Student No: 20205527

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University of Nottingham

Assessed Coursework Cover Sheet for Applied Psychology Postgraduate Courses

Module Title: FORENSIC PSYCHOLOGY RESEARCH DISSERTATION

Coursework Title: MISSING CHILD CASES IN SUSSEX AND WEST MERCIA: PREDICTING PERSISTENT RUNAWAYS

Word Count (excluding references and appendices): 5,614

This is to confirm that I submit this piece of assessed work in the full knowledge of the published guidelines on plagiarism and its consequences

Type name ......CLAIRE EMMA ROSALIE KOSTER.....

Application form

Application for approval of all studies involving **Healthy Human Participants only conducted by Staff and Students of the University of Nottingham which don't involve an invasive procedure**

1 Title of Project: Missing Child Cases in Sussex and West Mercia

2 Names, Qualifications ,Job Title, School/Divisional/Unit/Address, email of all Researchers:

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Other key researchers/collaborators: E. Hutchings, K. Browne, S. Chou

Students name and course: *Claire Emma Rosalie Koster, BSc*
Course: MSc Forensic Psychology and Criminology
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3 Type of Project:

This study will be analysing a pre-existing, anonymised database provided by the Sussex and West Mercia police forces on missing child cases over 4 months between 1st November 2016 – 1st March 2017.

4 <u>Location of study</u>:

Data analysis will take place at the University of Nottingham, but the study's outcomes will be relevant to Sussex and West Mercia.

5 <u>Description and number of participants to be studied</u>:

The database contains a total of 2,232 anonymised cases before elimination (1,140 M; 1,082 F; 9 Unknown). As this database refers to missing children (as opposed to 'persons'), inclusion criteria for this study required subjects to be under the age of 18 (0-17 years) at first recorded episode of running away. Subjects were also required to have returned to their homes or have been found since running away, to differentiate this data from 'abduction' cases.

To preserve confidentiality and anonymity, all cases have been assigned numbers between 1 and 2,232 for identification. This anonymization was completed by the Sussex and West Mercia police before handing data over to the University of Nottingham, so all researchers are blind to the subjects' identities. This avoids any potential biases that could arise.

6 <u>Summary of Experimental Protocol</u> - Please give details below (no longer than this side of A4) under the following headings: - 1. Background. 2. Aims (to include hypothesis to be tested Primary and secondary endpoints), 3. Research protocol and methods, 4. Measurable end points/statistical power of the study. 5. Key references. This section must be completed. This is in addition to a more detailed project proposal/protocol which should be attached to this application. Please use 10pt typeface.

1. Background

Children run away from home more often every year. This exposes them to extremely negative experiences, such as physical assault, sexual abuse or drug exposure, to name just a few. Approximately 50% of missing persons cases in the UK in 2016-2017 were repeat incidences (where the same child has gone missing on several occasions), demonstrating we need a better understanding of recidivist behaviours in runaways. Previous research has thus far indicated that certain factors might predispose a child to running away from home (e.g. family conflict or bullying in school), however these do not necessarily account for repeat cases. Research with regards to recidivist runaways is limited, having shown that predicting factors of running away once might not be equally indicative of recidivism (Baker et al., 2003).

Running away does not only impact the child in question, however. It also impacts their families, communities and help services; a single missing person investigation has been estimated to cost the police between £1,325 and £2,415 (Shalev Greene & Pakes, 2013). In 2016-17, this totalled to cost the UK between £263 and £480 million (National Crime Agency, 2019).

The current study aims to replicate a previous project using Welsh data on missing children (Hutchings, Browne, Chou & Wade, 2019) with data from Sussex and West Mercia. This study will analyse a significantly larger sample of missing children in these regions, and explore what factors might classify runaways as 'low risk' (one-time runaway) or 'high risk' (repeat runaway). The outcomes for this study can help on both an individual level (identifying children at high risk and intervening) and an organisational/economic level (prioritisation of cases allowing better allocation of resources).

2. ***Aims***

This study aims to aid Sussex and West Mercia police forces in bettering their interventions by tailoring a more targeted approach to helping children. Being able to identify predictors of running away can allow help services to identify high risk cases more efficiently, and prioritise these cases over those which appear more low-risk.

The second aim is to deepen understanding of how sexual exploitation interacts with other variables related to running away, as this has previously been established to be one of five significant risks in running away (Hutchings, Browne, Chou & Wade, 2019).

3. Research protocol and methods

An anonymised database of 2,232 cases provided by the Sussex and West Mercia police forces (601 Sussex; 1,631 West Mercia) will be analysed with SPSS Statistics 24 using cross-tabulations, Chi square analysis and logistic regression. This should give us an indication as to which factors are more or less predictive than others of one-time versus multiple runaway episodes.

4. Measurable end-points / statistical power of study

This study has high generalisability and ecological validity, as it includes all valid missing child cases in Sussex and West Mercia over an entire year. Missing children tend to be highly reported as their absence is noted by their carer, parent or school extremely quickly, and so this database is assumed to be generalizable. In terms of validity, the data was yielded from real-world cases, and so can be applied back into the real world.

5. Key references

Amy J. L. Baker, Mary M. McKay, Cynthia J. Lynn, Hans Schlange, Alicia Auville, Recidivism at a shelter for adolescents: First-time versus repeat runaways, *Social Work Research*, Volume 27, Issue 2, June 2003, Pages 84–93, https://doi.org/10.1093/swr/27.2.84

Greene, K. S., & Pakes, F. (2012). Establishing the cost of missing person investigations.

Hill, L., Taylor, J., Richards, F., & Reddington, S. (2016). 'No-One Runs Away For No Reason': Understanding Safeguarding Issues When Children and Young People Go Missing From Home. *Child abuse review*, *25*(3), 192-204.

Hutchings, E., Browne, K. D., Chou, S., & Wade, K. (2019). Repeat missing child reports in Wales. *Child abuse & neglect*, *88*, 107-117.

Radu, M. B. (2017). Who runs away from home and why? How families, schools, and bullying influence youth runaways. *Sociology Compass*, *11*(11), e12537.

Tucker, J. S., Edelen, M. O., Ellickson, P. L., & Klein, D. J. (2011). Running away from home: A longitudinal study of adolescent risk factors and young adult outcomes. *Journal of youth and adolescence*, *40*(5), 507-518.

7 <u>Lay Summary of project</u> (in lay words):(maximum 200 words) ***Summaries which include***
language which is too technical for lay members of the Committee will be rejected.

This study aims to identify what factors might predict a child running away from home several times versus only once. To do this, information collected by the Sussex and West Mercia police forces has been handed over to the University of Nottingham for analysis. If we are able to identify factors that are particularly predictive of multiple runaway episodes, we can provide more detailed information for help services (such as police, health or social services) to better their techniques in aiding and these children. Not only does this improve services *after* running away, but this information can also help us better *protect* children who are at risk of leaving their homes. This will then be furthered by looking specifically at sexual exploitation of those who have run away from home.

8 <u>Will written consent be obtained from all volunteers?</u>

Written consent is not obtainable as the dataset is totally anonymous. Consent has been received from Sussex and West Mercia police to analyse this anonymised data on missing children from both police services.

9 <u>Will an inconvenience allowance be offered</u>

No inconvenience allowance is required, as no subjects will be contacted in any way during this study, or identifiable in the written report. This is a pre-existing database.

10 <u>FUNDING</u>

This study will not require any funding, as any materials required have already been obtained by the researchers (e.g. database, SPSS Statistics 24). This study will not require any printing or other services.

11 Studies involving NHS Staff, organisations, Services

Does the study involve any premises, services staff who hold a contract with a hospital, Primary Healthcare or Social Care Trust?

N/A

12 How will the subjects be chosen?

N/A

13 Describe how possible participants will be approached.

N/A

14 What sources of information will be included? i.e, pre-existing research database, student records, visits to other organisation, online resource

Pre-existing database, comprised of anonymised data from COMPACT and MISPER systems.

