Study to Identify Risk Factors that Predict Which Children Will Repeatedly Go Missing

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ABSTRACT

Missing children face significant risks and although most return safely, a number remain missing or encounter serious harm. Children who frequently run away are especially vulnerable, being more susceptible to dangers like alcohol, drugs, exploitation and sexual abuse. Therefore, the current research aimed to identify risk factors associated with a child repeatedly going missing, to shed light on this crucial yet rarely investigated area.

Our analyses of real missing children data from one UK police force from June 2018 to July 2019 (*N* = 909), revealed that over 80% of all missing child reports are repeat disappearances. A small minority of children who repeatedly go missing (8.3%), also accounted for more than half of all missing episodes. Moreover, the likelihood of a child going missing on multiple occasions is associated with having a history of criminal exploitation, being a perpetrator of violence, having adverse childhood experiences, being arrested and being in care. Finally, these factors can be incorporated into a risk assessment to accurately identify those individuals most at risk of going missing repeatedly.

The results have practical implications, providing a means for police and partner agencies to reliably identify high-risk children even before they go missing, allowing them to put prevention strategies in place, and thereby improving safeguarding within their limited resources.

Keywords: Repeat missing children, missing persons, missing children, vulnerability, practical implications, risk factors

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LIST OF ABBREVIATIONS

ACE	Adverse Childhood Experience
ACPO	Association of Chief Police Officers
APPG	All Party Parliamentary Group
CE	Criminal Exploitation
BLR	Binary Logistic Regression
CEOP	Child Exploitation and Online Protection Centre
CoP	College of Policing
CSE	Child Sexual Exploitation
DASH	Domestic Abuse, Stalking and Honour Based Violence
DCSF	Department for Children, Schools and Families
DFA	Discriminate Function Analysis
DoE	Department of Education
EBP	Evidence Based Policing
HART	Harm Risk Assessment Tool
KIRAT	Kent Internet Risk Assessment Tool
NCA	National Crime Agency
NSPCC	National Society for Prevention of Cruelty to Children
ONS	Office of National Statistics
SJP	Structured Professional Judgement

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AUTHORS DECLARATION

None of the information in this thesis has been presented before. The thesis is not based on joint research.

CHAPTER 1: INTRODUCTION

A missing person is: “anyone whose whereabouts is unknown whatever the circumstances of the disappearance. They will be considered missing until located and their well-being or otherwise established.” (Association of Chief Police Officers [ACPO], 2010, p. 8). Missing persons are the main non-crime problem for the police (Babuta & Sidebottom, 2018), impacting people from every walk of life (Shalev-Greene et al., 2019). Recent figures reveal the enormity of the problem, with police across England and Wales in 2018/19 handling 382,960 calls about missing people (NCA, 2020). Going missing exposes an individual to harm (College of Policing [CoP], 2019), either physical, such as exploitation and abuse, or psychological and emotional harm.

Missing Children

Missing children dominate the literature because they are the most vulnerable in cognitive, emotional, and physical capabilities and go missing the most. Statistics show 60% of all missing incidents involve children (Department of Education [DoE], 2014). Children go missing for a myriad of reasons. Running away often follows conflict at home, such as domestic violence, or neglect (Rees, 2011). Although many children leave voluntarily, they may have no alternative (Kurtz et al.,1991; Wade, 2002). Some may be escaping from something, for example, bullying, while others may be “pulled” towards something, such as drug-taking, or crime (Newiss, 1999).

Although the majority of children return safely, some come to serious harm (NCA, 2016). Many use drugs, one in eight survive by stealing, and one in eleven beg for food and money (Smeaton, 2009). Biehal et al. (2003) found that one in eight runaways were physically hurt, and one in nine reported sexual abuse. Recently, research has focused on exploitation. Child criminal exploitation occurs where an individual or group takes advantage of an imbalance of power to coerce, control, manipulate or deceive a child into criminal activity (Home Office, 2019). Sturrock and Holmes (2015) found missing children are higher risk of trafficking, criminality, and violence. Going missing is also a critical risk factor for sexual exploitation (Jago et al., 2011).

Children who repeatedly go missing are especially concerning, often having underlying vulnerabilities. Unfortunately, these repeat disappearances are frequent, with 38% of missing children returning home, only to go missing again within three months (NCA, 2019). Children who go missing three or more times are particularly vulnerable to dangers such as physical and sexual exploitation. Some studies have found specific categories of children run away more often (Hutchings et al., 2019). For example, those in care are at disproportionately high risk, often due to factors such as bullying from staff and other children and a desire to be with family (Hayden & Goodship, 2013). Overall, however, most studies are small and localised, reducing the generalisability of the findings, and researchers have examined only limited factors from the many potential influences. Consequently, the causes of repeat missing behaviour remain mostly unknown (Sidebottom et al., 2019).

Demand on Services and the Need for Research

The police have the “duty of care” for missing children (Hayden & Shalev-Green, 2016), including risk assessment, family support, and searching for the child. Ideally, police practice should have a basis in scientific evidence about what works best (Sherman, 1998), an approach referred to as “evidence-based policing” (EBP) (Hoggett & Stott, 2012). Unfortunately, this is challenging, as research is limited, and findings diffuse slowly into police practice (Fyfe et al., 2015).

It is crucial to improve professional practice for missing persons, especially given the 20% year-on-year increase in missing people nationally (NCA, 2019). In particular, missing children are a significant demand on public services, with estimates suggesting missing person investigation equates to 14% of police time and annually costs between £394 million and £509 million, more than burglary and assault together (Babuta & Sidebottom, 2018). Missing children also draw in other professions, including the Local Authority Children's Services, education and health providers. These costs are high and come when public service demand is increasing (Home Office, 2019), but funding is limited (Pepper et al., 2020).

Research Aims and Objectives

The current study will explore the extent, patterns and correlates of repeat disappearances by children. Then, by adopting a pragmatic stance (Fishman, 1999), the research will incorporate the pertinent factors into an evidence-based risk assessment, which will provide a means to reliably identify those individuals who are most likely to go missing repeatedly. The potential for harm increases every time a child runs away and developing such a tool will enable police forces and partner agencies to prioritise and target their preventive resources to support those who are the most vulnerable. Just as accurate forecasts of crime hotspots are useful when an officer is deciding where to patrol, a reliable forecast for a missing child will assist a police officer in determining what action to take to ensure they do not go missing again. There are three key objectives:

1. Investigate the prevalence of repeat disappearances by children.
2. Identify risk factors associated with a child going missing repeatedly.
3. Develop a statistical model of risk factors that can be used in practice by police, to identify those individuals most at risk of going missing repeatedly.

CHAPTER 2: LITERATURE REVIEW

The chapter addresses each objective. Section one examines the prevalence of repeat missing children, and section two considers factors that increase the likelihood of a child going missing repeatedly. Section three evaluates the use of statistical forecasting in the Criminal Justice System and how the police could apply it to missing children. The final section outlines the current study and introduces pragmatic psychology as an underlying epistemological framework.

Objective 1 – The Prevalence of Repeat Disappearances by Children

Compared to adults, children are more likely to go missing repeatedly (Sowerby & Thomas, 2016). Estimates show that between 29% (Rees, 2011) and 75% (Sidebottom et al. 2019) of all missing child incidents are repeats. Obtaining an accurate figure is challenging, as many missing children go unreported, often due to a reluctance by the families to approach the police due to a negative perception of the authorities (Verhoeven et al., 2000). However, just as crime concentrates among places and offenders, it appears a small percentage of children go missing a disproportionate number of times.

Similar concentrations exist throughout the crime analysis literature (Babuta & Sidebottom, 2018). For instance, a small proportion of all locations experience most crimes (Sherman, 1998), a limited number of victims suffer the majority of harm (Dudfield et al. 2017), and a few offenders have the most criminal convictions (Farrington et al. 2013).

Sherman (2007) refers to this as the “Power Few”, the small percentage of victims, or offenders that suffer the most harm. Power few distributions provide the police with preventative opportunities. Targeting resources on those few perpetrating or suffering the most should yield the best results. For example, Barnham et al.

(2017) studied domestic violence cases from one UK police force and found that 3% of offenders were responsible for 90% of all of the harm. Similarly, Dudfield et al. (2017) found just 3% of victims in one police force, suffered 85% of all of the harm.

To date, only a few studies have explored whether power-few distributions exist for missing children. Using police records from a Canadian city, Huey et al. (2020), found that 71 per cent of all missing children came from just five locations. Babuta and Sidebottom (2018) examined missing person cases from a UK police force and found that 5.2% of children who went missing ten or more times accounted for 30.4% of all childhood disappearances. Similarly, using data from another UK force, Sidebottom et al., (2019), found that 4.4% of children accounted for 28.4% of all missing incidents.

Although it is difficult to generalise from three localised studies, the limited findings suggest in samples of missing children, a small minority of individuals will account for a sizeable proportion of all missing incidents. This is critical for the police, as targeting this group, could lead to sizeable reductions in the number of missing reports, preventing excessive demand on resources. Therefore, the first objective of the current study, is to examine the prevalence of repeat missing children to understand if there is a small group who go missing a disproportionality high number of times, with a view to focusing intervention on those individuals.

Objective 2 – Risk Factors Associated with Going Missing Repeatedly

It is not coincidental that some children go missing more frequently than others (Biehal et al., 2003), as a myriad of potential factors are involved. Within the literature, there are few psychological explanations of why people engage in such behaviour. Most discussion focuses on common associations between going missing and demographic and behavioural factors such as age, gender and drug misuse.

However, general strain theory (GST), which seeks to explain crime and delinquency, may offer a sound theoretical framework to underpin missing persons behaviour and motivations.

GST has been applied to the behaviour of adults and children and argues that strains and stressors increase the likelihood of negative emotions like anger and frustration. These emotions then create pressure for corrective action, and crime and delinquency are possible responses (Agnew, 1999). GST proposes a broad range of strains that may contribute, including loss of positive stimuli (e.g., parental separation, unemployment), presentation of negative stimuli (bullying, abuse) and failure to achieve a goal (wealth, excitement and independence). As a response, crime and delinquency may allow the individual to address the source of strain (retaliation, violence) or alleviate the negative emotions (illicit drug use). Empirical tests of GST have linked the experience of strain to aggressive behaviours in school (Brezina et al., 2010), workplace violence (Hinduja, 2007), and substance abuse (Swatt, 2007). Applying GST to the current study, children experiencing strains such as abuse or parental separation could use running away as a coping strategy to escape such stressors.

Understanding potential strains and factors will allow the police and social care to target at-risk individuals, better understand the context of their disappearance, and find potential ways to reduce the number of times they go missing. Unfortunately, due to methodological constraints such as limited access to relevant data, research is scant. Randomised control trials test cause and effect (Goldacre, 2013), but as it is unethical to deliberately expose a child to risk or take no action when one goes missing, there are none. Instead, existing studies use less rigorous cross-sectional designs, demonstrating correlations but not the underlying cause or direction of the effect. For example, a UK survey found links between drug misuse and missing children (Rees, 2011). However, it is unclear if drugs are the cause (drugs increase risk-taking behaviour) or effect (being missing puts the child in risky situations) of going missing. Despite these limitations, six broad categories of factors have emerged, influencing the likelihood of a child repeatedly going missing. These are; being in care, an adverse family background, exploitation and crime, demographics, mental health, and substance misuse.

