Almond, L, Matin, E and McManus, M

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Journal of Interpersonal Violence

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Journal:	*Journal of Interpersonal Violence*
Manuscript ID	JIV-19-506.R1
Manuscript Type:	Original Research
Keywords:	Homicide, Violent Offenders, Anything related to < Homicide

PREDICTING THE CRIMINAL RECORDS OF MALE-ON-FEMALE UK HOMICIDE OFFENDERS FROM CRIME SCENE BEHAVIORS

Abstract

Offender profiling follows the idea that if offenders' crime scene actions can be empirically linked to their background characteristics, it will be possible to predict one from the other (Canter, 2011). There is a lack of research exploring whether homicide offenders' crime scene actions are predictive of their criminal histories, despite the potential utility of such information (Almond, McManus, Bal, O'Brien, Rainbow, & Webb, 2018). The current study addresses this gap in the literature.

A sample of 213 adult male-on-female homicides with sexual or unknown motive was drawn from a UK-wide database. Relationships between 13 pre-conviction variables and 29 crime scene behaviors were explored using a bivariate statistical approach. Subsequently, binary logistic regression models were used to predict the presence, or absence, of specific pre-convictions based on a *combination* of offence behaviors. Analyses highlighted 16 statistically significant associations between key offence behaviors and previous convictions, these associations were often "less likely" to result in previous conviction. The analysis failed to find any association for various other variables, most notably sexual pre-convictions. Results indicate offenders' criminal histories can be predicted from their offence behaviors, though not all pre-convictions may be similarly suited. Implications for practice are discussed.

Introduction

The majority of homicides in the United Kingdom are solved relatively quickly after the offence occurred (Nicol, Innes, Gee, & Feist, 2004). In about one quarter of homicide cases, however, investigators are confronted with complex scenarios, in which possible suspects and relationships between involved individuals cannot be identified quickly (Francis et al., 2004). Homicides involving stranger or child victims, sexual elements, an unknown motive, or serial offences are usually more difficult to detect and consume considerable amounts of police resources, attract increased media attention, and are often perceived as especially severe, baring the potential to negatively impact the public's general fear of crime and, thus, their perceptions of police efficiency (Cole & Brown, 2014; Francis et al., 2004; Innes, 2003).

Within the UK, practitioners' experience in such difficult-to-solve cases is often complemented with empirically grounded investigative support provided by Behavioral Investigative Advisers (BIAs, Rainbow & Gregory, 2009). One of the core competencies of BIAs is their ability to make logical, evidence-based inferences on likely offender characteristics based on the behavioral assessment of a crime scene. This form of investigative support, commonly referred to as *offender profiling*, can be a valuable instrument to assist police in prioritising potential nominals and efficiently directing scarce resources in demanding investigations (Cole & Brown, 2014; Rainbow & Gregory, 2009). Offender profiling generally rests on the assumption of homology, i.e. offenders who commit crimes in a similar manner will also share similar background characteristics (Alison, Bennell, Mokros, & Ormerod, 2002; Mokros & Alison, 2002). Based on this tenet, offender profiling seeks to establish so-called "A to C equations", investigating *if* and *how* crime scene actions (A) can be linked to offender background characteristics (C), in order to allow for predictive inferences in unsolved criminal cases (Canter, 2011). With regard to practical utility, profiling inferences made by BIAs should ideally relate to offender background information that is overt, objective, and readily available to investigators, such as the offender's likely age, sex, or previous criminal convictions (Alison et al., 2005). In addition, investigative advice given by BIAs must be transparent as to how adequately and reliably it is backed by scientific research (Alison, Smith, Eastman, & Rainbow, 2003; Almond, Alison, & Porter, 2007). Taken together, this highlights the need for a broad and pragmatic research foundation on which to base profiling claims on.

A number of international studies have extended the available evidence base for offender profiling attempts in homicide cases over the last decades (e.g. Cole & Brown, 2014; Francis et al., 2004; Fujita et al., 2016; Horning, Salfati, & Crawford, 2010; Salfati & Canter, 1999; Santtila, Häkkänen, Canter, & Elfgren, 2003; Trojan & Salfati, 2011). However, relatively few studies have examined *specifically* whether homicide offenders' *criminal histories* can be inferred from their crime scene actions. Criminal history profiling follows the idea that an offender's prior criminal experience, such as encounters with the criminal justice system or previously successful criminal strategies, will influence future behaviors this offender exhibits in the commission of a crime (Beauregard & Bouchard, 2010; Beauregard & Martineau, 2013; Davies et al., 1997). The current lack of studies exploring links between homicide offenders crimes scene actions and their pre-convictions is unfortunate given the potential usefulness of such information to investigations, as 1) most homicide offenders appear to have criminal antecedents of some kind (Broidy, Daday, Crandall, Sklar, & Jost, 2006; Cole & Brown, 2014; Greenall & Richardson, 2015; Soothill, Francis, Ackerley, & Fligelstone, 2002) and 2) information on previous criminal convictions is easily available to investigators through police databases as long as their offending has been in the UK (Alison et al., 2005).

