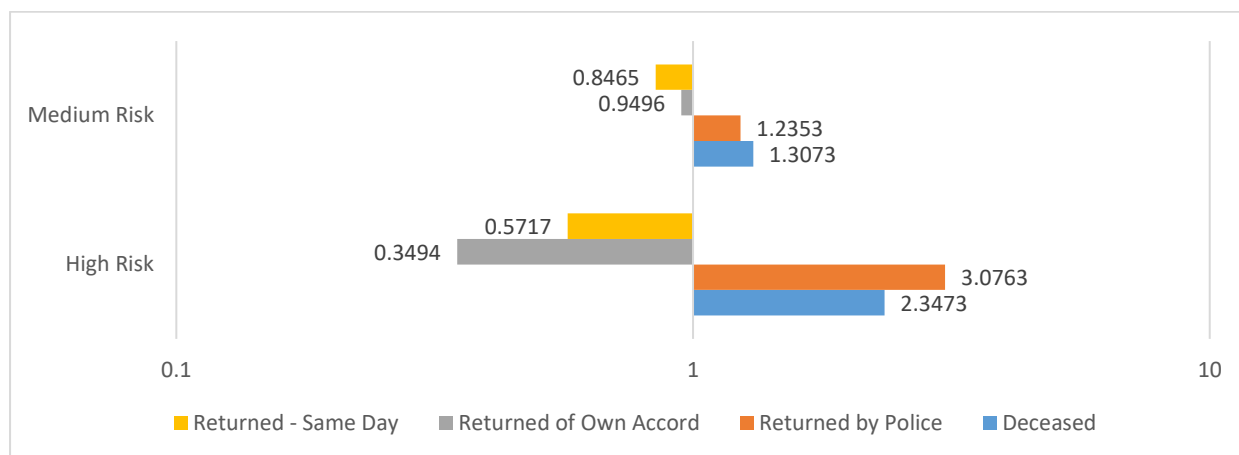


Figure 7: Odds Ratio for Risk Rating (medium or high, as compared with low) by Model Outcome.

Judging from the graph, it is also obvious that MPS risk grades reflect the amount of operational resources dedicated to finding the missing persons: **medium and high risk grades increased the odds of being returned by the Police by a factor of 1.24 (+24%) and 3.08 (+208%), respectively, relative to a low risk grade.**

Including the MPS risk gradings into the statistical models predicting real risk may however be problematic, as they are not independent of other factors that influence the outcome. Being graded high risk is primarily a prediction of risk, but will influence the outcome by determining the nature of the police response, and our analyses do not easily allow for identifying when police action led to a safe return.

To assess the importance of the risk ratings for the statistical models, we compared model fits with and without this variable for the model that predicted whether or not a person would be found deceased. Despite being statistically significant, risk ratings had a relatively minor influence on model fit, with only small decreases in model accuracy when the risk rating was removed⁷. To avoid the aforementioned caveat and given this observation, MPS risk ratings have been excluded from the regression models reported below.

For a number of variables, we noticed discrepancies between the results of the regression model that predicted the MPS risk rating as opposed to the model used to predict real risk (here, whether a person was found deceased). Figure 8 shows the ORs estimated by the

⁷ As indicated by a decrease in the pseudo R-squared score from 0.173 to 0.168

“predicted risk” model (orange bars) versus the “real risk” model (blue bars). Both models were generally in agreement for informants that were social workers, carers, friends or family members. **Discrepancies however emerged for persons that were reported missing by their partner or by medical staff, where the likelihood of obtaining a high risk grade was higher than the likelihood of being found deceased.**

