When children go missing: identifying risk factors to predict repeat incidents

Abstract

Purpose: Missing children face significant risks, and although most return safely, several remain missing. Children who are repeatedly reported missing are especially vulnerable, being more susceptible to dangers, including alcohol and drug misuse, exploitation, and sexual abuse. This study aimed to identify risk factors associated with repeat missing children incidents, as this is an under-researched area. **Design:** The study analysed police records of missing children from one UK police force, covering incidents reported from June 2018 to July 2019 (N = 907). Quantitative methods were used to investigate the characteristics and backgrounds of missing children predicting repeat disappearances. **Findings:** Over 80% of all missing child reports were repeat incidents. Notably, just 8.3% of children accounted for more than half the total incidents recorded. Several significant risk factors for repeated disappearances were identified, including prior criminal exploitation, violent behaviour, adverse childhood experiences, previous arrests, and being in care. These factors were found to predict children at greater risk of repeatedly going missing. **Originality:** The study provides novel data-driven insights into the predictors of repeat reports of missing children based on police data. The findings have important implications for developing proactive policing risk assessments, enabling constabularies and policymakers to identify and support children at a greater risk of going missing *before* they go missing. The research contributes to improved safeguarding practices and more efficient allocation of police resources.

Keywords: repeat missing children, missing persons, vulnerability, police data, police investigations, risk factors, risk assessment.

Introduction

In the year 2022/2023, incidents of missing children account for approximately 63% of all missing person cases nationwide (National Crime Agency; NCA, 2023). Many leave home as a result of adverse circumstances such as domestic violence and abuse (DVA), child neglect, or persistent family conflict (Rees, 2011). Although Baker *et al.* (2003) relied on broad self-reported measures of "problems occurring at home", research frameworks like Adverse Childhood Experiences (ACE) have narrowed down the focus to early exposure to trauma as a significant contributor to engagement with offending behaviour. Although some departures may appear voluntary, they often reflect the perceived lack of viable alternatives (Kurtz, Jarvis and Kurtz,1991) or be motivated by involvement in crime, substance misuse, or exploitative relationships (Smeaton, 2009).

Although most children return safely, some experience serious harm (National Crime Agency [NCA], 2016), including being initiated into drug use, suffering violence, and being forced into stealing, begging, or selling themselves for sex. For instance, Biehal, Mitchell and Wade (2003) found that one in eight runaways were physically harmed, and one in nine reported sexual abuse. In addition to this, research has emphasised the connection between the disappearances and criminal exploitation of children, with the latter being coerced and manipulated into committing illegal activities as a means for survival (Jago *et al.,* 2011; Home Office, 2019; Shalev-Greene and Pakes, 2014). While it was outside the scope of this study to examine abduction cases, recent work has explored the behavioural characteristics of non-familial child abductors (Jones et al., 2023), highlighting the importance of considering extra-policing factors in the wider missing persons context. Repeat missing incidents are especially concerning, with statistics demonstrating almost 40% of children going missing right after being returned home (NCA, 2019), or 57% going missing again within two months (Bezeczky and Wilkins, 2022). Going missing multiple times has also been associated with a higher likelihood of being further exploited, criminally or sexually. For instance, it is known that 90% of groomed children go missing at least once, with repeated reported disappearances often signalling ongoing violence and abuse (Hutchings *et al.,* 2019). Additional vulnerabilities, such as being a child in care, increase the likelihood of disappearance (Hayden and Goodship, 2013; Hutchings *et al.,* 2019).

Missing children place a significant demand on public services, with a single missing person investigation equating to an average of 14% of police time, and an annual cost of £394 to £509 million, and 5.2% of UK children who went missing at least ten times accounting for 30.4% of all reported childhood disappearances (Babuta and Sidebottom, 2018). Similarly, Sidebottom et al. (2019) found that 4.4% of children accounted for at least 28.4% of all missing incidents. Aligning with this, estimates indicate that between 29% (Rees, 2011) and 75% (Sidebottom et al., 2019) of all missing child incidents are repeats and research is beginning to discuss the benefits of focussing on a 'power few' individuals or locations in an attempt to proactively target resources (Greene and Hayden, 2014; Huey et al, 2020; Thomas and Ferguson, 2023). For example, Thomas and Gerguson (2023) tracked 2026 young people reported missing for ten years and found 1/3 went missing more than once, with 60% habitually going missing. Greene and Hayden (2014) identified private care homes were the most common location from which people went missing (57.1%), and almost all (99.5%) were aged 18 years and under. Obtaining an accurate figure is challenging, as many missing children go unreported, often due to a reluctance by the families to approach the police, making it difficult to map and investigate repeat missing children behaviours (Biehal, Mitchell and Wade, 2003).