Furthermore, the few existing studies so far are divided by a fundamental dispute in the general offender profiling literature, concerning which statistical approach should be preferred for linking crime scene actions to offender characteristics (Alison, Goodwill, Almond, Heuvel, & Winter, 2010). Some authors have favoured direct bivariate associations to explore the relationship between single offence behaviors and prior offences (e.g. Almond et al., 2018; Cole & Brown, 2014; Davies et al., 1997; Lea, Hunt, & Shaw, 2011; Scott, Lambie, Henwood, & Lamb, 2006; ter Beek, van den Eshof, & Mali, 2010). In the context of stranger rape, for example, Almond et al. (2018) found in their replication of the classic Davies et al. (1997) study that stranger rapists who forced their entry were 2.5 times more likely to have a previous conviction for burglary, whereas offenders who disabled their victim's phone were nearly 5 times more likely to have previously been convicted for a violent crime. Contrarily, other authors have employed a thematic approach, which investigates how themes or typologies of crime scene actions relate to clusters of offender characteristics (e.g. Horning et al., 2010; Salfati, 2000; Salfati & Canter, 1999; Santtila et al., 2003; Trojan & Salfati, 2011). While the dispute over the most appropriate statistical approach for offender profiling might not yet be ultimately resolved, there is some evidence that direct bivariate associations outperform thematic approaches in their predictive power (Goodwill, Alison, & Beech, 2009).

Despite the general dearth of research and the ongoing methodological dispute, some studies have shed light on possible relationships between offence behaviors and previous convictions in the context of homicide (e.g. Cole & Brown, 2014; Horning et al., 2010; Salfati & Canter, 1999; Trojan & Salfati, 2011). Employing a direct, bivariate statistical approach on a sample of difficult-to-detect homicide cases, Cole and Brown (2014) found, for example, that killers who were under the influence of alcohol or drugs during the offence, were more than twice as likely to have a previous conviction for violent offences, whereas murderers who took pieces of their victim's clothing with them were nearly 2.5 times more likely to have been previously arrested for a sexual offence. Using a more thematic approach, Horning et al. (2010) demonstrated that homicide offenders, who showed some degree of specialisation towards violent, sexual, or acquisitive crimes in their criminal histories, were more likely to engage in goal directed behaviors at the crime scene, such as controlling the victim or sexually and materially exploitative behaviors, when compared to non-specialist offenders.

However, the majority of the existing studies thus far are arguably based on non-contemporary samples and have either contained a limited number of previous conviction categories (Cole & Brown, 2014) or have grouped multiple previous convictions into broader clusters or typologies (Horning et al., 2010; Salfati & Canter, 1999; Trojan & Salfati, 2011). Thus, exploring a larger and more specific set of previous conviction variables may help to not only answer whether offenders' criminal histories can be reliably predicted from their crime scene actions, but also whether certain pre-convictions may be better suited for prediction than others. In addition, previous studies have mostly analysed samples including both male and female killers, even though research has repeatedly highlighted differences in crime scene behaviors, criminal histories, and general psychological functioning between the two groups (Jurik & Winn, 1990; Putkonen, Weizmann-Henelius, Lindberg, Rovamo, & Häkkänen-nyholm, 2011; Trägårdh, Nilsson, Granath, & Sturup, 2016), Similarly, prior studies indicate that offenders with female victims may differ from killers that target male victims (Muftić & Baumann, 2012), indicating more extensive arrest records and differences in weapon involvement and methods of killing in femicide offenders (Goetting, 1991). There may, therefore, be a need to specialise predictive profiling efforts towards what appear to be distinct homicidal offender sub-populations.

In conclusion of the theoretical, practical, and methodological considerations outlined above, the study proposed here aimed to explore the relationships between a large set of homicide offender pre-convictions and specific crime scene behaviors using a bivariate statistical approach. The sample utilised was focussed on a large, yet specific homicide offender sub-group, i.e. adult male-on-female offenders with adult victims. To increase the practical applicability of any findings, this study used a contemporary sample of investigative policing data drawn from a database of hard-to-solve homicide cases with sexual or unknown motive. In doing so, this study addresses the need for a separate, offence-specific, up-to-date empirical basis BIAs can refer to when aiming at predicting an unknown offender's likely criminal history in cases of unsolved homicide.

Method

Database

The present study is based on secondary case data provided by the National Crime Agency's (NCA) Serious Crime Analysis Section (SCAS). SCAS operates a unique, UK-wide database holding details of rape, homicide, and abduction cases that meet specific criteria. For homicide, these criteria include cases where BIA support may typically be requested, i.e. homicides with a known sexual motive as well as homicides with unknown motive, in which the offender-victim relationship is unknown or stranger (Rainbow & Gregory, 2009). SCAS receive case files from all UK police forces, which are then coded and entered into a Violent Crime Linkage Analysis System (ViCLAS) database involving a rigorous quality control process and highly trained staff to ensure input accuracy and interrater reliability (Almond et al., 2018). The dataset utilised herein was provided to the author in a clean, pre-coded, and anonymised form.

Sample

For this study, a sample of solved homicide cases involving a single female victim and a single male offender was drawn from ViCLAS by SCAS based on the following criteria: First, offences must have occurred between 1985 and 2017. Second, both victim and offender must have been adults (above the age of 16) at the time of the offence. Third, data must be taken from cases involving single offenders and single victims only. And finally, for serial homicides, only the first victim must be included in the dataset to avoid any biases resulting from an overrepresentation of certain serial offenders. After eliminating four cases in which no pre-conviction information was available, a final sample of 213 cases was obtained.

