Solving burglary offences

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SOLVING BURGLARY OFFENCES: BUILDING A MODEL TO PREDICT CLEARANCE OF BURGLARY FOLLOWING INITIAL INVESTIGATION

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INTRODUCTION

This study is concerned with the identification of factors which are associated with the clearance of burglary offences, and with the development of a predictive solvability algorithm that could be used by police forces, allowing improvements in resource prioritisation. Burglary is a crime that can have a major impact both financially and psychologically on victims, whilst also influencing feelings of public safety within communities. Over a decade ago, Brand and Price (2000) estimated the total cost of Burglary offences to the U.K. per year. Specifically, for residential and non-residential burglaries they estimated a total annual cost to British society of £5.3billion. Despite the high level of impact that burglaries have, burglary is an offence with extremely low detection levels.

In a financial climate where policing resources are scarce, it is important to consider whether investigative resources can be allocated through algorithmic prediction of the outcome, following the initial investigation into the burglary offence, in order to concentrate resources on crimes which are solvable. Despite Meehl (1954) having shown that prediction formulae are frequently superior, and seldom if ever inferior, to human decision makers, Sherman (2013) states that as of 2012 it was still difficult to find a police agency that used a statistical model of solvability to allocate investigative resources. Therefore there is much to be gained from identifying solvability factors and building an algorithmic prediction model which is capable of being implemented into an active policing agency.

EXISTING RESEARCH

Research into identifying solvability factors for crime appears to begin with Isaacs (1967) who examined 1905 crimes and found that in cases (n=349) where there was a suspect named by the victim 86% were solved, but in cases (n=1556) without named suspects, 88% were unsolved. Greenwood (1970) also found that cases where suspects had been named were more associated with arrest than where only a description, or other types of evidence, was available. These studies identified that the types of evidence available to investigators may impact the potential for cases to be solved.

The RAND Corporation built upon this research by examining case assignment files for a range of crime types to demonstrate how detectives use their time, and by analysing solved cases to identify the methods by which they were solved. They found that most solved cases involved either an arrest at the scene (around 22%), identification of an offender at the time of reporting (around 44%), or investigative actions they describe as being "routine" (around 34%) such as showing mug-shot albums to witnesses. They concluded that "case solutions reflect activities of patrol officers, members of the public and routine clerical processing more than investigative techniques" (Chaiken et al., 1976, p.1), and that the information provided by the victim to the initial responding officer is the most important factor (Greenwood and Petersilia, 1975).

These findings were based on a methodology with a low response rate and small sample size, but other researchers have found that most detections are due to actions taken by the initial attending officer at the scene (Coupe and Griffiths, 1996; Brandl and Frank, 1994), and that general follow-up investigations by detectives were ineffective in non-homicide investigations (Weisburd & Eck, 2004).

Eck (1983) examined burglary and robbery offences to test three hypotheses relating to the mechanism by which crimes are solved.

The first, the circumstance-result hypothesis, was drawn from the findings of the RAND study, and the theory that the outcome of cases occurs irrespective of the effort put into a secondary investigation. This theory is somewhat supported by colloquialisms of homicide investigators who describe cases as self-solvers where officers obtain prosecutions easily, and whodunits which have “a more problematic and extended search” to identify a suspect (Innes, 2003, p.197).

The second, the effort-result hypothesis, drew on the findings of Folk (1971) who stated that investigative effort determined the outcome of cases, regardless of leads.

The final hypothesis, the triage hypothesis, posited three types of cases. Firstly, those which practically solve themselves and where little to no detective work is required. Second came the suggestion of a new group of cases where there are leads and the cases are solvable, but solution of these cases relies on investigative work. Thirdly, there are cases which may never be solved, and which certainly cannot be solved using a proportionate level of resourcing. The triage hypothesis therefore presented a set of cases where, if investigative effort is concentrated, it may be possible to improve the chance of solving cases. Eck's (1983) findings supported the triage hypothesis, as some information found during the initial investigation was found to be predictive of whether an arrest was made, but that this finding also applied to the presence of actions performed by detectives following on from the initial investigation.

It is unlikely that the groupings of cases are quite as clean as suggested by Eck (1983), with some cases which would be predicted to be unsolved being solved, and some apparent self-solvers which are never detected (Coupe, 2014b). However, Eck's triage hypothesis provides an explanation for crime solvability which fits with most available evidence, and provides scope for improvements in investigative efficiency through use of solvability analysis in the allocation of crime for investigation. As noted by Bradbury and Feist (2005), technological advances, such as improved forensic capabilities, may change proportions of these groups by making some previously unsolvable cases solvable with reasonable levels of resourcing.

IDENTIFICATION OF SOLVABILITY FACTORS

Olphin and Mueller-Johnson (In Press) defined solvability factors as 'items of information, including leads, which are components of the crime or are available for investigators to act upon, and when examined together are determinant of the likelihood of solving a crime.' Coupe

(2014a) discussed two types of studies examining solvability factors; solvability studies examining multiple factors have mainly considered burglary and robbery, and studies of clearance and detection have considered the effects of various factors on other crime types such as assault, rape and homicide (Ousey and Lee, 2010; Paré et al., 2007; Roberts, 2008; Wellford and Cronin, 1999). Both types demonstrate that there are characteristics of investigations which are differentially present in solved and unsolved cases.

To date, the majority of solvability studies have examined volume or acquisitive crimes; a category of crimes that includes theft, burglary, robbery and criminal damage. However, these authors are not aware of any previous research which has moved beyond the identification of factors to design an algorithmic prediction model for burglary offences. As found by Greenwood and colleagues (1975), on-scene capture of suspects and suspect identity information have both been found consistently to be more prevalent in solved than unsolved cases (Burrows et al., 2005; Coupe and Griffiths, 1996; Eck, 1979; Eck, 1983; Paine, 2012; Stevens and Stipak, 1982). This result has been found across a range of crime types including non-residential burglary (Coupe and Kaur, 2005), robbery (Newiss, 2002) and vehicle crime (Burrows et al., 2005). Pelfrey and Hanna (2011) examined solvability of business burglaries, and found that not only was a name beneficial, the likelihood of clearance improved with each level of information one had about a suspect, with a full identification being optimal, followed by name and description, then full description, and then name with no description.