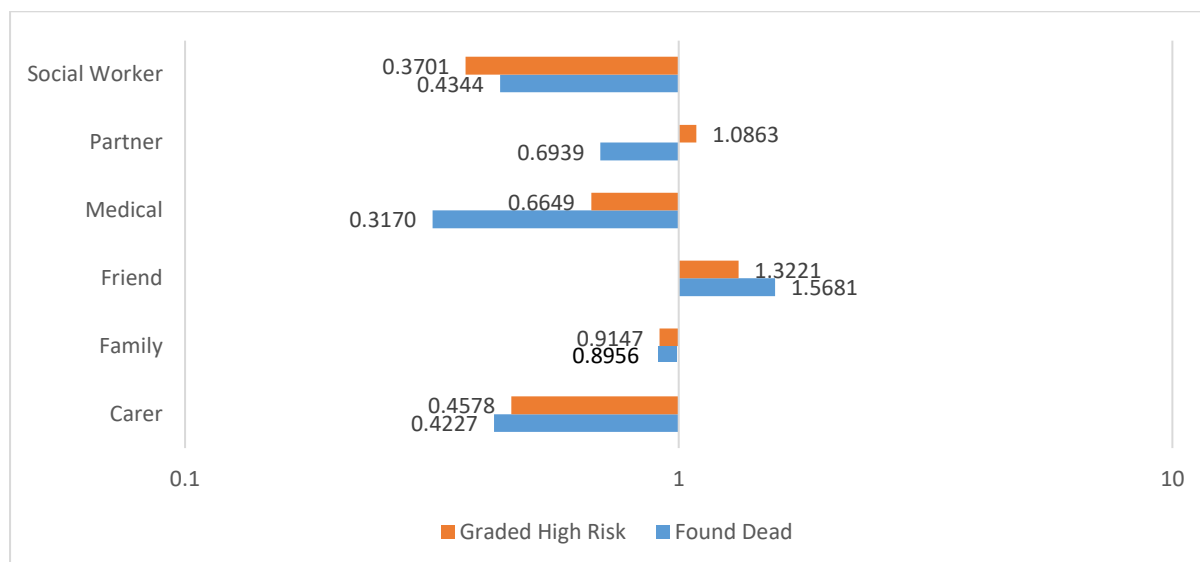


Figure 8: Odds Ratios for informant, predicted vs real risk.

4. Conclusions and next steps

Our modelling has highlighted that that Black and Asian ethnicities are indeed less likely to receive a high risk grade than White persons (ORs of 0.85 and 0.87 respectively, that is, 15% and 13% lower odds of being graded high risk than White people), but their real risk (odds of being found deceased) is also lower. Asian and Black people were less likely to be found deceased (ORs of 0.75 for both, 25% lower odds) or hospitalised (ORs of 0.72 and 0.83 respectively, 28% and 17% lower odds) than White people, and were more likely to return of their own accord (ORs of 1.06 and 1.16 respectively, 6% and 16% higher odds than White people). However, members of both Asian and Black minorities were less likely to be returned by the Police than White people (ORs of 0.96 and 0.85 respectively, 4% and 15% lower odds), which may – in part – reflect their lower chances of receiving a high MPS risk rating.

The likelihood of an outcome for each missing person (including coming to serious harm) varies by age and demography, but the perceived risk grading are a strong predictor, suggesting that officers are generally accurate in forecasting risk.

Further analysis could focus on more clearly identifying the impact of police action, and – if feasible - differentiating missing subjects who returned of their own accord (and could have been safely deprioritised) from those who only returned due to police intervention. Vignette studies could also be used to further explore MPS decision-making. Machine-learning based prediction and a decision making framework (as we have implemented for strip search decisions) may further help officers in prioritising the cases most likely to be at risk.

Technical Annex

Annex A – College of Policing Risk Definitions

No apparent risk (absent)

There is no apparent risk of harm to either the subject or the public.

Actions to locate the subject and/or gather further information should be agreed with the informant and a latest review time set to reassess the risk.

Low risk

The risk of harm to the subject or the public is assessed as possible but minimal.

Proportionate enquiries should be carried out to ensure that the individual has not come to harm.

Medium risk

The risk of harm to the subject or the public is assessed as likely but not serious.

This category requires an active and measured response by the police and other agencies in order to trace the missing person and support the person reporting.

High risk

The risk of serious harm to the subject or the public is assessed as very likely.

This category almost always requires the immediate deployment of police resources – action may be delayed in exceptional circumstances, such as searching water or forested areas during hours of darkness. A member of the senior management team must be involved in the examination of initial lines of enquiry and approval of appropriate staffing levels. Such cases should lead to the appointment of an investigating officer (IO) and possibly an SIO, and a police search adviser (PoISA).

There should be a press/media strategy and/or close contact with outside agencies. Family support should be put in place where appropriate. The MPB should be notified of the case without undue delay. Children's services must also be notified immediately if the person is under 18.

Annex B –Technical Note: Predicting high risk gradings

For the analysis reported in the main text, we have fitted a logistic regression model to mispers data to examine which variables are associated with the outcomes of interest (i.e., MPS risk gradings and risk of serious harm). To validate our results, we used these and additional variables to predict whether particular mispers would receive a high risk grading or not. For this work, we fitted a Random Forest classifier to a subset of the original data (the “training set”) and then used this classifier on the remaining “test set” (i.e., data the classifier had not seen during training).