Sample demographics show that on average, offenders (M = 31.38, SD = 9.42) were younger than victims (M = 37.83, SD = 19.95) with most offenders being of European descent (89.2%), in relation to offenders of African Caribbean (6.1%), Asian (2.8%), and Oriental or Arabic (1.4%) descent. One offender was classified as of unknown descent (0.5%). Table 1 displays the frequencies of relationships between offenders and their victims in this sample.

Procedure

Variables extracted from ViCLAS related to either *previous convictions* of the offender at the time of the index offence or specific *behavioral offence characteristics* that were observed at the crime scene. Offence behavior variables were pre-coded by SCAS in a dichotomous format with 1 indicating presence and 0 indicating absence (or unknown status) of specific behaviors and crime scene characteristics. A total of 29 offence behavior variables (see Table 2) broadly falling into the categories of *sexual behaviors*, *weapon involvement*, *method of killing*, *body disposal*, *theft*, *precautions*, and *other behaviors*, were selected for the analysis based on a number of previous studies on homicide (Cole & Brown, 2014; Greenall & Richardson, 2015; Pell, 2017; Wright, 2017).

Some low frequency variables (e.g. different recorded types of vaginal penetration) were combined into broader, superordinate categories (e.g. general vaginal penetration). Notably, variables relating to precautions taken were grouped to reflect whether offenders manipulated the *crime scene* (e.g. destroyed forensics), the *victim* (e.g. blindfolding, gagging), or *themselves* (e.g. wearing gloves, condoms) to avoid detection or facilitate the offence. Variables relating to the method of killing (blunt force, sharp force, asphyxia/strangulation) and variables concerning theft from the crime scene (personal items, valuables, clothing stolen) were coded from free text boxes by the author. It should be noted that in cases of homicide, it is generally unlikely to obtain a complete and exhaustive picture of a killer's offence behaviors solely through observing the crime scene. This implicates that 1) the absence of a recorded variable does not necessarily equal the absence of the respective behavior, and 2) the presence of a recorded variable cannot guarantee that the offender carried out that behavior

In addition to these offence behavior variables, a total of 13 pre-convictions (see Table 3) were selected, based on variables used in previous studies on sexual homicide (Greenall & Richardson, 2015) and rape (Almond et al., 2018).

Statistical Analysis

This study aimed to replicate the methodology originally introduced by Davies et al. (1997) for their investigation of stranger rapists' pre-convictions in a new context – that of male-on-female homicide offenders. Specifically, this study adopted the statistically more sophisticated approach recently employed by Almond, et al. (2018) in their contemporary replication of the Davies et al. (1997) study.

Data was analysed in two stages. In *stage one*, separate chi-square tests were employed to investigate whether any direct associations between offence behavior variables and conviction variables could be identified. Where test assumptions were violated (expected frequencies must be > 5 in each cell), Fisher's exact tests were used (Field, 2013). In order to account for multiple testing on the same sample, Bonferroni-Holm corrections were applied to adjust p-values. To further qualify any significant associations, Odds Ratios (OR) were calculated to assess the likelihood of an offender having a specific pre-conviction based on the presence or absence of single behaviors during the offence. An OR > 1 indicates that the probability of a pre-conviction *A* is increased if an offence behavior *B* was observed, whereas the probability of *A* is decreased if *B* was not observed (and vice versa for ORs < 1) (Liberman, 2005). According to Chen, Cohen, and Chen (2010), the strength of the identified associations can be considered low (OR < 1.5), medium (OR 1.5 - 5), or high (OR > 5).

In *stage two*, logistic regression models were used to predict an offender's previous convictions based on a combination of significant offence behavior variables identified in stage one. A separate forced-entry logistic regression was performed for each pre-conviction type. In addition, it was assessed how much each predictor variable contributed to the predictive accuracy of the model and if these contributions were statistically significant. To evaluate their usefulness to practitioners, each of the models' ability to predict a certain pre-conviction was compared with the "best guess" investigators would face without knowledge of any offence behavior (i.e. a guess based only on the base rate of a particular pre-conviction in this sample). As an additional measure of model performance, Receiver Operating Characteristics (ROC) Area Under the Curve (AUC) values were calculated.

Results

Descriptive Statistics

Table 2 displays the frequency of offence behavior variables in this sample. While only a minority of offenders had previous convictions for sexual crimes (14.6%), the majority of cases in this dataset (73.2%) can be classified as sexual homicides based on behaviors observed from the crime scene, according to the criteria proposed by Ressler et al. (1988). More specifically, most of the cases involved some degree of disrobement of the victim (66.2%), whereas overt sexual behaviors (41.8%) and injuries to victims' sexual areas (16.4%) were less commonly observed. A relatively large group of offenders in this sample engaged in some form of theft from the victim (44.1%). Similarly, a sizeable minority took precautions in relation to the homicide crime (40.8%).

Frequencies of offenders' previous convictions are displayed in Table 3. Most offenders (73.7%) had been convicted at least once prior to the index homicide, with theft (45.1%), violence (39.0%), burglary (35.2%), and criminal damage (33.3%) being the most frequent conviction categories. However, there is also a sizeable minority of offenders (26.3%) without any previous criminal history.

