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Can harm be predicted? On the development and validation of a statistical model for predicting harm in missing person incidents

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ABSTRACT
A small but significant proportion of missing episodes result in serious harm or death. In this study, we developed and validated a statistical model for predicting missing incidents where harm occurs. Data were provided by two police forces in England and Wales for the period January 2015 to December 2021. Of the 44,294 missing incidents we analysed, 4% were recorded by the police as resulting in harm ($n =$ 1902). Ten variables were found to significantly increase the risk of harm, including increased age, female sex, suicide ideation, mental health concerns and being harmed in a previous missing episode. What predicted harm was also shown to vary by age group. Using a standard train/test framework, our statistical model yielded an acceptable level of predictive performance – an area under the receiver operating characteristic curve score of 0.75 – but was not superior to the current police risk assessment method both in terms of *recall* (the proportion of harm cases that were successfully identified) and *precision* (the proportion of identified cases which actually resulted in harm). If generalisable, our findings (1) call for a re-examination of the questions currently used in police missing person risk assessments and (2) suggest that a validated risk prediction model can complement police decision making in missing person investigations.

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Introduction

The police are routinely called upon to establish the whereabouts of missing people. In 2021/22, the police in England and Wales recorded around 294,000 missing person incidents (NCA 2023); an average of over 800 incidents per day. In most cases (over 70%), the missing person is found safe and within a day of them being reported missing (Fyfe *et al*. 2015, Galiano López *et al*. 2023, NCA 2023). There are, however, a small but significant proportion of incidents in which the missing person experiences harm, including physical injury, criminal victimisation and sexual assault (Rees and Lee 2005, Doyle and Barnes 2020, Ferguson *et al*. 2023, Fox *et al*. 2024). In 2021/22, there were 859 missing incidents (<1%) in England and Wales which resulted in fatality (NCA 2023, Whibley *et al*. 2023).

The demand associated with locating missing people invariably outstrips available police resources. Decisions must therefore be made about how to allocate resources in a consistent and proportionate manner. To support decision-making, each missing incident in England and Wales

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is subject to a police risk assessment (see Bayliss and Quinton 2013, Eales 2017, Halford 2024). The purpose of the risk assessment is to estimate the likelihood that a missing person will experience harm or is a threat to others. Harm is not formally defined within the risk assessment framework; however, while harm when missing can take many forms (see Fox *et al*. 2024), the focus in this context is likely to be on tangible forms, such as physical injury. The police risk assessment is an ongoing process, drawing on information collected by call handlers alongside information gathered through police enquiries and the investigatory process. It typically involves a standardised set of around nineteen questions relating to the missing individual and the circumstances of their disappearance (see Appendix 1).

Missing incidents are graded on the basis of risk assessment. At the time of writing, there are four risk gradings used by the police in England and Wales: 'no apparent risk/very low risk', 'low risk', 'medium risk' and 'high risk'.[1] The risk grading is used to guide police activities in a missing person investigation, determining the allocation of police resources, the nature and intensity of police deployment and enquires, and informing any subsequent safeguarding activities. Missing incidents assessed to be at higher risk typically receive more immediate and proportionally greater resources.

Risk assessment is, thus, an integral part of a missing person investigation, and is routinely practiced by all police forces in England and Wales (and elsewhere). It is therefore surprising that, to date, limited research has been directed at the missing person risk assessment process. Little is currently known about those factors which increase (or decrease) the likelihood of a missing person experiencing harm, and the extent to which harm can be accurately predicted. This lack of research is acknowledged by the College of Policing, who report that the '[missing person risk assessment] questions are based on practitioner experience and have not been subject to evaluation' (2023). Likewise an inquiry by the All-Party Parliamentary Group for Runaway and Missing Children and Adults concluded that

> the risk assessment question set currently used by UK police needs to be explored/verified by academics … there is little to no research to support that we are currently asking the right questions, in the right order, to obtain the best information to inform our decision making. (Coffey 2018, p. 7)

This study was an initial step to help address these research gaps. Using a large police dataset, the goal of the study was to develop and validate a statistical model for predicting whether missing incidents result in harm, and explore whether such a model could usefully support police decision making. In this sense, our study forms part of a growing body of work on the potential for statistical approaches to support police decision making (see, for example, Oswald *et al*. 2018, Meijer and Wessels 2019, Završnik 2021). The remainder of this article is organised as follows. The next section reviews the literature on the prevalence and predictors of harm experienced by missing people. We then describe the data and methods used in this study, including our analytical approach for developing and validating a risk prediction model. The results then follow. We end the paper by discussing the limitations of this study and the implications of our findings for police practice.

How often are missing people harmed?

Two lines of research help to determine the extent and nature of harm experienced by missing people. The first makes use of police data, estimating the prevalence of harm based on the number of missing incidents recorded by the police as resulting in adverse outcomes, including 'death', 'self-harm', 'sexual assault' and 'injury'. Across England and Wales, analysis of police data converge on two consistent findings: (1) a small proportion of missing incidents result in harm (typically less than 10%) and (2) missing adults are more likely than missing young people to experience harm (NCA 2023). Missing incidents resulting in death consistently make up less than 1% of cases (Whibley *et al*. 2023).

Analysis at the police force level largely confirms national trends. Tarling and Burrows (2004), for example, analysed a random sample of 1008 missing incidents recorded by the London Metropolitan Police. They found that in 96% of cases, the missing person was recorded as being found safe and unharmed. Vo (2015) analysed 5984 missing incidents recorded by Thames Valley Police, and concluded that 98% of missing people did not experience harm, as measured therein. Likewise in Devon and Cornwall, an analysis of over ninety thousand missing incidents found that 4% of missing people were recorded as experiencing harm (Doyle and Barnes 2020).

A long known problem with using police data is that not all incidents are brought to the attention of the police. In the context of crime, this is known as the 'dark figure of unreported crime' (Buil-Gil *et al*. 2021). Going missing is not a crime, but the same notion of a dark figure still applies: not all missing incidents are reported to the police and some people might be more (or less) likely to be reported missing than others. The same is true of harm as measured using police data; not all harms experienced by missing people will be disclosed to or identified by the police (Missing People 2022). The likelihood of disclosing harm might also vary across population groups (Fox *et al*. 2024). Moreover, it is plausible that there may be biases in the *kinds* of harm that are and are not disclosed to the police (i.e. sexual-related harm vs self-harm). Taken together, these limitations mean that estimates of harm using police data are likely to under-count the extent of harm and may reflect variations in reporting practices.

In an effort to overcome the limitations of using police data, a second line of research has drawn on alternative (non-police) data sources to estimate the prevalence of harm experienced by missing people. These studies typically report higher levels of harm. Rees (2011), for example, analysed self-report data from a representative sample of 14 to 16-year-old children in England, and found that 'around one in nine (11%) young people said that they had been hurt or harmed while away from home on the only or most recent occasion' (p. 16). Moreover, a recent study by the charity Missing People (2022) reported that as many as three in four missing adults experienced some form of harm when missing, ranging from threats of violence to sexual assault.

What factors influence whether a missing person is harmed?