Being in Care

Children in care are overrepresented in missing persons reports (Biehal et al., 2003). Care includes local authority, voluntary and independent sector residential care homes and foster care placements. One in ten looked after children go missing each year, compared to one in two hundred children living with their family (NCA, 2019). Some disparity may be attributable to reporting procedures, carers being more vigilant due to their professional role (Hayden & Goodship, 2013). Also, many children in care probably started to go missing before they entered the care system (Hayden & Shalev-Green, 2016) so again distinguishing correlation or causation is difficult. Despite this, there is still a clear association, which has received remarkably little research investigation. Children may be trying to get away from something (push factors), such as arguments with staff, bullying from other children, or to get to somewhere or someone (pull factors), such as the desire to see family and friends (Finkelstein et al.,2002).

GST may also provide a helpful lens. A key challenge to GST has been to explain why some individuals resort to crime or delinquency as a coping mechanism when others facing similar circumstances do not. GST proposes that particular variables may increase the likelihood of negative coping, such as a lack of social support or other coping resources (Agnew, 1992). Children in care may lack support and loving relationships, which may increase their likelihood of going missing.

Consequently, the current study hypothesised that children in care are more likely to go missing repeatedly (H1).

Adverse Family Background

Abuse and neglect are risk factors for running away. Hutchings et al. (2019) examined missing child cases from a UK police force and found that children who frequently went missing (three or more times in twelve months), were twice as likely to have a history of abuse and neglect. However, studies are limited, and the variables used are often poorly defined. For example, Baker et al. (2003) used a self-report questionnaire to measure levels of emotional abuse experienced by teenage runaways. Unfortunately, the study did not fully explain the variables, leading to subjectivity in the responses. For example, the questionnaire asked the children whether they had experienced problems at home, but without a full explanation, this can have different meanings to different people.

Research into Adverse Childhood Experiences (ACEs) may, however, help to fill this gap. ACE studies explore the impact of adverse childhood experiences on adulthood. Results provide strong evidence of a link between early physical and emotional abuse, loss of a parent, domestic abuse, divorce and parental drug use, to offending, physical illness and substance abuse later in life (Child Exploitation and Online Protection Command [CEOP], 2011; Dube et al., 2006). GST may also help to explain this negative relationship. GST describes chronic strain – repeat exposure to continuous strain that leads to negative emotional traits, like anger (Agnew, 2006). The more someone experiences a strain, the more likely they are to develop these traits, and the more extreme their response. A dysfunctional homelife is a unique strain because it leaves fewer alternatives for avoidance, and therefore running away may be the only option in order to escape.

Although ACE studies have not focused on missing children, given their profound influence on mental and physical health, and their potential as “push” factors, we hypothesised that children suffering an ACE are more likely to repeatedly go missing (H2).

Exploitation and Crime

Missing children are vulnerable to criminalisation and sexual exploitation. Sturrock and Holmes (2015) found evidence of gangs recruiting children to sell drugs. The National Crime Agency report that 80% of police forces have found cases of gang exploitation, with 15-16-year-old males being most at risk (NCA, 2017). Research also identifies running away as the top risk factors for child sexual exploitation (CSE) (Jago et al., 2011). Estimates show 90% of children who have been subject to grooming will also go missing (Department for Children, Schools and Families [DCSF], 2009) and those who go missing repeatedly, are twice as likely to have been sexually exploited (Hutchings et al., 2019). This potentially could either be a “pull” factor (they go to meet an abuser as they do not recognize the grooming as such), or a “push” factor (they are being abused and runaway as a means of escape). Emerging evidence also recognises that children who go missing from local authority care are particularly vulnerable to CSE (All-Party Parliamentary Group [APPG], 2019).

Crime can be a cause as well as a consequence of going missing. A child may run away to avoid punishment for committing a crime. Alternatively, a child may commit crime as a result of being missing. For example, Shalev-Greene and Pakes (2014) found evidence of survival crimes. In a sample of 51 children reported missing three or more times over one year, 82% had been arrested at least once, the most common offences being assault and theft. Based on these findings, we hypothesised that children suffering criminal exploitation (H3), children who have been arrested (H4) and children who have been perpetrators of violence (H5), are more likely to go missing repeatedly.

Demographics

Studies generally find girls are more likely to run away (Slesnick et al., 2013). UK statistics show females aged 12-17 years go missing the most (NCA, 2019). Data from the charity Missing People follows this trend, with 71% of 13-17-year-olds reported missing being female (Biehal et al., 2003). The gender difference may be due to the perception females are more vulnerable, increasing the number of missing reports; males may have alternative strategies to face or cope with distress, or it may be females are more susceptible to grooming (Smeaton, 2013).

For age, the picture is still unclear. Most research suggests older children are more likely to go missing, with those 13 to 17 years reported missing the most (Babuta & Sidebottom, 2018; Graham & Bowling, 1995; Rees, 2011; Rohr, 1996). One possible explanation is older children experience more complex and interrelated life problems (Baker et al. 2003). In contrast, younger children are also more closely supervised and have less opportunity to runaway (Social Exclusion Unit, 2000). Therefore, we hypothesised that gender (being female) (H6) and age (being older) (H7), would be significant risk predictors for children to repeatedly go missing.

Mental Health

Strong associations exist between mental illness and going missing (Tarling & Burrows, 2004). UK statistics show depression and mental health are present in 25% of all missing reports (NCA, 2016). Looking specifically at adults, Gibb and

Woolnough (2007) analysed police missing reports and found 80% involved mental illness, including bipolar disorder, depression, psychosis/schizophrenia and dementia. This compares to an estimated one in six people in the UK who suffer mental health problems every week (McManus et al., 2016). Similarly, Holmes et al. (2013) looked at 5000 missing person cases and found 60% of persons who went missing had a mental health problem. Whilst studies have so far focused on adults and not repeat missing children, they are still valuable for this research and indicate the likely effect.

Although carers and family may be more likely to report people with mental health issues missing (Sveticic et al., 2012), there appears a link between mental health and going missing. One possible explanation is that running away is a coping response to a crisis (Stevenson et al., 2013). Self-harm is another coping mechanism (McDougall et al., 2014) and research has found on average up to a third of missing incidents reported to the police involve suicide or self-harm (APPG, 2019). It could be people go missing to harm themselves or to hide once they have done so. More research is urgently needed however, as studies have only used police data, but as many police forces do not routinely record if a missing person has self-harmed, the actual figures are likely to be significantly higher. Consequently, we hypothesised that children with a history of mental health and self-harm are more likely to go missing repeatedly (H8).

Substance Misuse

Although no studies have specifically examined substance misuse and running away repeatedly, several studies have found substance misuse does increases the risk of going missing (Browne & Falshaw, 1998; Hutchings et al., 2019). Thompson et al. (2002) surveyed children admitted to emergency homeless shelters in America and found that 65% reported using drugs or alcohol. As highlighted previously, a weakness for many such studies, however, is establishing the direction of the effect. Drugs could either be a cause of going missing (increasing risk-taking behaviour), or a consequence (putting the child in risky situations where drugs are available). Further research is needed; however, the existing evidence suggests that children with a history of substance misuse are more likely to go missing repeatedly (H9).

Summary

Few studies have compared the attributes of children who have been missing once, compared to those who go missing frequently. A range of personal and social factors may be involved, but the evidence is from small, cross-sectional samples, and further research is needed. The research has also primarily examined individual risk factors and not their interrelatedness. The variety of factors involved suggest there may also be complex interactions that give rise to different pathways to missing behaviour. For example, situational factors like poor relationships or lack of engagement at school, could increase a child’s vulnerability to criminal exploitation or drug misuse.

Based on previous findings and in combination with practitioner experience, this study will include the following factors, in combination, into our scope of examination: being in care, adverse family background, criminal exploitation, being arrested, being a perpetrator of violence, age, gender, history of mental health and self-harm, and substance misuse.

Objective 3 – Identifying Those Individuals Most at Risk of Going Missing Repeatedly

The last objective focuses on practical application and using the salient variables (identified in objective 2), to develop a risk assessment for operational police officers to be able to reliably identify the individuals most at risk of going missing repeatedly. Currently, after locating a missing child, the police complete a safe and well check to establish what support they may require. Safeguarding options range from taking no action, up to detaining the child under a Police Protection order. Correctly anticipating whether the child will run away again is vital. However, presently, there is no quantifiable or statistical method to help, and instead, the risk assessment relies on the professional judgment of the officer. Therefore, developing a more evidence-based tool/measure is crucial and will allow officers to more reliably identify the most vulnerable and quickly put prevention strategies in place before they go missing again. This section considers what type of measure may be most appropriate. Firstly, evaluating professional judgement (the current approach), the section then identifies two alternatives: statistical forecasting and structured professional judgement.

Professional Judgement

Traditionally, police officers use experience to make decisions, especially in missing person investigation. Known as professional judgement (Barends et al. 2015), other stages of use include whether/when to arrest, bail, prosecution and conviction (Hyatt & Barnes, 2014). While professional judgement is flexible, making it invaluable for dynamic and complex situations, it is also prone to errors (Barends et al., 2015) such as cognitive bias (a systematic error in thinking). For example, researchers assessing the ability of social workers to detect child abuse found professional judgement was only slightly better than guessing (Behavioural Insights Team, 2014).

Professional judgement is particularly ineffective for risk decisions, for example those involving financial risk or personal loss (Arad-Davidson & Benbenisty, 2008). Although there are no studies specific to missing persons, domestic violence research has found professional judgement led to inconsistent decision making, and a tendency for officers to over-estimate some factors like violence, while neglecting others like coercion and control (Robinson et al. 2016). These weaknesses are concerning given the enormous risks involved with missing children. The need for consistent, well-informed decisions has led to the development of evidence-based policing (EBP) (Keay & Kirby, 2017). Sherman (1998, p.2), proposed that “police practices should be based on scientific evidence about what works best”. EBP is growing, and methods such as statistical forecasting are now commonplace (Oswald et al., 2018).

Statistical Forecasting in Policing

Statistical forecasting eliminates human decision making and instead assigns values to risk variables such as violence, or substance misuse, to arrive at the probability of some outcome. Research consistently shows statistical forecasting is more accurate at predicting risk than professional judgement (Kahneman, 2011). The Kent Internet Risk Assessment Tool (KIRAT) is one example. The proliferation of indecent images of children on the internet has exceeded the resources required to investigate the suspects effectively. The KIRAT is an evidence-based framework for prioritizing the most dangerous offenders (those most likely to commit hands-on sexual offences against children). Using fourteen questions about the suspect (previous behaviour, access to children, current behaviour and circumstances), it produces a risk score (low, medium or high). Research has found that the model could correctly classify 97.6% of high-risk offenders and 62.3% of low-risk offenders (Long et al., 2016), considerably higher than personal opinions of police officers.

Recent advances in technology have led to a more advanced form of statistical forecasting - predictive policing. Predictive policing is primarily used to forecast crime (Meijer & Wessells, 2019). For example, Kent Police use predictive mapping to identify crime hotspots and have found it to be twice as effective as traditional intelligence-led methods (Kent Police, 2014). More recently, predictive policing is making predictions about individuals. Durham police developed the Harm Assessment Risk Tool (HART), which uses variables including past convictions, demographics, and postcode to predict the chance of individuals reoffending (Urwin, 2016). HART can predict reoffending with 63% accuracy, significantly higher than the professional judgement of police officers (Oswald et al., 2018; Vettor et al., 2014).

Several studies have applied statistical forecasting to missing persons. Researchers successfully predicted the distance a lost person would travel based on factors such as age, sex and mental condition (Gibb & Woolnough, 2007). Newiss (2011) further developed this to identify health and lifestyle factors which could predict if a missing person would come to harm. For example, for a missing middle-aged male with depression, the likelihood of self-harm, or suicide increase. Adults who have recently ended a relationship, or those facing allegations of sexual abuse, are also at a high risk of harm (Eales, 2017).