The police have a statutory duty of care for missing children, which includes conducting risk assessments, coordinating local searches, and providing support to affected families (Hayden and Shalev-Greene, 2016). However, a persistent increase in missing reports, around 20% annually, and the limited availability of policing resources mean constabularies might struggle to appropriately respond to missing children's cases, and even more so, in identifying repeat offences (Home Office, 2019; NCA, 2019; Pepper, Rogers and Martin, 2020). Beyond risk and vulnerability factors, recent studies have also examined public responses to missing person appeals, such as prospective person memory and own-race bias (Hunt & Mojtahedi, 2025), though these questions lie outside the focus of the present study.

Missing children: demographic and behavioural characteristics

Age and gender

Insights on gender characteristics for missing children vary across publications and countries, with some authors reporting higher numbers of female victims (Galiano López *et al.*, 2018; van de Rijt *et al.*, 2018), making up almost 70% of police-reported incidents containing a child sexual exploitation flag (Independent Inquiry Child Sexual Abuse; IICSA, 2023). On the contrary, other sources indicate that boys either more commonly go missing than girls (Bezeczky and Wilkins, 2022; Fox *et al.,* 2024) or are comparatively found at a greater distance from where they originally went missing (O'Brien *et al.,* 2021). In addition to these positions, several studies have found no statistical differences in missing reports incidence by gender (Mewett and Thomas, 2024; Randone and Thomas, 2022),

Variations based on a combination of gender and age ranges have also been flagged across countries. For example, data from Belgium suggest missing boys were overrepresented in all age categories, except in the age group 13-17 years; and no gender differences across age ranges were observed by key stakeholders in France, the Netherlands and Lithuania (European Commission, 2024). Similarly to Belgium, in the UK, females aged 12-17 years accounted for the highest proportion of missing children reports, and 71% of missing 13-17-year-olds were female (Biehal, Mitchell and Wade, 2003; NCA, 2019). While age is at times reported as a significant factor, its influence is not consistently documented in the literature. Overall, it appears that older children, especially over the age of 13, are more likely to be reported as missing (Babuta and Sidebottom, 2018; Rees, 2011). This could be due to the increased complexity of life changes during adolescence (such as decreased parental monitoring, increased chances of victimisation and inter-familial conflict, and/or engagement in delinquent behaviour), which appeared to heighten the risk of voluntary and involuntary disappearances in children (Baker *et al.,* 2003; Tucker *et al.,* 2011). On the other hand, young children may be simply more likely to be under the constant supervision of an adult, which naturally reduces their capacity to run away and/or go missing (Woolnough and Cunningham, 2020).

Mental health

There is a strong association between mental health and reported missing children (Tarling and Burrows, 2004). UK data suggests, for example, that mental illness concerns are registered in 25% of all missing persons cases, with prevalence ranging from 60 to 80% in other published studies (Gibb and Woolnough, 2007; Holmes *et al.,* 2013). Whilst studies have so far focused on adults, these findings might have implications for children who repeatedly go missing. Authors like Stevenson *et al.* (2013), for instance, report that running away might be a coping mechanism for a possible mental health crisis, in similar ways that have been documented for self-harm and suicidal ideation (APPG, 2019; McDougall, Armstrong and Trainor, 2010).

Risk factors for repeat victimisation in missing children

Currently, risk assessments for repeat victimisation rely on officers' subjective and experiential judgment that the child is likely to run away from home again. As such, the method lacks consistency and is vulnerable to bias (Robinson *et al.,* 2016) and disparities in definition (e.g. what constitutes merely 'repeat' and what should be classified as 'chronic' missing person cases) have been discussed (see Ferguson and Picknell, 2022; Harris and Shalev Green, 2016). Statistical forecasting offers a more objective alternative by assigning values to specific variables that might pose as risk factors, producing more accurate probabilistic estimates. Tools like the Kent Internet Risk Assessment Tool [KIRAT[1]] and the Harm Assessment Risk Tool [HART] have supported policing with measures of risk that were better targeted than officers' judgment (Long *et al.,* 2016; Oswald *et al.,* 2018). Despite this, statistical forecasting has been criticised and found to be only useful in limited situations: it has been shown to potentially oversimplify complex human behaviours (Cooke and Michie, 2014), assume future disappearances or crimes can only mirror previous actions (Capson *et al.,* 1997), and has occasionally relied on incomplete or inaccurate recorded data (NCA, 2016).