Paine and Ariel (2013) found that footprints, fingerprints and DNA were more prevalent in solved than unsolved cases, a finding which is consistent with the findings of some other authors (Bond, 2007; 2009; Coupe and Griffiths, 1996), though others have disputed their value (Burrows et al., 2005), though this may be due to lack of statistical power of their testing strategies. Despite findings and policy documents which suggest the value of forensic evidence, Robinson and Tilley (2009) demonstrated that use of forensic techniques was inconsistent, with some police areas utilizing forensic resources more than others.

Other factors which have been found to relate to increased solvability for volume offences are: the offence being witnessed (Donnellan, 2011; Paine, 2012), offence commission during daylight hours (Coupe and Blake, 2006; Coupe & Girling, 2001), availability of CCTV (Robb et al., 2015), availability of resources (Coupe and Griffiths, 2000) and reporting early in commission of offence (Coupe and Blake, 2005). Speed of response has been suggested as being linked to solvability (Blake and Coupe, 2001; Clawson and Chang, 1977) but this may only be the case if the crimes are reported immediately (Bieck and Kessler, 1977) or within five minutes of the offence (Spelman and Brown, 1981).

Lockwood (2014) found that burglaries which occurred in areas with higher levels of broken windows style police enforcement were more likely to be associated with an arrest, and that residential burglaries were no more likely to be solved than non-residential burglaries. Tillyer and Tillyer (2015) demonstrated that committing offences in groups may lead to higher likelihood of being caught, as the likelihood of arrest for robbery increased significantly as the number of co-offenders increased.

The variety of factors demonstrated to be connected to offence solvability, combined with the risk of missing factors which do not occur frequently, shows the value of large datasets with a wide range of variables when attempting to predict whether offences will be solved.

CASE SCREENING AND PREDICTION OF SOLVABILITY

Grove and Meehl (1996) examined 136 studies over a wide range of topics, and demonstrated that the algorithmic or statistical method is almost invariably equal to, or superior to, the clinical or practitioner method. They concluded (Grove & Meehl, 1996, p.320) that 'to use the less efficient of two prediction procedures in dealing with such matters is not only unscientific and irrational, it is unethical. To say that the clinical–statistical issue is of little importance is preposterous.'

Despite such a wealth of research identifying factors which relate to solvability of volume crimes, and strong evidence that statistical prediction improves decision making in other fields (Grove & Meehl, 1996), algorithmic prediction models are not yet being used to allocate investigative resources (Sherman, 2013). Both Greenberg and colleagues (1973), and Eck (1979) have designed case screening models for burglary which were based on individual predictive capability from bivariate analyses. Greenberg and colleagues (1973) predicted case clearance with between 67 and 92 percent accuracy. Eck (1979) replicated the above research and found that it was possible to predict investigative outcome accurately in 85% of cases. However, this method did not examine the difference between errors which waste resources and errors which incorrectly file cases which would have been solved, and incorrectly filed 6% of cases. With clearance rates in some forces being as low as 10.68% (Paine, 2012, p.34), this could reduce the clearance of burglary substantially. The authors of this present paper believe that an algorithmic model can improve upon this level of accuracy.

Targeting allows prioritisation of scarce resources, and the fact that police time accounts for a large percentage of restricted police budgets implies that, if some resources are not wasted on unsolvable investigations, 'it seems logical that detectives would have a better chance of clearing the smaller number of remaining solvable cases' (Williams and Sumrall, 1982, p.112).

The current paper aims to fill gaps in current research by conducting a large scale multivariate analysis of burglary solvability factors, including factors which have been unavailable to other research due to not being stored electronically, before moving the research forward in a practically usable manner by producing a predictive model which is capable of being implemented into an active policing agency.

METHODOLOGY

Previous researchers may have struggled to identify important solvability factors for one of two reasons; first, insufficient sample sizes and lack of statistical power which would prevent the identification of factors with low prevalence in the data, and second, as Olphin (2015) identified, the lack of electronically recorded data for some potential solvability factors. This research resolves the first problem through a large dataset, whilst systematically coding a large number of variables by conducting a free-text analysis which reduces the second problem i.e. the risk that factors which relate to solvability of burglary will be missed because they have not been electronically recorded.

DEFINING CLEARANCE

It was originally intended that Home Office (HO) Outcome, as updated in 2014, was to be used as the outcome variable to indicate whether the offence was solved or not, as it is the current mechanism for recording of crime clearance in the UK (Home Office, 2014). However, these outcomes were not coded for some cases in the dataset which were recorded prior to April 2014 making their use problematic. As a result, it was decided to use sanction detection as the outcome variable to determine whether the case was solved (detected) or unsolved (filed undetected), as this was coded for all cases in the dataset. Sanction detection includes all outcomes where an offender has been identified, and a criminal justice sanction (e.g. Caution, Charge, Summons) has been imposed upon the offender.

A small number of cases (n=7) had inconsistencies in the data pertaining to offence outcome due to change from using detections to using HO outcomes. There were two places that outcome could be recorded and these cases had different values in these boxes, so outcome could not be determined. Any offences with inconsistencies were removed from the analysis. All cases which were cleared by being taken into consideration (TIC), where suspects admit to offences that the police were not able to solve in order to have them taken into consideration at court, or which were identified as having been solved during the initial investigation, were also removed as these had not been solved through allocation for secondary investigation as a result of the evidence that had been gleaned in the initial investigation.

DATA SELECTION

Approximately three years (from April 2012 to May 2015) of police recorded data on burglary in a U.K. Police Force was selected for analysis. This date range was selected in order to avoid a change in crime recording software which was used by the Constabulary, ensuring a sufficiently large sample of offences, whilst simultaneously ensuring that data downloaded were all recorded in the same manner, and with the same data rules.