Exploring Male-on-Female Homicide Offenders' Behaviors and Conviction Histories

To explore whether any bivariate associations between single crime scene behaviors and specific pre-convictions could be found, chi-square analyses were conducted. No significant associations were found for several crime scene behavior variables as well as the pre-conviction variables *criminal record*, *drugs*, *public order*, *robbery* and *sexual crimes*, whereas *arson* and *homicide* were excluded from the analysis due to their extremely low frequency within this sample. A total of 16 statistically significant relationships ($p < .05$) were obtained, for which Table 4 shows Odds Ratios as a measure of effect size and direction.

Precautionary behaviors.

If an offender took *precautions relating to the crime scene*, he was nearly 3 times *less* likely (OR < 1, therefore 1/0.36 = 2.78) to have a previous conviction for *weapon-related crimes*, $\chi^2(1) = 4.213$, $p = .040$.

Sexual behaviors.

If *vaginal penetration* did occur during the homicide, the likelihoods of several pre-convictions were reduced significantly, with *theft*, $\chi^2(1) = 5.910$, $p = .015$, and *violence*, $\chi^2(1) = 4.626$, $p = .031$, being 2 times and *weapon-related crimes* nearly 2.5 times *less* likely, $\chi^2(1) = 4.039$, $p = .044$. Similarly, pre-convictions for *violent crimes* were 2.5 times *less* likely if the offender *moved the victim's clothing to expose* her, $\chi^2(1) = 4.054$, $p = .044$. Contrarily, a previous conviction for *fraud* was 2 times *more* likely if the victim was found *naked*, $\chi^2(1) = 3.885$, $p = .049$.

Weapon involvement.

If there was evidence that an offender *brought a weapon* to the crime scene, pre-convictions for *criminal damage*, $\chi^2(1) = 4.034$, $p = .045$, and *theft*, $\chi^2(1) = 4.996$, $p = .025$, were about 2.5 times *less* likely, whereas prior *violence-related* convictions were nearly 3.5 times *less* likely, $\chi^2(1) = 7.094$, $p = .008$. However, the use of a *bludgeoning weapon* increased offenders' likelihood of having a previous conviction for *fraud*, $\chi^2(1) = 5.102$, $p = .024$, making it more than 2 times as likely.

Method of killing.

Killing the victim through *blunt force* increased an offender's likelihood of having a previous *criminal damage* conviction, $\chi^2(1) = 4.393$, $p = .036$, making it nearly twice as likely. Associated in the opposite direction, *weapon-related* pre-convictions were almost 3.5 times *less* likely, $\chi^2(1) = 7.561$, $p = .006$, if death was caused through *asphyxia/strangulation*.

Other behaviors.

The use of a *vehicle* in association with the index homicide made a pre-conviction for *criminal damage* nearly 2.5 times *less* likely $\chi^2(1) = 5.932$, $p = .015$. If the offence comprised an element of *arson*, the likelihood of prior convictions for *violent crimes* ($p = .030$), and *burglary* ($p = .010$), were increased (due to the low frequency of arson as an offence element, Fisher's exact tests are reported). Similarly, a *burglary* pre-conviction was more than 2.5 times *more* likely if a *burglary element* was present in the index homicide, $\chi^2(1) = 8.213$, $p = .004$.

After applying Bonferroni-Holm corrections (dividing the uncorrected $\alpha = .05$ by the number dependent variables k = 11, $\alpha_{corr.} = .0045$), only the association of *burglary element* with *burglary* pre-conviction reached statistical significance. Therefore, results obtained so far should be interpreted with caution.

Logistic Regression Models

The significant bivariate associations identified in the first step of the analysis were then entered into binary logistic regression models to predict the presence or absence of a specific pre-conviction based on a *combination* of offence behaviors.

Burglary.

Using a logistic regression model, it was attempted to predict whether offenders did or did not have a previous conviction for *burglary* based on the presence or absence of a *burglary element* in the index homicide offence (see Table 5). While the variable *arson element* was also found to be associated with burglary pre-convictions in the previous step, it had to be excluded from the logistic regression analysis as it violated basic assumptions of the model (expected cell frequencies were less than 5 in more than 20% of cells if arson element was included). The remaining one-factorial model reached statistical significance, $\chi^2(1) = 7.925$, $p = .005$, with *burglary element* contributing significantly to the model

(p = .005), as indicated by the Wald criterion. The whole model explained between 3.7% (Cox and Snell R^2) and 5.0% (Nagelkerke R^2) of the variance in the dependent variable burglary pre-conviction, correctly classifying 66.2% of all cases.

Criminal Damage.

Two of the three previously identified crime scene behaviors, namely *vehicle used* and *death blunt force,* were entered into a logistic regression (see Table 5) to predict the presence or absence of a *criminal damage* pre-conviction (*weapon brought by offender* was excluded due to violations of model assumptions). The resulting model reached statistical significance, $\chi^2(2) = 10.801$, $p = .005$, with both *vehicle used* (p = .016) and *death blunt force* (p = .034) contributing significantly to the model. Overall, the model correctly classified 66.7% of all cases, explaining between 4.9% (Cox and Snell R^2) and 6.9% (Nagelkerke R^2) of the variance in the pre-conviction variable *criminal damage*.