15 Whose permission will be sought to access this information (eg GP, consultant Head of Organisation)?

Permission has been obtained by the Chiefs of the Sussex and West Mercia police departments. A contract of confidentiality has been provided and signed.

16 For interview/focus groups:

N/A

17 Data Storage and Data management

N/A

18 <u>What ethical problems do you foresee in this project?</u>

No ethical problems are foreseen in this project.

19 <u>What are the possible limitations of the proposed design of this study?</u>

Using a retrospective study might overestimate the significance of the outcomes, as it is only looking at cases that *did* occur, with no control group for comparison. However, this is the data that was provided by police forces who have requested this specific study to be carried out. Using only quantitative data for the second phase of this project (investigating sexual exploitation) might reduce the meaningfulness of the data, as information consists of 'yes/no' answers, as opposed to a scale of severity, which might have provided a deeper insight into how different extents of sexual exploitation might contribute to running away.

DECLARATION: I will inform the Medical School Ethics Committee as soon as I hear the outcome of any application for funding for the proposed project and/or if there are any significant changes to this proposal. I have read the notes to the investigators and clearly understand my obligations as to the rights, welfare and dignity of the subjects to be studied, particularly with regard to the giving of information and the obtaining of consent.

Signature of Lead Investigator: **Date:**

***Nb If you are student your supervisor must sign this form otherwise it will be rejected*

Name and address for correspondence with applicant:

Please submit your completed application to:

Administrative Support
Faculty of Medicine & Health Sciences Research Ethics Committee
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DISSERTATION PROJECT PROPOSAL

University ID: 20205527

Primary Supervisor: Professor Kevin Browne (90%)

Secondary Supervisor: Dr. Elizabeth Paddock (10%)

Overview of the topic

A recent report by The National Crime Agency (2019) stated an increasing trend in missing persons in 2016-17 compared to previous years, with 'repeat missing' cases (reports of the same child missing more than once) making up 48.5% of all missing cases in the UK that year. Approximately 63% of this number involved children. However, this report does not distinguish whether children have been abducted or chose to run away from home. Running away is defined as a child leaving the home voluntarily without the permission of their parents or carers. It is estimated that 70% of missing child cases are runaways (Biehal et al., 2003). This demonstrates the severity of runaway frequency.

Running away has been found to have significant negative impacts on children and adolescents. Although running away is defined as 'voluntary', it should be noted that volition may vary: *voluntarily* leaving in order to be with an older boyfriend versus *voluntarily* leaving an abusive home due to a perceived lack of alternative solutions are two vastly different situations, but both are defined as 'runaways'.

Despite aiming to escape negative home environments, it is well established that children who run away are at a higher risk of being exposed to (more) harmful factors outside of their home. Incidences might include sexual abuse, physical violence or robbery, resulting in long term outcomes such as drug dependency (Tucker, Edelen, Ellickson & Klein, 2011) or dropping out of school (Aratani & Cooper, 2015).

There are two subgroups identified within runaway children: those who run away once and those who do so several times (repeat missing cases, defined here as 'recidivists'). As of yet, there is limited evidence available to health and emergency services to specifically tailor their interventions to recidivist cases. Although literature does distinguish between the two subgroups, not many specifically address the predictors of recidivism (Oriade, 2015). Moreover, research has found that factors which might predict running away, might not predict recidivism; Baker and colleagues suggested emotional problems predicted behaviour in serial runaways, whereas family changes were more predictive of those who repeated for the first time (Baker, 2003). The current study aims to help bridge this gap in order to improve the help and services we provide for runaway youths.

This was first attempted by Hutchings and colleagues for Welsh missing child cases in 2019, finding that five significant risk factors could predict up to 73% of runaway cases. These factors included being looked after (i.e. living outside of a parental home, such as a foster home or institution), substance use, sexual exploitation, being known to Youth Offending Services and having a history of abuse or neglect (Hutchings, Browne, Chou and Wade, 2019).

Childhood sexual exploitation (CSE) is defined as 'actual or attempted abuse of a position of vulnerability, power, or trust, for sexual purposes, including, but not limited to, profiting monetarily, socially or politically from the sexual exploitation of another' ("WHO Sexual Exploitation and Abuse Prevention and Response", 2017). Being a victim of CSE appears to have particularly severe consequences on the individual - consequences that will usually persist into adulthood.

Sexual exploitation can both be a reason for leaving the home (e.g. being abused by a teacher at school or family member) and a consequence of doing so (e.g. being sexually assaulted or exploited on the streets or in a shelter). Long term outcomes of sexual exploitation in childhood vary, including mental illness (anxiety, depression), substance abuse or delinquency. The most notable association seems to be that juveniles and adults convicted of sexual-related offences report significantly higher incidences of childhood sexual exploitation than non-sexual offending controls did (Jespersen, Lalumière & Seto, 2009; Whitaker et al., 2008). If CSE might increase the risk of perpetration of sexual offences in future, this demonstrates in itself an inherent need to identify CSE and its risk factors. It is important to note than not all individuals who experience CSE offend later in life.

The current study aims to replicate this by analysing a missing children's database provided by Sussex and West Mercia police forces, combining information from the COMPACT and MISPER systems. It is imperative to identify factors that might predict a child's likelihood to run away from home in order to protect them. Predicting these variables may not only prevent a child from going missing, but can also improve our ability to identify and address the causal issues a child is facing that might encourage running away multiple times.

This study aims to find predictive variables that might increase the risk of a child running away from home multiple times (identified as a 'high risk' group) as opposed to just once (identified as a 'low risk' group). By analysing police records, this study aims to provide insight for police and intervention services into identifying risk factors for low risk versus high risk groups, and how or why one might transition between these. The key aim is therefore to prevent low risk children from transitioning to high risk, and providing better statistical evidence for child/health/emergency services to intervene after a child's first episode of running away from home. To follow this up, statistical analyses will specifically be conducted to identify how CSE impacts a child's risk of running away from home once versus more than once, and how it might interact with the other dependent variables being investigated (outlined below).

Research Questions

Although this research will also be useful in contributing to preventative measures for *any* runaway episodes, the main focus remains on preventing isolated runaway cases from being repeated. This study aims to answer the following two questions:

1. What variables predict repeat runaway episodes compared to one-time episodes?
2. To what extent does sexual exploitation in childhood predict runaway episodes?

The first question is broad and open-ended, as we simply aim to explore the data sets provided by Sussex and West Mercia police to provide a more accurate insight into this region's missing child cases and how repeat cases can be prevented.

The second question is more targeted, and applies to the second phase of this project, aiming to study the relationships between sexual exploitation in childhood and other variables involved with running away. This variable was chosen as the original study by Hutchings and colleagues also indicated this to be one of five significant risk factors for repeated runaway cases. Ideally, future studies might further investigate the other four identified variables, too.

Proposed Methods

Participants

The participant sample for this study will include anyone reported as missing to the Sussex and West Mercia police. As this study is investigating missing child cases, data consists of only missing persons under the age of 18 (0-17 years). The total sample size consists of 2,232 cases (1140 male), including 601 Sussex cases and 1,631 West Mercia cases prior to elimination. This sample is considered highly representative as it includes all missing cases from these regions, and missing children incidences tend to be very highly reported (as their guardian will notice almost immediately). All cases are anonymised, labelled by numbers for identification (1 to 2,232).

Procedure; Method

This will be a retrospective study, analysing a pre-existing dataset aiming to identify predictors of recidivism of running away, in order to better tailor Sussex and West Mercia's interventions following a child's first runaway episode. Data has already been collected (using COMPACT and MISPER systems) and provided by the Sussex and West Mercia police departments. It is important to note that data was anonymised and password protected and decoded by the data providers and required re-coding upon receival, so all researchers are blind to any identifiable information. An advantage of a retrospective method is that it reflects real life data, and so predictions are based off actual occurrences. Using a pre-existing database is preferred as alternative methods (such as surveys, interviews or focus groups) would be significantly more time consuming and expensive.