Offences where burglary was committed in order to commit grievous bodily harm and offences of aggravated burglary were removed from the dataset prior to analysis as these offences are inherently different from burglaries where the intent was to steal (and thus may have different solvability factors), and do not occur with sufficient frequency to analyse them as a distinct category. In addition, attempted burglaries were also not included in this analysis, as they have been shown to have a different solvability profile to burglaries that have been completed (Paine, 2012). These data selection rules provided 9655 burglary offences for analysis.

DATA SOURCES AND VARIABLES IDENTIFIED

The data comprised both electronically recorded categories as well as officer free text that had to be coded manually. In all, data were compiled for 253 variables (68 manually coded from officer free text fields and 185 coded from downloads of Police systems). This initial list of 253 variables was narrowed down to 40 after removing those variables which were found to have very little explanatory power in terms of solvability.

DATA DOWNLOADED FROM POLICE SYSTEMS

Data were downloaded from Police systems to provide information relating to forensics, crime incident information, MO (modus operandi), and other markers that are electronically recorded. These data were examined and included with relative ease in the analysis, with some dummy variables such as whether an offence occurred in an outbuilding being coded from these automatically recorded variables.

DATA CODED FROM FREE-TEXT INVESTIGATION REPORTS

Some data that have been previously demonstrated to be useful for explaining solvability are not recorded electronically by the Constabulary. Instead, officers updated their initial investigation in a free text field, so the free-text report completed by the initial attending officer was also downloaded for all 9655 burglaries in the dataset, and these were coded manually to identify all investigative and evidential opportunities that the officers had identified in their notes. As different officers record information in different ways, and some information is recorded in lists (e.g. H2H conducted, 21 Birch Close – NSOH, 23 Birch Close – Saw everything and is giving a statement, 25 Birch Close – NSOH), it has not been possible to automate this process (e.g. CCTV not present at attacked address, but CCTV is available over the road and shows the offenders). A search for No CCTV would show this as having none, which is incorrect.

ANALYTICAL PROCEDURES

To avoid the predictive algorithm being tested on the dataset it was built from, the data were split into two equal size groups using a random sequence generator (Random.org). One half (n=4828) were used to build the model, and the other half (n=4827) to test the accuracy of the model.

Potential factors were examined independently of one another to begin with using chi square tests to assess whether there was a difference in prevalence of each factor between solved and unsolved cases. The effect size of each identified factor was assessed using the Campbell

Collaboration Effect Size Calculator, based on work by Lipsey and Wilson (2001), to assess the impact that each variable exerts individually on whether a case is solved.

To examine the extent to which case solvability can be predicted, all factors which were found to have significantly different prevalence between solved and unsolved cases in the bivariate tests were then examined for cross correlation. To avoid multicollinearity errors, any variable combinations with Pearson's r>0.9 would have one of the variables removed before the remaining variables were included in logistic regression analyses, using whether the case was cleared or not as the dichotomous dependent variable. An iterative process was used to determine the optimal combination of variables which would be included in the logistic regression in order to fit the build dataset best. A statistically weighted predictive model was then designed using the output of the optimal logistic regression, and this was then applied to the second half of the data to establish its accuracy of prediction.

FINDINGS

IDENTIFICATION OF SOLVABILITY FACTORS

From bivariate analysis of the 253 variables coded through a combination of electronic downloads and free-text coding, 31 were found to be more prevalent in solved than unsolved cases. These factors are shown in Table 1 below, along with the type of data that was required to access the variable. The factors that have been identified are split fairly equally (16 from free-text and 15 from electronic download) in terms of their data type.

Table 1 about here

Attempts were made to separate out different levels of suspect information, but these data were not present in either the electronic forms, or the free-text investigation reports. Instead the variable 'suspect information provided' refers to any level of information relating to a suspect; ranging from a description to a full name and address. 'Between times' is the amount of time between the last known time that the offence had not been committed and the first known time that it had been committed (e.g. when the victim left for work, and when they arrived home and found their house had been burgled). 'Report time' is the time between the offence being discovered and it being reported to police. The measure of CCTV is a combination of an electronically recorded field and whether evidential CCTV was described by the initial attending officer; if either are present then this measure is positive. 'Gaming username enquiries' are available when a gaming console which has an online gaming username associated with it (newer PlayStations and Xboxes) has been stolen, and 'telecommunications enquiries' are available when a telephone number is known for the offender, or a mobile device that can be traced has been stolen.

There were factors which one might expect to be important, but which did not show a significant relationship with whether cases were solved or not. These factors were; tool marks being found by forensic investigators, a press release being conducted by investigators, the victim being unwilling to support an investigation, or providing a negative statement (a statement stating that they would not assist a prosecution), stolen items being found for sale online, the offence being a distraction burglary where vulnerable victims are distracted in order for the burglary to occur, or the victim having markers for vulnerability.

In addition to the 31 positive solvability factors, nine factors were identified which are significantly more prevalent in unsolved than solved cases. These are described therefore as case-limiting factors; cases whose presence indicates that the case may be less likely to be solved. These case-limiting factors are presented in Table 2 below.

Table 2 about here

EFFECT SIZE ANALYSIS

The importance of different variables in determining solvability may be examined by the statistical strength of their relationship with cleared and uncleared offences. Figure 1 shows the statistical effect size of variables examined in this research, both in tabular format and as a forest plot.

Figure 1 about here

The five most important factors in determining solvability of burglary offences were identified as; an arrest being made, suspect information being provided, between times being less than one hour, there being no CCTV available (case-limiting), and whether DNA was recovered. There were also many factors which play a smaller, but not insignificant part, in determining whether burglary offences are cleared.