Structured Professional Judgment (SJP), on the other hand, offers a balanced approach to risk assessment, combining evidence-based practice with individual (non-algorithmic) decision-making (Douglas and Kropp, 2002). Although mostly used in clinical risk assessment (National Institute for Mental Health in England, 2004), SPJ retains human oversight while grounding decisions in data and research. Its application for behavioural predictions (as opposed to simple description) of missing incidents has shown

[1] KIRAT is an evidence-based framework for prioritising the most dangerous offenders, including child sexual abusers. Using fourteen questions about the suspect (previous behaviour, access to children, current behaviour and circumstances), it produces a risk score (low, medium or high), correctly classify 97.6% of high-risk offenders and 62.3% of low-risk offenders (Long *et al.,* 2016).

promising results (Bonny, Almond and Woolnough, 2016). Hutchings *et al.* (2019) used it to identify five key predictors of reported missing children's cases (being in care, substance misuse, suspected sexual exploitation, being known to youth offending services and having a history of abuse and neglect). Creating a checklist that could guide more effective police interventions for children showing at least three of the five key factors. Some of these findings have been reiterated in other research, for example Bezeczky and Wilking (2022) similarly highlight being in care as a potential risk factor for repeatedly going missing. The success of SJP in identifying children at risk of going missing from home made it the most suitable tool to expand on the current body of research to address repeat missing children's incidents.

The current study

This study advances previous research on repeat missing children by offering practical and practitioner-oriented solutions. While earlier studies identified risk factors associated with going missing (Bonny, Almond and Woolnough, 2016; Hutchings *et al.*, 2019), they have generally not translated their findings into actionable suggestions to support police staff decision-making when a child is reported missing and quantify risk.

The present study adopts a pragmatic psychology framework (Fishman, 1999) to investigate the prevalence of repeat incidents, (defined as children who were reported missing on more than one occasion) and to identify variables associated with higher risks for repeat victimisation. To facilitate the development of an easy-to-deploy statistical model to identify children most at risk of going missing repeatedly, the analysis categorised cases into two groups; those reported missing once and those reported missing more than once. The research objectives were therefore:

(1) What is the prevalence of repeat disappearances among children?

(2) What factors are increasing the likelihood of a child going missing repeatedly?

In line with the presented evidence from the literature, the authors hypothesised that, in the UK, gender (being female) and age (being older), and a history of mental health issues would be significant risk predictors for children to repeatedly go missing.

Method

Design

An observational research study design was chosen as the most appropriate for this study, given that the dataset included data originally collected by the police on reported incidents of missing children. The design enabled the investigation of real-world data, allowing the researchers to identify patterns and associations between potential variables that increase the risk of repeat victimisation.

Ethics

Ethical approval [ID 30118] was granted by Bournemouth University. The research involved secondary analysis of pre-existing police records of missing child incidents, meaning informed consent from individuals was not required. A formal data-sharing agreement was established with the participating police force, and all relevant permissions and vetting procedures were authorised prior to data access.

The principal ethical consideration was the confidentiality and protection of sensitive victim data. To address this, all datasets were anonymised. Direct identifiers (e.g. names, police reference numbers, postcodes etc.) were removed, and indirect identifiers that could reasonably be linked to publicly available information were also excluded. This ensured that no child or family could be identified from the research materials or outputs.

Sample

The sample comprised all missing child reports (n=1,004) from one UK police force over a one-year period (July 1, 2018 – June 30, 2019). Of these, sixty children were excluded, since they were reported missing for reasons other than voluntarily running away from home (missing due to abduction, being lost, trafficked, etc.). Moreover, thirty-five appeared to have gone missing outside of the targeted police area and were therefore also excluded. The final sample included 907 children who were involved in a total of 3,213 child missing cases reported to the police.