Overall, however, support for predictive policing is inconsistent (Vetter, 2014). By using an algorithm, Berk and Sorenson (2005) found that they could predict 60% of future domestic violence offences. Similarly, Greater Manchester Police found predictive crime mapping, was ten times more effective at reducing burglary than traditional foot patrol (Fielding & Jones, 2012). However, other studies are less favourable. Sanders et al. (2015) used predictive modelling to estimate the risk of individuals becoming involved in gun violence, but after twelve months, there was no significant effect.

Overall, it appears that statistical forecasting is not always reliable, and flaws in its methodology may explain this. Firstly, the assumption that all people are the same. Algorithms only deal with data that can be coded and formalised, compared to human analytical thinking. By grouping people and not considering the individual (Cooke & Michie, 2014), critics claim context is lost, and decisions are oversimplified (The Law Society of England and Wales, 2019). Oversimplification could be especially problematic for going missing, as the drivers can be hugely complex (Missing People, 2019).

Secondly, statistics rely on the future replicating the past (Copson et al.,1997), and therefore, any dramatic changes could make a forecast suspect. For example, recent years have seen profound changes in how children socialise, with 83% of 12-15-year-olds now owning a smartphone (Office for National Statistics [ONS], 2018). These factors are likely to affect missing behaviour, meaning any predictive model could quickly become outdated.

The final flaw is assuming the data is accurate. If the information does not accurately represent the problem, outcomes may be suspect. For example, a large proportion of missing episodes go unreported (NCA, 2016), and therefore the data provides an incomplete snapshot of the problem and consequently prediction is potentially based upon a limited sample (University of Huddersfield, 2016).

In summary, these flaws show a tension between statistical forecasting and professional judgement, which may make it unsuitable for missing person investigation. The weaknesses in human decisions highlight the need for a predictive risk assessment model. However, the uncompromising approach of statistical forecasting means it cannot easily change or adapt to recognise the diversity of missing children. This has led to a third type of risk assessment – structured professional judgement.

Structured Professional Judgement

Structured professional judgment (SJP) attempts to resolve concerns around the inflexibility of algorithms while recognising the weaknesses of human decision making. SPJ still uses prediction models and algorithms to identify risk factors, but decision-makers retain the flexibility to consider additional case-specific factors (Doyle & Dolan, 2002). Bridging the gap between professional judgement and statistical forecasting (Douglas & Kropp, 2002), SPJ has become the gold standard risk assessment technique (National Institute for Mental Health in England, 2004).

The Harm Assessment Risk Tool (HART) (described above) is applied in this way. Recognising that the risk assessment does not have all the information, it therefore only supports human decision-makers, rather than replacing them. The custody officers with both their local knowledge and their access to other data systems retain their discretion to override the model's prediction if necessary and given appropriate justification.

Overall, however, there has been little rigorous assessment of SPJ. Douglas et al. (2005) found that it was equally as effective as the predictive approach when assessing the risk of violence among criminal offenders, but others have had less success. For example, the Domestic Abuse, Stalking and Honour-based Violence Risk Identification, Assessment and Management Model (DASH), is used by the majority of police forces when working with victims of domestic abuse. DASH uses

SJP, by producing a risk grading (standard, medium or high), but leaving officers discretion to raise the risk, if it appears higher than the score suggests. In one of the few critical assessments of its effectiveness, Almond & et al. (2017) found it was a poor predictor of future victimisation. One possible explanation is that as SJP still allows the practitioner considerable discretion when interpreting the answers to the questions, it is therefore still vulnerable to some of the same criticisms as professional judgement.

To a limited extent, missing person research already uses SJP. Bonny et al. (2016) found that several personal factors could successfully predict if an adult would go missing. For example, if an individual was known to social services, had mental health issues, took drugs, and had suicidal ideations, they would be a high risk of becoming a missing person. These findings were the first step in developing a standardised checklist, which could be used by practitioners to prioritise missing adults. Building on this, Hutchings et al. (2019) explored data collected on missing children by Gwent Police, looking at thirty factors, ranging from demographics to family background and medical history. The study identified five significant risks common to repeat missing children. These were; being in care, substance misuse, suspected sexual exploitation, known to youth offending services and a history of abuse and neglect. Researchers proposed providing the police with a checklist, and if a child had three or more of the factors, they would be a high risk of going missing repeatedly.

In conclusion, SPJ recognises that good practice is evidenced-based, yet at the same time recognises the existing knowledge can be incomplete, and imperfect for making decisions about individual cases. SPJ is flexible and supports and guides professional judgement rather than replacing it and given the complexity of missing children, makes it the most suitable approach for this study.

Current Research

Where this study departs from the previous research on repeat missing children, is by focusing attention on a practical solution. Although past research identifies risk factors for running away (see Bonny et al., 2016; Hutchings et al., 2019), studies have not provided usable results that will benefit either the police or missing person investigation, and this may be down to studies being researcher rather than practitioner-led. For example, although an operational police officer may be aware that a cared for child is at risk of going missing (Lees, 2011), there is no formal way to quantify the risk and use it as a base for decision making. For the present study, the real-world application is crucial and to achieve this, the research uses Pragmatic Psychology.

Pragmatic Psychology is goal-focused and problem-driven. Rather than identifying a theory which can then be applied, for a pragmatist, the application comes first (Fishman, 1999). The pragmatic framework has three main principles, and these are; focusing on practical problems and solutions; taking into account what the practitioner wants and ensuring the results are relevant to their needs; and finally, ensuring methods are rigorous and scientific.

By using a pragmatic approach, the findings must first be useful within the policing environment. For example, although Bonny et al. (2016) identify factors that make children more likely to go missing, their results do not form a risk assessment. Instead, this study intends to give officers the ability to make a timely risk assessment when they locate a missing child.

Secondly, the findings must be useable and take the operational context of missing persons into consideration. For example, Hutchings et al. (2019), use detailed family history as a risk factor, but officers would not have access to this information during routine policing. As a result, the risk factors in this study must be immediately available through the usual police practice. Officers do not have ready access to data from other local agencies, and therefore this will not be included.

Finally, the results must be scientific. The police must be transparent and accountable in decision making. As such, any pragmatic recommendations emanating from this research need to be scientific. Pragmatic Psychology assists by ensuring the enquiries are structured and systematic.

In summary, responding to missing children is a leading source of demand and cost to the police. The proposed study will first establish the prevalence of repeat missing incidents in children and then identify a set of risk factors associated with repeat missing behaviour. The final aim is to develop these factors into a statistical model to identify those individuals most at risk of going missing repeatedly. The present study will build on the work Hutchings et al. (2019), by using a larger sample size of children, and also by ensuring the findings are useful to practitioners.

CHAPTER 3: METHODOLOGY

By taking a pragmatic approach (Fishman, 1999), the study sought to; (1) investigate the prevalence of repeat disappearances by children; (2) identify risk factors increasing the likelihood of a child going missing repeatedly; and (3) develop an easy-to-deploy statistical model to identify those children most at risk of going missing repeatedly.

The study used logistic regression to analyse a dataset of pre-existing missing persons (*N*=909), comparing the attributes of two groups: children who run away more than once (*n*=389); and those who are "one-off" runaways (*n*=518). The chapter outlines the research strategy, introducing Pragmatic Psychology as the theoretical stance. The design, sample, data collection, data analysis and ethical considerations are also described.

Design

Researchers should select a methodology consistent with their goals (Lincoln & Guba, 1985). As the objective was to solve a real-world policing problem (missing child risk assessment), a pragmatic approach was appropriate. Pragmatism deals with useful knowledge that helps solve practical problems (Rorty, 1999). As solutions are the goal, the approach does not advocate any specific strategy, but instead encourages researchers to consider "what works" best to solve the practical problem. The study employed a quantitative approach, using secondary data, as access was granted to a large police dataset of missing children cases.

Sample / Data

The sample comprised of all missing child reports to Dorset Police in one year (1^{st} July 2018 – 30^{th} June 2019). After exclusions (discussed below), this left 909 individual children who were involved in 3213 separate missing incidents. The following parameters were set.

1. ***Geographical Location***. Previous research has found significant regional differences in missing children (NCA, 2017). As the study was concerned with making predictions about children who go missing in Dorset, only children reported missing to Dorset Police were included.
2. ***Operational Definitions.*** The study used policing definitions to ensure the findings were practical and relevant to the police. A missing person was defined as; "anyone whose whereabouts is unknown whatever the circumstances of the disappearance. They will be considered missing until located and their well-being or otherwise established" (Association of Chief Police Officers [ACPO], 2010, p. 8). A child was defined as; "anyone who has not yet reached their 18th birthday" (Children's Act, 1989, para. 16).
3. ***Sample Frame.*** The sample was limited to the most recent data available (30th June 2018 - 1st July 2019). Although purposive sampling can be prone to bias, it was necessary to;
    - account for seasonal variations - more children go missing in the school holidays, making it imperative to include a full calendar year, and
    - ensure the data was up to date - statistics suggest changes in missing behaviour over time (NCA, 2017).
4. ***Exclusion Criteria.*** The purpose was to examine runaway behaviour. The research, therefore, excluded sixty children who were reported missing for other reasons (abduction, lost, human trafficking). In addition, Dorset Police also only hold background information for children in Dorset. Consequently, it

was necessary to remove thirty-five cases involving children who lived elsewhere.

5. ***Dependent (Response) Variable***. The dependent variable was the number of times each child went missing during the 12 months of the study (30th June 2018 - 1st July 2019). The outcome was coded as either; single missing episode (low risk) or repeat missing episodes (high risk). One consideration was to divide the outcome into multiple levels, for example, low, medium and high risk. Operationally, however, risk increases substantially every time a child runs away, with repeat disappearances often indicating underlying vulnerabilities and being linked to various forms of exploitation and abuse (Sidebottom et al., 2019). Setting the threshold as a simple binary outcome was, therefore, the most appropriate measure.
6. ***Independent Variables.*** Ten variables were measured for each child (nine categorical, one continuous). Table 1 contains the full list, including their operational definitions.

Table 1

Description of Variables Included in the Analysis

Variable	Measurement	Description
No. times missing	Categorical Low/High	Number of times the child has been reported missing in the 12th month period. Low = 1, high =>1
Age	Continuous	Age on the first missing episode in the 12-months.
Gender	Categorical M / F	Gender of missing child.
Adverse Childhood Experience (ACE)	Categorical Yes /No	Adverse Childhood Experiences (ACEs) are traumatic experiences before the age of 18.

Table 1 (continued)

Variable	Measurement	Description
History of drug misuse	Categorical Yes / No	A reasonable belief that the child has used an illegal drug at any point in their life.
Violent history	Categorical Yes / No	Describes whether the child is known to have previously been a perpetrator of violence.
Previous arrest history	Categorical Yes /No	Whether the child has been arrested for any offence before going missing.
Self-harm	Categorical Yes /No	Intentional harm including, cutting or burning skin, punching or hitting, poisoning with tablets or liquids, or similar.
Mental health	Categorical Yes / No	A diagnosed mental health disorder.
Family status (cared for child)	Categorical Yes / No	Includes local authority, voluntary and independent sector residential care homes and foster care placements.

Procedure

The data came from missing person reports held by Dorset Police. Each missing child has a digital record including

- current family circumstances,
- background and medical history,
- circumstances of their disappearance,
- risks such as physical or mental illness, or dangerous associations and
- details of the investigation.

Officers collect the information from multiple sources (friends, family, professionals) and manually enter it into the record. Although there are no statistics for errors in this kind of reporting method, all reports are checked by a supervisor, increasing their reliability.