LOGISTIC REGRESSION

To control for multicollinearity, all variables were compared against all other variables using Pearson correlation tests. There were no pairs of variables where multicollinearity would have been problematic, and so all variables which were identified as being significant in the earlier bivariate tests were incorporated into logistic regression models. Logistic regression is an appropriate method to use when the dependent variable is binary (in this case solved or not solved). To obtain the most accurate fit for the logistic regression, variables were removed and combined in different combinations over 15 iterations in order to design the logistic regression which is shown below in Table 3.

Table 3 about here

Whether an arrest was made was not included, as this will be used as an automatic allocation criterion; if a person is in custody then the police have a legal duty to investigate efficiently. A number of variables are not significant when included in the logistic regression. However, they were included, as models that were examined without them present had greater levels of error in the direction of filing cases which would have been solved. Therefore it appears that some factors do not occur frequently enough to show as significant, but they still seem to play a part in avoiding filing of crimes that should be investigated. The logistic regression was statistically significant, $\chi^2(29)=453.818$, $p<0.001$.

PREDICTIVE MODELLING

The predictive algorithm was created using the base of $logit(p) = b0 + b1X1 + b2X2 + b3X3 + \ldots + bkXk$. (Medcalc Software, 2014) and the resultant formula can be seen in Figure 2 below. Where any of the variables are present in the dataset they are coded as one and where not present, as zero.

Figure 2 about here

The basic result from the logistic regression uses a cut-off point of 0.5 for determining accuracy in order to minimise the overall error rate, meaning that errors are balanced equally between incorrect allocation and incorrect filing. This could lead to victims of solvable crimes being potentially let down. The balance between resource usage and detection levels can be altered by moving the cut-point in a weighted model (see Eck (1979)). If we weight the loss of incorrectly filing solvable cases higher than incorrectly allocating cases that will not be solvable, it is necessary to choose a cut-off point that leads to very few incorrectly filed cases whilst still balancing against the number of unsolvable cases that are allocated.

To select an appropriate cut-off point, error rates were plotted, using the build dataset, for a range of cut-off scores, and these are displayed in Figure 3.

Figure 3 about here

Determining the cut off point for use in a live implementation is a decision that should be made by decision makers from the policing agency responsible, so that they can choose a cut-off point which allows them to retain and investigate offences at a level where they have sufficient resources to investigate cases properly, whilst reducing the number of cases which would have been solved, but which are closed without investigation. It would be possible for a policing agency with extremely limited resources to select a lower cut off point, or for a higher cut off point to be selected for offences where losing successful cases would be of higher risk, or for crimes which cause greater harm.

Using Figure 3, the region of cut-off scores between 3.2 and 2.8 were assessed as reducing the incorrectly allocated cases (wasted resources) as much as possible, whilst minimizing the number of incorrectly filed cases (disappointed victims).

ACCURACY OF SCREENING MODELS

The predictive accuracy of the new statistical model produced through this research was tested on the second half of the dataset, and is presented below for cut-off points of 3.2 and 2.8 using a graphical representation which has been adapted from Eck (1979), which is demonstrated in Figure 4.

Figure 4 about here

Figure 5 shows the percentages (and quantities) of cases that are correctly and incorrectly predicted by the new statistical model using the more conservative cut-off point of 3.2. At this cut-off point, 93% of cases that are solvable would be correctly allocated, whilst 39% of unsolvable cases would be filed correctly, resulting in a 33.5% reduction in workload when compared to a system of investigating all burglary offences reported to the Police force each year. Based on the total mean number of crimes per year in our sample, this equates to approximately 1049 investigations per year.

Figure 5 about here

Figure 6 shows the percentages (and quantities) of cases that are correctly and incorrectly predicted by the new statistical model using a cut-off point of 2.8. At this cut-off point, 87% of solvable cases would be correctly allocated, but 52% of unsolvable cases would be correctly identified.

Figure 6 about here

When compared to a system of investigating all burglary offences, the use of a cut-off of 2.8 would result in a reduction of workload of 42.2%. Based on the total mean number of crimes per year in our sample, this is the equivalent of a reduction in workload of 1321 investigations per year. It is important to remember though that some cases will have been solved due to additional information coming to light, this is something that the model cannot 'see' and therefore actual accuracy is hypothesized to be higher, and following testing it may be possible to safely use an even more stringent cut-off point.

DISCUSSION

Previous research has found investigative factors that are indicative of case clearance (Eck, 1983; Roberts, 2008). This research has identified forty factors which are associated with the clearance of burglary offences; thirty-one positive 'solvability' factors, and nine negative 'case-limiting' factors. This research has then developed upon earlier research by designing and testing a predictive solvability model for burglary using a large dataset which examined both electronically retained, and free-text data.

Many of the factors identified as being related to clearance are consistent with findings of previous researchers, with on-scene capture of a suspect and suspect identity information (Burrows et al., 2005; Coupe and Griffiths, 1996; Eck, 1983; Greenwood et al, 1975), CCTV (Robb et al., 2015), availability of witness evidence (Donnellan, 2011), short between-times (Coupe and Blake, 2005), and rapid reporting (Spelman and Brown, 1981) all being found to be important in the prediction of clearance. Whilst DNA, fingerprints and shoe marks have been found to be incredibly important in the clearance of burglary offences, as was found by many other researchers (Bond, 2007;2009; Coupe & Griffiths, 1996; Paine & Ariel, 2013), the same cannot be said for all types of forensic evidence. It appears that tool marks being recovered does not add to the likelihood of clearance of a case.

By taking the time to combine the electronically available information with an in-depth analysis of free-text investigative reports, this research has built upon the earlier research through identification of additional factors that had not previously been found to be related to clearance. Seizure of items or suspect's clothing, and recovery of stolen property provide additional opportunities for forensic investigation which would not be apparent from the forensic systems at the time of the initial investigation. Other types of evidence that were not available when many police systems were initially designed; gaming username enquiries (when a PlayStation or Xbox is stolen), telecommunications opportunities being available (theft of an electronically trackable item, or availability of a suspect's mobile number), and financial enquiries relating to card or account usage, have also been shown to be important, whilst not being recorded electronically. The offence being considered part of a series was also not available electronically, despite its importance.