Data collection

The original file contained three variables related to the number of times missing, and demographic characteristics. Access to these records was secured through the police intranet, which retrieved data for all 907 cases. The intranet was used to access structured risk assessments, intelligence logs, crime reports, and safeguarding referrals, each of which contributed specific information (e.g. demographics and immediate risk indicators, victimisation and parental offending, family context). Additional data on police interactions, including arrests, stop checks, victimisation, and intelligence, were extracted from the police intranet by the researchers. Once the dataset was collated, ten variables were retained for each child (nine categorical, one continuous): frequency of missing reports, age, gender, adverse childhood experience (ACE), history of drug misuse, violent history, previous arrest, self-harm, mental health diagnoses, and family status.

Adverse Childhood Experiences (ACEs) were operationalised using a broad but consistent definition, drawing on categories identified in the Child Exploitation and Online Protection Centre (CEOP, 2011) report. Specifically, ACEs included: (1) physical or emotional abuse, (2) loss of a parent, (3) exposure to domestic abuse, (4) parental substance misuse, and (5) parental offending. These categories were selected as they represent the most consistently identified ACE factors in policing contexts and were available within the police data systems accessed for this study. ACEs were not provided as a pre-coded dataset. Instead, the first author manually reviewed each child's case records, including structured risk assessment forms completed at the time of the missing episode, intelligence logs, crime reports, and safeguarding referrals. This manual review process was applied consistently across all cases to ensure that information relevant to ACE categories was captured systematically. Information relevant to ACE categories was extracted directly from these records to ensure consistency across cases and to avoid reliance on whether police systems had pre-coded ACE data.

To assess the stability of the logistic regression model, the dataset (N = 907) was randomly split into two halves. One subsample (n = 451) was used to build the model, and the second subsample (n = 456) was used for validation. This split-sample approach follows Fafchamps and Labonne (2017), who argue that re-running the model on a separate subsample provides a test of predictive accuracy. As recommended by Austin and Steyerberg (2017), predictive performance was evaluated by comparing the accuracy between the development and validation samples. Validation results showed that the model remained a significant improvement over the baseline model (χ^2 (7) = 253.072, $p < .001$). The overall accuracy was almost identical across samples, declining by only 1.9% in the validation dataset. Prediction accuracy for low-risk children improved slightly (+0.3%), while prediction accuracy for high-risk children fell by 6%. These results suggest the model performed consistently across both subsamples, indicating it is accurate, fits the data well, and may be generalisable to similar child populations not included in the model development.

Data analysis

SPSS v25 was used for data analysis. The study used logistic regression to analyse the dataset of N=907 missing child cases, comparing two groups: children who were reported missing more than once (classified as *repeats*, n = 389, 42.8%), and those who were not previously reported as missing at the time of the study (non-repeats, n = 518, 57.0%). Children in the first category were labelled as high-risk, while those reported missing only once were labelled as lower risk of going missing again.

To develop and validate the risk assessment model, the dataset was randomly divided into two equal parts using the Random Sample of Cases function in SPSS. One subsample was used to construct the model, and the second was reserved for validation of its performance.

Results

Demographic characteristics

A total of 907 children were reported missing. Most children were aged 12 years or over (87.4%), with a mean age of 14.01 years (SD = 2.17), when they were first reported missing. Of these, 507 were males (56.0%), and 400 were females, showing an equal distribution across the sample. Most missing children in the dataset suffered ACE (64.4%), and 21.5% were in care of the local authority (compared to only 1% of the National average – DoE, 2019). Risky behaviours were present in nearly a third of the sample, and 12.0% participants had previously self-harmed. Children went missing an average of 3 times each (*SD* = 6.20). Notably, the 389 repeat missing children were involved in 83.9% of the total incidents reported to the police (N = 2,755). Of these, 75 (19.3%) were reported missing ten times or more over the period of one year.

Inferential statistics

Following assumption testing, a correlational analysis was performed to investigate the relationship between categorical independent and dependent variables (see **Table 1**).

Table 1
Variables Correlations

	Variable	1	2	3	4	5	6	7	8
1.	Age[a]								
2.	Gender [F=0, M=1]	.094**							
3.	ACE	.064	-.007						
4.	Drug misuse	.240**	.121**	.340**					
5.	CE	.206**	-.086*	.367**	.659**				
6.	Violence	.169**	.224**	.360**	.535**	.415**			
7.	Prior arrest	.213**	.140*	.269**	.525**	.459**	.451**		
8.	Self-harm	.107**	-.147*	.128**	.014	.057	.118**	.032	
9.	Family status	.261**	-.080	.322**	.350**	.377**	.315**	.371**	.088

Note. Variables 3-9 are yes/no binary variables, with Yes = 1 and No = 0. CE: criminal exploitation. ACE: adverse childhood experience. [a]Age: Pearson's *r*. *p < .05; **p < .001. Source: Authors' own work.