Procedure; Estimated Timeframe

This study is estimated to be completed quickly as data has already been collected, and any necessary materials are readily available to the researchers (SPSS Statistics 24). The first phase of this project aims to be complete by January 2020, and the second phase by April 2020.

Proposed Analytical Methods

Data analysis will be conducted as soon as possible using SPSS Statistics 24. This will be done by conducting cross-tabulations to find any positive relationships between the independent variable (two levels; High Risk; Low Risk) and the sixteen dependent variables, listed below.

- Gender
- Age at first report
- Child in care / known to social services
- Previous victimisation
- Substance misuse
- Family discord
- History of abuse
- History of violence
- Self-harm
- Sexual exploitation
- Antisocial or violent behaviour
- Known to Youth Offending Services
- Criminal records
- Mental illness
- Poor school attendance

If positive relationships between any of the above variables and risk group are found, these will be analysed with a Chi square analysis. Significant results will be put into a logistic regression to see how much each variable contributes to predict recidivism. This will occur in be conducted for both combined sets. If differences between these sets differ significantly, then analysis will be conducted individually for each.

In this project's second phase, data of sexual exploitation in these missing cases will be analysed, aiming to identify how this specific variable might influence other risk factors to repeated runaway cases. The independent variable in this phase will be Sexual Exploitation, with two levels (Present; Absent). The dependent variables are the same as those previously listed, except 'Sexual Exploitation' will be replaced by 'Number of Runaway Cases'.

Bibliography

Aratani, Y., & Cooper, J. L. (2015). The effects of runaway-homeless episodes on high school dropout. *Youth & society*, *47*(2), 173-198.

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Whitaker, D. J., Le, B., Hanson, R. K., Baker, C. K., McMahon, P. M., Ryan, G., ... & Rice, D. D. (2008). Risk factors for the perpetration of child sexual abuse: A review and meta-analysis. *Child abuse & neglect*, *32*(5), 529-548.

WHO Sexual Exploitation and Abuse Prevention and Response. (2017). Retrieved 1 November 2019, from https://www.who.int/about/ethics/sexual-exploitation_abuse-prevention_response_policy.pdf

Missing Child Cases in Sussex and West Mercia: Predicting Persistent Runaways

MSc Forensic and Criminological Psychology

The University of Nottingham

School of Medicine

Division of Psychiatry and Applied Psychology

To be submitted to the Child Abuse Review with corresponding author Professor Kevin Browne.

Claire Emma Rosalie Koster

University ID: 20205527

Primary Supervisor: Professor Kevin Browne (90%)

Secondary Supervisor: Dr. Elizabeth Paddock (10%)

Abstract

A child goes missing every five minutes in the UK, exposing them to dangerous circumstances and severe consequences. This study aims to discover what variables might predict the transition from one-time (low risk) to repeat (high risk) runaway episodes in Sussex and West Mercia. A large anonymised dataset was provided by the Sussex and West Mercia police forces, consisting of 1,188 missing child cases, of which 1,158 had run away from home in these regions between 1st November 2016 and 28th February 2017. Using an exploratory approach, Chi squared analyses and a binary logistic regression were carried out in order to determine what factors were most significantly associated with runaway risk. These analyses resulted in a final 7-factor model: being in social services care, being known to the Youth Offending Services, being above the age of 12 years, having a criminal record, substance abuse, child sexual exploitation and family discord. This 7-factor model resulted in an accurate classification of 70% of cases. In order to better protect children by preventing repeat runaway episodes, this model should be applied in addition to current methods to better classify children as low risk or high risk. These suggestions are discussed further.

1. Introduction

Every five minutes, a child runs away from home ("Young runaway statistics", 2020). This study aims to indicate what variables might predict the transition from one-time to repeat missing episodes in Sussex and Mercia, in order to provide more accurate advice to these regions' police forces. Being able to predict and distinguish between one-time cases ('low risk') and repeat cases ('high risk') will permit more effective prioritisation of certain cases over others, and allocate resources in a more cost-and-time-effective way. It would also determine who required further intervention and the necessity of a return interview.

1.1 Runaways

Running away is generally defined as a child or adolescent leaving home overnight without permission from their parents or carers ("Running Away - Definition, Description, Common problems", 2019). This behaviour is also specified as 'voluntary' to differentiate it from abduction; seventy percent of missing children are found to have voluntarily left home, for example (Biehal, 2003). The extent to which runaway cases can be described as voluntary needs to be viewed along a continuum, however, as children and adolescents often run away to escape abusive home environments and family conflict for lack of a better alternative (Radu, 2017). In their research on Welsh missing child cases, Hutchings, Browne, Chou and Wade (2019) distinguished between 'push' and 'pull' factors that surround a young person's decision to run away from home (Biehal & Wade, 2000). Push factors are defined as circumstances that precede the runaway episode that 'push' the child or adolescent out of their home (such as abuse, conflict or poverty), whereas pull factors are those that increase the appeal of leaving home. Pull factors might include the desire to be with an older boyfriend or girlfriend, or seeking independence and emancipation from one's family.

1.2 Recidivism and Runaway Subgroups

Previous research distinguishes between subgroups within the runaway population: one-time runaways (defined here as 'low risk') and serial/repeat runaways (defined here as 'high risk'). Youths might have different reasons or triggers for multiple runaway episodes. Emotional problems have been found to be associated with repeat runaway cases, whereas changes in family structure and length of time spent in a shelter whilst away from home have been found to associate significantly with second-time runaways (Baker et al., 2003). A particularly interesting finding by a cross-sectional study in the United States stated that not all factors that predicted the likelihood to run away were predictive of *repeated* episodes of running away; only family poverty, school connectedness and neighbourhood satisfaction were found to be significantly associated with high risk cases and their frequency (Oriade, 2015). Despite these findings, there is limited research investigating the differences between these two subgroups, or how one might evolve from low risk to high risk. The current study aims to identify what variables might predict repeat episodes of runaways in Sussex and West Mercia, in order to guide intervention services (police, health, social services) to be more targeted, and in turn more effective.

1.3 Motivations for Running Away

Children and adolescents may have various motivations or 'push factors' for running away, whether only once or on multiple occasions. Research has found associations between likelihood for running away and negative perceptions of their environment and safety such as bullying (Radu, 2019), lack of freedom or the pursuit of a relationship (Hoikkala & Kemppainen, 2015), or being a victim of sexual exploitation (Hershberger, Sanders, Chick, Jessup, Hanlin & Cyders, 2018). However, a study by Karam and Robert (2013) found that during interviews with runaways, youths indicated a different reason for running away from home on each occasion.

These factors can also be classed into two categories: intrinsic motivation (internal factors, such as wanting to be with a significant other or seeking independence) and extrinsic motivation (external factors, such as family conflict, physical, emotional or sexual abuse in the home, or substance abuse). This categorisation is a helpful way to approach push factors, as it allows for more specifically tailored interventions; intrinsic motivations can be addressed by one-on-one counselling with the youth, whereas extrinsic motivations might be resolved through family therapy or substance rehabilitation programmes, for example. This may also allow for easier prioritisation of factors, and more appropriate use of help services.

1.4 Consequences of Running Away

It has been well established that running away from home can have severely negative consequences on a child or adolescent, which may or may not be known to the youth before running away. These include increased risk for depression and drug abuse (Tucker, Edelen, Ellickson & Klein, 2011; Bender, Brown, Thompson, Ferguson & Langenderfer, 2015), post-traumatic stress disorder (Whitbeck, Hoyt, Johnson & Chen, 2007; Thompson, Maccio, Desselle & Zittel-Palamara, 2007), deliberate self-harm (Morewitz, 2016) and increased street victimisation such as assault, sexual exploitation or robbery (Bender, Brown, Thompson, Ferguson & Langenderfer, 2015), among many others. These consequences may have life-long effects on the individual (e.g. academic attainment and family relationships; Pearson, Thrane & Wilkinson, 2017) thereby highlighting the need to reduce risk of running away in youths.