Analysis of free-text fields also allowed negative factors such as no CCTV being available, no suspects being found, and negative results or non-completion of house to house enquiries, to be accessed. These were all shown to be exceptionally useful in determining those cases which do not have sufficient available evidence to solve.

It is likely that these factors have not been found previously due to them being difficult to access, with most police services recording them in inaccessible free-text reports, rather than in electronic records. This demonstrates the importance of accessing as many different sources of information as possible and provides strong argument for policing agencies to update their data systems and ensure that data are being stored in an accessible and useful manner, rather than just in free-text fields.

An interesting finding is the non-significance of factors relating to vulnerability. While not putting investigative efforts in when a vulnerable person is involved may be at odds with a key policing tenet of protecting the vulnerable, our results suggest that we should be treating those cases somewhat differently. It is not clear that spending investigative resources on cases that will not be solved because there is a vulnerability marker is the best way to protect the vulnerable. It may instead be possible to free up resources from investigating a case which will not be solved, in order to provide additional support, or security advice, to the vulnerable victims to prevent repeat victimization, and thus protect them from future harm.

Whilst the identification of individual factors which are linked to clearance is of interest, and may assist with determining which investigative resources are most important to invest in, this research has also analysed the factors collectively, and has demonstrated that they can be combined to design a predictive model capable of identifying whether cases are solvable or not to a high degree of accuracy.

This research has also identified a large number of cases which the model would identify as solvable, but which were previously unsolved. These cases all have solvability factors associated with them, and therefore if officer workloads are reduced by concentrating on cases that are identified as being solvable by the algorithm, it is possible that some of these cases, that were previously missed opportunities, would be solved. This is something that would require further testing but may associate the use of solvability algorithms with improved clearance rates, making police services more effective, and could in turn influence public perceptions of police legitimacy.

The models designed in this research have been tested on a separate data set and have been demonstrated to be capable of helping the police to reduce demand by between 33.5% and 42.2% when measured against a model where all cases are investigated. This would result in a reduction in demand of between 1049 and 1321 cases. Heeks and colleagues (2018) estimate the cost of investigation of burglary to be £530 per offence. Whilst it is acknowledged that not all of this cost can be attributed to the secondary investigation, this provides potential resource savings of up to £555,970 at a cut-off of 3.2, or up to £700,130 at a cut-off of 2.8.

CONCLUSIONS

This research has demonstrated that it is possible to predict whether burglary offences will be solved from analysis of the evidence recovered during initial investigation, by building a predictive model of solvability for burglary using data from a U.K. Police force. The model was then externally validated by being run on a test dataset which was disparate from the one used to build the model, and has been shown to be capable of reducing demand by up to 42.2%, with a potential resource saving of up to £700,000.

In addition to building a predictive model for clearance of burglary, this research has evidenced that there is important information that is not being recorded electronically, and which is not therefore available for research, or for use in algorithmic solutions to policing issues. It is therefore recommended that policing agencies examine the methods by which they are recording data to ensure that it is recorded in a retrievable and useful manner, rather than in inaccessible free-text reports or paper records.

Whilst the likely allocation levels of the model built in this research can be ascertained from examining the test dataset results, the next step would be trialing the model in real-time to see how it performs. Ideally, a randomised controlled trial of the model should be undertaken that would allow the effects of the implementation of the model to be assessed. This could include an assessment of any change in solvability rate due to using the model and, depending on the design, could also allow for a cost-benefit analysis to be performed. For the model to be applied in real time, there are choices which need to be made in relation to mandatory allocation rules, and the cut-off value which will be used to allocate cases. As seen above, there are already some mandatory allocation rules built into the model, but these can be added to or amended if required. It is also possible that many of the cases which are found to be incorrectly filed would be found to be reopened due to forensic results or additional evidence being provided. If this is the case, it may allow for the cut-off value to be lowered in future implementations, resulting in increased resource savings, with minimal impact upon cases that would be solved.

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TABLES AND FIGURES

Figure 1. Effect size of factors identified as being related to solvability of burglary offences

Indicator	Est. Std. Diff. in Means	Lower 95% C.I. Limit	Upper 95% C.I. Limit	χ^2	P-Value
Arrest Made	0.5747	0.5135	0.636	338.216	0.000
Suspect Information Provided	0.46	0.3996	0.5204	222.793	0.000
Between Times Less than 1 hour	0.3701	0.3102	0.43	146.796	0.000
DNA Recovered	0.3637	0.3038	0.4235	141.902	0.000
Prints Recovered	0.3425	0.2828	0.4022	126.32	0.000
Burglary occurred in a dwelling	0.3402	0.2805	0.3999	124.673	0.000
CCTV Present (Either Measure)	0.3389	0.2792	0.3986	123.769	0.000
Definite Victim Statement or ABE Interview	0.2894	0.2299	0.3489	90.951	0.000
Report Time Less than 15 minutes	0.2731	0.2137	0.3325	81.143	0.000
Witnessed by Officer	0.2688	0.2094	0.3282	78.671	0.000
Are there witnesses other than the victim	0.2534	0.194	0.3127	70.04	0.000
Stolen Items Recovered	0.2443	0.185	0.3036	65.185	0.000
Shoe Mark Recovered	0.2176	0.1584	0.2768	51.865	0.000
Suspect's Clothing Seized	0.1969	0.1378	0.2561	42.578	0.000
Other Sample Recovered	0.1851	0.126	0.2442	37.655	0.000
Forceful Entry	0.18	0.1209	0.2391	35.643	0.000
Entry Rear	0.1791	0.12	0.2382	35.276	0.000
Entry Window	0.1686	0.1095	0.2277	31.283	0.000
Items Seized	0.1626	0.1036	0.2217	29.131	0.000
Domestic Indicator	0.1593	0.1002	0.2184	27.951	0.000
Entry Door	0.1589	0.0998	0.2179	27.798	0.000
Gaming Username Enquiries	0.1242	0.0652	0.1832	17.039	0.000
Victim witnessed offence	0.1188	0.0599	0.1778	15.599	0.000
Telecommunications Opportunities Available	0.1174	0.0584	0.1763	15.218	0.000
Scene Photographed	0.1093	0.0504	0.1683	13.208	0.000
Item located at second hand shop	0.0968	0.0379	0.1557	10.363	0.001
Part of Series	0.0867	0.0278	0.1456	8.313	0.004
Victim is Unemployed	0.0858	0.0269	0.1447	6.969	0.008
Discovered By Police	0.0794	0.0204	0.1383	4.49	0.034
VRM Provided	0.0637	0.0048	0.1226	4.058	0.044
Financial Enquiries Card or Account Usage	0.0605	0.0016	0.1194	8.142	0.004
Report Time Over 18hrs	-0.102	-0.1609	-0.043	11.494	0.001
Stolen Property - Cycle	-0.1192	-0.1782	-0.0603	15.707	0.000
Stolen Property - Industrial Equipment	-0.1368	-0.1958	-0.0778	20.647	0.000
House to House not Conducted	-0.142	-0.201	-0.083	22.238	0.000
Negative House to House Conducted	-0.1633	-0.2224	-0.1043	29.382	0.000
No Witnesses Clearly Stated	-0.215	-0.2742	-0.1558	50.666	0.000
Offence Occurred in an Outbuilding	-0.2521	-0.3115	-0.1928	69.374	0.000
Between Times Over 12hrs	-0.3315	-0.3912	-0.2718	118.567	0.000
There is no CCTV available	-0.3701	-0.4299	-0.3102	146.779	0.000
Grand TOTAL	0.120945	0.06165	0.1802375		