Age appears positively associated with drug misuse, CE, violence, prior arrest, self-harm and family status, suggesting that as children grow older, their exposure to or involvement in these behaviours is more likely to be registered. The data also shows a weak, although significant, correlation between gender, specifically being male, and a greater incidence of violence, drug misuse, and prior arrests in their case file. Correlation results indicate that drug misuse was positively correlated with criminal exploitation, history of violence, prior arrest, and family status. Perpetrators are known to lure children into criminally exploitative situations by using drugs and alcohol, suggesting potential overlaps of multiple vulnerabilities leading to exploited children being reported as missing.

Similarly, drug possession is a common reason why a child is arrested (Shalev, 2010), and there is also a well-established link between substance misuse and an individual's risk of becoming a perpetrator or victim of violence (Babor *et al.*, 2010). In line with this, violence appeared to be both a consequence and a predictor of further risk. Due to this overlap in concepts and a lack of supporting theory to explain why drug misuse may lead to running away, the variable was removed to limit variables redundancy and improve interpretability.

Identify risk factors associated with going missing repeatedly

Once correlations were identified, the sample was split randomly into two equal parts; one development sample (n = 453) to create the model and another validation sample to measure its performance. To identify the risk factors that may contribute to the predictive model, separate statistical tests were undertaken to check for associations between each factor and the high-risk group (**Table 2**).

Table 2

Risk Factors for Children Being Reported Missing.

Variable	N (453)	Non-repeat missing	Repeat missing	Chi^2 value	*p*-	OR
CE	143	2.9	28.7	181.440	<.001	33.056
Violence	128	5.3	23.0	97.038	<.001	10.037
ACE	301	25.4	41.1	107.441	<.001	13.748
Self-harm	53	4.4	7.3	7.587	.006	2.255
Previous arrest	84	1.1	17.4	102.085	<.001	31.600
Family status	104	2.2	20.58	114.571	<.001	20.976
Mental health	35	3.1	4.6	3.645	.064	1.964
Gender (Female)	211	24.5	22.1	1.255	.263	.809
Age*	453	*M* = 13.66, SD = 2.40	*M* = 14.53, *SD* = 1.70	*t* (453) =- 4.324	<.001	

Note: Chi–square test or independent samples *t*-test as appropriate for comparisons. *Independent samples *t*-test. M and SD represent mean and standard deviation, respectively. Source: Authors' own work.

Children with a history of criminal exploitation, an ACE, a history of violence, self-harm, previous arrest history, and living in care, were all significantly more likely to go missing repeatedly. An independent-samples t-test found that children were significantly older in the high-risk group compared to the low-risk group ($t(453) = -4.23$, $p<.001$), suggesting that older children are more likely to go missing repeatedly.

A binary logistic regression (BLR) was performed to understand the effect of age, gender, mental health, family status, arrest history, self-harm, ACE, history of violence, and CE on repeat victimisation.

The logistic regression model was statistically significant $\chi 2$ (9) = 340.381, p <.001. Nagelkerke R^2 was 0.71, suggesting strong explanatory power for this type of model, with 85.7% of the cases being correctly classified (**Table 3**).

Table 3.

BLR for High-Risk Children.

Variable	*B*	Wald $x^!$	*p*	OR	95% CI
CE	2.937	57.520	<.001	18.868	40.311 - 8.832
Violence	0.800	3.958	.047	2.225	1.012 - 4.891
ACE	1.940	3.958	<.001	3.176	3.177 - 15.234
Self-harm	0.259	0.283	.594	1.296	.499 - 3.360
Previous arrest	1.514	6.744	.009	4.545	1.450 - 14.252
Family status	2.386	28.903	<.001	10.875	4.556 - 25.959
Mental health	0.626	1.195	.274	1.869	.609 - 5.738
Gender	-0.136	0.174	.677	.873	.461 - 1.653
Age	0.047	0.415	.519	1.049	.908 - 1.212

Note: Source: Authors' own work.