Fraud.

The two significant crime scene behaviors of *victim naked* and *bludgeoning weapon* were entered into a logistic regression model (see Table 5) to predict whether offenders did or did not have a previous *fraud* conviction, with the resulting model being statistically significant, $\chi^2(2) = 8.450$, $p = .015$, and both *victim naked* (p = .050) and *bludgeoning weapon* (p = .026) contributing significantly to the model. The full model accounted for between 3.9% (Cox and Snell R^2) and 6.0% (Nagelkerke R^2) of the variance in *fraud* pre-conviction status, correctly classifying 78.9% of all cases.

Theft.

Chi-square analyses previously identified two crime scene behaviors to be significantly associated with *theft* pre-conviction status. A logistic regression model (see Table 5) including both variables (*vaginal penetration* and *weapon brought by offender)* reached statistical significance, $\chi^2(2) = 11.474$, $p = .003$, and both *vaginal penetration* ($p = .014$) and *weapon brought by offender* ($p = .025$) made significant contributions to the prediction. This model correctly classified 61.0% of the cases and explained between 5.2% (Cox and Snell R^2) and 7.0% (Nagelkerke R^2) of the variance in *theft* pre-conviction status.

Weapons.

The crime scene behaviors *precautions scene, vaginal penetration,* and *death asphyxia/strangulation* were identified as significantly related with *weapon-related pre-convictions*. Except for *vaginal penetration* (excluded due to violation of assumptions), all of these variables were entered into a logistic regression model (see Table 5) that reached statistical significance, $\chi^2(2) = 13.533$, $p = .001$, with both *precautions scene* ($p = .039$) and *death asphyxia/strangulation* ($p = .007$) contributing significantly to the model. In total, the model classified 81.7% of the cases correctly and accounted for between 6.2% (Cox and Snell R^2) and 10.0% (Nagelkerke R^2) of the variance in *weapons* pre-conviction status.

Violence.

Of the four crime scene behaviors previously identified to be associated with *violence-related pre-convictions*, only *vaginal penetration* and *weapon brought by offender* were included in a logistic regression model as depicted in Table 5 (*arson element* and *clothing moved to expose* were excluded due to violations of model assumptions). This model successfully predicted the pre-conviction variable *violence*, $\chi^2(2) = 12.795$, $p = .002$, and both *vaginal penetration* ($p = .028$) and *weapon brought by offender* ($p = .009$) contributed significantly to the model. Correctly classifying 61.0% of all cases, the model accounted for between 5.8% (Cox and Snell R^2) and 7.9% (Nagelkerke R^2) of the variance in *violence pre-conviction* status.

Prediction and performance of logistic regression models

Mirroring the original Davies et al. (1997) paper, Table 11 shows the logit values of all logistic regression models produced in the current study. These models predict the probability of whether an offender does or does not have a specific pre-conviction based on the presence or absence of a combination of crime scene behavior for each case in the sample using a model equation. To predict the probability of a *theft* pre-conviction in a case in which, for example, the offender engaged in *vaginal penetration,* but did not *bring a weapon* to the crime scene, the log-odds would equal:

$$.171\ (constant) - .768 * 1\ (vaginal\ penetration) - .949 * 0\ (weapon) = \ -.597.$$

The probability of a theft pre-conviction would then be:

$$\frac{e^{-.597}}{1 + e^{-.597}} \quad \text{or} \quad 35.5\%.$$

In terms of model performance, the percentage of cases correctly classified by the logistic regression models based on their probability estimations using crime scene information (criterion: > 50% vs. < 50%) is only slightly higher (*burglary, theft*) or equal (*criminal damage, fraud, weapons, violence*) to the performance of a simple "best guess" approach that uses only base-rate pre-conviction information of this sample (e.g. probability of an offender having a *fraud* pre-conviction irrespective of his crime scene behavior is 21.1%). As an additional measure of the models' discriminant performances, ROC AUC analyses were conducted. AUC values displayed in Table 6 are equivalent to the probability with which proposed logistic regression models will assign a randomly chosen case, in which the offender *did* have a certain pre-conviction, with a higher probability estimation than a randomly chosen case, in which the offender *did not* have this pre-conviction (Fawcett, 2006). AUC probabilities range from 58.4% (*burglary*) to 66.2% (*weapons*), suggesting overall poor to medium model performances (Rice & Harris, 2005)

Discussion

The purpose of this study was to explore whether male-on-female homicide offenders' criminal histories could be predicted from their crime scene actions. By using a contemporary set of investigative policing data and a large number of previous conviction variables, this study aimed at extending the available evidence-base for criminal history profiling in cases of hard-to-solve homicide. The present research successfully demonstrated that 1) single crime scene actions could be empirically linked to single previous conviction variables using a bivariate statistical approach and that 2) multivariate statistical models were able to predict the probability of a specific pre-conviction based on a combination of offence behaviors observed from the crime scene. This study, therefore, successfully replicated the methodological approach proposed by Davies et al. (1997) and later Almond et al. (2018) in a new criminal context, i.e. hard-to-solve male-on-female homicide cases. Theoretical and practical implications of the obtained results are proposed and discussed with regard to a number of methodological limitations.