There is now a large body of international research into those factors that increase the likelihood of someone going missing (for a recent review see Ferguson 2022). Less apparent are studies on what predicts the risk of harm in missing incidents. Two exceptions are relevant to this study. Doyle and Barnes (2020) investigated the correlates of harm using a large dataset of missing person incidents recorded by Devon and Cornwall Police. The prevalence of harm was found to vary substantially across different demographic groups. Females aged 18–64 and males aged 65 and over exhibited the highest risk of harm (7.4% and 7.3% of incidents, respectively) whereas males and females under 18 exhibited the lowest risk (1.2% and 2.1% respectively). In terms of the predictors of harm, Doyle and Barnes (2020), using bivariate methods, identified seven factors which increased the likelihood of experiencing harm (being visually impaired, having reduced mobility, being suicidal, having a mental illness, going missing for the first time, not being in a care placement, and having a disability) and three factors which decreased the likelihood of experiencing harm (being flagged as a child sexual exploitation risk, being in care, and being a repeat missing person).

Doyle and Barnes (2020) then repeated their analysis for six specific categories of missing person based on age (under 18, 18–64 and 65 and over) and gender (male and female). Two findings warrant mention here. First, no variable was found to be a statistically significant predictor of harm across *all* six categories. The most robust determinant of harm was suicide ideation, which emerged as a significant predictor in all missing groups except males over 65. Second, the strength and direction of the relationship between some variables and harm varied across different categories of missing. Across their entire sample of missing incidents, for example, being in care and being a repeat missing person lowered the chances of experiencing harm. Among young people, however, these same factors were found to increase the likelihood of experiencing harm when missing. On the basis of their findings, Doyle and Barnes (2020) called for the current one-size-fits-all police risk assessment to be discarded in favour of a more nuanced, data-driven risk assessment process tailored to different age and gender categories.

Phoenix and Francis (2023) reported a similar study using data recorded by one UK police force for the calendar year 2015 ($n = 4746$). Importantly, Phoenix and Francis (2023) used a different (and arguably less precise) measure of harm to that of Doyle and Barnes (2020): namely, how a missing incident was recorded by the police as being resolved, with harm being defined as those missing incidents in which a missing person was 'arrested', 'harboured and/or abducted', 'found deceased' and/or 'found in hospital'. Logistic regression analysis identified 10 statistically significant predictors of harm, as measured therein. Age was found to be important: missing people aged 19–40 and 40 and over were more likely to experience harm than missing people aged 18 and under. Missing males were also found to experience harm in a greater proportion than missing females. Of the 19 risk factors considered in their analysis – the same risk factors that we consider in this study – five were found to increase the probability of a missing person being harmed (being involved in a violent or racist incident, having a physical or mental illness, having drug or alcohol dependencies, having a reported reason for going missing, and a variable relating to 'other' unlisted factors) and two factors were found to lower the risk of harm (making preparations for going missing, and an inability to interact with others). Extending previous research, Phoenix and Francis (2023) also demonstrated that those factors that reliably predicted harm were not the same as those factors that predicted which missing incidents were graded by the police as high risk. For example, while the variables 'out of character' and 'victim of major crime' increased the chances that a missing incident was graded as high risk, neither variable was found to be statistically associated with harmful outcomes.

The current study

Most missing people are found safe and quickly, but a small proportion experience harm. Risk assessment is therefore critical to the effective management of missing person investigations, with incidents assessed as higher risk of harm receiving greater resources. Despite being routinely practiced by all police forces, there is limited research on the utility of the police missing person risk assessment process. Moreover, whilst a handful of studies have investigated the *predictors* of harm, we are aware of no studies that have *validated* the practical utility of a predictive model; in other words, quantified the statistical performance of a predictive model to determine whether it might usefully support police decision making. Addressing these research gaps is the goal of this study.

Methods

Data

Data were provided by two police forces in England and Wales. Both police forces use the same risk assessment questions and the COMPACT (Community Policing and Case Tracking) records management system, which is the dominant missing persons management system used by the police in England and Wales (NCA 2023). The data comprised all missing person incidents recorded between 1 January 2015 and 31 December 2021.

Each missing incident contained the following information: a unique reference number, an anonymised person identifier, information on the missing individual (such as age, gender and ethnicity), information on the missing incident (such as time and date reported missing, location last seen), 'yes/no' answers to the nineteen questions asked as part of the missing person risk assessment (see Appendix 1), the initial and final risk grading ('no apparent risk', 'low risk', 'medium risk' and 'high risk') and, crucially for this study, whether the missing person was recorded by the police as experiencing harm (discussed in more detail below).

It is important to note that we did not compute any new variables from these data, such as the distance travelled when missing. Though it is plausible that factors such as these may be associated with the likelihood of a missing person experiencing harm – the outcome of interest in this study – they would only be known *after* a missing person had been located. Since the goal of this study was to develop an operationally useful risk prediction model, we limited our analysis only to those variables which are routinely available to the police at the time of risk assessment. This is a point we return to in the Discussion.

Outcome variable

As indicated previously, the goal of this study was to develop and validate a statistical model for predicting harm in missing incidents. In the police data we analysed, all closed missing incidents included a 'yes/no' variable denoting whether a missing person experienced harm. If the answer was 'yes', a further variable indicated the type of harm experienced. In our data, harm was categorised in six ways: 'physical injury', 'emotional harm', 'accidental harm', 'self-harm', 'sexual offence victim' and 'death', and combinations thereof. For the purposes of our analysis, these six categories of harm were combined to form a single indicator of harm experienced when missing. As discussed above, it should be kept in mind that harm, as measured herein, relates to harm *as measured by the police*, and therefore may be affected by under-reporting and/or reporting practices.

Candidate predictor variables

Twenty-five variables (21 binary, 1 continuous and 3 categorical) were considered for inclusion in our statistical model (see Table 1). As already mentioned, our variable selection was deliberately limited to only those variables available to the police at the time of risk assessment.

Statistical modelling

There are a range of different approaches to predictive modelling (see Grant *et al*. 2018). When building a predictive model, key choices include not only the selection of the statistical approach itself, but also the way in which performance is evaluated and quantified. In this study, as alluded to

Table 1. Variables included in a logistic regression as predictors of harm in missing incidents.

1. Age at time of missing incident (in years)
2. Ethnicity (Asian, Black, Mixed, White, Other, Not Stated)
3. Sex (female, male, transgender, unknown)
4. Does the missing person have a disability? (Yes or no)
5. Is the missing person in social services care? (Yes or no)
6. Where did the missing person go missing from? (Children's care home, care home for the elderly, healthcare setting, home, place of education, place of employment, other)
7. Is the person vulnerable due to age or infirmity or any other similar factor? (Yes or no)
8. Is going missing out of character? (Yes or no)
9. Is the person suspected to be the subject of a significant crime in progress, e.g. abduction? (Yes or no)
10. Is there any indication that the person is likely to commit suicide? (Yes or no)
11. Is there a reason for the person to go missing? (Yes or no)
12. Are there any indications that preparations have been made for an absence? (Yes or no)
13. What was the person intending to do when last seen, e.g. going to the shops or catching a bus, and did they fail to complete their intentions? (Yes or no)
14. Are there family or relationship problems or recent history of family conflict and/or abuse? (Yes or no)
15. Are they the victim or perpetrator of domestic violence? (Yes or no)
16. Does the missing person have any physical illness or mental health problems? (Yes or no)
17. Are they on the Child Protection register? (Yes or no)
18. Has the missing person previously disappeared and suffered/was exposed to harm? (Yes or no)
19. Do you believe that the person may not have the ability to interact safely with others or is in an unknown environment? (Yes or no)
20. Do they need essential medication that is not likely to be available to them? (Yes or no)
21. Are there any ongoing bullying or harassment concerns, e.g. racial, sexual, homophobic or local community concerns or cultural issues, etc? (Yes or no)
22. Were they involved in a violent and/or racist incident immediately prior to disappearance? (Yes or no)
23. Are there any school/college/university/employment or financial problems? (Yes or no)
24. Are there any drug or alcohol dependency issues? (Yes or no)
25. Are there any other unlisted factors which the officer or supervisor considers should influence risk assessment? (Yes or no)