1.5 Demographic Differences in Runaway Youths

Research has suggested gender differences in runaway youths, with females in particular being more likely to run away from home. This has been consistently supported across decades of research; in 1989, for example, an analysis by the US Government found the majority of runaway youths in shelters were female (GAO, 1989), a finding supported by studies in later years (Tyler & Bersani, 2008). This gender difference is likely linked to specific push factors, however, such as sexual exploitation. Females are more likely to suffer from sexual abuse or exploitation, and consequently more likely to run away from home to prevent future abuse or harm, for example (Tyler et al., 2001). Despite this, females are at higher risk of victimisation the more often they run away (Whitbeck & Simons, 1990). However, in 2017, the UK government reported almost a quarter of homeless individuals applying for aid were 16-24 years old, the majority of whom (62%) were male. This was also confirmed in a study by Yoder, Whitbeck and Hoyt (2001), finding that although there were no gender or racial differences in likelihood of running away for the first time, males and Caucasian youths showed a higher likelihood of spending time on the streets during these periods. Research does seem to indicate females being more likely to run away from home with regards to specific factors such as sexual abuse, however the gender distribution in general (non-exploited) runaway circumstances appears to be almost equal.

It appears that age differences are also related to gender differences; previous research has indicated that runaways between 6-11 years of age were more likely to be male, whereas runaways aged 12-16 years were more likely to be female (Edelbrock, 1980). In terms of age, an important factor to consider is how old the youth is at time of first runaway episode. Research suggests most runaways are adolescents; 68% of runaways in a study by Hammer and colleagues were between the ages of 15 and 17 (Hammer, Finkelhor & Sedlak, 2002). Pergamit (2010), however, points out that this research does not paint an accurate picture as to what age these adolescents *first* run away.

1.6 Sexual Exploitation in Runaway Youths

Sexual exploitation is defined by the World Health Organisation as 'actual or attempted abuse of a position of vulnerability, power, or trust, for sexual purposes, including, but not limited to, profiting monetarily, socially or politically from the sexual exploitation of another' ("WHO Sexual Exploitation and Abuse Prevention and Response", 2017).

Child sexual exploitation (CSE) can both be a cause for (Beckett, 2011; Hutchings, Browne, Chou & Wade, 2019; Saewyc, O'Brien, Miller & Edinburgh, 2019) and/or a consequence of (Klatt et al., 2014; Saewyc & Edinburgh, 2010) running away from home or care. Although destinations vary (such as streets or shelters), not all runaway cases include running to unknown locations; some children may run to the homes of friends or family relatives to avoid harmful home situations (Houmoller et al., 2011), but even these supposedly 'safer' environments can expose children to sexual victimisation. In 2011, for example, Wade found that one in six youths who had run to the homes of friends were sexually or physically assaulted, as well as one in twenty of those who run to the homes of relatives.

1.7 Consequences of Sexual Exploitation in Childhood

Being a victim of CSE in childhood has a vast array of negative consequences. The first is an increased risk of becoming an offender later in life; several meta-analyses found that adult perpetrators of sexual assault reported significantly more sexual victimisation in childhood than controls (Jespersen, Lalumiere & Seto, 2009; Whitaker et al., 2008). This was also found to be the case in juvenile perpetrators of sexual offences (Seto & Lalumiere, 2010). Other consequences might include engaging in antisocial behaviours (e.g. delinquency; Pedneault, Babchishin, Lalumiere & Seto, 2019) and mental health issues such as depression and anxiety in childhood (Spataro, Mullen, Burgess & Wells, 2004; Aydin, Akbas, Turla, Dundar, Yuce & Karabekiroglu, 2015) and adulthood (Molnar, Buka & Kessler, 2001; Amado, Arce & Herraiz, 2015).

In the interest of child protection, the current study also aims to investigate whether sexual exploitation in childhood and risk of running away interact significantly, or whether CSE is more predictive of running away than other variables.

1.8 Impact on Services

Missing person cases affect more than just the individual in question, such as police, social and hospital services, amongst other areas. The economic impact of even one missing case on the police has been estimated to fall between £1,325.44 to £2415.80, although it has been suggested that the upper bound is more realistic (Shalev Greene & Pakes, 2012). This estimation does not include the economic impact on other services that are included in these investigations. This study's purpose of creating an additional screening tool to improve intervention services for missing cases is therefore also economically beneficial to police forces and their available funds.

1.9 Aims and Hypotheses

This study aims to explore several variables and their predictive influence regarding one-time versus repeat runaway cases in Sussex and West Mercia, to allow for better identification and classification of these incidences in future. As this is an exploratory study using pre-existing data, there are several null hypotheses.

i. The first hypothesis proposes that there will be no significant gender differences between one-time runaways (low risk) and repeat runaways (high risk).
ii. The second hypothesis proposes that there will be no significant age differences between one-time runaways (low risk) and repeat runaways (high risk).
iii. The third hypothesis proposes that there will be no significant difference in sexual exploitation between one-time runaways (low risk) and repeat runaways (high risk).

These null hypotheses allow for a more unbiased analysis of the data, as this study simply aims to explore runaway cases in Sussex and West Mercia without pre-existing expectations.

2. Method

2.1 Data

The anonymised data used in this study was acquired from a missing persons database collected by the police forces of Sussex and West Mercia, comprised of COMPACT and MISPER systems.

Data collected in the four months between 1st November 2016 and 28th February 2017 from Sussex and West Mercia were collated. This resulted in 2,232 cases prior to data cleansing (601 Sussex; 1,631 West Mercia). As this number reflected records and not individuals, duplicate cases were eliminated, resulting in a total of 1,188 missing children. Cases under the age of five were classed as 'abduction' and eliminated, leaving a final dataset of 1,158 cases. Sussex cases accounted for 26.9% of the final dataset (N=312), and West Mercia cases accounted for the remaining 73.1% (N=846).

In order to preserve anonymity and confidentiality, each case was assigned a number between 1 and 1,158 for identification. The University of Nottingham Research Ethics Committee provided full ethical approval for this study.

2.2 Procedures and Treatment of Data

A criterion variable was established based on those who ran away once (low risk) and those who ran away more than once (high risk). Preliminary analysis showed that 30 cases were abduction cases under the age of 5 years, leaving 1,158 cases who ran away. Of these cases, 47.5% were one-time runaways (N= 550), and 52.5% ran away more than once (N=608).

This was followed by cross-tabulations and Chi squared analyses to establish any associations between variables and low risk and high risk groups. The criterion variable was Runaway group (low risk; high risk) and the 16 routinely collected predictor variables were as listed below:

- Gender
- Age
- Substance abuse
- History of violence at home
- History of abuse and neglect
- Child sexual exploitation
- Being known to Youth Offending Services
- Being in social services care
- Previous victimisation or bullying
- Having a criminal record
- Family discord
- Being on the Child Protection Register
- Self-harm
- Mental Health issues
- Antisocial behaviour or violence
- Poor school attendance

Bonferroni corrections were applied to the 16 Chi squared analyses at a limit of $p<0.01$ in order to reduce the effects of multiple testing. Applying a Bonferroni correction reduces the risk of a Type I error (finding a false positive result) by requiring associations to reach a significance level of $p<0.01$ in order to be considered valid. Following measures of association, a binary logistic regression was carried out using highly significant variables as predictors to establish whether the low risk group of those who run away once could be distinguished from the high risk group who run away more than once (criterion variable). Table 1 demonstrates the method used to calculated the classification accuracy of the final regression model (Leventhal, 1988).

Table 1
Method used to calculate predictive accuracy of 7-factor model.