First, results suggest that not all prior convictions may be similarly suited for prediction based on behavioral characteristics of a crime scene. While this study was successful in linking *some* pre-conviction variables to certain offence behaviors, it failed to find any empirical association for several other pre-convictions, namely *criminal record*, *drugs*, *public order*, *robbery,* and *sexual crimes.* The general finding that only some pre-convictions seem to be related to offence behaviors is mirrored in previous studies that have used a similar bivariate linking approach (e.g. Almond et al., 2018; Cole & Brown, 2014), which lends some support to the assumption that the link between offender characteristics and crime scene behaviors in general may be highly idiosyncratic. Accordingly, it has been argued that homology as the core tenet of offender profiling (i.e. two offenders who commit a certain type of crime in a similar way will show similar characteristics) may only be valid for *specific* offence behaviors and *single* offender characteristics (e.g. Taylor, Snook, Bennell, & Porter, 2015; ter Beek et al., 2010). This opposes the idea that broader offence behavior clusters (e.g. themes) could be empirically associated with a standard set of background characteristics (e.g. offender types), which indeed has proven difficult in prior research (Mokros & Alison, 2002; Trojan & Salfati, 2011). Therefore, it is argued here that further efforts are needed to isolate and understand *direct* links between key offence behaviors and individual background characteristics.

In the context of criminal history profiling, the few existing studies exploring these direct, bivariate relationships, however, differ in their findings on which pre-convictions *exactly* could and could not be linked to crime scene behaviors. While both this study and Almond et al. (2018), for example, did not find any association between offence variables and a history of sexual crime, Cole and Brown (2014) found prior sexual offences to be positively associated with the lack of precautionary behaviors at the scene and theft of clothing from the victim. More studies will be needed to establish, whether some (and if so, *which*) pre-convictions may generally be better suited for prediction from crime scene behaviors than others, and whether differences exist with regard to the type of crime (e.g. rape vs. homicide), or subsamples of offenders (e.g. male vs. female offenders, targeting female vs. male victims).

Among the key findings in the current study is the association of crimes containing a *burglary element* with a prior conviction for *burglary* (more than 2.5 times more likely). This finding is consistent with evidence for criminal specialisations among homicide offenders, which highlights a large sub-group displaying histories of predominantly instrumental crimes, such as *theft, burglary*, or *robbery* (Trojan & Salfati, 2016). As most homicides in the current study contained overt, or covert sexual behaviors (73.2%), it is interesting to note that for cases of stranger rape, the crime scene behavior *forced entry* has been identified as a significant predictor of prior convictions for acquisitive crime types (i.e. *burglary, theft, robbery*) in multiple studies (Almond et al., 2018; Davies et al., 1997; Scott et al., 2006). Previous research has further highlighted a link between sexual homicide and a history of burglary (e.g. Schlesinger & Revitch, 1999), with some authors suggesting that repeat burglary offenders may escalate from non-contact burglaries towards burglaries featuring more serious, interpersonal offence elements depending on a number of circumstantial factors (Pedneault, Harris, & Knight, 2015). Taken together, *burglary elements* within homicides and serious sexual crimes appear as key indicators of previous *burglary* crimes in the literature, even though a generalisation of this finding towards other types of acquisitive crimes (e.g. *theft, robbery*) could not be supported in the current study.

Interestingly, sexual behaviors were predominantly negatively associated with prior conviction variables in this sample. If *vaginal penetration* was observed, the likelihoods of prior *theft, weapons,* and *violence* pre-convictions were reduced, whereas *clothing moved* further decreased the likelihood of prior *violence* convictions. An exemption was found in prior *fraud* convictions being two times *more* likely if the *victim was found naked*. These findings have not yet been recorded, given that prior bivariate criminal history profiling studies either did not examine specific sexual behaviors (Almond et al., 2018), or did not find any relationships between sexual behaviors and prior convictions (Cole & Brown, 2014). Similarly, behaviors indicating some degree of premeditation were also negatively associated with pre-conviction variables in the current sample, with *weapon brought* decreasing the likelihood of prior *theft, violence,* and *criminal damage* convictions and *weapon*-related pre-convictions being less likely if *precautions concerning the crime scene* were observed. While it may be tempting to derive *theoretical* implications from the present findings, it should be borne in mind that this study was very much exploratory and was neither conceptualised to explicitly test nor retrospectively allow for inferences on underlying psychological constructs that may explain the cause for the identified associations. This is generally the case in studies employing a direct, bivariate profiling approach (Crabbé et al., 2008). However, the present study's success in finding some offence behaviors predictive of homicide offenders' pre-convictions has important *practical* implications.

In unsolved cases of homicide, the availability of an empirical basis that allows to estimate the probability of an offender having a certain pre-conviction based on his behaviors at the crime scene would undoubtedly be beneficial to the investigation. Using the predictive models identified in this study, such probabilities could be calculated at the beginning of an investigation. Outcomes may assist in prioritising potential nominals according to the degree of similarity between theirs and the most likely criminal history of the offender, as predicted by the models. Similarly, the statistical models proposed here may suggest new lines of enquiry if, for example, not all predictive behaviors included in the models have yet been confirmed as present or absent in a given investigation. Overall, this study may not only contribute to improving detection rates of homicide offences, it may also increase the efficiency with which police resources are allocated in homicide investigations, thereby reducing the time and financial efforts associated with apprehending offenders (Alison et al., 2010; Rainbow & Gregory, 2009). Most importantly, the present findings are therefore directly relevant to the work of BIAs by providing an evidence base on which they are required to base their investigative claims and inferences on (Alison et al., 2003; Almond et al., 2007). The practical utility of the results obtained herein is, however, qualified by a variety of limitations.