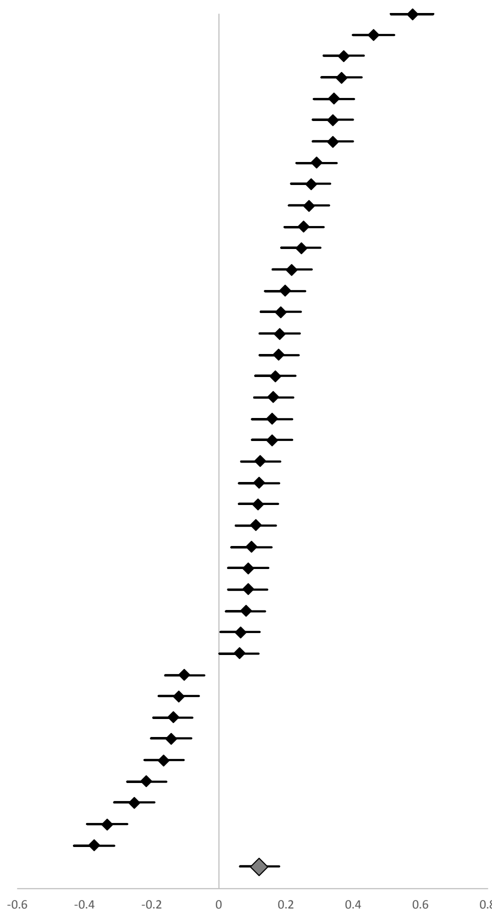

Figure 2. Predictive Algorithm

Case Solvability Score (Higher Score is Less Solvable) = 2.5917734249 + the sum of the relevant values for the factors that are present as follows:	
(If Gaming Username Enquiries is present **-4.1501993945**)	(If Item located at second hand shop is present **-2.8212215962**)
(If Discovered By Police is present **-1.6088851600**)	(If DNA Recovered is present **-1.2432782388**)
(If Domestic Indicator is present **-0.9613807375**)	(If Financial Enquiries Card or Account Usage is present **-0.8676973571**)
(If Prints Recovered is present **-0.7089646728**)	(If Part of Series is present **-0.5828106700**)
(If Stolen Items Recovered is present **-0.5781382287**)	(If Telecommunications Opportunities Available is present **-0.5742982424**)
(If Either CCTV measure is positive is present **-0.5509179989**)	(If Unemployed is present **-0.5078199848**)
(If Are there witnesses other than the victim is present **-0.5019885667**)	(If Witnessed by Officer is present **-0.4490801532**)
(If Time to Report Less than 15 minutes is present **-0.4286801654**)	(If There is Suspect Information Provided is present **-0.4064605307**)
(If Shoe Print Recovered is present **-0.3194626005**)	(If Forceful Entry is present **-0.2954104448**)
(If Between Times Less than 1 hour is present **-0.2037576893**)	(If Items Seized is present **-0.1057116916**)
(If Suspect Clothing Seized is present **-0.0495460319**)	(If Other Sample Recovered is present **-0.0201816735**)
(If Time to Report Over 18 hours is present **+0.0941689671**)	(If Negative House to House Conducted is present **+0.2047767659**)
(If No Witnesses Clearly Stated is present **+0.2454850535**)	(If House to House not Conducted in Initial Investigation is present **+0.3131791432**)
(If Between Times Over 12 hours is present **+0.3424270166**)	(If There is no CCTV available is present **+0.5928572330**)
(If Offence Occurred in an Outbuilding is present **+0.7883362897**)	