		Predicted		
		Times Run Away		
Observed		*Once (Low risk)*	*Repeat (High risk)*	***Actual Total***
Times Run Away	*Once (Low risk)*	d	b	b+d
	Repeat (High risk)	c	a	a+c
Predicted Total		c+d	a+b	**1,158 (N)**

Using this method, the following may be calculated:

- **Incidence of running away more than once:** the actual number of children in the total dataset who have run away more than once.
- **Positive predictive accuracy:** the percentage of children in the high risk group who subsequently do run away more than once.
- **Negative predictive accuracy:** the percentage of children in the low risk group who subsequently do not run away more than once.
- **Risk ratio:** the likelihood of children running away more than once in the high risk group compared to those in the low risk group.
- **Sensitivity:** the percentage of children who ran away more than once who were correctly classified as high risk.
- **Specificity:** the percentage of children who ran away only once who were correctly classified as low risk.

2.2.1 Recoding Data

Originally, the 'Age' variable was not binary (ranging from 0-17 years old), and so this was recoded to 'below the age of 12' and 'above the age of 12'. Ages between 0-5 were excluded from analysis as this young age would constitute 'abduction'.

Additionally, a lot of data was registered in the system as 'unknown'; these were recoded as 'system missing' instead of 'No', as this would otherwise have skewed the data.

3. Results

3.1.1 Incidence

This study included 1,158 runaway cases reported to the Sussex and West Mercia police forces over a five-month period. Of these 1,158 cases, 550 were reported to have runaway only once (47.5%), whereas 608 were reported missing more than once (52.5%). Within the high risk group (N=608), repeat cases ranged from 2 to 84 times across the four months of data collection, with an average of four times per child (SD = 7.19).

3.1.2 Demographics

In the Sussex database (N=312), the majority of runaway cases were over the age of 12 years (96.2%, N=300). There was also a difference shown in gender, with 55.1% (N=172) of cases being female. This supports previous research that adolescent females are at highest risk of running away. The age statistics for West Mercia cases (N=846) echoed those of Sussex, with 91.6% (N=775) of individuals being over the age of 12 years. Gender, however, showed the opposite result with

45.2% being female (N=382). Frequency statistics of the combined dataset are demonstrated in Table 2.

Table 2
Combine collected by Sussex and West Mercia police on child runaway cases, 2016-2017 (N=1,158)

	Valid N	**Yes**		**No**	
		N	%	N	%
Demographic					
Female	1,183	562	47.5	621	52.5
Age >12	1,158	1075	90.5	113	9.5
Family Factors					
On Child Protection Register	847	109	9.2	738	62.1
Family Discord	1,035	770	64.8	265	22.3
Child Abducted Under 5 Years	1,188	30	2.6	1158	97.4

Risk of Harm to Self and/or Others					
Previous Victimisation	947	58	4.9	889	74.8
Substance Misuse	973	214	18.0	759	63.9
History of Abuse	901	405	34.1	496	41.8
History of Violence	990	100	8.4	890	74.9
Self-Harm	1,158	14	1.2	1144	98.8
Sexual Exploitation	1,158	160	13.8	998	86.2
Antisocial Behaviour or Violent	1,036	26	2.2	1010	97.5
Criminal Record	1,158	180	15.5	978	84.5
Mental Health	490	148	12.5	342	28.8
Runaway once only	1,158	550	47.5	608	52.5
Service Involvement					
In Social Services Care	1,158	383	32.2	805	67.8
Known to Youth Offending Services	1,158	437	37.7	721	62.3
Poor School Attendance	951	180	15.2	771	64.9

Note. N = number of cases

3.1.3 Family Factors

Family-related variables did not show a strong positive trend in the Sussex group, with 35.9% indicating discord in the family home (N=112), and only 3.2% reporting a history of domestic violence in the home (N=10). Despite 12.5% (N = 39) of cases being on the child protection register, 38.8% of children were in social services care at the time of incidence (N=121). West Mercia again shows the converse: the vast majority of runaways reported family discord (75.7%, N=640), but only 31% were in social services care (N=262). Similarly, only 10% of cases showed a history of domestic violence (N=85).

3.1.4 Risk of harm to self and/or others

Very few Sussex cases show presence of previous victimisation at school or in the community (4.5%, N=14); a similar result to those in West Mercia (5.1%, N=43). Substance misuse also shows a similar case in both regions, with 23.7% and 16.5% engaging in substance use, respectively (N=74; N=140). As for history of abuse, 34.6% of Sussex runaways reported this (N=108), and 33.9% of West Mercia cases (N=287). There was almost zero incidence of self-harm in either region, with Sussex showing only 0.3% (N=1), despite mental illness presence being 15.4% (N=48) and West Mercia only 1.5% (N=13), despite mental illness being reported in 11.7% (N=99) of cases. Sexual exploitation was significantly higher in the West Mercia cohort, at 17.4% (N=147), compared to 3.8% in the Sussex cohort (N=12). In terms of antisocial or violent behaviour, West Mercia reported presence of this in only 1.1% (N=9), although this was slightly higher in Sussex, at 4.5% (N=14). Finally, there were no reported criminal records in Sussex, as opposed to 21.3% in West Mercia (N=180).

3.1.5 Service Involvement

Results show that 38.5% of Sussex runaways (N=120) and 31% of West Mercia runaways (N=262) were in social services care. Interestingly, none of the Sussex cohort were known to Youth Offending Services (YOS), whereas over half of West Mercia's cohort were (51.7%, N=437). Finally, school attendance was generally not poor; only 22.1% of Sussex children (N=69) and 13.1% of West Mercia children (N=111) were reported to show poor attendance.

3.2 Statistical Analyses

The samples of Sussex and West Mercia were added together for the purpose of statistical analysis, looking at the associations between predictor variables and the criterion of running away once or running away more than once. Results of the Chi squared analyses are displayed in Table 3.

Table 3
Variables of children going missing once versus more than once, as shown by Chi^2 analysis.

	Valid N (1,158)	**Children reported missing once (%) N=550**	**Children reported missing more than once (%) N=608**	**Chi^2**	**Degrees of freedom (df)**
Demographic					
Female	1,153	78.9	51.3	7.279**	1
Age >12	1,158	88.4	96.9	30.633****	1

Family Factors					
On Child Protection Register	847	6.4	11.8	28.404****	1
Family Discord	1,035	67.2	80.7	24.758****	1
Risk of Harm to Self and/or Others					
Previous Victimisation	947	5.2	7.0	1.280	1
Substance Misuse	973	14.1	29.5	33.272****	1
History of Abuse	901	40.4	49.2	7.097**	1
History of Violence	990	5.8	10.8	11.003**	1
Self-Harm	1,158	0.7	1.6	2.306	1
Sexual Exploitation	1,158	8.1	19.0	33.380****	1
Antisocial Behaviour or Violent	1,036	3.4	1.7	3.060	1
Criminal Record	1,158	7.5	23.0	59.697****	1
Mental Health	490	29.4	30.9	0.112	1

Service Involvement					
In Social Services Care	1,158	17.5	52.7	129.586****	1
Known to Youth Offending Services	1,158	24.7	50.4	88.110****	1
Poor School Attendance	951	18.0	19.8	0.484	1

*$p<0.05$
**$p<0.01$
***$p<0.001$
****$p<0.0001$

Of the original 16 variables, 11 were found to be significantly associated with Runaway Group in the Chi squared analyses, as shown above in Table 3 and listed below:

- Gender
- History of Abuse and Neglect
- History of (Domestic) Violence
- Being on the Child Protection Register
- Child in social services care
- Substance abuse
- Family discord
- Sexual exploitation
- Known to Youth Offending Services
- Criminal record
- Being above the age of 12

These significant factors were the starting point for the logistic regression to create a predictive model. Those variables considered to be highly significant after another Bonferroni correction had been applied ($p<0.0001$) were used as predictor variables. This eliminated the variables of Gender, History of Violence and History of Abuse, resulting in an 8-factor model. To gain a better understanding of these 8 variables and their associations with each other, a correlation matrix was run to eliminate any highly correlating variables, and the variable 'On Child Protection Register' was removed, leaving a 7 factor model as demonstrated in Table 4.