Limitations

First, some statistical issues should be noted regarding the results in this study. To identify, which crime scene behaviors were significantly related to which offender pre-convictions, this study utilised multiple chi-squared tests, but only *one* of the identified relationships (*burglary element* with prior *burglary* conviction) remained significant after applying Bonferroni-Holm corrections. As the probability of obtaining false positive results is inflated when large numbers of tests are performed on the same sample (Asendorpf et al., 2013), it may, therefore, be that this study has identified some variables as linked, when in fact, they are not. Furthermore, while the sample in this study can be considered large (N = 213) regarding the context of hard-to-solve homicide, the sample size was relatively small in comparison to other studies that rely on logistic regression models (Cramer, 1999), resulting in the parameter estimations of the present models being less stable and potentially susceptible to biases (Field, 2013; Nemes, Jonasson, Genell, & Steineck, 2009).

Second, measures of predictive accuracy indicated that the complex logistic regression models utilised in this study had an overall poor to medium performance, making them only slightly better than a guess based solely on pre-conviction frequencies in this sample. While this highlights the value of simple base rate information for offender profiling efforts, the models provided herein may still be useful in rare cases, in which crime scene behaviors indicate a divergence from the base rate norm (e.g. probability of *theft* pre-conviction > 50% if no *vaginal penetration* and no *weapon brought* vs. 45% base rate).

On a more conceptual level, this study was based on solved homicide cases only, therefore, excluding those offenders who may be most proficient in avoiding detection. It has been argued that measures other than prior convictions, such as previous charges or arrests, may be more indicative of an offender's criminal history (Almond et al., 2018). Therefore, generalisations from the current findings should be treated with some degree of caution.

Caution is further advisable, as the data used herein was not explicitly collected for research purposes, but ultimately stemmed from police records. Although the data is subject to a rigorous quality control progress before being entered into the SCAS database, the completeness of the data cannot be guaranteed, especially regarding the level of detail requested for some of the offence behavior variables. Although all behaviors that were evident would have been coded, due to the fact that the victim is not able to report on the offender's behavior in a homicide, there is the potential that not all behaviors that occurred in the offence were coded. As this piece of applied research was conceptualised as a practical instrument for police investigations, reliance on policing data may arguably increase the ecological validity of this study (Mokros & Alison, 2002).

There is also a potential bias in the results towards those who do not have a substantial previous criminal history. As behaviors such as sexual behaviors and weapon brought to the scene are more likely to be recorded due to forensic evidence i.e. semen or weapon left at the scence may be biased towards those that are less criminally competent which may then be reflected in their criminal history. There may be plenty of other cases with similar behaviors that occurred in the offence but are not evident – and this may be a reflection of the perpetrator's criminal competence/sophistication/history.

Finally, the proposed statistical models were constructed to optimise their predictive accuracy in the current sample, which may contain random errors and other idiosyncrasies, especially with regard to the small sample size (Levine, Blair, & Carpenter, 2017). It is therefore important to validate the findings on a separate sample, in order to determine accuracy shrinkage and predictive performance for new cases, that were not used to construct the models (Cole & Brown, 2014; ter Beek et al., 2010). As the present sample is exhaustive and contains all homicide cases that matched the inclusion criteria in the UK, further research would have to either rely on data from other countries or future cases from within the UK, raising questions of regional or temporal comparability between the samples.

Conclusion

In conclusion, this study has provided a broad empirical overview on links between a large set of offender criminal history variables and crime scene behaviors in cases of homicide. By proposing statistical models that allow for predictions of the most likely criminal history of an offender as indicated by his specific offence behaviors, the current results may be of practical utility to homicide investigations. However, as several statistical and conceptual limitations of this study must be considered, it is argued here that the current results should only be used for practical applications with appropriate caution and transparency towards the study's shortcomings. In the UK, this transparency is ensured by experienced BIAs through providing observational grounds, warrants, research backing, rebuttal(s), and an indication of strength for each advisory investigative claim made, following the principles of Toulmin's philosophy of argument (Alison et al., 2003; Rainbow, 2008). In this way, BIA advice can be useful to inform and justify subsequent decisions made by investigators. This approach enables a synergy of evidence-based research, such as the present one, and investigators' practical experience, which is ultimately directed at maximising efficiency and success in criminal investigations.

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Table 1

Frequency of relationship categories between offenders and their victims.