Figure 3. Cut-Off Point Analysis

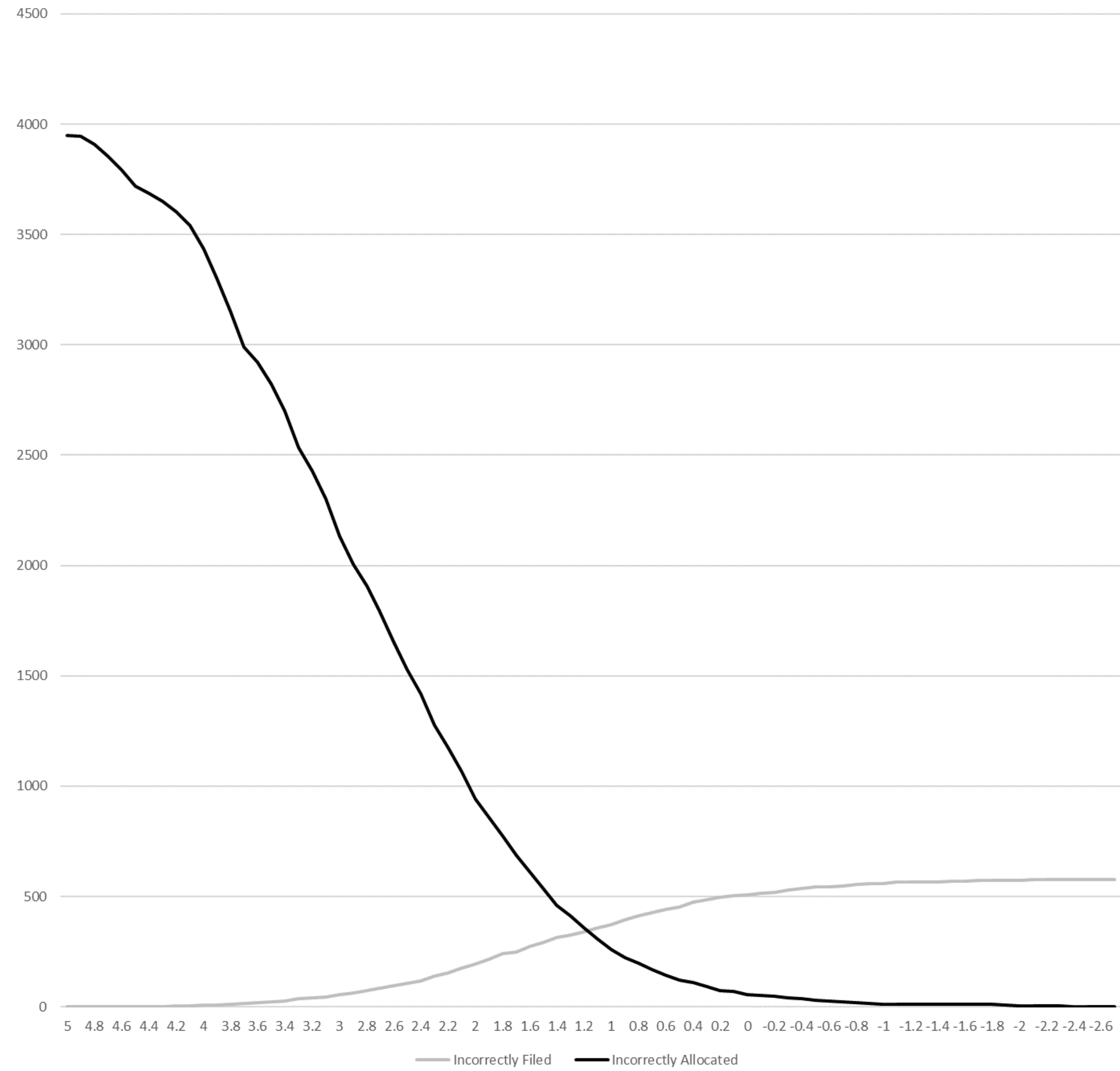

Figure 4. Model Accuracy (adapted from Eck, 1979)

		Real Case Outcome	
		Case Cleared	Case Not Cleared
Model Predicted Case Outcome	Case Cleared	Correct Prediction	Wasted Investigation
	Case Not Cleared	Lost Clearance	Correct Prediction

Figure 5. Model Accuracy using 3.2 as cut-off

		Real Case Outcome	
		Case Cleared	Case Not Cleared
Model Predicted Case Outcome	Case Cleared	93% (536)	61% (2429)
	Case Not Cleared	7% (41)	39% (1521)

Figure 6. Model Accuracy using 2.8 as cut-off

		Real Case Outcome	
		Case Cleared	Case Not Cleared
Model Predicted Case Outcome	Case Cleared	87% (502)	48% (1909)
	Case Not Cleared	13% (75)	52% (2041)

Table 1. Variables found to be more prevalent in solved cases

Variable	Chi Square	Method Obtained
Arrest Made	$\chi^2(1)=338.216$, $p<0.05$	Free-text Coding
Suspect Information Provided	$\chi^2(1)=222.793$, $p<0.05$	Free-text Coding
Between Times Less than 1 hour	$\chi^2(1)=146.796$, $p<0.05$	Downloaded Data
DNA Recovered	$\chi^2(1)=141.902$, $p<0.05$	Downloaded Data
Prints Recovered	$\chi^2(1)=126.32$, $p<0.05$	Downloaded Data
Burglary occurred in a dwelling	$\chi^2(1)=124.673$, $p<0.05$	Downloaded Data
Definitely Video (Downloaded) or CCTV is Evidential (Freetext)	$\chi^2(1)=123.769$, $p<0.05$	Combination
Definite Victim Statement or ABE Interview	$\chi^2(1)=90.951$, $p<0.05$	Free-text Coding
Report Time Less than 15 minutes	$\chi^2(1)=81.143$, $p<0.05$	Downloaded Data
Witnessed by Officer	$\chi^2(1)=78.671$, $p<0.05$	Free-text Coding
Are there witnesses other than the victim	$\chi^2(1)=70.04$, $p<0.05$	Free-text Coding
Stolen Items Recovered	$\chi^2(1)=65.185$, $p<0.05$	Free-text Coding
Shoe Mark Recovered	$\chi^2(1)=51.865$, $p<0.05$	Downloaded Data
Suspect's Clothing Seized	$\chi^2(1)=42.578$, $p<0.05$	Free-text Coding
Other Sample Recovered	$\chi^2(1)=37.655$, $p<0.05$	Downloaded Data
Forceful Entry	$\chi^2(1)=35.643$, $p<0.05$	Downloaded Data
Entry Rear	$\chi^2(1)=35.276$, $p<0.05$	Downloaded Data
Entry Window	$\chi^2(1)=31.283$, $p<0.05$	Downloaded Data
Items Seized	$\chi^2(1)=29.131$, $p<0.05$	Free-text Coding
Domestic Indicator	$\chi^2(1)=27.951$, $p<0.05$	Downloaded Data
Entry Door	$\chi^2(1)=27.798$, $p<0.05$	Downloaded Data
Gaming Username Enquiries	$\chi^2(1)=17.039$, $p<0.05$	Free-text Coding
Victim witnessed offence	$\chi^2(1)=15.599$, $p<0.05$	Free-text Coding
Telecommunications Opportunities Available	$\chi^2(1)=15.218$, $p<0.05$	Free-text Coding
Scene Photographed	$\chi^2(1)=13.208$, $p<0.05$	Free-text Coding
Item located at second hand shop	$\chi^2(1)=10.363$, $p<0.05$	Free-text Coding
Part of Series	$\chi^2(1)=8.313$, $p<0.05$	Free-text Coding
Victim is Unemployed	$\chi^2(1)=8.142$, $p<0.05$	Downloaded Data
Discovered By Police	$\chi^2(1)=6.969$, $p<0.05$	Downloaded Data
VRM Provided	$\chi^2(1)=4.49$, $p<0.05$	Free-text Coding
Financial Enquiries Card or Account Usage	$\chi^2(1)=4.058$, $p<0.05$	Free-text Coding