A history of CE increased the odds of repeat victimisation by 18.9 times compared to children with no prior CE. Being in care increased the odds of repeat victimisation by 10.9 times; with previous arrest and ACE increasing the odd of the same outcome by 4.5 and 3.2 times, respectively. Lastly, having prior experience of violence more than doubled the odds of repeat victimisation in missing children. No other variable was associated with increased odds of repeated reports. To determine the most appropriate predictive model, two logistic regression models were compared against a baseline. Model 1 included all nine variables in the dataset irrespective of their statistical significance (approach suggested by Hosmer *et al.,* 2013). Whereas model 2 only incorporated the five variables with significant associations with going missing.

Upon inspection, Model 1 (9 predictors) correctly classified 90.4% of low-risk children and 79.7% of high-risk children, showing an overall mean accuracy of 85.7%. Model 2 (5 predictors) had the exact same classification accuracy for low-risk children (90.4%) and a slightly lower accuracy for high-risk children (78.2%), resulting in a slight decrease in overall accuracy (85.0%). Overall, although Model 1 offered a marginal improvement in accuracy (a negligible gain of 0.7%), it relied on several additional variables that are difficult to obtain in a police context (e.g., data on self-harm and/or medical records). In line with this, Model 2 was chosen as the most effective to balance accurate predictive performance and operational feasibility for policing. The chosen model consisted of the following five predictors: history of criminal exploitation, violence, ACE, previous arrest history, and family status. A test of this model (2) versus the base rate model was statistically significant ($\chi 2$ (5) = 337.067, $p < .001$), meaning that even with fewer predictors, the model provided a substantial improvement over random and/or frequency-based predictions.

To validate the model, we adopted Picard and Berk's (1990) method, re-running the model using the other half of the sample (n=456). The results obtained using the validation sample showed the model was still a significant improvement from the baseline model ($\chi 2$ (7) = 253.072, $p <.001$). When comparing the development and validation models, the overall accuracy was almost identical (from 85% to 83.1%), falling by just 1.9%. The prediction accuracy for low-risk children improved slightly (from 90.4% to 90.7%), rising by 0.3%, but there was a slight decrease in the accuracy for high-risk children (from 78.2% to 72.2%), falling by 6%. The model performed equally well on both samples of data, indicating the model is accurate, fits the data well, and can be generalised to other similar children not included in this dataset.

Research application

The study aimed to provide the police with a useful and reliable forecasting tool to predict the likelihood of a child going missing repeatedly. Previous research from Hutchings and colleagues (2019) used binary logistic regressions (BLR) to identify risk factors for repeat victimisation in missing children via a simple summation checklist to identify those at greater risk of going missing multiple times. Building on this previous work, the current study looked to improve predictive accuracy through the use of probabilistic modelling. Rather than assigning equal weight to each risk factor (as done by Hutchings *et al.,* 2019), this study's approach used the log-odds derived from the logistic regression model to generate a probability of subsequent missing report for each child.

The statistical model is defined as:

$$\log(\text{odds})=\beta_0 +\beta_1 X_1 +\beta_2 X_2 +\ldots+\beta_k X_k$$

The resulting probability that a child will go repeatedly missing was then calculated using the

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following logistic transformation, allowing practitioners a straightforward probability value:

$$\mathbf{P(Y = 1)} = \exp(\beta_0 + \beta_1X_1 + \beta_2X_2 + ... + \beta_kX_k) / [1 + \exp(\beta_0 + \beta_1X_1 + \beta_2X_2 + ... + \beta_kX_k)]$$

Table 4 illustrates the final model incorporating the five key predictors, each contributing to a distinct log-odds value, based on its statistical weight to inform prioritisation based on case characteristics, safeguarding needs, and resource availability.

Table 4
Best Fitting Logistic Regression Model for High-Risk Children

Variable	*B*	*p*	Odds Ratio
CE	2.988	<.001	19.850
Violence	0.822	.034	2.275
ACE	1.936	<.001	6.932
Previous arrest	1.598	.005	4.944
Family status	2.362	<.001	10.610
Constant	-3.319	<.001	.036

Note: Source: Authors' own work.