above, we did not seek to identify an *optimal* model – by, for example, exhaustively examining all possible modelling approaches – but rather sought to establish a benchmark level of predictive performance using standard statistical approaches. Our findings therefore essentially represent a lower bound for the predictive capability of such an approach.

We used logistic regression as our core modelling approach. Logistic regression is a standard approach for modelling binary outcomes (harm vs no harm) using multiple predictor variables. As our initial step, we applied this model to the full dataset of all missing incidents, including all 25 predictor variables listed in Table 1. This allowed us to identify which variables showed a statistically significant association with harm (using a standard *p*-value threshold of 0.05) and to quantify the strength of these relationships.

Based on this initial analysis, we then constructed a predictive model containing only those variables that were found to be statistically significant predictors of harm. We then sought to measure the predictive performance of this model; that is, how well it is able to classify cases of harm as either 'yes' or 'no'. When evaluating a predictive model, it is essential that its performance is measured by applying it to data that is distinct from that which was used to construct the model; that is, previously 'unseen' data. If this is not the case, the performance may be artificially inflated because the model already incorporates the cases it is trying to predict (known as 'over-fitting').

A standard approach to address over-fitting is to split the data into two distinct sets: a 'training' set and a 'test' set. The model is constructed using the training set only, and its predictive performance is then measured by applying it to the test set. In this study, we used a version of this approach known as five-fold cross-validation. This involves the dataset being split into five equally-sized sets ('folds') and the train/test procedure being carried out five times: in each case, one-fold acts as the test set and the remainder is used as the training set. This strategy ensures that any findings are robust to the choice of train/test split.

For each of the five runs, the model generates a predicted probability of the outcome – in this case, harm – for each missing incident in the test set. These can be converted to binary predictions by applying a decision threshold: cases above the threshold are predicted to experience harm, and cases below the threshold are not. The accuracy of these predictions can then be measured by comparing them to the true observed outcomes (i.e. whether that missing incident was recorded by the police as resulting in harm).

A common measure to assess predictive performance is the 'area under the receiver operating characteristic curve' (AUROC, see Hosmer *et al.* 2013). The AUROC – which we explain in detail in a later section – ranges from 0 and 1 and summarises how well the model is able to flag cases that result in harm while minimising the number of cases that are incorrectly flagged (false positives). Importantly, the AUROC has a straightforward interpretation: the closer the AUROC value is to 1, the higher the performance (in the context of this study, the better the model can identify missing incidents that result in harm). One intuitive way to think of the AUROC value is as the probability that a case experiencing harm will receive a higher predicted probability than a case not experiencing harm: if the value is 0.85, for example, this means there is an 85% chance that a harm case would be ranked higher than a no-harm case.

Software and code

All data processing and analysis was performed in Python, using the libraries Pandas, Statsmodels and Scikit-learn. Code to replicate the analysis, showing the full analytic workflow, is available from the authors.

Ethics statement

The current study was reviewed and exempted by the Department of Security and Crime Science ethics board at University College London on the basis that it used anonymous data from which no individuals were identifiable.

Results

Descriptive statistics

Between 1 January 2015 and 31 December 2021, the two participating police forces in England and Wales recorded 44,294 missing incidents involving 19,873 missing persons. The imbalance between the number of missing individuals and incidents is consistent with previous research (Babuta and Sidebottom 2020, Sidebottom *et al*. 2020, Galiano López *et al*. 2023), and indicates that some people went missing repeatedly. Of the 44,294 missing incidents, 4% ($n = 1902$) were recorded by the police as resulting in harm. This encompasses a range of harm types – described previously – with 'self-harm' ($n = 848$) and 'physical injury' ($n = 671$) accounting for the majority of cases. There were 201 missing incidents that resulted in fatality.

Table 2 presents descriptive statistics both for the entire study sample and separately for missing incidents where harm was and was not recorded. Three variables have missing or invalid values – disability ($N = 6480$), social services ($N = 1196$) and sex ($N = 20$) – and these values are omitted when calculating percentages. We could not identify any systematic patterns in the missing values.

Considering the full sample of missing incidents, the mean age of a missing person was 24 (SD = 15.6). Most missing incidents involved a person of white ethnicity (91%), largely reflecting the ethnic profile of the participating police force areas. Males accounted for slightly over half of all missing incidents (56%). Over three-quarters of incidents related to people recorded as going missing from home (76%). Missing incidents from children's care homes and healthcare settings accounted for 11% and 6% of cases, respectively. Vulnerability, as measured by the police,[2] was common among those individuals recorded as missing – identified in 74% of missing incidents and by far the most

Table 2. Descriptive statistics for all missing incidents ($n = 44,294$) and separated for missing incidents resulting in harm ($n = 1902$) and no harm ($n = 42,089$).

Characteristics	Full sample	Harm	No harm
Age in years, mean (SD)	24 (15.6)	34 (18.9)	24 (15.3)
Sex, male (%)	24,788 (56.0)	1049 (55.2)	23,544 (56.0)
Ethnicity, white British (%)	39,031 (90.6)	1736 (94.7)	37,067 (90.4)
Disability (%)	7618 (20.1)	462 (28.5)	7124 (19.8)
In social services care (%)	14,541 (32.8)	314 (16.5)	14,075 (33.4)
Missing from home (%)	33,720 (76.1)	1594 (83.8)	31,900 (75.8)
Missing from healthcare setting (%)	2458 (5.5)	108 (5.7)	2338 (5.6)
Missing from children's care home (%)	4936 (11.1)	108 (5.7)	4788 (11.4)
Risk factor questions			
Vulnerable (% yes)	32,669 (73.8)	1263 (66.4)	31,254 (74.3)
Out of character (% yes)	10,899 (24.6)	746 (39.2)	10,137 (24.1)
Subject to crime (% yes)	1682 (3.8)	55 (2.9)	1619 (3.8)
Likely to commit suicide (% yes)	5290 (11.9)	753 (39.6)	4524 (10.7)
Reason for going missing (% yes)	14,613 (33.0)	691 (36.3)	13,849 (32.9)
Preparation for absence (% yes)	3865 (8.7)	180 (9.5)	3656 (8.7)
Failure to complete intentions (% yes)	8334 (18.8)	361 (19.0)	7939 (18.9)
Family problems/conflicts (% yes)	12,433 (28.1)	537 (28.2)	11,847 (28.1)
Victim/perpetrator of domestic violence (% yes)	3261 (7.4)	174 (9.1)	3076 (7.3)
Mental health concerns (% yes)	15,219 (34.4)	1019 (53.6)	14,168 (33.7)
Subject of a child protection plan (% yes)	5649 (12.8)	109 (5.7)	5513 (13.1)
Suffered harm in prior missing episode (% yes)	2740 (6.2)	225 (11.8)	2505 (6.0)
Lacks ability to interact with others (% yes)	3032 (6.8)	155 (8.1)	2863 (6.8)
Requires essential medicine (% yes)	2778 (6.3)	201 (10.6)	2565 (6.1)
Ongoing bullying/harassment issues (% yes)	847 (1.9)	38 (2.0)	807 (1.9)
Involved in violent or racist incident (% yes)	739 (1.7)	50 (2.6)	689 (1.6)
Education/employment/financial issues (% yes)	3674 (8.3)	137 (7.2)	3523 (8.4)
Drug or alcohol dependencies (% yes)	6926 (15.6)	332 (17.5)	6569 (15.6)
Other factors influencing risk (% yes)	6430 (14.5)	372 (19.6)	6019 (14.3)