Table 4

The 7 factor model used in the logistic binary regression (N= 1,158)

	B	***S.E.***	***Wald***	***Degrees of Freedom***	***Significance***	***Exp (B)***
Child in social services care	1.39	.15	88.87	1	.000	4.01
Substance misuse	.51	.18	8.18	1	.004	1.67
Family discord	.34	.15	5.13	1	.024	1.41
Sexual exploitation	.50	.21	5.72	1	.017	1.64
Known to YOS	.72	.17	17.66	1	.000	2.06
Criminal record	.46	.23	3.96	1	.046	1.60
Age above 12	.56	.21	7.24	1	.007	1.75
Constant	-1.51	.21	50.44	1	.000	.22

This model had a good percentage outcome of correct prediction of runaway risk, with a correct classification of 70% of cases.

3.2.1 Weighting Variables

The regression results showed a much higher Exp(B) score for children being in social services care (4.01) and being known to Youth Offending Services (2.06), meaning children in social services care are four times more likely to be high risk, and those known to YOS being twice as likely. These variables were then weighted with scores of 4 and 2, respectively. This was done by recoding data into the same variables, and replacing a score of 1 with 4, if the variable was present. All other variable weightings remained as 1, as indicated by their Exp(B) scores. A compute statement was run to result in a new 'Weighted' score, against which the original 'Non-Weighted' score was compared.

The 'Non-Weighted' scores' highest possible classification percentage was 68%, when cut-off at a score of 4 and above. The 'Weighted' score was therefore better, as this resulted in a classification percentage of 70%, when cut-off at a score of 5 and above. Cases with a total score of 5 and above should therefore classed as 'high risk', and 4 and below as 'low risk'. The minimum possible score is 0 (no variables present), and the maximum score is 11 (all variables present, including weighted values). Figure 1 visually represents the chosen cut-off point.

Figure 1: *Histogram displaying identified cut-off point between one time runaways (low risk) and repeat runaways (high risk)*

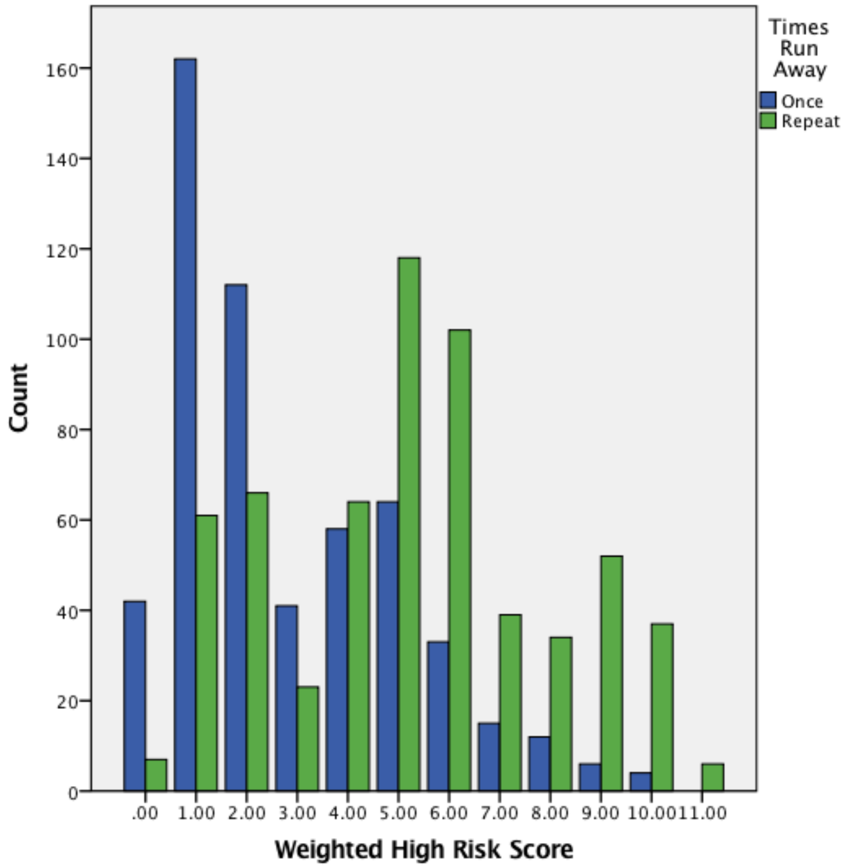

Table 5 shows the classification results.

Table 5
Classification results of the 7-factor regression model with two weighted variables (N=1,158)

		Predicted		
		Times Run Away		
Observed		*Once (Low risk)*	*Repeat (High risk)*	***Actual Total***
Times Run Away	*Once (Low risk)*	361	188	549
	Repeat (High risk)	159	450	609
Predicted Total		520	638	**1,158**

Using the Leventhal's (1988) method demonstrated in Table 1, the model's predictive accuracy was assessed as follows:

- Incidence of running away more than once: (a+c)/N = 51.3%
- Percentage of individuals at high risk of running away more than once: (a+b)/N =53.7%
- Positive predictive accuracy of 7 factor model: a/(a+b) = 70.5%
- Negative predictive accuracy of 7 factor model: d/(c+d) = 69.4%
- Risk ratio: a/(a+b) / c/(c+d) = 2.3
- Sensitivity: a/a+c = 73.9%
- Specificity: d/(b+d) = 65.8%
- Odds ratio: a+d/b+c = 2.3

4. Discussion

A binary logistic regression analysis demonstrated 7 out of 16 routinely collected variables to be significant in predicting low risk young people who runaway once from high risk young people who runaway more than once in a sample of 1,158 runaway cases reported to the police in Sussex and West Mercia, with 70% accuracy. These seven factors were as following:

- Being in social services care
- Substance abuse
- Family discord
- Sexual exploitation
- Being known to Youth Offending Services
- Having a criminal record
- Being above the age of 12

These scores were weighted based on the magnitude of their contribution towards being in the high risk group, to result in a summative 'Weighted High Risk Score'. These scores are visible in Figure 1, identifying the best cut-off point for transitioning from low risk to high risk; scores of 4 and below were classified as low risk, and 5 and above as high risk. Results showed the odds ratio was 2.3, indicating that individuals in the high risk group in Sussex and West Mercia are 2.3 times more likely to runaway than those in the low risk group.

Some variables differed between the Sussex and West Mercia databases, and as such could not significantly predict individuals in the high risk group when these datasets were combined. However, the 11 out of 16 variables found to be significant in the Chi squared analyses were those similar between both datasets. This does not suggest that the 5 non-significant variables were not important with regards to their own specific database, but simply that the 11 variables found to be significant were used to create a more reliable screening tool for larger sample sizes.

In applying such a model to the databases of other geographical areas, it is therefore possible that the 11 risk factors initially found to be predictive of repeat runaways in Sussex and West Mercia may not be the same for other locations. Different areas should therefore first study which of the 16 routinely collected risk factors are predictive in their respective area, to then develop an individually tailored approach.

A key strength of this study is the use of a pre-existing database provided by the Sussex and West Mercia police forces. Using an exploratory method with real data allowed for an unbiased approach, particularly using null hypotheses. Another advantage of using this data set is its generalisability; although this data was collected across only four months in two areas of the UK, it has high ecological validity in that it realistically demonstrates the incidence of runaways in Sussex and West Mercia. We may believe that this data is a true representation of missing child cases in these areas, as children under the age of 18 live with guardians and will therefore quickly be spotted missing and reported to authorities. It is unusual for a missing child not to be reported.

This study is the second of its kind, following in the footsteps of Hutchings, Browne, Chou and Wade's original study in Wales (2019). Comparing results, the original study's predictive accuracy was 90%, compared to this study's accuracy of 70%. This demonstrates the importance of individually tailored models per region, as 70% was the maximum predictive accuracy possible in Sussex and West Mercia simply based on the information gathered and provided per case. For example, the Welsh study's final model involved only five predictor variables (compared to seven in the current study), including 'history of abuse and neglect', which was not a significant predictor in the Sussex and West Mercia database. However, the other four variables in the original study's model did overlap with this study (substance abuse, CSE, known to YOS and in social services care). Although these models are both tailored specifically to each respective region, future research should aim to establish a 'general' checklist including the overlapping variables as a baseline for other areas in the UK. Different regional police forces could then use this exploratory approach to investigate any individual or regional risk factors that should be added to the checklist for their region specifically. This would allow for the most effective identification between one-time and repeat runaways per UK area. This is not to say, however, that the other nine variables not included in the final model are irrelevant; these should still be collected in future for a robust perspective of the missing child's situation. These results simply imply that the seven factors in the model are the most important and should be taken most seriously in allocating resources and help to the individual.

