Linking Different Types of Crime using Geographical and Temporal Proximity

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Abstract

In the absence of forensic evidence (such as DNA or fingerprints), offender behavior can be used to identify crimes that have been committed by the same person (referred to as behavioral case linkage). The current study presents the first empirical test of whether it is possible to link different types of crime using simple aspects of offender behavior. The discrimination accuracy of the kilometer-distance between offense locations (the intercrime distance) and the number of days between offenses (temporal proximity) was examined across a range of crimes, including violent, sexual and property-related offenses. Both the intercrime distance and temporal proximity were able to achieve statistically significant levels of discrimination accuracy that were comparable across and within crime types and categories. The theoretical and practical implications of these findings are discussed and recommendations made for future research.

Keywords: serial crime, comparative case analysis, offender behavior, linkage analysis, behavioral case linkage

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One of the most compelling and well-supported findings in criminology is that the majority of crime is committed by a minority of offenders (e.g. Kershaw, Nicholas, & Walker, 2008; Laub, 2004; Piquero, Farrington, & Blumstein, 2007). In the United States (US), for example, estimates suggest that approximately 5% of offenders are responsible for 30% of felony convictions (Office of the Legislative Auditor, 2001). Findings such as these suggest that an effective way for the police to tackle and reduce crime is to target serial and repeat offenders who are responsible for a disproportionate amount of crime.

Targeting serial offenders specifically, however, requires the police to identify serial offenses (referred to hereafter as *linked crime series*), which are essentially two or more crimes committed by the same offender or the same group of offenders (Woodhams, Hollin, & Bull, 2007). The most reliable way of identifying linked crime series is through the recovery of forensic evidence, such as DNA or fingerprints, left at the scenes of several different crimes (Grubin, Kelly, & Brunsdon, 2001). However, despite the impression that television programs such as CSI create, the availability of forensic evidence is surprisingly limited, with less than 1% of recorded crimes yielding such evidence (House of Commons, 2005). Therefore, the police often need to rely on other approaches to linking crime. One potential alternative is to use behavioral similarity, whereby crimes that show evidence of similar offender behavior are judged to have been committed by the same offender/s (referred to as *linked* crimes), whereas those that involve different behavior are said to have been committed by different offenders

(referred to as *unlinked* crimes). This procedure is known by several names, including linkage analysis and comparative case analysis, but the term behavioral case linkage will be used in the current paper.

Behavioral Case Linkage

Behavioral case linkage is an investigative procedure that has received growing attention both practically and academically over the last 30 years (e.g. Bennell & Canter, 2002; Grubin et al., 2001; Labuschagne, 2006). This interest is unsurprising given the potential investigative benefits of successfully linking crimes. Most importantly, linkage allows the collation and pooling of information from various crime scenes, which potentially increases the quantity and quality of evidence against an offender and, therefore, the likelihood of a successful prosecution (Grubin et al., 2001). For a full review of the benefits associated with behavioral case linkage see Woodhams et al. (2007).

The success of behavioral case linkage in a practical context rests on offenders behaving in a consistent and distinctive manner throughout their crimes (Bennell, 2002; Woodhams et al., 2007). That is, if behavioral case linkage is to work in a valid and reliable way, then offenders must demonstrate some degree of similarity from one crime to the next in the way they behave during their crimes (consistency) and their behavior must also be different from that of other offenders (distinctive). These assumptions of offender behavioral consistency and behavioral distinctiveness are the theory that underpins the practice of behavioral case linkage.

There is a growing body of empirical evidence to support the theoretical assumptions of behavioral case linkage (e.g. Bennell & Canter, 2002; Santtila, Junkkila,

& Sandnabba, 2005; Santtila, Pakkanen, Zappalá, Bosco, Valkama, & Mokros, 2008). These studies have investigated the consistency and distinctiveness of a variety of offender behaviors, including (but not limited to) the method of entry, the type of property stolen and the type of property targeted (in studies of auto theft, burglary and robbery) and the degree of planning, control, sexual behavior and violence (in studies of robbery, rape/sexual assault and homicide).