Note: (1) That the unit of analysis here is the missing *incident*, and that some individuals go missing repeatedly and therefore feature multiple times in our data (see Appendix 3); and (2) whether harm occurred was unknown in a small proportion of cases ($n = 303$) and so some incidents from the full sample are not included in either of the latter two categories.

prevalent of all the 19 risk assessment questions. Mental health concerns (34%) and family conflict (28%) were also frequently identified. Other risk factors were seldom present. For example, a missing person 'being subject of a crime in progress', 'making preparations for their disappearance', 'being the victim or perpetrator of domestic abuse', 'suffering harm in a previous missing episode', 'lacking the ability to interact safely with others', 'requiring essential medicine', 'being involved in ongoing bullying or harassment issues', 'being involved in a violent or racist incident' or 'having educational, employment and/or financial issues', was identified in less than 10% of missing incidents.

Comparing missing incidents that did and did not result in harm (columns 3 and 4 of Table 2), we see that missing incidents where harm occurred tended to involve older people, individuals with disabilities, incidents in which the missing behaviour was judged to be out of character, where there is a suicide risk, mental health concerns and where harm had occurred in previous missing episodes (further analysis on the relationship between age and harm is presented in Appendix 2). Moreover, in missing incidents resulting in harm, there was a lower proportion of individuals known to social services, individuals who are subject to a child protection plan and cases of individuals going missing from children's care homes.

Model development

We now consider which variables predict the risk of harm in missing incidents. When fitting our logistic regression model, we omitted any cases where data were missing for one or more variables: 7742 cases were omitted for this reason, and so model fitting was based on the remaining 36,552 missing incidents. Of the 25 variables included in our model (see Table 1), 10 were found to be statistically significant correlates of harm ($p < 0.05$): 'age', 'gender', 'ethnicity', 'location missing from', 'out of character', 'likely suicide', 'mental health', 'harmed in previous missing episode', 'vulnerability' and 'other factors'. These results are presented graphically in Figure 1 as odds ratios, which specify how many times higher the odds of harm are for a missing incident where a given characteristic is present (these results are also presented in table format in Appendix 3). If variable X has an odds ratio of 2, for example, it means that the odds of experiencing harm are twice as high for a missing incident with characteristic X as they are for one without. This means that an odds ratio of 1 corresponds to no effect, while values greater than 1 denote an increase in the risk of harm and values less than 1 indicate a decrease in the risk of harm.

Suicide ideation was identified as the strongest predictor of harm – the odds of harm occurring in missing incidents where this factor is present are nearly four times as high as in those where it is not. Experiencing harm in a previous missing incident is also a strong predictor of harm (OR = 1.90). In the opposite direction, individuals missing from either places of education or healthcare settings are shown to be *less* likely to experience harm. Perhaps the most unexpected finding concerns vulnerability, where our analysis suggests that individuals recorded as vulnerable were *less* likely to experience harm, as seen by the odds ratio below 1. The reasons for this are unclear. One possibility is that incidents flagged as vulnerable are assigned greater police resources, with the consequence that individuals are more likely to be found before harm occurs. It is not clear, however, why this would apply to vulnerability but not to other likely flags. Another explanation is that the vulnerability flag is particularly common amongst younger individuals (i.e. under 18); it is applied in around 87% of such cases, compared with 55% of over-18s. Incidents involving such individuals tend to have a lower risk of harm (see Appendix 2), and so the effect of vulnerability may partially reflect this. Yet another explanation is that the term 'vulnerability' means different things to different people (those reporting a missing person, call handlers, the police), and is applied too loosely to be of any value in discriminating harm from no-harm missing incidents. There is some suggestive evidence for this in the sense that the vulnerability flag was selected for nearly three-quarters of all missing episodes.[3]

Beyond identifying the statistically significant predictors of harm, also noteworthy is the *absence* of a significant association for many of the other variables considered in our analysis, most notably