Another implication for these results are how Sussex and West Mercia police forces can apply this to their response routines. For example, as this model shows substance abuse to be a strong predictor variable, establishing and cultivating strong links and communication with local substance help services would allow for smoother and more efficient responses to future runaway cases. The same can be applied to the other six variables.

The main caveat in applying this model, however, is that although the calculated sensitivity (73.9%) met the threshold of Leventhal's criteria (1988), the model's specificity did not (65.8%), meaning the model still produces a lot of false alarms. One way in which this could be improved is by increasing the cut-off score between risk groups (for example, classifying scores of six and above as high risk, rather than five). However, Figure 1 shows that shifting this cut-off score upwards to six would result in the loss of 120 real cases. Therefore, the current cut-off score is still the best available. Despite these potentially high false alarm rates, the model is still worth applying on the recognition that other factors must be taken into account, based on this low negative predictive accuracy; in terms of child protection, it is better to investigate a number of false alarms of sexual exploitation or substance abuse, for example, than to miss actual cases. It is therefore imperative that this screening tool be used as an additional feature to an already-existing child protection or missing child investigation procedure. This screening tool on its own is not sufficient, as it does not classify cases with 100% accuracy.

In response to the study's hypotheses, the first null hypothesis was accepted, as gender was not included in the final binary logistic regression analysis. Although its association with runaway group was found to be significant in the Chi squared analysis, this was not strong enough to be included in the final model when corrections were applied. The second null hypothesis was rejected, as age was found to be a significant predictor in identification of risk group, with individuals above the age of 12 being more likely to runaway more than once (and be in the high risk group). The third and final null hypothesis was also rejected, as sexual exploitation was also a significant predictor variable in the final model; cases indicating sexual exploitation were more likely to run away more than once (and be in the high risk group). These results are in line with the current literature regarding runaways and their motivations for doing so.

Conclusion

In conclusion, the 16 routine variables can be narrowed down to an effective checklist of seven to identify repeat runaways over one-time runaways: being in social services care, substance abuse, family discord, sexual exploitation, being known to YOS, having a criminal record and being over the age of 12. The gender differences were not significant enough to meet the requirements of the binary logistic regression model, however being over the age of 12 and reporting sexual exploitation did, thereby accepting the first null hypothesis and rejecting the second and third. In future, other UK regions should conduct these analyses on their own databases to establish individual factors that may predict running away in their respective area, in order to improve their current missing child procedures and better protect children at risk of running away from home.

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Forensic Research Project:

Executive Summary

The target audience for this executive summary is the police, specifically the Sussex and West Mercia police forces.

Background and rationale

Every five minutes, a child goes missing in England. When a child runs away from home, it is usually to avoid harmful circumstances in their home, however this exposes them to different, if not more, dangerous settings outside of their home. For example, being on the streets can put a young person at an increased risk for sexual exploitation, robbery or assault, to only name a few. Additionally, the more often a child runs away from home, the more these risks increase. This study was based on an original study by Hutchings, Browne, Chou and Wade (2019) on missing child cases in Wales. Upon this original study's publication, the Sussex and West Mercia police forces approached the University of Nottingham Forensic Psychology department with their own databases for similar analysis.

Research aims and hypotheses

Therefore, this study aimed to identify which factors best predicted a child's transition from running away once (low risk) to running away multiple times (high risk) in the UK regions of Sussex and West Mercia. This study employed an exploratory approach with the provided datasets to identify which factors were specifically predictive of running away more than once in these regions. Due to this exploratory outset, the hypotheses for this research were null:

(1) Age would not differ significantly between groups

(2) Gender would not differ significantly between groups

(3) Sexual exploitation would not differ significantly between groups

How data was collected and analysed

A large anonymised dataset was provided by the Sussex and West Mercia police forces to the University of Nottingham's Forensic Psychology department. This retrospective data consisted of all missing child cases between the ages of 0-17 years of age, from 1st November 2016 to 28th February 2017. Firstly, the dataset had to be cleansed, as many of the cases were the in fact the same individual recorded multiple times (repeat runaway episodes ranged from 2-84 times within the four-month timeframe). This resulted in 1,188 cases (871 West Mercia; 317 Sussex), with information on 16 routinely collected variables. However, 30 cases of children under the age of five were a result of child abductions, and were subsequently not included in analysis. The final dataset of 1,158 cases (846 West Mercia; 312 Sussex) were entered into analysis. Sixteen Chi squared analyses were run to find any significant associations between each variable and Runaway Group (low risk; high risk), resulting in 11 significant associations. These 11 were as follows:

1) Gender (being female)
2) History of abuse and neglect
3) History of (domestic) violence
4) Being on the Child Protection Register
5) Being in social services care
6) Substance abuse
7) Being known to Youth Offending Services (YOS)
8) Having a criminal record
9) Being above the age of 12

Due to multiple testing, a Bonferroni correction had to be applied in order to reduce the risk of a false positive result simply due to high amounts of testing. This set our threshold for inclusion into the binary logistic regression at $p<.0001$ rather than $p<.05$. This removed 'History of Abuse and Neglect', 'History of Violence' and 'Gender' from the list of variables. Finally, 'Being on the Child Protection Register' was highly correlated with other variables, and so this, too, was removed to increase accuracy. This resulted in a final model of 7 predictor variables in the binary logistic regression.

The presence of these 7 variables were coded as 1 (Yes) or 0 (No; Unknown). It was found that two of these factors ('Being in social services care' and 'being known to YOS') contributed more heavily towards the risk than the remaining five. These were therefore weighted at values of 4 and 2 respectively, with the other five factors remaining at a value of 1. These scores were added to total a 'High Risk Score', at which different cut-off values were tested for an individual to transition from low-risk to high-risk.

Key findings of the research

The final model was able to classify low risk versus high risk individuals at 70% accuracy. This accuracy was maximised at a cut-off point of 4; a score of 5 and above was classified as high risk, and a score of 4 and below was classified as low risk.

Implications of findings

These findings provide helpful insight for how Sussex and West Mercia can in future classify their missing child cases more efficiently, in order to provide better help and improve resource allocation. It is important to identify which factors put a child most at risk for running away, however it must be noted that these findings are specific to the Sussex and West Mercia regions, and not necessarily applicable to the whole of the UK. This model does still result in a lot of false alarms, but false alarms are better than missed actual cases on child exploitation, so this screening tool should still be implemented. This must only be done in addition to already existing procedures regarding protection of missing children to improve these, and not on its own, however.

Recommendations

With regards to the Sussex and West Mercia forces, it is recommended to allocate more focus to the 7 variables outlined by the regression model as being most predictive of transitioning from one-time to repeat runaways. It is also recommended that this procedure be carried out for difference forces across the UK to provide better individual tailoring per region.

References

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Forensic Research Project: Powerpoint Slides

MISSING CHILD CASES IN SUSSEX AND WEST MERCIA

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RESEARCH AIMS AND RATIONALE

- A child runs away from home every five minutes, putting them at risk for dangerous and traumatising experiences. Some of these include depression, drug abuse, PTSD, as well as sexual victimisation or robbery.
- Following the structure of Hutchings and colleagues' Welsh study (2019), this study aimed to discover what variables predict how many times a child might runaway from home, specifically the transition from one-time (low risk) to repeat runaways (high risk).
- Understanding and predicting these factors allows for better protection and intervention for children who run away, as well as more efficient resource allocation by police services.