Random Forests tend to be more accurate than logistic regression models in prediction tasks, and importantly, they do not assume that the relationship between the input and output variables is linear. For example, the partial dependency plots in Figures 4 and 5 (which have been generated using a Random Forest classifier) all illustrate u-shaped relationships between the target variable (MPS risk grading) and the input variable of interest (age in Fig. 4, number of previous missing person reports in Fig. 5).

Here, a Random Forest model was fitted on the training set (66.6% of the original data, that is, around 200k records) using the defaults of the Scikit Learn Python library. The target variable was whether or not the record was initially graded as high risk. The input variables involved all variables previously included in our logistic regression model, as well as all local demographic and financial data at LSOA level provided by the ONS for both the subject’s missing LSOA and the surrounding area, as calculated by the spatial lag of each factor (full code and output tables are available on request). Model performance was then assessed on the test set (33.3% of the original data, that is, around 100k records). The Random Forest model accurately predicted over 92% of risk gradings in the test set (see Table 8).

Table 8: Model Classification Report

	Precision	Recall	F1-Score
Not High Risk	0.93	0.99	0.96
High-Risk	0.69	0.13	0.22

Accuracy			0.92
Macro Average	0.81	0.56	0.59
Weighted Average	0.91	0.92	0.9

While the model is far from perfect – due to the imbalanced nature of our sample, it performs far better on the dominant class – it is accurate on a large portion of our dataset (as seen by the 0.9 weighted average F-1 score).

Using this Random Forest model, we also calculated “feature importances”, which allow for identifying the variables most important for successfully predicting the outcome (see Fig 10). Feature importance is calculated by permuting individual features, and examining the reduction in model performance as measured by the area under the Receiver Operating Characteristic (ROC) curve. In layperson’s terms, the change in the model’s ability to correctly predict the target is measured before and after one input variable has been replaced with random values, which allows for estimating the importance of this variable for prediction success. In our case, age was the most important predictor, with the model losing nearly 30% of its predictive ability when the subject’s age was unknown. Overall, the feature importances obtained from the Random Forests model corroborate the results of the logistic regression: age, suspected self-harm, and previous high risk gradings are reliable predictors of future risk. By contrast, while ethnicity does play a role, it is relatively minor (being White is the 34th most important feature).

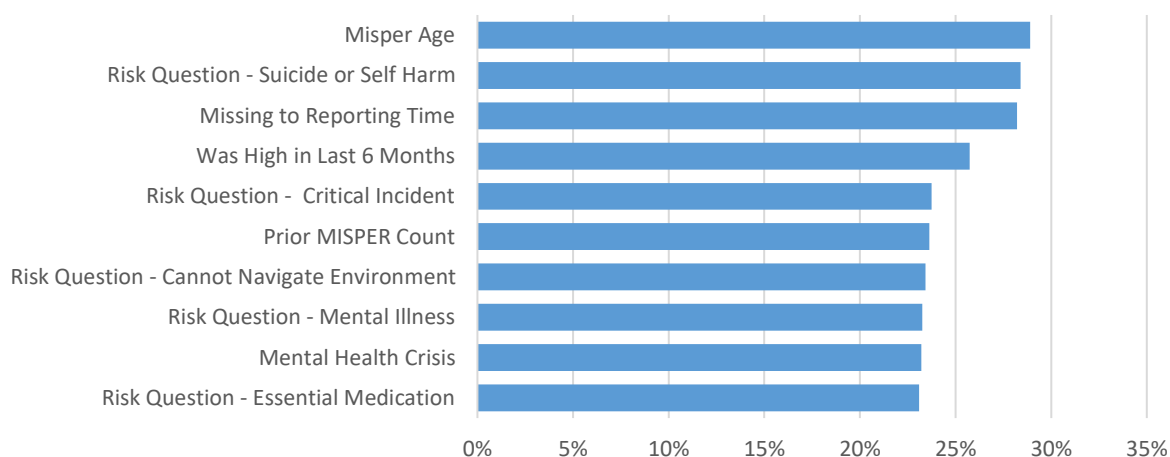


Figure 9: Top 10 Features (sorted by percentage loss in forecasting accuracy)

Annex C – Comparison by borough

Table 9: Likelihood of high risk grading by borough, compared to Westminster

Borough	Odds Ratio
Hackney	1.63
Southwark	1.56
Haringey	1.53
Hillingdon	1.47

Borough	Odds Ratio
Redbridge	0.65
Kensington & Chelsea	0.69
Tower Hamlets	0.82
Westminster	1.00