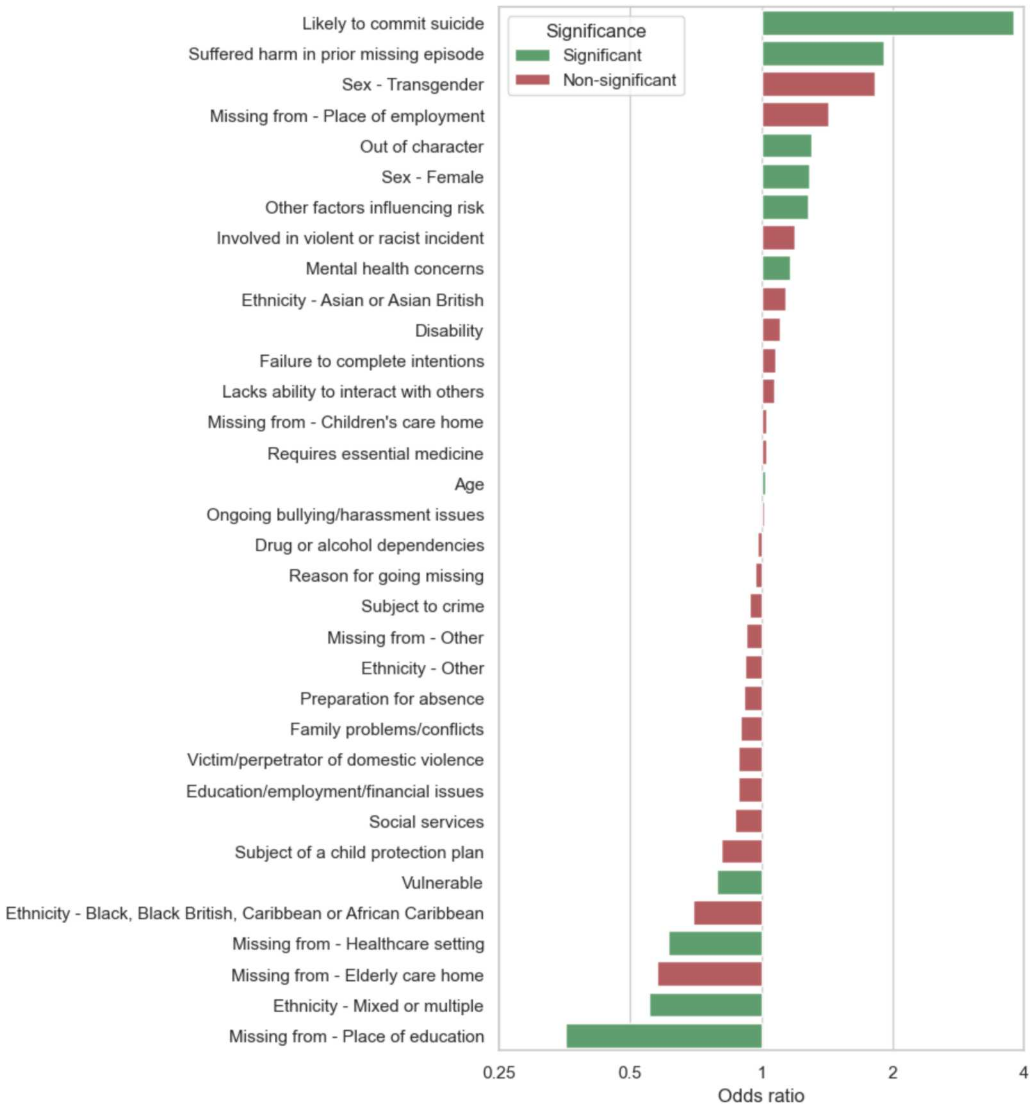

Figure 1. Odds ratios denoting the effect associated with each variable in the model for all missing incidents. The central value of 1 corresponds to 'no effect', and any deviations to the right (left) of this correspond to a positive (negative) association with harm. The values are plotted on a logarithmic scale, which means that distances in the positive and negative direction are equivalent. Some factors have large odds ratios but their effects are not significant – this is typically because the characteristic is not sufficiently common to establish significance.

thirteen of the nineteen questions asked as part of the police missing person risk assessment. This indicates that, in our data at least, these variables do not have predictive power with respect to harm, after controlling for the effect of other variables.

Model validation

The 10 statistically significant predictors of harm were retained to create our predictive model. Extending previous research (Doyle and Barnes 2020, Phoenix and Francis 2023), we then sought to assess the ability of this model to identify missing incidents that resulted in harm. To do this, we performed cross-validation with a fully random five-fold partition of data. As mentioned previously, this results in five predictive models, the performance of each of which can be measured with respect to its corresponding test set.

To measure predictive performance, we used ROC curve analysis, and the ROC curve for one of our models is shown in Figure 2. The ROC curve shows the trade-off between the false positive rate (the proportion of no-harm incidents incorrectly predicted to experience harm) and the true positive rate (the proportion of incidents where harm occurred that were correctly identified as such) as the threshold for determining harm/no-harm is varied. The top left corner of the graph area represents perfect performance (all cases of harm flagged, and no no-harm cases flagged), and the closer the curve is to this corner, the better the predictive performance of the statistical model. The area under the ROC curve (AUROC) measures how closely the curve approaches this, ranging from 0 (worst possible) to 1 (perfect) – a value of 0.5 is equivalent to random guessing.

Results indicate that our predictive model for all missing incidents had an average AUROC score across all five folds of 0.75. Expressed differently, there is a 75% chance that an incident resulting in harm would be ranked higher by our predictive model than an incident that did not result in harm. Using standard measures, this is considered an acceptable level of predictive performance (Hosmer *et al*. 2013).

While the ROC curve summarises performance across all possible decision thresholds, use of the model in practice requires the selection of a specific threshold (i.e. a particular point on the curve). This selection can be made with performance in mind, but also involves resource considerations: a lower threshold means that more cases will be flagged as resulting in harm. For this study, some concrete insight can be gained by setting the threshold to such a level that the proportion of flagged missing incidents matches the proportion of incidents classified by the police as 'high risk' using the conventional risk assessment process. In our data, this classification is given in 15.1% of cases. The model was then run with this threshold set, meaning that this proportion of cases was flagged. The results are presented in the form of a 'confusion matrix' shown in Table 3.

Two key measures provide an indication of predictive performance: *recall*, which measures the proportion of harm cases that were successfully flagged, and *precision*, which measures the proportion of flagged cases which actually resulted in harm. For our predictive model, recall is 46.7%

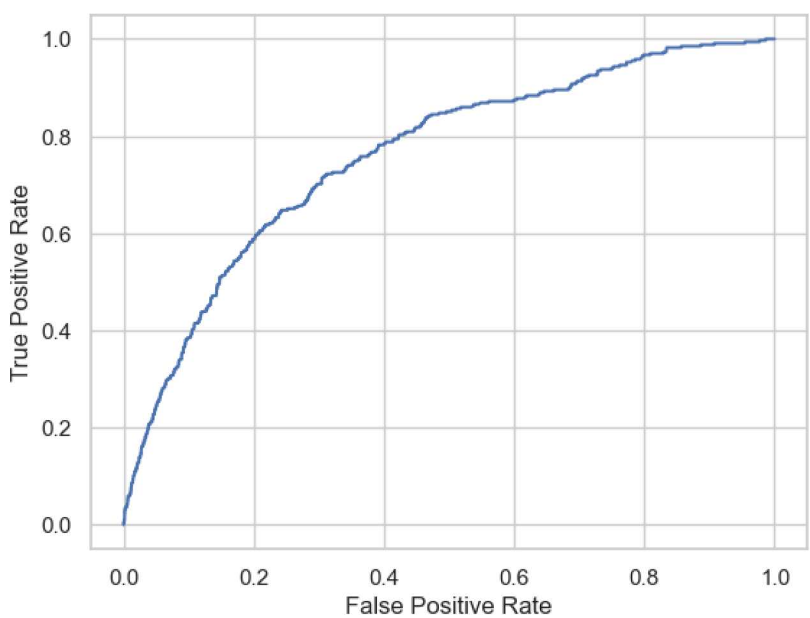

Figure 2. ROC curve for the predictive model to identify the risk of harm in missing incidents.

Table 3. Confusion matrix showing the performance of our predictive model.

		Predicted	
		No harm	Harm
Actual	No harm	7076	1125
	Harm	192	168

Note: Each missing incident is classified according to its predicted outcome and the true outcome: the top left and bottom left cells therefore represent correct predictions.

and precision is 13.0%. These relatively low values are unsurprising given that harm in missing incidents (as recorded by the police) is rare: the model flags just under half of all cases that were recorded as resulting in harm, but the majority of cases which are flagged (86.8%) do not result in harm. For comparison, if the police risk rating of 'high' is treated as the flag, the recall is 46.3% and the precision is 13.2%, which is essentially equivalent to the performance of our predictive model. At this threshold, therefore, the model does not outperform the current police risk grading system.

It is noteworthy, however, that there is relatively little overlap between the missing incidents flagged by our predictive model and those missing incidents which were actually assigned a 'high risk' grading: only 59.1% of high risk cases are flagged, and 57.8% of flagged cases were graded as high risk. As can be seen from Table 4, the instances of harm detected by the two methods are quite distinct: some of those which were not flagged by the predictive model were graded as high risk, while some missing incidents which received a lower risk score were correctly identified by our predictive model. This finding suggests that a validated risk prediction model might usefully complement police decision making, a point we return to in the Discussion.