1. ***Data Collection.*** Information from the missing person reports was extracted on the 19th July 2019 and transferred into a Microsoft Excel spreadsheet. The download contained three of the variables (number of times missing, age and gender). To obtain the remaining data, the researcher manually accessed each child's Dorset Police person record, which contains details of all police interactions, including arrests, stop checks, victimisation and intelligence.
2. ***Identification of Variables.*** The variables were selected based on previous studies. Five other experienced professionals knowledgeable in missing children, were then given the variables and asked to comment, in line with pragmatic psychology which advocates the use of applied experience in conjunction with academic rigor in research design. There was a consensus that the listed factors could be predictors of repeat missing behaviour. Also, the data was deemed 'authentic' as it was extracted directly from police records. Alison et al. (2001) argue police records are the best way to examine police phenomenon, as the information reflects reality.
3. ***Recording and Coding.*** Individual records were opened and scrutinised for evidence of the variables. To ensure reliability and consistency (Bryman, 2008) a specially designed data collection tool and codebook were utilised throughout (Appendix A). A binary classification was used, coding the presence of the behaviour as one and the absence as zero. The codebook

provided explicit instructions, and categories were designed to ensure they were mutually exclusive.

4. ***Missing Data.*** An important aspect of handling data is devising a strategy for missing information (Bryman, 2008). In five cases, information was missing and unobtainable. Where multiple scores are missing for a person, Bryman and Cramer (2005) recommend omitting the case as it is likely there are problems in the way the information was collected. Therefore, due to the small number, these cases were removed from the dataset.

Data Analysis

This study aimed to examine the extent to which children go missing and predict a dichotomous outcome (high risk vs low risk of going missing again). The data analysis occurred in four stages.

Stage 1 - Investigating the Prevalence of Repeat Missing Episodes. Descriptive statistics were used to examine the patterns and prevalence of repeat missing episodes.

Stage 2 - Identifying Risk Factors for Repeatedly Running Away. The study used regression analysis (see stage 3) to predict whether a child would go missing repeatedly. To avoid overfitting the model (identifying spurious relationships), or underfitting (failing to capture the underlying structure of the data), each variable was compared against the high-risk group. Chi-Square tests were used for categorical variables and a t-test for Independent Samples for the continuous variable (age). Any risk factor predicting the high-risk group with $p < 0.2$, was included in the regression model (stage 3). The advantage of using a higher significance level ($p < 0.2$ instead of $p < 0.05$) is that essential variables are less likely to be missed (Kirkwood & Sterne, 2003). All variables met the p <0.2 level of significance.

Stage 3 – Testing the Assumptions & Developing a Statistical Model. Binary logistic regression (BLR) was used to predict the likelihood of a child repeatedly going missing. BLR assesses the predictive ability of a set of independent variables (predictors) on a categorical dependent variable (outcome), in this case, either high risk vs low risk of going missing. Pragmatically it is not really necessary for police to predict the *number* of times a child may go missing (and this is unavailable due to the constraints of this dataset being limited to a year), but merely *whether* or not they are likely to be a repeat missing person, in order to target them for potential interventions. Discriminant function analysis (DFA) was a possible alternative test. DFA is also used for categorical group prediction but differs in that it assumes multivariate normality, making it unsuitable for the binary predictor variables in this study (Rice, 1994).

Other areas of criminal justice research advocate the use of BLR to predict outcomes, setting the precedence for this method. For example, in a similar study, Hutchings et al. (2019), used BLR to predict the likelihood of a child going missing. Similarly, Davies et al. (1998) used BLR to estimate the likelihood of a rape offender possessing particular criminal convictions and Cole & Brown (2013) used BLR to predict characteristics (age, previous convictions) of murder offenders.

Logistic regression has several key assumptions (Bewick et al., 2005), the first being that the predictor variables are not highly correlated. To check for multicollinearity, each variable was compared, using either Pearson's r (continuous vs nominal), or Chi-square and the phi coefficient (nominal vs nominal).

All variables were entered simultaneously into the model (enter method) as none of the variables was deemed more important than others (hierarchal, sequential). The research also wanted to investigate all of the variables rather than adding them in or taking out based upon statistical rationale (stepwise, forward, backward).

Having fit the model, variables that did not show significance at the 5% level were eliminated, on the basis that they were not contributing to the model. Following the elimination of non-significant variables, the logistic regression was re-run, and the result was the final model.

Stage 4 - Testing the Model. Verifying the predictive ability of a model is a critical step, and it should perform equally well for new data, as it did in the development stage. One method of doing this is internal validation, randomly splitting the data set into two parts: one to develop the model and another to validate its performance. With this split-sample approach, the researcher measures performance on similar, but independent data. As there was a large sample of data, this was used. The data was randomly into two parts (50:50), the first sample was used to develop the model, and the second to validate its performance.

Ethical

Due to the extremely sensitive nature of the data, all data was robustly anonymised at source, by removing all direct identifiers such as names, police reference numbers and postcodes. All indirect identifiers that could potentially link with other publicly available information were additionally removed. All relevant data sharing permissions and vetting procedures were authorised and agreed by Dorset Police, and ethical approval was gained from Bournemouth University Ethics (Appendix B).

CHAPTER 4: RESULTS

Stage 1 - Investigating the Prevalence of Repeat Disappearances

Descriptive statistics were used to describe the main features of the sample. In total, 909 children were included, with no missing data.

Demographic Variables

The majority of children were aged over 12 years (87.4%), with the mean age of 14.01 years and a standard deviation of 2.17. Figure 1 shows this distribution of missing children by age and gender.

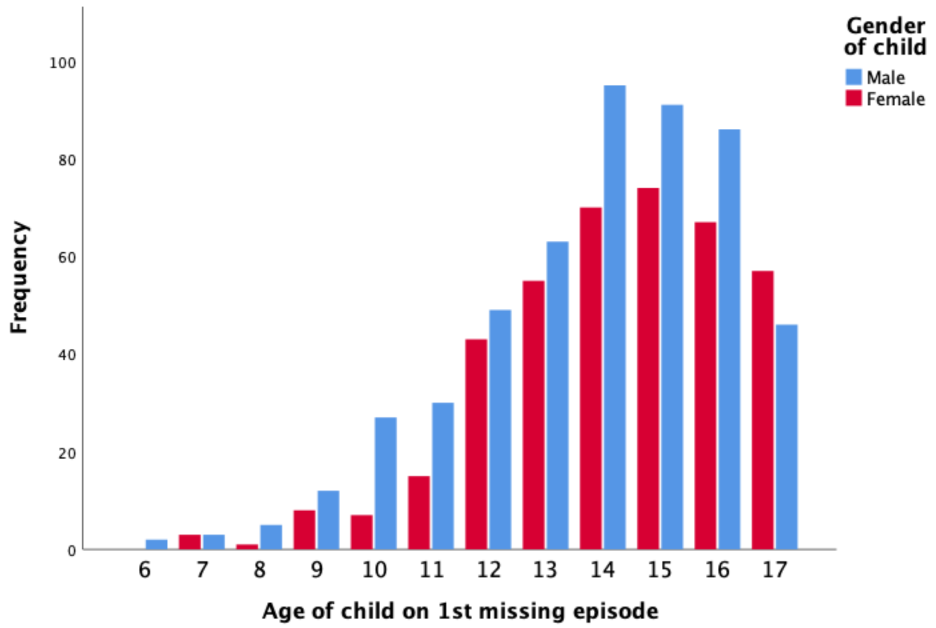

Figure 1. Number of Missing Children by Age and Gender.

Although males account for slightly more disappearances at all ages, except 17 years, overall gender differences within the sample were not significant (males 56%; female 44%). This is contrary to previous literature which found more females go missing between the ages of 12-17 years. However, previous studies are based on much larger samples, which may explain the variation in results.

Behavioural Variables

Table 2 displays the frequency of behavioural variables. There is a clear trend towards difficulties at home, with most missing children having suffered an Adverse Child Experience (ACE) (64.4%) and over 1/5 (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% of the sample had self-harmed, highlighting the risks faced by these children whilst missing.

Table 2

Frequency of Behavioural Variables Within the Sample (N = 909).

Variable	***n***	**%**
Family Factors		
Adverse Childhood Experience (ACE)	585	64.4
Risk Taking Behaviour (by child)		
Drug Misuse	268	29.5
Suspected victim of criminal exploitation	269	29.6
History of violent behaviour	253	27.8
Previous arrest	155	17
Self-harm	109	12
Service Involvement		
In care	195	21.5

Frequency of Repeat Missing Episodes

Table 3 breaks down the extent of repeat disappearances. For the 12-months, there was a total of 3213 missing person episodes, relating to 909 unique children. The disparity between individuals and incidents reveals repeat disappearances. Most children, 57.2% (*n* = 518) went missing only once (categorised as low risk of becoming a repeat missing), and 42.8% (*n* = 389) went missing more than once (categorised as high risk of being a repeat missing).

Table 3

Extent of Repeat Disappearances by Children in the Sample

No. of Disappearances	Number (%) of children recorded as missing	Number (%) of missing child episodes
1	518 (57.2)	518 (16.1)
2	150 (16.5)	300 (9.3)
3	70 (7.7)	210 (6.5)
4	27 (3.0)	108 (3.4)
5	25 (25.0)	125 (3.9)
6	16 (16.0)	96 (3.0)
7	10 (1.1)	70 (2.2)
8	9 (1.0)	72 (2.2)
9	9 (1.0)	81 (2.5)
10 or more	75 (8.3)	1633 (51.0)
Total	909	3213 (100)

Table 3 shows that although single missing episode children (*n* = 518) represented 57.2% of all individuals in the sample, they accounted for only 16.1% of all missing child episodes. Compared to the 389 children who went missing more than once, accounting for 83.9% of the total episodes (2755 episodes). The table also shows that the distribution of disappearances is highly skewed, with the small minority of children who went missing ten or more times (*n* = 75) making up just 8.3% of the sample, but collectively accounting for 1633 missing episodes - 51% of the total disappearances. This small cohort (the 'power few') who go missing a disproportionate number of times are significant outliers, suggesting that they may form a distinct subset, with unique characteristics and suffering distinctive risks.

Stage 2 – Testing the Assumptions.

Correlation analyses were conducted using Pearson's *r* for the association between the continuous and nominal variables and phi coefficient and chi-square calculations for nominal variables and dichotomous variables (see Table 4).

Table 4

Pearson and Phi Correlations of the Variables.

	Variable	1	2	3	4	5	6	7	8
1.	Age[a]								
2.	Gender	.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.	Previous 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. Abbreviation: CE, criminal exploitation. ACE, adverse childhood experience.

[a]Age: Pearson's *r*.

*$p < .05$; **$p < .001$

For Pearson's *r*, Cohen (1988) suggests the following guidelines for estimating the relationship's magnitude, defined by *r*: 0 to 0.2 very weak; 0.2 to 0.4 weak; 0.4 to 0.6 moderate; 0.6 to 0.8 strong. Based on this, for age, all correlations ranged from very weak to weak, the strongest being between age and family status; $r = .26$, $p < .001$. As multicollinearity was minimal, age was retained in the analyses. The remaining variables were compared with one another using chi-square calculations and the phi coefficient. Previous research recommends the following criteria for estimating the magnitude or strength of the phi coefficient: 0 to 0.3 for a small effect; 0.3 to 0.5 for a medium effect; and 0.5 or higher for a large effect (Allen, 2017).

The majority of variables showed only a "small" or "medium" association, meaning minimal multicollinearity. Drug misuse was the anomaly however, showing a strong relationship with criminal exploitation ($r = .66$, $p < .001$), violence ($r = .54$, $p < .001$), and previous arrest ($r = .53$, $p < .001$). Although there is no agreed standard for excluding in multicollinearity (instead it is dependent on the purpose of the analysis), these correlations indicate significant multicollinearity and therefore, potential difficulties when interpreting the logistic regression model. A possible solution was to remove drug misuse from the analysis but doing so risked the loss of valuable information. It was important, therefore, to consider the variable in more detail, before making a decision.