Annex D – Risk Assessment Questions

P1	10 years old or under, 11 to 14 years of age, 15 to 17 years of age, over 65 years of age
P2	On the Child Protection Register
P3	Needs essential medication or treatment not readily available to them, e.g. diabetes, epilepsy, etc
P4	Belief that person may not have the physical ability to interact safely with others or an unknown environment, e.g. amnesia, visually impaired, Down's Syndrome
P5	Mental illness or psychological disorder that may increase risk of harm to themselves or others
P6	Drug dependency
P7	Alcohol dependency
C1	Suspicion of abduction / murder
C2	Suspected suicide or self harm
C3	Involved in violent and/or racial/ homophobic/ transphobic/ domestic violence incident or confrontation prior to disappearance
C4	Out of character e.g. unusual behaviour prior to disappearance, disappeared with no prior indication, etc
C5	Inclement weather conditions
C6	Family/relationship problems or recent/history or family conflict/abuse
C7	Employment problems
C8	Financial problems
C9	School or College problems
C10	Ongoing victim of bullying or harassment, e.g. racial, sexual, homophobic, transphobic etc. or local community concerns
C11	Previously disappeared and suffered or was exposed to harm whilst missing
C12	Other unlisted factors which the officer or supervisor feels should influence the risk assessment
C13	The person is normally resident in the UK and is believed to have travelled abroad
C14	The person is normally resident abroad and is believed to have gone missing whilst in the UK
C15	The person reporting or the family believe that there are other special factors to be considered
X1	Are there any community concerns about this persons disappearance?
X2	Is there any reason to treat this persons disappearance as a critical incident?

Annex E – Logistic Model Odds Ratios: MPS risk rating (predicted risk)

Feature	P Value	0.0500	0.9500	Odds Ratio
Constant	0.0000	0.0424	0.0555	0.0485
P1	0.4999	0.9778	1.0472	1.0119
P2	0.0000	0.8071	0.8990	0.8518
P3	0.0000	0.8751	0.9415	0.9077
P4	0.0000	1.7703	1.9161	1.8418
P5	0.0000	1.3189	1.4194	1.3682
P6	0.0000	0.6380	0.6984	0.6675
P7	0.0000	0.7283	0.7998	0.7632
C1	0.1956	0.5397	1.1345	0.7825
C2	0.0000	3.5630	3.8329	3.6955
C3	0.5694	0.9336	1.0385	0.9846
C4	0.0000	1.1076	1.1839	1.1451
C5	0.1249	0.9290	1.0090	0.9682
C6	0.0000	1.1650	1.2589	1.2110
C7	0.0000	0.8045	0.9028	0.8523
C8	0.0001	0.8401	0.9438	0.8904
C9	0.0000	0.6975	0.7716	0.7336
C10	0.3502	0.9155	1.0318	0.9719
C11	0.0000	1.2125	1.3318	1.2708
C12	0.0000	1.3665	1.4788	1.4215
C13	0.0000	0.6208	0.7132	0.6654
C14	0.0000	0.5395	0.6362	0.5859
C15	0.2713	0.9764	1.0885	1.0310
X1	0.0000	0.5257	0.6044	0.5637
X2	0.0000	2.9417	3.3395	3.1343
Child Sexual Exploitation Flag	0.0037	0.7027	0.9338	0.8100
Child Criminal Exploitation Flag	0.0000	0.3273	0.5022	0.4054
Mental Health Crisis Flag	0.0000	2.2890	2.5942	2.4368
Domestic Incident Flag	0.0000	2.5621	3.4802	2.9861
Owning Borough - Barking and Dagenham	0.6483	0.8524	1.1045	0.9703
Owning Borough - Barnet	0.0173	1.0239	1.2770	1.1435
Owning Borough - Bexley	0.5138	0.9264	1.1651	1.0389
Owning Borough - Brent	0.4138	0.8543	1.0669	0.9547
Owning Borough - Bromley	0.0005	1.0909	1.3677	1.2215
Owning Borough - Camden	0.0078	1.0407	1.3005	1.1634
Owning Borough - Croydon	0.0004	1.0837	1.3207	1.1964
Owning Borough - Ealing	0.0000	1.1486	1.4157	1.2752
Owning Borough - Enfield	0.5543	0.8671	1.0795	0.9675
Owning Borough - Greenwich	0.9252	0.8868	1.1414	1.0061
Owning Borough - Hackney	0.0000	1.4697	1.8104	1.6312