The following example demonstrates how the formula can be applied in practice. For a child with no history of criminal exploitation (CE = 0), displaying no other risk factors, the logistic regression equation will be equal to the model intercept (*bo* = -3.319):

Log (odds) = $b_0 + b_1 \times CE = -3.319 + (2.988 \times 0) = -3.319$

Odds = $e^{-3.319} = 0.036$

Probability of repeat victimisation = 0.036 / (1+0.036) = 0.035 (3.5%)

This means that the odds of repeat victimisation with no history of CE are 3.5%. On the other hand, if the child has previously been criminally exploited (CE = 1), the formula changes as follows:

Log (odds) = -3.319 + (2.988x1) = -0.331

Odds = $e^{-0.331} = 0.718$

Probability of repeat victimisation = 0.718 / (1+0.718) = 0.417 (42.0%)

The finding indicates a 42% chance they will go missing repeatedly if they have a history of CE. The formula can then be adjusted to include multiple co-existing risk factors to estimate the likelihood that two further hypothetical children will be reported as missing more than once, based on their case-specific characteristics and circumstances. For instance, a child who has been criminally exploited and has a history of violence (A), has an estimated 62.0% chance of repeatedly going missing. In comparison, a minor coming to the attention of the police with four of the five key behaviours (B), has an estimated 98.2% chance of going missing repeatedly – a relative increase of approximately 58.4%.

Discussion

This study contributes to the growing literature on missing children by confirming and extending known risk factors while introducing new contextual indicators not previously examined in this way. Earlier research has established the importance of being in care, substance misuse, and criminal exploitation as predictors of repeated disappearances (Bezeczky and Wilkins, 2022; Hutchings *et al.*, 2019). The novelty of the present study lies in its systematic incorporation of Adverse Childhood Experiences (ACEs) and related contextual information, extracted directly from police records, into predictive analysis. By operationalising these factors alongside established variables, the study offers insights into the characteristics of children most at risk of repeat victimisation and provides an evidence base for more proactive and preventative safeguarding interventions.

The study confirmed that repeat disappearances among children are both prevalent and significantly associated with several demographic, social, and environmental risk factors. Understanding these influences is crucial for more effective risk assessment evaluations serving police and other criminal justice agencies for early, targeted, and proactive crime and victimisation prevention The data showed that repeat reports consisted of 80% of missing children cases (higher than studies have reported previously) and additionally highlighted that a disproportionate number of incidents are linked to a small subset of children, with just 8.3% (n = 75) being named in over half of the recorded incidents. Understanding this dynamic has important operational and strategic implications.

Policing, in parallel with crime types like domestic violence and abuse (DVA), sexual violence, and repeat offending more broadly, is mostly effective when preventative efforts are focused on high-risk individuals (Barbin *et al.*, 2025; Groves *et al.*, 2012). In this study, the benefits associated with identifying repeat missing children are considerable to reduce future harm, lower the demand on police resources, and improve case outcomes for vulnerable young people. Notably, it could be estimated that concentrating resources on those at greater risk of going missing could have reduced overall reports of child missing cases from 3,213 to 1,580 per year. The figure of 3,213 refers to the total number of recorded missing cases (i.e. incidents), not individual children. With an average cost of £2,415.80 per reported incident (Shalev-Greene and Pakes, 2013), implementing targeted risk assessment strategies could have saved over £3.6 million to constabularies.

Overall, risk factor analysis showed that repeat missing children differ significantly from those who were reported missing once. Some of the factors associated with repeat victimisation included being in care, having had adverse childhood experiences (ACEs), having been a previous victim of criminal exploitation (CE), having a history of arrest and/or violence, as well as being older. CE emerged as the strongest predictor, with exploited children being over 30 times more likely to be repeatedly reported as missing. This builds on earlier findings (e.g., Bezeczky and Wilkins, 2022; Hutchings *et al*., 2019) but extends them by systematically incorporating ACEs as indicators, which have not been operationalised in this way using police data. Furthermore, it aligns with previous literature pinpointing missing children's vulnerability and exposure to trafficking, gang recruitment, and other forms of exploitation. While the direction of causality cannot be determined (e.g., whether missing reports are a consequence of exploitation or the other way round), the association is unequivocal. This finding has two significant implications. Firstly, being reported missing could be seen as a potential early indicator of child exploitation, serving officers a timely window to prevent recidivism and further incidents. On the other hand, the study stressed the need to revise risk assessment protocols for police staff and constabularies, which were developed prior to the recent rise of CE awareness (APPG, 2019).