Considering the four variables (drug misuse, criminal exploitation, violence and previous arrest), there is an obvious overlap in concepts, and therefore the variables may be measuring the same information. For example, perpetrators often lure children into criminally exploitive situations by using drugs and alcohol (Barnardo’s, 2011). 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, 2010). 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.

Regression analysis has six other assumptions.

1. One dichotomous outcome variable, here labelled as a single missing episode (low risk) or repeat missing episodes (high risk).
2. Independent variables are continuous (age) or nominal (all other variables).
3. Variables in the study are independent (exclusive and exhaustive).
4. A large enough sample size. The recommended number of cases is 10 per predictor variable – i.e., 9x10 = minimum 90 cases (Peduzzi, 1996). With 909 cases, the study met this assumption.

The remaining assumptions relate to how the data fits the logistic regression. They were tested in stage 4 when the model was built, but for simplicity are summarised here.

5. There should be a linear relationship between any continuous independent variable and the logit transformation of the dependent variable. Age is the only continuous variable, and it was tested using the Box-Tidwell procedure (Box & Tidwell, 1962), demonstrating that it did not violate this assumption (see Appendix C).
6. There should be no outliers as these reduce the accuracy of the logistic regression. An analysis of standard residuals (*z* scores) was carried out on the data to identify any outliers. Field (2015) stipulates the following guidelines; only 5% should lie outside 1.96; only 1% should lie outside 2.58; scores with an absolute value greater than 3.29 are cause for concern as in an average sample a value this high is unlikely to occur. The analysis revealed only nine cases (1.8%) with scores outside of 1.96, satisfying the 1st

requirement. Eight cases (1.8%) were however outside of 2.58, and 6 cases had values higher than 3.29, suggesting there may be too many outliers in the data set, and consequently this assumption was not met.

There are several strategies for dealing with outliers. However, crucially, they may not always produce a damaging effect on the regression equation and therefore should not be automatically removed (Hawawini et al., 2003). The first method is to examine each case in more detail (Field, 2015), checking for errors or explanations for the extreme values. On doing so, six cases were incorrectly coded. The errors appear to have been due to human error when inputting the data and were corrected. A further sample of 10% was checked, but no other errors were found. Appendix D provides full details of the cases and the changes made.

The remaining three outliers (see Appendix D) appeared legitimate observations. In order to determine the extent to which they influenced the regression equation, two regression models were compared, the first including the outliers and the second without (Hecht, 1991) (Appendix D). Removing the outliers had a minimal statistical impact. There was no change in the statistical significance of the overall model fit, and the change in overall prediction accuracy was only 0.6%. Furthermore, there were only three outliers (0.2% of the sample), and the highest was 3.486 - only fractionally over the upper boundary of 3.29 (Field, 2015). Based on this, these outliers were retained. As such all assumptions were either met or dealt with accordingly.

Stage 3 – Identify Risk Factors Associated with Going Missing Repeatedly

At the start of stage 3, the sample was split randomly into two equal parts; one development sample to create the model and another validation sample to measure its performance (see stage 5). The resulting development sample included 453 children.

In order to identify the risk factors which may add to the predictive model, separate statistical tests were undertaken to check for associations between each factor and the high-risk group. Chi-square tests were used for the categorical variables and an independent samples *t*-test for age which is a continuous variable. Table 5 summarises the results.

Table 5

Risk Factors for Children Being Reported Missing.

Variable	*N* (Total = 453)	Children reported missing once %	Children reported missing more than once %	Chi2 value (*df* = 1)	*p*-value (two tailed)	*OR* [95% CI]
History of criminal exploitation	143	2.9	28.7	181.440	<.001	33.056 [17.638, 61.949]
History of violence	128	5.3	23.0	97.038	<.001	10.037 [6.069, 16.600]
ACE	301	25.4	41.1	107.441	<.001	13.748 [7.792, 24.256]
Self-harm	53	4.4	7.3	7.587	.006	2.255 [1.250, 4.068]
Previous arrest history	84	1.1	17.4	102.085	<.001	31.600 [12.476, 80.042]
Family status – in care	104	2.2	20.58	114.571	<.001	20.976 [10.518, 41.833]
Mental health	35	3.1	4.6	3.645	.064	1.964 [0.972, 3.969]

Table 5 (continued)

Variable	*N* (Total = 453)	Children reported missing once %	Children reported missing more than once %	Chi2 value (df = 1)	*p*-value (two tailed)	*OR* [95% CI]
Gender Female	211	24.5	22.1	1.255	.263	.809 [.558, 1.173]
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.

Except for gender and mental health, all variables significantly influenced the dependent variable. 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. Concerning age, an independent-samples *t*-test found that children were significantly older in the high-risk group compared to the low-risk groups (*t* (453) = -4.23, *p* <.001), suggesting that older children are more likely to go missing repeatedly.

Practical application is an essential component of this research, and therefore, odds ratios were calculated, to examine the impact of each factor. For example, Table 5 shows the odds of being a repeat missing is 33 times greater if the child has been subject to criminal exploitation. The more impactive the factor, the more useful it is likely to be to a practitioner. Previous research recommends the following criteria for estimating the effect size of odds ratios: small (<1.5), medium (1.5-5), or large effect (>5) (Chen et al., 2010). Based on this, history of exploitation, violence, arrest and family status all had a large effect. Self-harm and mental health had a medium effect on whether a child went repeatedly missing.

Univariate and bivariate statistics can be useful for practitioners to make basic predictions around the likelihood of a child going missing repeatedly. However, such approaches are more prone to practitioners' biases and neglect the different additive effects the risk factors may have in combination. Therefore, we proceed to the next stage of data analysis using multivariate statistics.

Stage 4 - Developing a Statistical Model

Binary logistic regression (BLR) was used to predict the probability of a child repeatedly going missing using the 9 risk predictors (with $p < 0.2$) identified in stage 3. In BLR, the baseline model gives the best prediction when no other values are known. Overall, the majority of children (57.2%) went missing just once, and therefore this is the "best guess" and is likely to be correct 57.2% of the time.

By entering the nine predictors, the resulting enhanced model was a significant improvement from the baseline model ($\chi2$ (9) = 340.381, p <.001), and was able to correctly classify 90.4% of the children who went missing once and 79.7% of those who went missing repeatedly. The overall success rate therefore increased from 57.2% to 85.7%. The model explained 70.7% (Nagelkerke R^2) of the variance in missing outcome. The Hosmer and Lemeshow test result suggested it was a good fit to the data as it was not significant (p =.0.065). Table 6 summarises the logistic regression results.

Table 6

Logistic Regression for High-Risk Children.

Variable	*B*	Wald x^2	*p*	*OR* [95% CI]
History of criminal exploitation	2.937	57.520	<.001	18.868 [40.311, 8.832]
History of 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 history	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]

Employing a $p < .05$ criterion of statistical significance, criminal exploitation, violence, ACE, family status and previous arrest history, had significant partial effects. Self-harm, mental health, age and gender were not significant.

In order to find the best fitting and most parsimonious model, we tested 2 models against the baseline model. Model 1 included all nine variables in the dataset regardless of their statistical significance (approach suggested by Hosmer et al., 2013). Whereas model 2 only used the five risk factors with significant associations. As Table 7 shows, model 2 only slightly reduced the accuracy when compared to the full model. More specifically, the predictions for low-risk children remained the same, and the accuracy for high-risk children reduced by only 1.5%.

Table 7

Comparison of Percentage Improvements in Predictions from Logistic Regression Analysis.

Model	% Correct prediction		Overall
	Low risk	High risk	
Base Rate	100	0	57.2
Model 1 (9 variables*)	90.4	79.7	85.7
Model 2 (5 variables**)	90.4	78.2	85

Note: * Criminal exploitation, violence, ACE, self-harm, previous arrest history, family status, mental health, gender and age. ** Criminal exploitation, violence, ACE, previous arrest history and family status.

The full model only improves overall prediction by 0.7%. Furthermore, although age and gender are readily available, data concerning self-harm and mental health are subjective and more difficult and time-consuming to obtain. Often the information comes from witnesses, or medical records, meaning it can be missing or unknown. Therefore, the additional time spent waiting for and collecting this information does not justify the improvement in the model. As a result, the four non-significant factors were removed.

The final model consisted of 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, $p < .001$). The model was able to correctly classify 78.2% of high-risk children and 90.4% low risk children, for an overall success rate of 85.0%. The result is a considerable improvement from best guessing alone, where the prediction is likely to be correct just 57.2% of the time.

Stage 5 - Testing the Model

As an attempt to validate the model established in stage 4, we adopted Picard and Berk's (1990) method, re-running the model using the other half of the sample (*n*=456). When using this split-sample approach, one method to obtain a reliable measure of the model's predictive ability is to compare the accuracy in each sample (Austin & Steyerberg, 2017). If results between samples are considerably different, then the model is unlikely to predict new observations as well as initially indicated.

The results obtained using the validation sample showed the model was still a significant improvement from the baseline model (χ2 (7) = 253.072, p <.001). Table 8 compares the accuracy of the development and validation models. The overall accuracy was almost identical, falling just 1.9%. The prediction accuracy for low-risk children improved slightly, rising 0.3%, but there was a slight decrease in the accuracy for high-risk children, falling by 6%. Therefore, the model performed equally well on both samples of data, indicating the model is accurate, fits the data well and would transfer to other similar children not used in the model development.

Table 8

Comparison of Percentage Improvements in Predictions from Logistic Regression Analysis (Development vs Validation).

Model	% Correct prediction		
	Low risk	High risk	Overall
Base Rate	100	0	57.2
Development	90.4	78.2	85
Validation	90.7	72.2	83.1
Difference in Predictions	0.3%	6%	1.9%

Stage 6 – Power Few Subgroup

Table 3 identifies a small subgroup of children who go missing 10 or more times and collectively account for 51% of the total disappearances. This subgroup are significant outliers, suggesting they could suffer a unique set of risks. A further binary logistic regression was carried out to determine whether specific predictors can predict higher recidivism in going missing. The outcome was categorised as either high risk (2 missing episodes, n = 151) or power few (10+ missing episodes, n = 75).

By entering the original nine predictors, the resulting model was a significant improvement from the baseline model ($\chi 2$ (9) = 68.215, p <.001), and was able to correctly classify 88.1% of the children who went missing once, but only 58.7% of those who went missing more than 10 times. The model was now only able to explain 36.2% (Nagelkerke R^2) of the variance in missing outcome (compared to 70.6% for the original model – stage 4). The Hosmer and Lemeshow test result suggested it was a good fit for the data as it was not significant (p =.0.602). Table 9 summarises the logistic regression results. Employing a $p < .05$ criterion of statistical significance, only previous arrest history and family status now had a significant effect. These results indicate the power few, are a distinct subgroup, facing different risks than the lower recidivism missing children.

Table 9

Logistic Regression for Power Few Children.

Variable	*B*	Wald x^2	*p*	*OR* [95% CI]
History of criminal exploitation	0.237	.362	.547	1.268 [.585, 2.747]
ACE	1.277	2.592	.107	3.586 [.758, 16.970]
History of violence	0.534	1.769	.184	1.706 [.776, 3.749]
Self-harm	-0.160	0.094	.759	1.296 [.307. 2.367]
Previous arrest history	1.454	13.809	<.001	4.280 [1.988, 9.216]
Family status	0.640	3.145	.046	1.897 [4.556, 25.959]
Mental health	0.261	0.147	.701	1.298 [.342, 4.925]
Gender	-0.754	3.459	.063	.470 [.212, 1.041]
Age	-0.179	2.638	.104	.836 [.674, 1.038]

Stage 7 – Practical Application

The final goal of the research was to provide the police with a useful and reliable forecasting tool (the logistic regression model), to predict the likelihood of a child going missing repeatedly as used by Davies et al (1998). In a similar study, Hutchings et al. (2019), used BLR to identify risk factors for going missing repeatedly and then used them as a simple summation checklist. The more risk factors a child scored, the more vulnerable they were. The current study looked to improve on the accuracy of this method, by using the log-odds from the logistic regression model, to produce a probability that the child would go missing again.