Owning Borough - Hammersmith and Fulham	0.0011	1.0895	1.4095	1.2392
Owning Borough - Haringey	0.0000	1.3822	1.6850	1.5261
Owning Borough - Harrow	0.0183	0.7105	0.9689	0.8297
Owning Borough - Havering	0.9024	0.8705	1.1301	0.9919
Owning Borough - Hillingdon	0.0000	1.3218	1.6410	1.4728
Owning Borough - Hounslow	0.0000	1.1736	1.4526	1.3056
Owning Borough - Islington	0.0000	1.2063	1.5059	1.3478
Owning Borough - Kensington and Chelsea	0.0000	0.5906	0.8037	0.6890
Owning Borough - Kingston upon Thames	0.7220	0.8490	1.1200	0.9752
Owning Borough - Lambeth	0.1992	0.9655	1.1833	1.0689
Owning Borough - Lewisham	0.5472	0.8735	1.0743	0.9687
Owning Borough - Merton	0.2075	0.9542	1.2406	1.0880
Owning Borough - Newham	0.0551	0.9977	1.2370	1.1109
Owning Borough - Redbridge	0.0000	0.5748	0.7333	0.6492
Owning Borough - Richmond upon Thames	0.0011	1.0923	1.4238	1.2471
Owning Borough - Southwark	0.0000	1.4015	1.7270	1.5558
Owning Borough - Sutton	0.0704	0.9903	1.2771	1.1246
Owning Borough - Tower Hamlets	0.0006	0.7250	0.9167	0.8152
Owning Borough - Waltham Forest	0.0000	1.2347	1.5284	1.3737
Owning Borough - Wandsworth	0.8916	0.9046	1.1221	1.0075
Subject Age - Years from 18	0.0000	1.0184	1.0201	1.0192
Missing to Reported Time (Z Score)	0.0000	0.6800	0.8395	0.7556
Reported to Grading Time (Z Score)	0.0000	1.0833	1.1186	1.1008
Prior missing person Count (Z Score)	0.0000	0.4185	0.4626	0.4400
In Foster Care	0.0000	0.6867	0.8177	0.7493
In Residential Care Home	0.0000	0.5216	0.6024	0.5606
Subject Gender Female	0.0000	1.0425	1.1061	1.0739
Subject Gender Transgender	0.6273	0.7850	1.4942	1.0830
Subject Gender Unknown	0.0000	2.3446	6.8165	3.9978
Subject Ethnicity - Afro Caribbean	0.0000	0.8221	0.8829	0.8519
Subject Ethnicity - Arab	0.0230	0.8045	0.9840	0.8898
Subject Ethnicity - Asian	0.0000	0.8312	0.9207	0.8748
Subject Ethnicity - Dark European	0.0054	0.8410	0.9704	0.9034
Subject Ethnicity - Oriental	0.0889	0.7614	1.0195	0.8810
Subject Ethnicity - Unknown	0.0119	1.0228	1.1996	1.1077
Informant Location - Home Address	0.0026	0.9092	0.9800	0.9440
Subject Nationality - British or English	0.0000	1.0549	1.1482	1.1005
Informant is carer	0.0000	0.4078	0.4575	0.4319
Informant is social worker	0.0000	0.3350	0.3821	0.3578
Informant is partner	0.0175	1.0133	1.1480	1.0786
Informant is friend	0.0000	1.2185	1.4282	1.3192
Informant is medical staff	0.0000	0.5889	0.6589	0.6229
Informant is family member	0.0000	0.8552	0.9357	0.8945
Created on Late Turn (1400-2300)	0.0000	1.1524	1.2459	1.1982

Created Early Turn (0700-1400)	0.0003	0.8871	0.9645	0.9249
Number of missing persons on Borough Last 8 Hrs (Z Score)	0.0388	0.9683	0.9992	0.9836
Previous High Risk missing person	0.0000	4.1362	4.6010	4.3624
ONS - LSOA Population - 0 to 15 y/o	0.0001	1.0002	1.0005	1.0003
ONS - LSOA Population - 45 to 64 y/o	0.0000	0.9992	0.9996	0.9994
ONS - LSOA Population - Mixed/multiple ethnic groups_2011	0.0000	0.9982	0.9992	0.9987
ONS - LSOA Population Economically Inactive (2011)	0.0340	0.9997	1.0000	0.9998

Annex F – Logistic Model Odds Ratios: Deceased (real risk), MPS risk rating *included*