Risk stratification: does age matter?

Previous studies suggest that the prevalence and predictors of harm vary by the age of the missing person (Doyle and Barnes 2020). To explore this in our dataset, we repeated the approach described above but performed analysis separately for missing incidents involving individuals aged 17 and under, 18–64, and 65 and over. Odds ratios are again used to denote the strength and direction of the relationship between each variable and harm (Figure 3). Statistically significant associations are shown in bold, while non-significant coefficients are greyed out. We selected age simply to serve as a case study. Similar analyses could of course be undertaken using other pertinent variables such as gender or mental health concerns.

Three features of Figure 3 are considered important. First is the *consistency* of some factors across the three selected age groups: factors such as 'suicide ideation', 'harmed in previous missing episode' and 'behaviour being out of character' are found to be consistent predictors of harm regardless of age. Second, the influence of some factors is highly *variable* across age groups, as was found by Doyle and Barnes (2020). An example of this is disability, which is positively associated with harm for adults over 65 but does not have a significant effect for other age groups. And third, consistent with the findings from our overall predictive model (Figure 1), it is clear that many of the variables included in our analysis – including those asked as part of the police risk assessment process – were not predictive of harm regardless of the age of the missing person.

Table 4. Predictive performance disaggregated by both police risk assessment and model prediction.

	Police risk assessment	Med/low/none		High	
	Prediction	No harm	Harm	No harm	Harm
Actual	No harm	6594	509	482	616
	Harm	157	36	35	132

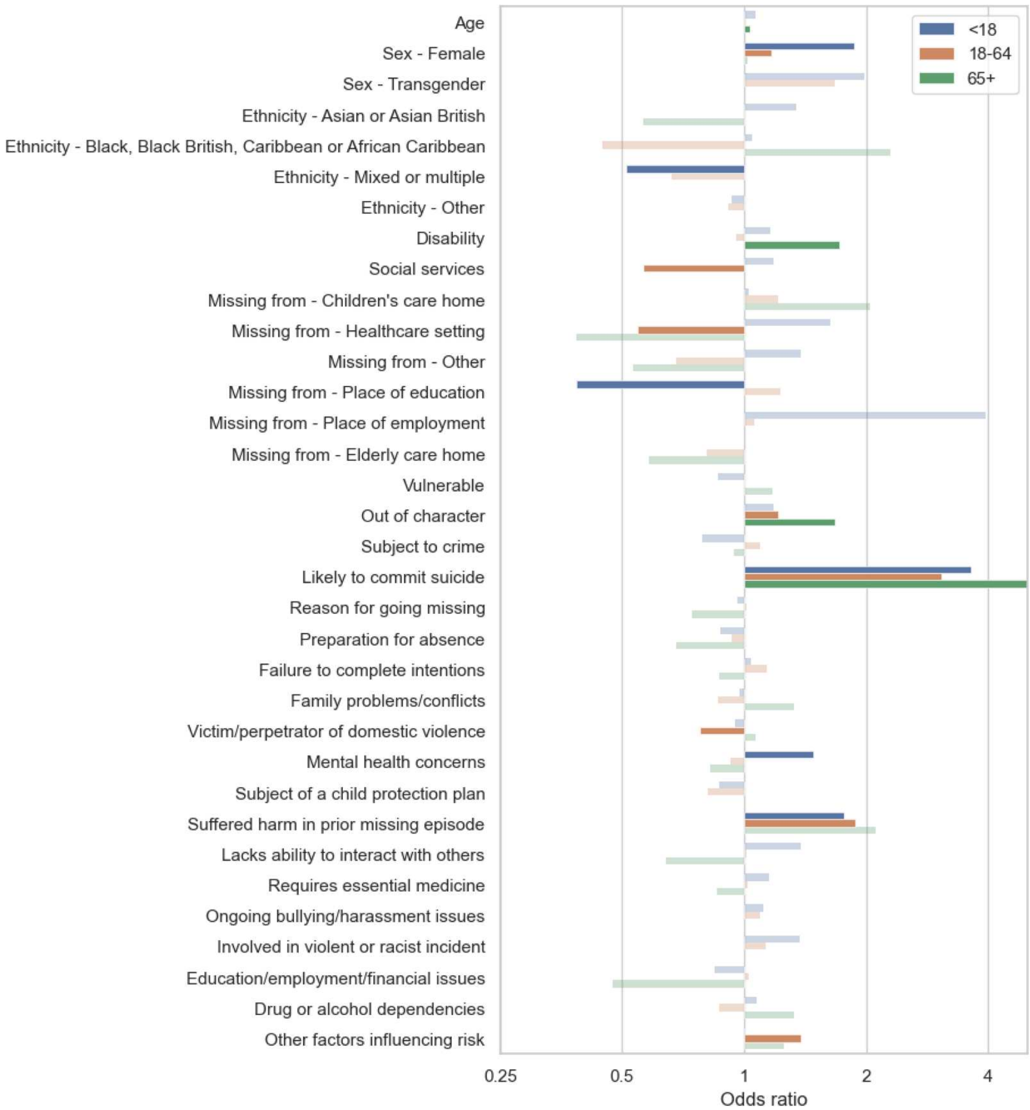

Figure 3. Odds ratios denoting the effect associated with each variable in the model for all missing incidents across three age groups. The central value of 1 corresponds to 'no effect', and any deviations to the right (left) of this correspond to a positive (negative) association with harm. Significant associations are shown in bold, while non-significant coefficients are greyed out. The values are plotted on a logarithmic scale, which means that distances in the positive and negative direction are equivalent.

Finally, we measured the predictive performance of the disaggregated predictive models for each age group. Findings are shown in Table 5. Again there are a number of observations of note. The first is that, in general, the predictive performance for these models is lower than it is for the original aggregated model, as shown by the lower AUROC scores (0.61–0.68). This is likely due to the predictive power of age itself: since age is strongly associated with harm – with recorded harm less prevalent in missing incidents involving children – the original model gained some of its predictive power by simply predicting lower risk for children. When age groups are disaggregated, this advantage is removed. A further observation is that model performance is, in all cases, lower than that of the current police risk classification scheme. This implies that, while predictive performance is nevertheless good, there are features of these incidents which predict the risk of harm but which are not captured by our statistical model.

Table 5. Predictive performance by age category.