The statistical model is:

- The log (odds the child will repeatedly go missing) = sum of the scores of the predictor variables in the model.
- Probability the child will repeatedly go missing = exponential (sum of scores) / 1 + exponential (sum of scores)

Mathematically it is:

- $\mathrm{Log}(\,odds) = \, bo + b_1X_1 + \, b_2X_2$
- $P\ (Y = 1) = \frac{Exp^{(b)}}{(1+Exp^{(b)})}$

Table 10 illustrates the final five variables which contribute to whether a child will repeatedly go missing (history of criminal exploitation, history of violence, ACE, previous arrest and family status) and their respective log odds.

Table 10

Best Fitting Logistic Regression Model for High-Risk Children

Variable	*B*	*p*	*OR* [95% CI]
History of criminal exploitation	2.988	<.001	19.850 [9.381, 42.004]
History of violence	0.822	.034	2.275 [1.063, 4.866]
Adverse childhood experience	1.936	<.001	6.932 [3.204, 14.998]
Previous arrest history	1.598	.005	4.944 [1.603, 15.244]
Family status	2.362	<.001	10.610 [4.526, 24.871}
Constant	-3.319	<.001	.036

The following example explains how the formula works. For a child with no history of criminal exploitation (CE = 0) and none of the other behaviours, the logistic regression equation will be equal to the intercept (bo) of the model (-3.319);

$$Log(odds) = \beta_0 + \beta_1 \chi = -3.319 + 2.988x0\ (CE)$$

To find the probability for children with no history of CE going repeatedly missing.

Log odds: $-3.319 + 2.988\ X\ 0 = -3.319$

Odds: $e^{-3.319+2.988(0)} = 0.036$

Probability: $\frac{ODDS}{1+ODDS} = \frac{0.036}{1.036} = 0.035$

Hence for a child who has not been a victim of CE, they are only 0.035 times as likely to go repeatedly missing as they are to go missing only once, or there is a 3.5% probability that a child who has no history of CE will go on to be a repeat missing child.

However, if the child has been criminally exploited (CE = 1);

$$Log(odds) = \beta_0 + \beta_1 \chi = -3.319 + 2.988x1\ (CE)$$

Log odds: $-3.319 + 2.988\ X\ 1 = -0.331$

Odds: $e^{-3.319+2.988(1)} = 0.718$

Probability: $\frac{ODDS}{1+ODDS} = \frac{0.718}{1.718} = 0.417$

They are now 0.417 times as likely to be a repeat missing child, or there is a 42% chance they will go missing repeatedly.

Table 11 illustrates how this formula could be used to estimate the likelihood that two further hypothetical children will go on to be missing repeatedly, based on their characteristics and circumstances. The key variables and their respective scores are taken from Table 9.

Table 11

Examples of Score Function Calculations to Estimate the Likelihood of a Child Repeatedly Going Missing.

	Child A		Child B	
Predictor variable	*Behaviour displayed?*	*Score*	*Behaviour displayed?*	*Score*
Constant	✓	-3.319	✓	-3.319
Criminal Exploitation	✓	2.988	✓	2.988
History of Violence	✓	0.822	✓	0.822
ACE	X	-	✓	1.936
Previous Arrest	X	-	✓	1.598
Family status	X	-	X	
Total (log odds of being repeat missing)		0.491		4.025
Probability child will repeatedly go missing ($exp^{(b)}/1 + Exp^{(b)}$)		0.620		0.982
Percentage		62.0%		98.2%

To summarise the rest of the table, child A who has been criminally exploited and has a history of violence, has an estimated 62% chance of repeatedly going missing and child B, who displayed four of the key behaviours has an estimated 98.2% chance of going missing repeatedly.

CHAPTER 4: DISCUSSION

Our analyses revealed that repeat disappearances were frequent and that several factors (demographic, social and environmental), were associated with an increased likelihood of going missing repeatedly. An improved understanding of these influences will help the police quickly and accurately identify high-risk children that require additional care and support, and also help develop more effective strategies to stop them from going missing in the future.

Risk Factors Associated with Going Missing Repeatedly

Just as accurate forecasts of crime hotspots are valuable for preventing crime, a better understanding of the correlates of repeat disappearances will allow the police and partner agencies to target preventative resources to those individuals most at risk of going missing again. Results from our analyses confirmed that repeat missing children exhibited a significantly higher number of risk factors than the single episode missing group. These risk factors were; being in care, suffering ACEs and criminal exploitation, being arrested, having a history of violence, suffering from mental health conditions, having a history of self-harm or substance misuse and being older. The next section examines each of the factors in more detail.

Criminal Exploitation (CE)

Being subject to criminal exploitation was the strongest predictor of the high-risk group, with victims of exploitation being thirty-three times more likely to be high-risk. The finding is consistent with previous research showing missing children are at serious risk of being targeted for involvement in gangs, trafficking, criminalisation, sexual exploitation and violence (Sturrock & Holmes, 2015).

Criminal exploitation takes a variety of different forms and can be a cause or consequence of going missing. Unfortunately, because of the study design and data availability, the type of exploitation was not recorded, and the direction of the effect could not be ascertained. Offenders may lure children away from home to become involved in criminality, for example, drug dealing or shoplifting (The Children's Society, 2019). Conversely, going missing can push a child towards exploitation by exposing them to unsafe and risky situations (Plass, 2007). Perpetrators may also specifically target locations that missing children tend to frequent (Children's Society, 2019). Future research could explore this further, by interviewing missing children who have been victims of exploitation, to understand how it influenced their decision to run away.

The findings have two practical implications. Firstly, due to under-reporting, little is known about CE (Children's Society, 2019), and the response from statutory agencies is mainly reactive; most children coming to attention when exploitation is already present in their lives. Going missing could therefore be an early warning sign of exploitation. By establishing a link in this study, caregivers and professionals can now be vigilant, providing the opportunity for early intervention and support. Secondly, the current police risk assessment for a missing child has been in use since 2003 (APPG, 2019), before child criminal exploitation became a significant risk. This research recommends that the assessment should be updated to prompt officers to consider whether a child may be a victim of exploitation.

Children in Care are More Likely to Go Missing Repeatedly

Children in care were twenty times more likely to go missing repeatedly. Our finding supports previous research (Hutchings et al., 2019; Biehal et al., 2003; Rees, 2011), and recent national statistics (NCA, 2019). To date, there is little empirical research, but possible explanations include; children in care are easier targets for exploitation (APPG, 2019); or they want more freedom (Finkelstein et al., 2004); or they run away to see family and friends (Kerr & Finlay, 2006).

It is unclear if this is causation or merely correlation. Many children entering care are from dysfunctional families, or are victims of exploitation, and therefore, may have already started to go missing (Children's Commissioner, 2019). Cared for children are also more likely to be recorded missing due to vigilant reporting by staff (CEOP, 2011). Nonetheless, children in care are particularly vulnerable, and these findings provide a powerful incentive to improve professional practice.

Firstly, early interventions such as educational work, counselling and support mechanisms could be beneficial, as may enhancing staff awareness of warning signs and recognising who may be at risk. Secondly, children are increasingly placed out of area (Foster, 2020) - a long way from family and friends, increasing the risk of them going missing (APPG, 2019). This social isolation also means such children are easy targets for exploitation by criminal gangs or sexual predators. The problem has led to the Office of the Children's Commissioner calling for an urgent Government review of the care system, and an immediate plan to reduce this practice (Children's Commissioner, 2019).

Adverse Childhood Experience (ACE)

Children who had suffered an ACE were thirteen times more likely to go missing regularly. Although no existing research has explicitly looked at this relationship, the finding intuitively makes sense. It supports the finding by Hutchings et al., 2019, which found children who went missing frequently, were twice as likely to have experienced abuse and neglect at some point in their lives.

Children potentially run away to escape family problems such as violence and abuse (Kiepal et al., 2012). Therefore, effective care for persistently missing children must incorporate family support, additional counselling services for the child and parenting interventions, especially following a family breakdown or changes in family structure. Mediation services may be particularly useful in engaging parents and children in discussions that can support the child in managing negative feelings associated with such changes (Hutchings et al., 2019). It is also beneficial for responding police officers to be aware of the potential of hidden harm in the family home, to better support the missing child when they are located, who for very valid reason may not want to return home.

Practically, however, due to the breadth of possible adverse experiences, they are a challenging risk factor to manage. Without detailed knowledge of the child and family, it may be difficult for a responding police officer to determine the presence or nature of the ACE. As a result, it would be useful for future research to examine the type of ACE (e.g. domestic violence, divorce, or parental drug misuse) in more depth.

Children Who Have Been Arrested

Repeat missing children were more likely to have been arrested, consistent with other research showing higher offending rates in missing children. For example, Sowerby and Thomas (2017) found that offending rates were 31 times higher for those who went missing repeatedly. Other illegal activities, such as drugs and prostitution, are also associated with going missing (Tarlings & Burrows, 2004).

Again, it is unclear whether the offending occurs before or after the child goes missing. Having already runaway, missing children may commit a crime in order to survive. For instance, shoplifting and theft arrests are frequent for young runaways as ‘survival strategies’ because they have no other means of supporting themselves (Shalev-Greene, 2011). Alternatively, missing children who have committed a crime may run away to evade the police (Sowerby & Thomas, 2016). Sturrock and Homes (2007) found that gangs often force children to go missing to commit crimes such as drug trafficking and violence.

Although more research is needed to understand the relationship, the results suggest the criminal justice system, for example, the Youth Offending Service, could be crucial to intervention and prevention efforts. The findings also have implications for police policy. Police custody facilities are designed to detain adults, offering little emotional support for children, and there are concerns that time in this environment could be harmful. In 2017, following a series of legal challenges against the detention of children in police cells, the Government released national guidance making it clear that police custody was inappropriate and should only be used for short periods when no alternative was available (Home Office, 2017). These findings provide further evidence of the negative impact of arresting a child.

History of Violence

Focusing specifically on the types of offending, repeat missing children were twice as likely to have been perpetrators of violence, echoing previous research. For example, Shalve-Greene (2011), examined police records for children reported missing more than three times in one year and found 82% were involved in crime and were arrested on at least one occasion, with assaults being one of the most common offences.

The relationship may be indicative of the lifestyle and emotional states of missing children, and the fact they are often exposed to situations which are dangerous. Practically, these findings not only help inform the risk assessment for missing children, they also indicate the need to focus more on the underlying drivers associated with a child’s repeat absences, for example through counselling or education. Merely returning a child home, will do little to address the underlying causes behind going missing.

One limitation to consider, however, is that as the missing person cases are from a police database, this may introduce a sampling bias. The police will only know about reported crimes, and therefore, the actual rates of criminality and violence in missing children is likely to be even higher.

Age of the Child

The bivariate analysis showed that the mean age of repeat missing children (14.5 years) was significantly higher than the single episode missing children (13.7 years). Other studies have found similar results. For example, using data from a different UK police force, Hutchings et al. (2019), found that children over 12 years were significantly more likely to go repeatedly missing, than those under 12. Some research suggests these differences could indicate that older children experience more complex life problems and going missing may be a coping mechanism (Baker et al., 2003). There are, however, potential confounding variables. For example, older children are less supervised and have more opportunity to run away (Social Exclusion Unit, 2000) and are also more likely to be exposed to substance misuse and peer initiation of risk-taking behaviours (Hutchings et al., 2019).