METHOD

- An anonymised database provided by the Sussex and West Mercia police forces was used for analysis, consisting of 1,158 individual cases of missing children between November 2016-March 2017. This raw dataset included 16 routinely collected variables.
- 16 Chi squared analyses were run to explore associations between each of the 16 variables and Runaway Group (low risk; high risk).
- Several binary logistic regressions were run to determine which factors were most predictive of running away more than once.

RESEARCH RESULTS

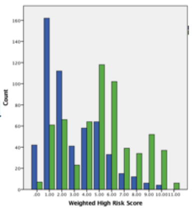
- 11 out of 16 $\mathcal{X}^2$ associations were significant, as shown in Table 1.
- The final regression model consisted of 7 predictive factors, in bold in Table 1. Two of these were weighted for their respective contribution to risk. This resulted in the best predictive accuracy of 70%.

Variable	$\mathcal{X}^2$
Female	7.279**
Age above 12	30.633****
On Child Protection Register	28.404****
Family Discord	24.758****
Substance Misuse	33.272****
History of Abuse	7.097**
History of Violence	11.003**
Sexual Exploitation	33.380****
Criminal Record	59.697****
Known to Social Services	129.586****
Known to Youth Offending Services	88.110****

*p<0.05
**p<0.01
***p<0.001
****p<0.0001

The cut-off score for low risk to high risk was found to be at 5 out of 11 and above.

This screening tool still results in a lot of false alarms, however this is a better alternative to missing actual cases of child exploitation, for example.



IMPLICATIONS AND SUGGESTIONS

- Sussex and West Mercia police forces can use this screening tool (Table 2, using the 7 factors in Table 3) in addition to current procedures to prioritise cases based on their risk score (5+) for more effective help provision and resource allocation.

Table 2: *Screening Tool for Risk Classification*

		Predicted		
		Times Run Away		
Observed		*Once (Low risk)*	*Repeat (High risk)*	***Actual Total***
Times Run Away	*Once (Low risk)*	361	188	549
	Repeat (High risk)	159	450	609
Predicted Total		520	638	**1,158**

Table 3: *Final 7 factors used in the screening tool, with weighting*

Variable	Weight	Variable	Weight
Age above 12	1	*Family Discord*	1
Substance Misuse	1	*Sexual Exploitation*	1
Criminal Record	1	*Known to Social Services*	4
Known to Youth Offending Services	2		

- In future, this method can be replicated for other regional forces, however these studies will need to first discover which variables are most predictive for their own region.
- This screening tool should not be used on its own due to high false alarm rates, but as an additional tool to improve current methods of child protection.

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Forensic Research Project:

Reflective Summary

I worked on this forensic research project between October 2019 to July 2020, a project that required a consistent commitment of time and effort. This study followed the structure of an original study by Hutchings, Browne, Chou and Wade (2019) on missing child cases in Wales. I conducted and wrote up this study with the intention of publication in the Child Abuse Review, alongside co-authors Professor Kevin Browne, Dr. Shihning Chou and Dr. Emma Hutchings.

Conceptualisation and Preparation

In terms of the conceptualisation of this project, I was offered this project as my own proposal (on interviewing sex offenders about factors influencing victim blaming in sexual assault) was not possible to execute (obtaining a sex offender sample) within the timeframe available and would therefore not have been in sufficient depth or gained a large enough sample size. The data was provided by Sussex and West Mercia police forces as part of a project funded by the Home Office Police Knowledge Fund in the interest of child protection.

In terms of preparation of this project, I had to do a lot of my own research into the topic of runaways and missing children, as I had never covered this before in my undergraduate degree or my own reading in general. I started my own research in October 2019, in particular focusing on journals and articles from 2013 onwards as the original Welsh paper reviewed literature up to this year. Once I gained a deeper knowledge and understanding around the topic, however, I became much more confident in my ability to successfully complete this project.

It was initially intimidating to know that this was a project intended for the Sussex and West Mercia police forces using Home Office funds, and so I did initially feel pressure to work even harder as it was meant to be published for use by these bodies.

Design

As this study followed the layout of the Hutchings paper, this provided me with clear guidelines in terms of thesis design, as it was essentially a replication of this project using different data and for different police forces. A key strength of this replication-based design was that it had potential to increase the reliability of the initial Welsh paper by successfully following its design and confirming its outcomes. A slight difference is that the regional database was different, and so naturally the influential/predictive factors in the final regression model would be different. Despite this, the study could still confirm reliability of the method used to create an individually tailored model.

Data Collection

Using a pre-existing database was very beneficial for this study for a variety of reasons. Firstly, this allowed me to have access to confidential police files on runaway cases that would not normally be available for data analysis by a postgraduate student. Secondly, it saved me having to collect my own data, which from previous experience can take a very long time. This allowed me to spend more time on the statistical analyses, some of which I hadn't done before. It also permitted a good thesis-coursework balance alongside my other modules and better time management. Thirdly, using an anonymised pre-existing database meant that full ethical approval was quick to obtain; there were no perceived risks to participants that required consideration or amelioration. Additionally, this database contained over 1,000 case reports (N = 1,188). I would never have been able to gain such a wide sample on my own or using experimental or interview methods, or such a large real-life sample demonstrating full ecological validity. One disadvantage of not collecting my own data, however, was having little control about missing or unknown data.

Data Analysis

I started cleansing and analysing data from mid-November 2019 through March 2020. I had to run 16 Chi squared analyses (and apply Bonferroni corrections) and several binary logistic regressions in order to establish the best predictive model (resulting in a 7-factor model). The most progress was made during our supervisions of 11^{th} and 12^{th} February 2020, during which the final regression model was established after a lot of exploratory trial-and-error testing. At first, I did find it difficult to get back into the statistical/SPSS mind-set, as it had been several years since my first-year undergraduate statistics classes at my previous university. On top of this, although we had a forensic statistics module every Wednesday morning throughout this course, I started my analyses months before the particular tests required for my thesis were covered in class, simply because I did not have to gather data myself and could get started on analysing data almost immediately following ethical approval. I therefore required extra help from my supervisor in our initial meetings during which we explored the data. Once I managed to understand the tests better and how to run them, I felt much more confident in exploring the data and analysing them. I also managed to complete any tasks between supervision sessions successfully on my own (such as calculating high-risk scores, or producing a histogram demonstrating the cut-off point between runaway groups).

Write-up

My writing-up process went smoothly over the course of the nine months. The most challenging aspect of this process was writing up the results section, including its tables and graphs. This section required a lot of rearranging in order to place each subsection in the most effective order. One issue I struggled with was distinguishing between 'Method: Procedure' and 'Statistical Analyses/Results' during my first draft, which my supervisor helped me correct. This first draft correction took place in a Skype supervision on 1st May 2020, during which Professor Browne and I went through each section of the draft and I made notes of anything that needed changing. I then completed these alterations to send back to my supervisor within 3 weeks.

Supervisions

I had several supervision sessions with my supervisor, Professor Kevin Browne, over the course of the academic year. The first sessions revolved mainly around reading different materials and gaining a better understanding of the topic and applying for ethical approval (9th and 24th October 2019). During this time, I wrote up my thesis introduction, reviewing the previous literature on the topic and how this study would provide a new insight to the field.

Once ethical approval was gained, our supervisions addressed statistical analysis, which at first consisted of sorting through data; what started with over 2,000 cases was narrowed down to 1,158 individual cases used in analysis. Some of this data also had to be re-coded into binary categories (Yes = 1, No=0, Unknown = -1) for all 16 variables.

One big influence to the course this year was the COVID-19 pandemic, however I was fortunate enough for my thesis not to be particularly affected, as I did not need to engage with participants in any way, which would have been greatly thwarted by social distancing rules. The one influence COVID-19 did have on this project was how it affected supervisions, which were moved online to Skype and emails. However, I was already far enough into my statistical analyses and write-up by this point in time that these online meetings worked well.

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Hutchings, E., Browne, K. D., Chou, S., & Wade, K. (2019). Repeat missing child reports in Wales. *Child abuse & neglect*, *88*, 107-117.