	17 and under			18–64			65 and over		
Prediction	AUROC	Precision	Recall	AUROC	Precision	Recall	AUROC	Precision	Recall
Model	0.64	5.7	17.0	0.68	15.1	49.2	0.61	14.2	62.1
Current risk grading		5.6	19.0		16.1	53.8		16.0	72.4

Discussion

To our knowledge, this study is the first to develop and validate a statistical model for predicting harm during missing episodes. We did this using a large dataset of all missing person incidents recorded by two police forces in England and Wales for the period January 2015 to December 2021. Analysis showed that the majority of missing incidents did not result in harmful outcomes, as measured by the police. Harm was recorded as taking place in 4% of incidents ($n = 1902$) and was more prevalent as the age of the missing person increased. These estimates are broadly reflective of national trends (NCA 2023). Logistic regression indicated that 10 of the 25 candidate variables were significant predictors of harm. The risk of harm was greater when the missing person (1) was deemed 'likely to commit suicide', (2) 'suffered harm in prior missing episode', (3) was behaving 'out of character', (4) was 'female', (5) was subject to 'other risk factors', (6) had 'mental health concerns' and (7) was 'older'. By contrast, harm was less likely (8) for missing people recorded as 'mixed race' (compared to 'white'), (9) in incidents from 'healthcare settings' and 'places of education' (compared to missing incidents from home) and, contrary to expectation, (10) in missing incidents where the missing person was identified as 'vulnerable'.

A statistical model comprising these 10 significant predictor variables yielded an acceptable level of predictive performance – using standard prediction metrics – and was roughly equivalent (but not superior) to the current police assessment method both in terms of *recall* (the proportion of harm cases that were successfully identified) and *precision* (the proportion of identified cases which actually resulted in harm). Both approaches yielded high recall but low precision, which is typical of forecasting efforts of rare outcomes (as is the case here). Interestingly, while both approaches yielded comparable overall predictive performance, there were notable differences in which missing incidents were flagged. Of those missing incidents that did result in harm, some were not flagged by the predictive model but were assessed by the police as 'high risk', while other incidents which received a lower police risk grading were correctly identified by our predictive model. We consider this to be an important finding. It suggests that, to some extent, our predictive model complemented the existing police risk assessment process, and that combining the two may yield practical benefits.

Finally, our results suggest that what predicts harm in one age group does not necessarily predict harm in another age group. Investigating the predictors of harm in missing incidents involving those aged 17 and under, 18–64 and 65 and over, we identified a handful of robust all-age determinants of harm – suicidal ideation, harmed in previous episode – but also many variables that were important for some sub-groups (e.g. disability for older adults) but not others. This finding is consistent with the pattern reported in Doyle and Barnes (2020).

Limitations

This study has several limitations. First, our analysis is based solely on police recorded missing incident data. These data have familiar shortcomings. As indicated previously, not all missing incidents are reported to the police, and some people might be more likely to be reported missing than others. These concerns are most pronounced when it comes to the measure of harm used in this study: some harms may be more or less likely to be identified by or disclosed to the police (e.g. sexual-related harm vs physical harm) and some people may be more or less likely to report harm to the police. For this reason, we acknowledge that our study findings may, to some extent, reflect variation in reporting practices. For example, our finding that missing incidents involving adults are more likely to result in harm than those involving children may reflect different thresholds for reporting to the police: people are less likely to report an adult as missing unless they have major concerns about their safety and wellbeing, whereas children may be reported missing in less concerning circumstances due to an abundance of caution (particularly by those with a duty of care). There is also evidence, however, that missing children often do not disclose harm (Fox *et al*. 2024), which provides an alternative explanation for this pattern. Crucially, we had no way of verifying the accuracy of information recorded in our data. This shortcoming is true of most police datasets, however, and is the case for comparable studies in the research literature (Doyle and Barnes 2020, Phoenix and Francis 2023).

Second, our data do not provide details of actions taken by the police in each case, and what steps were taken to establish the whereabouts of a missing person. We therefore have no way of knowing whether a missing person *would* have experienced harm had it not been for the activities of the police. This has potential consequences for our model, in particular because the level of response may act as a mediating factor between the predictive variables and the outcome. If the same factors that predict harm also result in a higher level of police response (because they tend to result in higher grading), then such factors might also partly reduce the risk of harm, because such individuals are more likely to be found by police before experiencing harm. If this is the case, then the predictive effects we have derived here are likely to represent an *under*-estimate of the true relationship with harm (since, in the absence of a prioritised response, the incidence of harm may have been even higher). Indeed this extends to variables that were not found to be significantly associated with harm: it may be that they are predictive of harm itself, but that this is counterbalanced by the aforementioned effect on police response to the extent that no effect is ultimately observed.

Third, the analysis reported here was limited to information that is routinely collected by the police. As already mentioned, this was a deliberate decision on our part so as to determine the extent to which readily available data at the time of risk assessment can be used to predict harm. The stated purpose of this study was to explore the *potential* of a statistical model to support police decision making; it was not to *maximise* the predictive power of a statistical model. If this were the objective, then it is likely that other variables not included here might generate improvements in predictive performance. Candidate variables include the duration of missing episodes or the distance travelled when missing. Yet these variables are only available *after* the event, and so whilst they *could* be included in a statistical analysis to work out what best predicts harm, they could not be included in a police risk assessment during an ongoing missing person investigation.

Fourth, our analysis does not enable any causal interpretations. We cannot, therefore, determine why, say, old age was found to be a reliable predictor of harm. And finally, there are limits to the generalisability of our findings, since our analysis relates to only two forces for a set period of time. In light of these limitations, further research is needed to determine the generalisability of our findings using data from elsewhere, and to gain insights into why some variables for some groups and in certain circumstances are reliable predictors of harm. With a larger dataset, including a higher number of incidents resulting in harm, it might also be possible to replicate our analysis focussing on specific types of harm, including fatalities.

Implications

We believe our findings, if confirmed elsewhere, have implications for police practice and harm reduction, in three main ways. First, our findings suggest that the current missing person risk assessment process might be enhanced by incorporating the insights of a validated statistical model, as was done here. While the two approaches yield comparable predictive performance, they also appear to identify different missing incidents where the risk of harm is high, thereby hinting at the benefits that may arise from a statistical model supplementing current police practice. To be clear, this proposal is not intended to increase the total number of missing incidents identified as high risk, and by extension increase the police resources devoted to missing incidents. Rather, combining the current police risk assessment method with a validated statistical model is intended to better identify those missing incidents warranting an immediate response. Put simply, the highest-risk cases from each method could be top-sliced and combined to produce an equal number of flagged cases to those currently identified, but where the accuracy is likely to be higher. In this sense, incorporation of a validated statistical model would inform the prioritisation of missing incidents.

Second, our results lend further support for calls to review the question set currently used in police missing person risk assessments (see Doyle and Barnes 2020). In this study, many of the standard risk assessment questions were found to hold no relationship with (police recorded) harm. One implication is that the same degree of predictive performance might therefore be possible using a stripped-back question set which, if scaled-up across the hundreds of thousands of missing incidents that occur each year, might lead to substantial time and cost savings. Related to this are calls for a standardised, one-size-fits-all risk assessment process to be discarded in favour of a more nuanced set of questions tailored to specific categories of missing person, such as age and gender (Doyle and Barnes 2020). Indeed, we are aware of one UK police force who are currently experimenting with the use of age-specific risk assessment questions (Doyle, personal communication). Again, the results of this study are aligned with such calls, in that we found notable variation in what predicted harm among different age groups.