History of Substance Misuse

There is some support for substance misuse being a risk factor for repeatedly going missing. The results of the univariate analysis show that there is a strong relationship between substance misuse and regular disappearances. Existing literature also supports this, with drug and alcohol issues being well-documented as linked to repeat missing behaviour (James et al., 2008). However, in our study, substance misuse showed a strong correlation with several other factors, including criminal exploitation, violence, and previous arrest, and it was, therefore, removed from the final prediction model. In a similar study, Hutchings et al. (2019) found drug misuse was a predictor of repeat missing behaviour in children, but their study did not check for multicollinearity between variables, which may explain why they retained the variable in their analysis.

More research is needed to explore the impact of this variable. Within police records, the definition of substance misuse is very general, covering a range of behaviours from binge drinking, to glue sniffing, up to taking class A drugs. More in-depth research, breaking the behaviour into distinct categories (substance misuse, to occasional use, to dependency), would help understand the impact of substance misuse and may also address multicollinearity issues. Based on these initial findings, however, drug and alcohol treatment may be a way to reduce repeat missing behaviour

Gender is Not a Significant Risk Predictor for Repeatedly Going Missing

Contrary to our hypothesis and the most current UK statistics (NCA, 2019), gender did not contribute to the predictive model, with no significant difference between the number of times males and females went missing. The previously identified gender difference was based on overall missing persons statistics, rather than specifically looking at repeat missing episodes. Therefore, it appears whilst overall females may go missing more, when it comes to repeatedly going missing, gender is not a factor. Based on these findings, there is no compelling case for gender to be included in the screening of missing children, and no requirement for interventions to be tailored based on gender.

Mental Health or Self-harm

Contrary to our hypothesis, neither mental health issues nor self-harm were significant predictors of repeat missing children, despite other research finding both to be substantial issues. For example, Stevenson and Thomas (2018) found those suffering mental illness were two and a half times more likely to go missing repeatedly. Similarly, Sowerby and Thomas (2017), found an overrepresentation of mental health issues in missing persons. For self-harm, although there has been less research, similar to going missing, it has been recognised as a coping mechanism, to escape problems and to cope with anxiety and emotional stress (Kiepal et al., 2012).

Potential biases within the sample, could, however, explain the inconsistency. Firstly, the current mental health data came from police records and not health records. The police have little training in recognising mental illness and often categorise someone as suffering from a mental health problem based on the opinion of a family member, or the person's self-diagnosis. Secondly, as self-harm can include such a wide range of behaviours from binge drinking, and self-neglect, to poisoning, and cutting, it may be too restrictive to categorise it into just a "yes or no" response. Finally, the impact of both mental health and self-harm could also be dependent upon many other factors, such as whether the child is taking medication or receiving treatment. As a result, rates for mental health and self-harm in the sample are likely to be underestimated. More research is needed to explore these risks in greater detail. Further questioning of missing children, upon their return, might reveal new insights.

Summary

Except for gender, self-harm and mental health, all predictor variables were associated with being high risk of repeatedly going missing. These findings could be used by practitioners to make basic predictions around the likelihood of a child going missing repeatedly. For example, if police officers knew no other information about a child other than they were in local authority care, it would be sensible to predict they were high risk of repeatedly going missing. There are, however, limitations to simple statistics, and they need to be interpreted with caution. Firstly, practitioners may "cherry-pick" the main findings, and report only the results which confirm their personal views on the child. For example, focusing on the child's history of exploitation (high risk). Secondly, risk factors may have different additive effects when presented in combination. For example, a child who has been arrested and is in care, maybe even more likely to go missing repeatedly. To avoid these limitations, we use multivariate analysis to refine these simplistic predictions.

The Prevalence of Repeat Disappearances by Children

Repeat missing children were a significant problem in the sample, with the vast majority of missing incidents being repeat episodes (84%). Even more striking, while most children (*n* = 518; 57.2%) went missing just once, 75 children (8.3%) went missing ten or more times, accounting for half (51%) of all missing occurrences for the year. These results support previous research (Babuta & Sidebottom, 2018; Sidebottom et al., 2019) and suggest just as a few recidivist offenders commit most crime, missing incidents are concentrated on a few particular children. Sherman (2007) describes this as the “power few”, the small percentage within a distribution, suffering the most amount of harm. In this study, further analysis suggests this group are distinct from other repeat missing children. When the same logistic regression was applied, it was unable to accurately predict membership of this higher recidivism group, therefore suggesting that these children may suffer different or additional risks. Future research could seek to identify the specific predictors that can predict higher recidivism in going missing.

Recognising the extent of repeat missing behaviour has significant implications for the police. Firstly, in other areas of policing such as domestic violence, focusing prevention efforts on the riskiest targets (people, places or locations) has been found to yield the most significant results (Groves et al. 2012). Therefore, having the ability to quickly and accurately identify high-risk children, and provide them with care and support, could produce the greatest benefits - preventing future missing episodes, reducing harm and driving down demand on police resources.

Targeting repeat missing children also has economic advantages. In this study, by concentrating prevention efforts on the 75 most frequently missing children, missing person reports for the year could half from 3213 to 1580. With an average cost of £2415.80 per missing episode (Shaleve-Greene & Pakes, 2013), this is an estimated saving of over £3.6 million. The estimate is conservative and does not include the costs imposed on other partner agencies, for example, local authorities.

In summary, this study provides compelling evidence that the minority of children create the majority of missing incidents. Sherman (2007) argues by focusing on and targeting resources towards the power few, harm will reduce faster. Therefore, targeting this vulnerable group will bring about maximum benefit, through superior safeguarding and substantial savings.

The power few approach does, however, raise ethical questions. While Sherman (2007) maintains that focusing efforts on the most vulnerable is both morally and financially the right thing to do, critics argue it is unfair to ignore some in favour of others (Gladwell, 2006). From an operational policing perspective, it is, therefore, crucial to remember that while research can enhance decision making, there is still the need to respond to *all* missing children based on their unique circumstances.

Identifying Those Individuals Most at Risk of Going Missing Repeatedly

The final objective focuses on practical application and using the salient variables to develop a risk assessment for operational police officers. By entering just five variables (ACE, criminal exploitation, being arrested, violence and family status) into a binary logistic regression model, it was possible to accurately predict which children were most likely to go missing repeatedly. Some variables (age, gender, mental health, self-harm) only slightly improved the model's accuracy. As such, the practical task of collecting the data would not be a cost-effective use of police time, so they were removed. Successful pragmatic research solves a practical problem (Fishman, 1999). Therefore, the final model must be both useable (accurate and reliable), and useful (have a positive impact) within the policing environment.

Accuracy and Reliability

The final model accurately predicts future missing episodes in over three-quarters of cases; compared to the base rate predictions, which were no better than chance. A principle of pragmatic psychology is to ensure results are relevant to the needs of the practitioner (Fishman, 1999). So, while these findings support using predictive variables to identify high-risk children, practical considerations include the cost of collecting the additional information and the consequences of forecasting errors. Although collecting the additional information can take extra time for a police officer, the model enhances predictions by over 20% and therefore seems to be ‘cost-effective’ to perform practically.

In terms of the consequences of errors. In this instance, there were two kinds; incorrectly predicting children to be low risk who are actually high risk (false negatives); and predicting high risk for a child that was not (false positives). For missing children, false negatives are substantially more problematic, as failing to identify and support a vulnerable child, could have far graver consequences than supporting a child who is not at risk.

By examining the results in more detail, just over one fifth (21.8%) of those who went missing more than once were incorrectly categorised as low risk. The high number of errors emphasises the challenge of predicting missing behaviour in children. Consequently, it would be risky to rely solely on this model when risk assessing a missing child. Instead, the present study suggests using the model as a form of structured professional judgement, where rather than deciding for the officer, the model supports and supplements the officer’s expert knowledge, particularly in a situation where the officer may have information over and above the five risk factors used within the model.

Impact Within the Policing Environment

The model could improve existing police practices in several ways. Firstly, it enhances the current risk assessment for missing children. All missing children receive a return interview, to explore the reasons why they went missing and the police and social care then use their professional experience to decide how vulnerable the child is, and what support is required to prevent them running away again (Department of Education, 2014). The new model proposes an evidence-based alternative. By using the proposed framework, professionals will be able to quickly and reliably identify high-risk children, even before they go missing, allowing prevention strategies to be put in place immediately. For example, police could monitor and target high-risk children with a more intensive intervention, such as a specially trained officer, or a multi-agency response. For low-risk children, an alternative, more risk-appropriate and less resource-intensive pathway could be found, for example, making use of an existing support network, such as a child's school. Not only will this preventative approach improve safeguarding, but it would allow the police to use their limited resource in the most effective way possible. Secondly, the model identifies the critical risk factors for going missing, which will assist with developing prevention and intervention strategies. Now, rather than being satisfied, a child is safe when they return home, professionals can specifically search for these problematical factors. If risk factors are present, appropriate strategies can be put in place to address them. This is particularly important as repeat missing incidences are often due to a lack of support or intervention in resolving the reasons why the child went missing (Hutchings et al., 2019).

CHAPTER 5: CONCLUSIONS & IMPLICATIONS - THEORY & PRACTICE

Results show that using background and lifestyle information makes it possible to predict the likelihood of a child going missing repeatedly. Although there are currently no theoretical models to explain this connection, the findings suggest that general strain theory may be suitable. The results from the study show repeatedly going missing is closely associated with negative emotions such as fear (criminal exploitation), anger (history of violence) and hostility (ACE). Agnew's (1999) general strain theory (GST) proposes that such emotions create pressure for corrective action, one of which could be avoidance, in this case, running away.

The uniqueness of this research, however, is the pragmatic focus and hence practical application. Although academic interest in missing children is increasing, so far it has failed to influence police policy significantly. Researchers frequently neglect to consult the police, and consequently, findings have little relevance to a frontline officer. For example, Sowerby and Thomas (2017) discovered frequently missing teenagers often display suicidal behaviour but did not provide a risk assessment to assist operational officers. In contrast, by using a Pragmatic Psychology framework, and focusing on practical application, operational police officers could quickly and easily adopt the findings. The final chapter outlines the practical recommendations from the research. The strengths and limitations are then discussed, as well as ideas for future study.

Practical Recommendations

Recommendation One: Prioritise Prevention

The police regularly approach missing children reactively, focusing on finding the child, and when they return, this is often seen as the end (Hedges & Shalev-Green, 2016). As it is now evident a sizeable proportion of missing incidents are repeated, this study proposes instead of concentrating on individual cases in isolation, it is crucial to take a holistic view and consider why children go missing and how to prevent reoccurrences. Taking a proactive approach and allocating preventive resources to those children most likely to go missing again could prevent excessive demand on police resources.

Recommendation Two: Frontline Officers Should Adopt the Five Variable Statistical Model as a Revised Method of Risk Assessment

The statistical model could be developed into a mobile phone application (app) for use by operational police officers, providing a reliable and convenient risk assessment to inform their investigative decision making. Officers would apply the model as a form of structured professional judgement to enhance their decision making. While some could argue the current results are already well known, for example, it is well-established children in care go missing more frequently; the model provides empirical support. It has also elicited some findings contrary to expectations. For example, suffering an ACE has a crucial impact on whether a child will repeatedly go missing, but often these experiences go undetected as professionals are unlikely to ask (Pearce et al., 2019).

The findings could also improve the initial risk assessment for missing children. The current risk assessment used when a person is first reported missing, has been in existence since 2003. The risk factors within it have evolved over many years and are primarily based on the professional experience of practitioners. The results from this study provide an evidence base for additional risk factors such as child criminal exploitation.