Table 2. Variables found to be more prevalent in unsolved cases

Variable	Chi Square	Method Obtained
There is no CCTV available	$\chi^2(1)=146.779$, $p<0.05$	Free-text Coding
Between Times Over 12hrs	$\chi^2(1)=118.567$, $p<0.05$	Downloaded Data
Offence Occurred in an Outbuilding	$\chi^2(1)=69.374$, $p<0.05$	Downloaded Data
No Witnesses Clearly Stated	$\chi^2(1)=50.666$, $p<0.05$	Free-text Coding
Negative House to House Conducted	$\chi^2(1)=29.382$, $p<0.05$	Free-text Coding
House to House not Conducted in Initial Investigation	$\chi^2(1)=22.238$, $p<0.05$	Free-text Coding
Stolen Property - Industrial Equipment	$\chi^2(1)=20.647$, $p<0.05$	Downloaded Data
Stolen Property - Cycle	$\chi^2(1)=15.707$, $p<0.05$	Downloaded Data
Report Time Over 18hrs	$\chi^2(1)=11.494$, $p<0.05$	Downloaded Data

Table 3. Logistic Regression

Variable	B	S.E.	Wald	df	Sig.	EXP (B)	95% C.I. for EXP(B)	
							Lower	Upper
Gaming Username Enquiries	-4.150	1.155	12.914	1	0.000	0.016	0.002	0.152
Item located at second hand shop	-2.821	1.311	4.631	1	0.031	0.060	0.005	0.778
Discovered By Police	-1.609	0.787	4.178	1	0.041	0.200	0.043	0.936
DNA Recovered	-1.243	0.194	41.134	1	0.000	0.288	0.197	0.422
Domestic Indicator	-0.961	0.569	2.855	1	0.091	0.382	0.125	1.166
Financial Enquiries Card or Account Usage	-0.868	0.568	2.338	1	0.126	0.420	0.138	1.277
Prints Recovered	-0.709	0.119	35.744	1	0.000	0.492	0.390	0.621
Part of Series	-0.583	0.212	7.527	1	0.006	0.558	0.368	0.847
Stolen Items Recovered	-0.578	0.273	4.493	1	0.034	0.561	0.329	0.957
Telecommunications Opportunities Available	-0.574	0.905	0.403	1	0.526	0.563	0.096	3.318
CCTV Present (Either Measure)	-0.551	0.178	9.630	1	0.002	0.576	0.407	0.816
Victim is Unemployed	-0.508	0.268	3.587	1	0.058	0.602	0.356	1.018
Are there witnesses other than the victim	-0.502	0.228	4.839	1	0.028	0.605	0.387	0.947
Witnessed by Officer	-0.449	0.950	0.223	1	0.637	0.638	0.099	4.110
Report Time Less than 15 minutes	-0.429	0.125	11.772	1	0.001	0.651	0.510	0.832
Suspect Information Provided	-0.406	0.178	5.213	1	0.022	0.666	0.470	0.944
Shoe Mark Recovered	-0.319	0.133	5.780	1	0.016	0.727	0.560	0.943
Forceful Entry	-0.295	0.133	4.966	1	0.026	0.744	0.574	0.965
Between Times Less than 1 hour	-0.204	0.163	1.556	1	0.212	0.816	0.592	1.123
Items Seized	-0.106	0.213	0.247	1	0.619	0.900	0.593	1.365
Suspect's Clothing Seized	-0.050	0.674	0.005	1	0.941	0.952	0.254	3.565
Other Sample Recovered	-0.020	0.166	0.015	1	0.903	0.980	0.708	1.357
Report Time Over 18hrs	0.094	0.224	0.176	1	0.674	1.099	0.708	1.705
Negative House to House Conducted	0.205	0.140	2.144	1	0.143	1.227	0.933	1.614
No Witnesses Clearly Stated	0.245	0.180	1.853	1	0.173	1.278	0.898	1.820
House to House not Conducted in Initial Investigation	0.313	0.161	3.802	1	0.051	1.368	0.998	1.874
Between Times Over 12hrs	0.342	0.135	6.478	1	0.011	1.408	1.082	1.833
There is no CCTV available	0.593	0.137	18.774	1	0.000	1.809	1.384	2.366
Offence Occurred in an Outbuilding	0.788	0.240	10.780	1	0.001	2.200	1.374	3.522
Constant	2.592	0.166	242.704	1	0.000	13.353		