The final implication relates to harm reduction. The missing person risk assessment process is by definition reactive. It is undertaken in response to someone being reported to the police as missing. Given the potential that missing people may experience harm, there are obvious advantages in developing interventions to reduce the risk of people going missing. As indicated above, this study identified several robust predictors of harm. From a proactive perspective, these variables may offer an important opportunity for better targeted and tailored interventions oriented towards those people and/or circumstances where harm is most likely. An obvious example concerns efforts to reduce the risk of elderly people going missing, given this group makes up a small proportion of all missing incidents but, in our data at least, exhibit a greater risk of being harmed. In a similar vein, the significant predictor variables identified here can guide the police and partners as to what information they might sensibly prioritise both in 'live' missing person investigations and afterwards – in the form of, say, return home or prevention interviews (see Boulton *et al.* 2023) – to inform efforts to curtail repeat disappearances. An example here relates to information on whether a person experienced harm in a previous missing incident. Our findings suggest that this is an important factor in determining whether that same person might experience harm in any future missing episodes.

Notes

1. For definitions of these risk gradings see: https://www.college.police.uk/app/major-investigation-and-public-protection/missing-persons/missing-persons
2. Measured using the question, 'Is the person vulnerable due to age or infirmity or any other similar factor? (Yes or No)'.
3. For a related discussion of the police use of the term vulnerability see Keay and Kirby (2018).

Disclosure statement

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Appendices

Appendix 1. Questions typically asked as part of the England and Wales police missing persons risk assessment

1. Is the person vulnerable due to age or infirmity or any other similar factor?
2. Behaviour that is out of character is often a strong indicator of risk; are the circumstances of going missing different from normal behaviour patterns?
3. Is the person suspected to be subject of a significant crime in progress, e.g. abduction?
4. Is there any indication that the person is likely to commit suicide?
5. Is there a reason for the person to go missing?
6. Are there any indications that preparations have been made for an absence?
7. What was the person intending to do when last seen, e.g. going to the shops or catching a bus, and did they fail to complete their intentions?
8. Are the family or relationship problems or recent history of family conflict and/or abuse?
9. Are they the victim or perpetrator of domestic violence?
10. Does the missing person have any physical illness or mental health problems?
11. Are they on the Child Protection register?
12. Previously disappeared and suffered or was exposed to harm?
13. Belief that the person may not have the ability to interact safely with others or in an unknown environment?
14. Do they need essential medication that is not likely to be available to them?
15. Ongoing bullying or harassment, e.g. racial, sexual, homophobic or local community concerns or cultural issues, etc?
16. Were they involved in a violent and/or racist incident immediately prior to disappearance?
17. School/college/university/employment or financial problems?
18. Drug or alcohol dependency?
19. Other unlisted factors which the officer or supervisor considers should influence risk assessment?

Appendix 2. On age and harm in missing incidents

Table 2 indicated that missing people who experience harm tend, on average, to be older than missing people who do not experience harm. To investigate this relationship further, we considered the proportion of incidents resulting in harm by age of missing person. The results are presented below. A positive association is evident: as the age of the missing person increased, so too did the proportion of missing incidents recorded by the police as resulting I harm. Missing adults aged 80 and over, thus, exhibited the greatest risk of experiencing harm during a given missing episode ($n = 58$, 11% of missing incidents involving this age group). To reiterate, it should be kept in mind that estimates on the prevalence of harm derived using police data may, to some extent, reflect differences in reporting habits and, in particular, variation in reporting thresholds. It is possible, for example, that the threshold for reporting a young person as missing is lower than that of an adult, with reports of missing adults thereby containing a higher proportion of cases where the reporting party has serious concerns about the person's health and safety.

Appendix 3

Table A1. Fitted coefficients and odds ratios for a logistic regression model of harm when missing ($n = 36{,}552$).

Variable	Coefficient	Odds ratio
Age	0.02*	1.02*
Sex – female	0.25*	1.29*
Sex – transgender	0.6	1.82
Ethnicity – Asian or Asian British	0.13	1.14
Ethnicity – Black, Black British, Caribbean or African Caribbean	−0.36	0.7
Ethnicity – mixed or multiple	−0.59*	0.55*
Ethnicity – other	−0.09	0.92
Disability	0.1	1.1
Social services	−0.14	0.87
Missing from – children's care home	0.03	1.03
Missing from – healthcare setting	−0.50*	0.61*
Missing from – other	−0.08	0.92
Missing from – place of education	−1.04*	0.36*

(*Continued*)

Table A1. Continued.

Variable	Coefficient	Odds ratio
Missing from – place of employment	0.35	1.42
Missing from – elderly care home	−0.55	0.57
Vulnerable	−0.24*	0.79*
Out of character	0.26*	1.30*
Subject to crime	−0.06	0.94
Likely to commit suicide	1.33*	3.80*
Reason for going missing	−0.04	0.97
Preparation for absence	−0.09	0.91
Failure to complete intentions	0.07	1.07
Family problems/conflicts	−0.11	0.89
Victim/perpetrator of domestic violence	−0.12	0.89
Mental health concerns	0.15*	1.16*
Subject of a child protection plan	−0.21	0.81
Suffered harm in prior missing episode	0.64*	1.90*
Lacks ability to interact with others	0.07	1.07
Requires essential medicine	0.03	1.03
Ongoing bullying/harassment issues	0.01	1.01
Involved in violent or racist incident	0.17	1.19
Education/employment/financial issues	−0.13	0.88
Drug or alcohol dependencies	−0.02	0.98
Other factors influencing risk	0.25*	1.28*

*Statistical significance at the $p = <0.05$ level. Also note that for some variables, effects should be interpreted relative to a given reference category – these are 'Sex' (Male), 'Ethnicity' (White British) and 'Missing from' (Home).

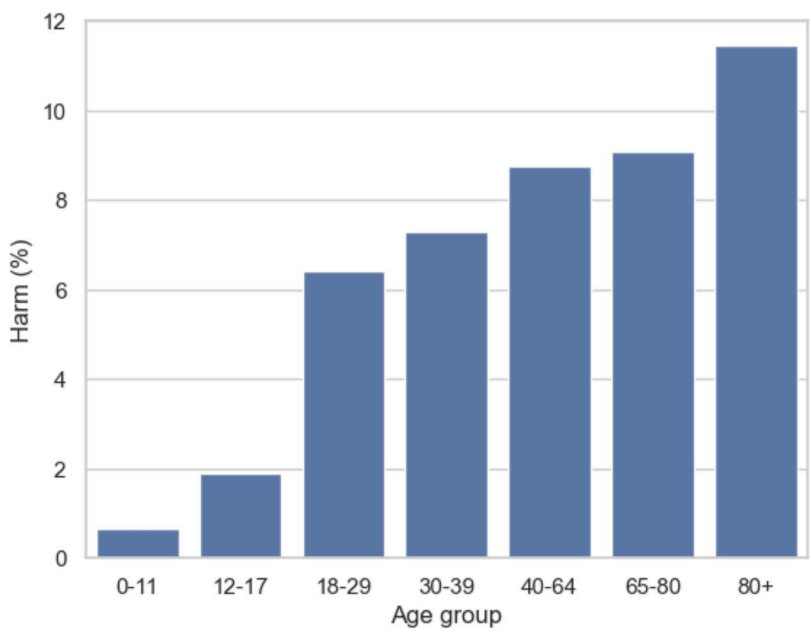

Figure A1. The proportion of missing incidents recorded by the police as resulting in harm by age group ($n = 44{,}294$).