Recommendation Three: Prioritise Repeat Missing Children

The frequency of going missing is often falsely interpreted by police officers as decreasing the level of risk (Newiss, 1999). Repeat missing children can be frustrating and time-consuming. The false sense of reduced risk is based on a notion they will return because they always do, or the stereotype that children who run away frequently are “streetwise” and can look after themselves. For example, Harris & Green (2016) interviewed fifty constables who regularly dealt with reports of repeat missing children and found negativity and frustration at the process. Such biased thinking could lead to officers failing to properly comprehend the risk. For example, drawing on interview data from nine UK police forces, Newiss (1999, p. 7) observes how, “the temptation for the police to view the report of a missing person as simply an administrative exercise would appear to be significantly increased when responding to repeat runaways”. The findings from this study dispel these myths and demonstrate repeat missing children take more significant risks and engage in more risky situations than children who go missing just once. Practically, the police could incorporate the results into missing person training to counteract negative attitudes, help police officers and staff recognise biases in their thinking and improve their decision making and risk assessment for missing children.

Recommendation Four: Intervention Requires a Multi-agency Approach.

By uncovering multiple factors (individual, familial and social) associated with repeat missing behaviour, the research highlights both the complexity of going missing and demonstrates many of the causes are beyond the scope of the police. Consequently, the complete response to missing children needs improving. Instead of relying on the police, and a one size fits all response to supporting a missing child, the problem requires a range of partners including health and social services. For example, given the close association between ACEs and going missing, family support and parenting interventions should be included.

Strengths and Limitations

Strengths

By using secondary data, the study had access to a large sample containing detailed information on over 900 children and their families – all cases reported to Dorset within a year. Gathering this first-hand would be impossible, both in terms of time and access, as participants would be unlikely to provide such sensitive information to a researcher. Also, secondary data collection avoids many access and ethical issues such as gaining access to and potentially re-traumatising the child.

Limitations

Using secondary data also brings a number of limitations, firstly, on data content and accuracy. Missing person records are for policing purposes, and consequently, information that may be useful to a researcher, for example, school attendance, may be missing. Also, the researcher is not involved in the initial recording of data, hence the reliability and accuracy of the data cannot be determined. Mental health data is particularly problematic, as there are no clear operational definitions, and recording is therefore reliant on the subjective interpretation of individual police officers who have little mental health training. For the present study, there was some mitigation as the police record all missing person reports in a standardised manner, and each one is quality controlled by a supervisor. However, as an alternative, future studies could use data from multiple sources, such as mental health services or school records.

The second limitation is regarding missing data. Children face risks which they do not disclose to the police. They may hide behaviours through fear, or concern about the potential consequences (Home Office, 2015). Many of the risk factors, such as childhood abuse, are also underreported (Lalor & McElvaney, 2010) and, the information the police do have, typically comes from family and friends, and is therefore subject to social desirability bias (Canter & Alison, 2003). Consequently, the number of risk factors is likely to be an underestimate. Rather than relying solely on police records which may result in a considerable loss of information, future research could interview missing children to uncover further risk factors and provide a much richer picture of the child's life and circumstances.

The third limitation is sampling issues. The present study examined missing behaviour for a12 month period, categorising those children missing once as low risk and those missing more than once, high risk. However, this sample could be unrepresentative of a child's overall missing behaviour, leading to inaccurate predictions. For example, a child graded as low risk may have been missing one day before or after this window. Also, sampling does not take into account how long the child was missing for. To limit these biases, the study used one year of data, as this was sufficiently broad to capture as much of the child's missing behaviour as possible and it was the same as that used by Hutchings et al. (2019), making the results directly comparable. To provide a more accurate picture however, future research could use a wider time frame, for example three years of data, or adopt a retrospective or prospective design where children are followed over an extended or set time period (e.g., for a year after they have first been reported missing).

Future Directions

Study Design

By adopting a cross-sectional design, it has not possible to attribute causation (Barends et al., 2015). For example, it is not clear if being in care is a cause or a consequence of going missing. Future research could use a cohort design. By selecting a group who do not have the outcome of interest (going missing), relevant variables could be measured, and the group observed over time to see if they develop the outcome (i.e., go missing). By identifying factors that exist before the child goes missing, this design distinguishes between cause and effect (Mann, 2003). Cohort designs can, however, be expensive and time-consuming. A cost-effective alternative could be to interview missing children to explore why they ran away. There is already a statutory requirement that all missing children are subject of a return interview, usually by a social worker, and this could be an ideal opportunity to address the knowledge gap.

Validating the Model

The study used a split-sample to validate the model (internal validation). Although convenient as it does not require additional data, internal validation does not predict how the model will perform on an entirely new sample, and consequently if it would work for children outside of Dorset. Similarly, statistics suggest missing behaviour and risk factors may change over time (NCA, 2017), and hence the sample and prediction model could quickly become outdated. This research is therefore an introduction and future research should focus on external validation, which involves testing the model in other locations, over different periods of time.

Regrouping Risk Factors

The police hold a variety of other information not included in this analysis. As it appears that going missing is multi-causal, future analysis could incorporate some additional risk factors, such as the age the child first went missing. Some of the risk factors cover a board spectrum of behaviours, and therefore, splitting the variable into more specific categories may be of interest. For example, for self-harm, the case files show many different descriptors such as, “self-harms”, “scratches herself” or “cutting”. Certain types of self-harm could have a more significant impact, and therefore, additional research drilling down further may improve the accuracy of the prediction model. On the other hand, some risk factors maybe combined, because some risk factors could be dependent upon other variables, such as the age of the child. For example, older children have greater freedom, and therefore may be more vulnerable to child criminal exploitation. Future research considering other risk factors in combination may be worthwhile.

Protective Factors

The focus has been on exploring the risk factors for running away, but few studies have considered protective factors. Some factors may reduce or prevent vulnerability (Rogers, 2000), by either reducing the effect of a risk factor or exerting an independent influence on the outcome. For example, research literature suggests that a positive family relationship and engagement at school could potentially act as protective factors (Oriade, 2015; Rees, 2011) against the effect of criminal exploitation. Future research may benefit from further exploration of these potential protective factors and further in-depth consideration of why those who ran away only once, desisted from future episodes.

Final Comments

The study aimed to investigate the problem of repeat missing children. The findings will make a significant contribution, especially towards improving the professional practice of the police and other agencies who deal with this group daily. As well as improving the care and support provided to some of the most vulnerable children, the practical implications of this research will also help reduce the demand they impose on already limited police resources.

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APPENDIX A

COPY OF DATA COLLECTION CODEBOOK

Variable Name	Coding	Description
No. times missing	1 = Low 1< = High	Number of times the child has been reported missing in the 12^{th} month period
Age (years)	Continuous	Age on the first missing episode in the 12-months
Gender	F = 0 M = 1	Gender of missing child
Adverse Childhood Experience	No = 0 Yes = 1	Adverse Childhood Experiences (ACEs) are “traumatic experiences before the age of 18 and remembered throughout adulthood.”
History of drug misuse	No = 0 Yes = 1	A reasonable belief that the child has used an illegal drug at any point in their life.
History of criminal exploitation.	No = 0 Yes = 1	Research has used the definition of child criminal exploitation (CE) used in current APP (police) guidance
Violent history	No = 0 Yes = 1	Describes whether the child is known to have previously been a perpetrator of violence.
Previous arrest history	No = 0 Yes = 1	Whether the child has been arrested for any offence before going missing.
Self-harm	No = 0 Yes = 1	Self-harm is defined using the NHS working definition - intentionally harm including, cutting or burning skin, punching or hitting, poisoning with tablets or liquids, or similar
Mental health	No = 0 Yes = 1	A diagnosed mental health disorder
Family status	No = 0 Yes = 1	Care includes local authority, voluntary and independent sector residential care homes and foster care placements. Foster care can be a relative, friend or another person who the child knows.

Instructions:

Open each child's police record and interrogate the following areas for evidence of the variables:

Location Within Police Records					
	Previous missing records	Arrest records	Intelligence logs	Stop search record	Other linked occurrences
ACE					
Drug Misuse					
CE					
Violence					
Self-Harm					
Family Status					
Previous arrest					
Mental Health					

APPENDIX B

ETHICAL APPROVAL

Bournemouth University

Research Ethics Checklist

About Your Checklist	
Ethics ID	30118
Date Created	10/01/2020 14:05:20
Status	Approved
Date Approved	30/01/2020 14:43:29
Date Submitted	19/01/2020 08:02:24
Risk	Low

Researcher Details	
Name	Greg Tansill
Faculty	Faculty of Science & Technology
Status	Postgraduate Research (MRes, MPhil, PhD, DProf, EngD, EdD)
Course	Postgraduate Research - FST
Have you received funding to support this research project?	Yes
Is this external funding?	Yes
RED ID	
Please provide the External Funding Body	Dorset Police
Is this internal funding?	
Please list any persons or institutions that you will be conducting joint research with, both internal to BU as well as external collaborators.	Dorset Police

Project Details	
Title	Study to identify risk factors that predict which children will repeatedly go missing
Start Date of Project	01/05/2019
End Date of Project	01/04/2021
Proposed Start Date of Data Collection	01/02/2020
Original Supervisor	Terri Cole
Approver	Liam Wignall
Summary - no more than 500 words (including detail on background methodology, sample, outcomes, etc.)	

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APPENDIX C

BOX TIDWELL PROCEDURE

The assumption of linearity in a logistic regression requires that there is a linear relationship between any continuous independent variable (age) and the logit transformation of the dependent variable (Field, 2015).

The Box-Tidwell (1962) was used to test linearity. This adds an interaction term between the continuous independent variables and their natural logs to the regression equation (Jaccard, 2001). The Binary Logistic procedure in SPSS Statistics was used to test this assumption. If the interaction terms are statistically significant, the original continuous independent variable has failed the assumption of linearity (Field, 2013). The age interaction had a significance value of .482, greater than 0.05, indicating that the assumption of linearity of the logit had been met.

APPENDIX D

OUTLIERS

There were nine standardised residuals, with values ranging from 4.023 to -5.448 (see table 12). After closer examination, cases 135, 233, 516, 749 and 813 were found to have been assigned to the incorrect outcome group. These errors were corrected. For case 87, the variable criminal exploitation had been coded as NO, when in fact there was evidence of criminal exploitation. Again, this error was corrected. Following these corrections, there were three standardised residuals ranging from -2.606 to 3.486. After examination, these were legitimate scores.

Table 12

Standardised Residuals for Logistic Regression Models

Case	Observed Group	Predicted Group	Standardised Residual (z score)
87	High	Low	3.960[e]
112	Low	High	-2.606
118	Low	High	-2.460
135	High	Low	4.023[e]
183	High	Low	3.486
233	High	Low	4.023[e]
516	Low	High	-5.251[e]
749	Low	High	-5.448[e]
813	High	Low	4.023[e]

Note. [e] Outlier caused by an error in data coding. Corrected and removed from the analysis.

Before deciding whether to keep the outliers in the model, it was first necessary to examine their impact. Two models were compared. Model 1 included all cases in the dataset, including the three outliers (approach suggested by Field., 2013). Model 2 was re-run, excluding the three outlying cases. As table 13 shows, model 2 only slightly increased the accuracy when compared to the full model

(model 1). There was also no change in the statistical significance of the overall model fit based on $\chi2$. The outliers were therefore retained in the dataset.

Table 13

Comparison of Percentage Improvements in predictions from Logistic Regression Analysis.

% Correct predictions	Low risk	High risk	Overall
Model 1 (including outliers)	90.4	78.2	85
Model 2 (excluding outliers)	91.2	78.6	85.6

Note: Model 1 included the outliers. For model 2, the outliers were removed.