Feature	P Value	0.0500	0.9500	Odds Ratio
Constant	0.0000	0.0076	0.0239	0.0135
Age 0-4	0.0032	0.0300	0.4949	0.1219
Age 5-10	0.0000	0.0236	0.2351	0.0744
Age 11-14	0.0000	0.0241	0.0728	0.0419
Age 15-16	0.0000	0.0424	0.1025	0.0659
Age 17-18	0.0000	0.1277	0.2742	0.1871
Age 19-20	0.0000	0.2461	0.5820	0.3785
Age 71-80	0.7257	0.6819	1.3056	0.9435
Age 81+	0.0632	0.4602	1.0210	0.6855
P1	0.8088	0.8616	1.2104	1.0212
P2	0.0093	1.1057	2.0466	1.5043
P3	0.0957	0.9765	1.3407	1.1442
P4	0.0000	0.4646	0.7130	0.5756
P5	0.0006	0.6412	0.8854	0.7535
P6	0.0007	0.5849	0.8665	0.7119
P7	0.7813	0.8064	1.1756	0.9737
C1	0.8928	0.1573	8.3520	1.1463
C2	0.0000	1.4370	2.0288	1.7075
C3	0.0001	0.4521	0.7690	0.5896
C4	0.0000	1.5007	2.0390	1.7493
C5	0.2322	0.7312	1.0789	0.8882
C6	0.0036	0.6310	0.9141	0.7594
C7	0.9465	0.7872	1.2503	0.9921
C8	0.8233	0.7711	1.2297	0.9738
C9	0.7195	0.7142	1.2615	0.9492
C10	0.0039	1.1434	2.0180	1.5190
C11	0.0846	0.6320	1.0298	0.8067
C12	0.2405	0.9280	1.3468	1.1180
C13	0.0189	1.0492	1.7057	1.3378
C14	0.4492	0.6501	1.2101	0.8870
C15	0.9073	0.7949	1.2951	1.0146
X1	0.6041	0.8029	1.4584	1.0821
X2	0.0322	1.0263	1.7944	1.3570
Missing to Reported Time (Z Score)	0.2126	0.9912	1.0405	1.0155
Reported to Grading Time (Z Score)	0.1007	0.9887	1.1375	1.0605
Prior missing person Count (Z Score)	0.0015	0.4843	0.8419	0.6386
Owning Borough - Barking and Dagenham	0.0278	0.2463	0.9223	0.4766
Owning Borough - Barnet	0.9779	0.6482	1.5242	0.9940
Owning Borough - Bexley	0.2309	0.4546	1.2095	0.7415
Owning Borough - Brent	0.9724	0.6611	1.5353	1.0075

Owning Borough - Bromley	0.2064	0.4452	1.1911	0.7282
Owning Borough - Camden	0.2038	0.4539	1.1835	0.7329
Owning Borough - Croydon	0.0058	0.3370	0.8320	0.5295
Owning Borough - Ealing	0.8700	0.6390	1.4606	0.9661
Owning Borough - Enfield	0.0746	0.4075	1.0434	0.6521
Owning Borough - Greenwich	0.3998	0.4733	1.3478	0.7987
Owning Borough - Hackney	0.5504	0.5522	1.3722	0.8705
Owning Borough - Hammersmith and Fulham	0.3104	0.4450	1.2936	0.7587
Owning Borough - Haringey	0.0203	0.3689	0.9194	0.5824
Owning Borough - Harrow	0.4242	0.4272	1.4301	0.7817
Owning Borough - Havering	0.5454	0.5016	1.4399	0.8499
Owning Borough - Hillingdon	0.0633	0.3832	1.0261	0.6271
Owning Borough - Hounslow	0.1277	0.4415	1.1080	0.6994
Owning Borough - Islington	0.3134	0.4904	1.2567	0.7850
Owning Borough - Kensington and Chelsea	0.3088	0.4160	1.3199	0.7410
Owning Borough - Kingston upon Thames	0.3214	0.4123	1.3374	0.7425
Owning Borough - Lambeth	0.6155	0.6046	1.3470	0.9025
Owning Borough - Lewisham	0.1366	0.4634	1.1108	0.7175
Owning Borough - Merton	0.0952	0.3350	1.0918	0.6048
Owning Borough - Newham	0.6258	0.5682	1.4050	0.8935
Owning Borough - Redbridge	0.0777	0.3678	1.0540	0.6226
Owning Borough - Richmond upon Thames	0.8704	0.5689	1.6118	0.9576
Owning Borough - Southwark	0.0304	0.3653	0.9511	0.5894
Owning Borough - Sutton	0.1318	0.3705	1.1385	0.6495
Owning Borough - Tower Hamlets	0.3482	0.4902	1.2858	0.7939
Owning Borough - Waltham Forest	0.7799	0.6050	1.4581	0.9392
Owning Borough - Wandsworth	0.3583	0.5269	1.2609	0.8150
In Foster Care	0.3272	0.7298	2.5715	1.3700
In Kinship (Familial) Care	0.7177	0.1997	10.3747	1.4395
In Residential Care Home	0.0242	0.3438	0.9283	0.5649
Gender Female	0.0000	0.4214	0.5724	0.4911
Gender Transgender	0.4871	0.0678	3.6055	0.4944
Gender Unknown	0.9994	0.0000	inf	0.0000
Subject Ethnicity - Afro Caribbean	0.0019	0.6346	0.9026	0.7568
Subject Ethnicity - Asian	0.0219	0.6067	0.9617	0.7638
Informant Location - Home Address	0.0006	1.1352	1.5834	1.3407
Nationality British/English	0.0005	0.6491	0.8874	0.7590
Informant Carer	0.0000	0.3262	0.6143	0.4476
Informant Social Worker	0.0000	0.3458	0.6450	0.4723
Informant Partner	0.0028	0.5517	0.8838	0.6983
Informant Friend	0.0002	1.2448	1.9981	1.5771
Informant Medical Staff	0.0000	0.2418	0.4428	0.3272
Informant Family	0.3119	0.7517	1.0954	0.9074
Created on Late Turn	0.2740	0.9264	1.3094	1.1014