Offender-victim relationship	n	(%)
Stranger	71	(33.3)
Friend/associate	37	(17.4)
Romantic partner	35	(16.4)
Prostitute	25	(11.7)
Unknown	21	(9.9)
Peripheral contact	11	(5.2)
Romantic ex-partner	9	(4.2)
Family	4	(1.9)

Table 2. *Frequencies of offenders' crime scene behaviors during the index homicide.*

Offence Behavior Variables	n	(%)
Precautionary behaviors		
Any precautions taken [a]	*87*	*(40.8)*
Precautions scene	55	(25.8)
Precautions victim	28	(13.1)
Precautions offender	16	(7.5)
Sexual behaviors		
Any overt sexual behaviors [a]	*89*	*(41.8)*
Vaginal penetration	67	(31.5)
Anal penetration	30	(14.1)
Oral penetration	8	(3.8)
Other sexual activity	24	(11.3)
Offence Behavior Variables	n	(%)
Any disrobement [a]	*141*	*(66.2)*
Victim naked	56	(26.3)
Victim partially disrobed	52	(24.4)
Clothing moved to expose	34	(16.0)
Injury to sexual areas	35	(16.4)
Sexual homicide [a, b]	*156*	*(73.2)*
Body disposal		
Body recovered indoors	113	(53.1)
Body concealed	53	(24.9)
Body dismembered	18	(8.5)
Weapon involvement		
Any weapon involved [a]	*142*	*(66.7)*
Stabbing weapon	73	(34.3)
Bludgeoning weapon	45	(21.1)
Ligature weapon	44	(20.7)
Weapon taken from scene	56	(26.3)
Weapon brought by offender	33	(15.5)
Theft		
Any theft [a]	*94*	*(44.1)*
Theft valuables	77	(36.2)
Theft personal	34	(16.0)
Theft clothing	28	(13.1)
Method of killing		
Death blunt force	81	(38.0)
Death asphyxia/strang.	73	(34.3)
Death sharp force	49	(23.0)
Other behaviors		
Vehicle used	55	(25.8)
Overkill	47	(22.1)
Burglary element	45	(21.1)
Arson element	9	(4.2)

Notes. [a] Variables printed in italics are collapsed behavior categories for descriptive purposes and were not included in the statistical analysis. [b] Cases were classified by the author as sexual homicides according to the criteria proposed by Ressler et al. (1988).

Table 3. *Frequencies of offenders' previous convictions at the time of the index homicide.*

Conviction Variables	n	(%)
Criminal record	157	(73.7)
Theft	96	(45.1)
Violence	83	(39.0)
Burglary	75	(35.2)
Criminal damage	71	(33.3)
Public order	48	(22.5)
Fraud	45	(21.1)
Weapons	39	(18.3)
Sexual	31	(14.6)
Robbery	26	(12.2)
Drugs	25	(11.7)
Arson	10	(4.7)
Homicide	8	(3.8)

Table 4

Odds Ratios for significant associations between crime scene behavior and conviction variables.

	Burglary	Criminal Damage	Fraud	Theft	Weapons	Violence
Precautions scene					0.36	
Vaginal penetration				0.48	0.42	0.51
Victim naked			2.01			
Clothing moved to expose						0.43
Weapon brought by offender		0.39		0.40		0.30
Bludgeoning weapon			2.30			
Death blunt force		1.86				
Death asphyxia/strang.					0.29	
Vehicle used		0.41				
Burglary element	2.62					
Arson element	7.00					5.89

Notes. Only Odds Ratios for bivariate associations that reached statistical significance ($p < .05$) are shown.

Table 5

Crime scene behaviors differentiating offenders with and without a pre-convictions.

	Burglary Pre-conviction		
	Yes (*n* = 75)	No (*n* = 138)	Sig**.**
Burglary element	32.0%	15.2%	*.005*
	Criminal Damage Pre-conviction		
	Yes (n=71)	No (n=142	
Vehicle used	15.5%	31.0%	*.016*
Death blunt force	47.9%	33.1%	*.034*
	Fraud Pre-conviction		
	Yes (n=45)	No (n=168)	
Victim naked	37.8%	23.2%	*.050*
Bludgeoning weapon	33.3%	17.9%	*.026*
	Theft Pre-conviction		
	Yes (n=96)	No (n=117)	
Vaginal penetration	22.9%	38.5%	*.014*
Weapon brought by offender	9.4%	20.5%	*.025*
	Weapons Pre-conviction		
	Yes (n=39)	No (n=174)	
Precautions scene	12.8%	28.7%	*.039*
Death asphyxia/strang.	15.4%	38.5%	*.007*
	Violence Pre-conviction		
	Yes (n=83)	No (n=130)	
Vaginal penetration	22.9%	36.9%	*.028*
Weapon brought by offender	7.2%	20.8%	*.009*

Table 6

Logit values, AUCs, and percentage improvements in correctly predicted cases compared to a base rate "best guess" for logistic regression models.

	Burglary	Criminal Damage	Fraud	Theft	Weapons	Violence
Model constant	*-.830*	*-.744*	*-1.744*	*.171*	*-.954*	*-.076*
Precautions scene					-1.061	
Vaginal penetration				-.768		-.710
Victim naked			.712			
Weapon brought by offender				-.949		-1.246
Bludgeoning weapon			.847			
Death blunt force		.640				
Death asphyxia/strang.					-1.274	
Vehicle used		-.915				
Burglary element	.964					
AUC	.584	.623	.626	.624	.662	.622
[95% CI]	*[.502, .666]*	*[.545, .701]*	*[.532, .721]*	*[.549, .699]*	*[.576, .748]*	*[.547, .697]*
Difference to "best guess" in % correct	+1.4%	–*	–*	+6.1 %	–*	–*

Note. * No difference between % pre-convictions predicted correctly using logistic regression model and % correct using only base-rate information from the sample.