The study also highlighted that children in care have odds 20 times higher of becoming repeat missing children. It is acknowledged that reporting of missing children from care (where professionals are required to follow strict Runaway and Missing From Home and Care protocols) may be higher than reporting of other missing children - where parents/responsible adults with no such regulations may be less may be less likely to report immediately due to a belief they may return soon, particularly if they have returned previously. However, this further exacerbates the complexity of CE-related runaways, as offenders might target care homes to exploit children's vulnerability after they have gone missing (Children's Society, 2019). The finding is consistent with evidence from the literature showing the connection between the presence of pre-existing vulnerabilities, the lack of stable accommodation, and children going missing (Hutchins *et al.*, 2019; NCA, 2019). Interestingly, out-of-area placements have been identified as drivers for both vulnerability and exploitation (Children's Commissioner, 2019; Foster, 2020).

A history of violent behaviour was also more prevalent among repeat missing children, in line with Shalev (2011), who noted that assaults were among the most commonly registered offence preceding missing reports. Similarly to CE, exposure to violence might equally be a precursor or a consequence of going missing. Addressing the emotional and psychological responses through targeted support prior to returning the children home could be an effective way to prevent further recidivism. Lastly, age was also identified as a significant predictor, with repeat missing children being on average older than those reported missing only once. As presented in the literature, older children might face more complex problems related to the transition into young adulthood, or being afforded more independence, increasing unsupervised opportunities to go missing (Hutching *et al.*, 2019).

Surprisingly, gender, pre-existing mental health concerns, and self-harm were not significant predictors of repeat victimisation. Although Meltzer and colleagues (2012) reported some evidence of gender-based differentiation, for this study, being male or female made no difference in the frequency of reports. More precise diagnostic measures (e.g., access to health records or post-incident interviews) could help shed further light on how mental health and self-harm might play a role in repeated child victimisation. Building on the study's findings, the model presented in this study highlighted a strong predictive power, with over 75% of children at high-risk being correctly identified. This is a 20% improvement compared with baseline predictions.

Police response to missing children is typically reactive, focused on recovery rather than on addressing the underlying causes of victimisation (Shalev-Greene and Alys, 2017). With several children going repeatedly missing, an investigative shift towards more proactive and preventative approaches is needed. As shown in this dataset, where a small portion of children was involved in the majority of reported incidents, allocating resources to children at greater risk of going missing could reduce demand and improve safeguarding. The novelty of this study lies in demonstrating that, alongside established predictors (such as being in care and criminal exploitation), ACEs and related contextual features extracted from police records can significantly contribute to identifying children most at risk of repeat disappearances. This represents a new direction for predictive modelling in this area. This study supports the use of statistical modelling to inform police risk assessment and provide an evidence-based overview of predictors that could be considered to improve current risk assessment frameworks.

Limitations and future research

The researchers recognise that there might be some variation for this crime type across constabularies, as well as differences registered during more extended periods of time. To provide a more accurate picture, future research could use a wider investigative time frame (e.g., at least three years of data) or adopt a longitudinal design. Additionally, secondary data analysis presents several limitations. First, police records are collected for operational and incident-related purposes, meaning that additional research-relevant data (e.g., school attendance) was not accessible for this dataset. Similarly, since the researchers did not collect the data first-hand, it is difficult to assess the reliability and accuracy of the information included by the police. This meant that some information, like mental health concerns, was more susceptible to the subjective interpretation of officers. While precautions were taken to mitigate the likelihood of inaccuracies on record, future research could benefit from triangulating police data with out-of-policing insights (e.g., school reports, medical records).

A further limitation is that some risk factors (e.g. adverse childhood experiences, exploitation) may become more evident only after multiple missing episodes, raising the possibility of bias towards repeat cases. However, all cases in this study were based on police records, which include a structured risk assessment for every missing episode, and the researchers manually reviewed each record (including intelligence logs and victimisation history) to capture contextual information as consistently as possible.

This reduces the likelihood that the model overfitted probabilities in favour of repeat missing children.

Lastly, although the logistic regression model predicting repeat missing incidents was validated using a split-sample approach, future research should further test its predictive accuracy on independent datasets drawn from different constabularies and over longer time periods. Such work would provide a more robust evaluation of the model's transferability and its potential application within operational policing contexts.

Conclusion

The study aimed to investigate the problem of repeat missing children. The findings make a valuable contribution to the literature, particularly in informing and enhancing the professional practice of constabularies and partner agencies who work with this vulnerable group. Beyond improving the identification and safeguarding of at-risk children, the practical implications of this research also offer means to reduce the significant demand on already stretched policing resources. By explicitly incorporating ACEs and related contextual factors into predictive analysis, the study advances existing knowledge and provides a foundation for future models of risk assessment in missing children cases.

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