Created on Night Turn	0.3145	0.7505	1.0967	0.9072
ONS - LSOA Pop. 0 to 15y	0.1746	0.9987	1.0002	0.9995
ONS - LSOA Pop. 45 to 64y	0.0787	0.9999	1.0019	1.0009
ONS - LSOA Pop. Mixed/multiple ethnic groups	0.7614	0.9973	1.0020	0.9996
ONS - LSOA Pop. Economically Inactive	0.0228	0.9983	0.9999	0.9991
Borough Business (Z score)	0.0953	0.9896	1.1385	1.0615
MPS Risk Grading: High	0.0000	1.8779	2.9342	2.3473
MPS Risk Grading: Medium	0.0058	1.0806	1.5817	1.3073

Annex G – Logistic Model Odds Ratios: Deceased (real risk), MPS risk rating *excluded*

Feature	P Value	0.0500	0.9500	Odds Ratio
Constant	0.0000	0.0091	0.0283	0.0161
Age 0-4	0.0078	0.0369	0.6063	0.1495
Age 5-10	0.0001	0.0309	0.3067	0.0973
Age 11-14	0.0000	0.0253	0.0759	0.0438
Age 15-16	0.0000	0.0432	0.1037	0.0670
Age 17-18	0.0000	0.1268	0.2718	0.1857
Age 19-20	0.0000	0.2416	0.5711	0.3715
Age 71-80	0.5116	0.8079	1.5342	1.1133
Age 81+	0.4672	0.5833	1.2806	0.8643
P1	0.8237	0.8603	1.2082	1.0195
P2	0.0246	1.0463	1.9417	1.4254
P3	0.0988	0.9753	1.3390	1.1428
P4	0.0000	0.4819	0.7405	0.5974
P5	0.0099	0.6895	0.9505	0.8096
P6	0.0003	0.5712	0.8452	0.6948
P7	0.6269	0.7912	1.1516	0.9545
C1	0.9501	0.1463	7.7618	1.0654
C2	0.0000	1.7937	2.4869	2.1121
C3	0.0001	0.4424	0.7582	0.5792
C4	0.0000	1.4908	2.0249	1.7375
C5	0.1816	0.7202	1.0641	0.8755
C6	0.0109	0.6531	0.9461	0.7860
C7	0.9119	0.7834	1.2435	0.9870
C8	0.7696	0.7650	1.2192	0.9658
C9	0.5974	0.6966	1.2313	0.9261
C10	0.0069	1.1136	1.9679	1.4804
C11	0.1013	0.6377	1.0410	0.8148
C12	0.1094	0.9664	1.4033	1.1646
C13	0.0631	0.9875	1.6046	1.2588
C14	0.3157	0.6244	1.1642	0.8526
C15	0.9327	0.7910	1.2912	1.0106
X1	0.9967	0.7369	1.3587	1.0006
X2	0.0027	1.1629	2.0536	1.5454
Missing to Reported Time (Z Score)	0.3174	0.9876	1.0392	1.0131
Reported to Grading Time (Z Score)	0.0139	1.0179	1.1698	1.0912
Prior missing person Count (Z Score)	0.0008	0.4694	0.8214	0.6209
Owning Borough - Barking and Dagenham	0.0371	0.2562	0.9589	0.4956
Owning Borough - Barnet	0.8874	0.6732	1.5800	1.0313
Owning Borough - Bexley	0.3285	0.4811	1.2775	0.7839
Owning Borough - Brent	0.8271	0.6881	1.5963	1.0480

Owning Borough - Bromley	0.3430	0.4827	1.2883	0.7886
Owning Borough - Camden	0.2659	0.4722	1.2299	0.7621
Owning Borough - Croydon	0.0161	0.3661	0.9024	0.5748
Owning Borough - Ealing	0.9576	0.6692	1.5282	1.0113
Owning Borough - Enfield	0.1221	0.4322	1.1041	0.6908
Owning Borough - Greenwich	0.5058	0.4966	1.4122	0.8374
Owning Borough - Hackney	0.7770	0.5945	1.4751	0.9364
Owning Borough - Hammersmith and Fulham	0.3894	0.4644	1.3484	0.7914
Owning Borough - Haringey	0.0412	0.3944	0.9812	0.6221
Owning Borough - Harrow	0.4543	0.4342	1.4525	0.7941
Owning Borough - Havering	0.5973	0.5125	1.4691	0.8677
Owning Borough - Hillingdon	0.1486	0.4261	1.1379	0.6963
Owning Borough - Hounslow	0.2150	0.4726	1.1837	0.7479
Owning Borough - Islington	0.4490	0.5212	1.3343	0.8340
Owning Borough - Kensington and Chelsea	0.3056	0.4154	1.3169	0.7397
Owning Borough - Kingston upon Thames	0.3476	0.4191	1.3582	0.7545
Owning Borough - Lambeth	0.7849	0.6340	1.4110	0.9458
Owning Borough - Lewisham	0.1970	0.4845	1.1611	0.7500
Owning Borough - Merton	0.1280	0.3504	1.1410	0.6323
Owning Borough - Newham	0.7225	0.5861	1.4483	0.9213
Owning Borough - Redbridge	0.0724	0.3648	1.0448	0.6174
Owning Borough - Richmond upon Thames	0.9661	0.6015	1.7004	1.0113
Owning Borough - Southwark	0.0552	0.3886	1.0104	0.6266
Owning Borough - Sutton	0.2237	0.4035	1.2365	0.7064
Owning Borough - Tower Hamlets	0.3655	0.4944	1.2962	0.8005
Owning Borough - Waltham Forest	0.9736	0.6495	1.5626	1.0074
Owning Borough - Wandsworth	0.4920	0.5555	1.3267	0.8585
In Foster Care	0.3098	0.7387	2.5962	1.3849
In Kinship (Familial) Care	0.6925	0.2068	10.7289	1.4894
In Residential Care Home	0.0224	0.3421	0.9215	0.5615
Gender Female	0.0000	0.4279	0.5810	0.4986
Gender Transgender	0.5112	0.0706	3.7418	0.5141
Gender Unknown	1.0000	0.0000	inf	0.0000
Subject Ethnicity - Afro Caribbean	0.0011	0.6253	0.8888	0.7455
Subject Ethnicity - Asian	0.0142	0.5957	0.9440	0.7499
Informant Location - Home Address	0.0011	1.1175	1.5591	1.3200
Nationality British/English	0.0023	0.6709	0.9168	0.7843
Informant Carer	0.0000	0.3087	0.5789	0.4227
Informant Social Worker	0.0000	0.3186	0.5923	0.4344
Informant Partner	0.0024	0.5483	0.8783	0.6939
Informant Friend	0.0002	1.2375	1.9869	1.5681
Informant Medical Staff	0.0000	0.2345	0.4286	0.3170
Informant Family	0.2510	0.7419	1.0812	0.8956
Created on Late Turn	0.2257	0.9361	1.3227	1.1128

Created on Night Turn	0.3849	0.7606	1.1113	0.9194
ONS - LSOA Pop. 0 to 15y	0.2280	0.9987	1.0003	0.9995
ONS - LSOA Pop. 45 to 64y	0.0799	0.9999	1.0019	1.0009
ONS - LSOA Pop. Mixed/multiple ethnic groups	0.6313	0.9971	1.0017	0.9994
ONS - LSOA Pop. Economically Inactive	0.0186	0.9983	0.9998	0.9990
Borough Business (Z score)	0.0919	0.9902	1.1392	1.0621