However, two behaviors in particular (spatial and temporal behavior) have demonstrated significant consistency and distinctiveness that often exceeds the level observed in other types of offender behavior (e.g. Ewart, Oatley, & Burn, 2005; Goodwill & Alison, 2006; Markson, Woodhams, & Bond, 2010; Tonkin, Santtila, & Bull, 2011). In these studies, spatial behavior has been operationalized as the kilometer-distance between offense locations (termed the intercrime distance) and temporal behavior as the number of days separating offenses (termed temporal proximity). These two measures of offender behavior essentially indicate how dispersed an individual's offenses are in terms of space and time.

This research has shown that linked crimes tend to be characterized by shorter intercrime distance and temporal proximity values than unlinked crimes. That is, crimes committed by the same person are less geographically and temporally dispersed than crimes committed by different offenders. For example, Markson et al. (2010) found that linked burglary crimes were, on average, separated by 1.08KM and 22 days, compared to unlinked crimes that were separated by an average of 16.25KM and 226.50 days. These differences also translated into statistically significant levels of discrimination accuracy

when tested using logistic regression and Receiver Operating Characteristic (ROC) analysis.

Findings such as these have enabled tentative recommendations to be made that can guide the linking of crimes in practice by police crime analysts. For example, Markson et al. (2010) have suggested that when the geographical distance between burglary crimes is less than 2.994KM and/or the number of days separating offenses is less than 71, these crimes might be considered as potentially committed by the same person. If, however, the crimes are separated by a greater number of kilometers and days, then they should be considered as potentially the work of separate offenders. These decision thresholds were identified using Youden's Index and the overall model containing these two measures of behavior yielded an AUC value of 0.95 with a sample that contained an equal proportion of linked and unlinked crime pairs. This is considered to be a high level of discriminative accuracy according to published standards (Swets, 1988). It is important to note, though, that recommendations such as these are specific to the particular geographical location studied and are not universally applicable to all geographical locations. Also, these findings are presented by researchers for illustration purposes only; it is strongly emphasized that they should not be adopted in practice until significant replication has occurred under conditions of greater ecological validity. Nonetheless, findings such as these indicate the potential contribution that research on case linkage can make to the investigation of crime and the work of police crime analysts.

However, not all of the behaviors tested in case linkage research have demonstrated consistency and distinctiveness. For example, the type of property targeted, the method of entering the property, and the items stolen during burglary and auto theft

crimes have demonstrated mixed evidence for consistency and distinctiveness (e.g. Bennell & Canter, 2002; Markson et al., 2010; Tonkin, Grant, & Bond, 2008). Thus, it is clear from these findings that, although some behaviors may display consistency and distinctiveness, this should not be expected for all types of offender behavior (Bateman & Salfati, 2007; Bennell & Canter, 2002). This is an important finding from a practical perspective because it indicates that police crime analysts who are engaged in conducting behavioral case linkage should only focus on certain types of offender behavior, whilst ignoring those that do not demonstrate consistency and distinctiveness. This further illustrates the contribution that research in this area can make to the criminal justice system, as research can highlight those offender behaviors that facilitate the most accurate and reliable linking of crimes. This can provide the police with an evidence-based approach to linking crimes that maximizes accuracy whilst minimizing the time and effort associated with behavioral case linkage (by cutting down the number of behavioral features analysts use to link crime).

The tentative evidence for consistency and distinctiveness in spatial behavior is explicable to some extent given the wealth of research on criminal spatial behavior and environmental criminology, which has shown that offenders tend to commit their offenses over relatively restricted geographical areas (e.g. Lundrigan & Canter, 2001), they prefer short rather than long journeys to crime (e.g. Canter & Hammond, 2006; Santtila, Laukkanen, & Zappalá, 2007; Sarangi & Youngs, 2006), and they tend to offend in areas that are familiar to them (e.g. Alston, 1994; Bernasco, 2010; Bernasco & Kooistra, 2010; Clarke & Felson, 1993; Felson, 1986, 1994). Thus, consistency in spatial behavior (i.e. short intercrime distances) emerges because many offenders return to

similar geographical regions from one crime to the next. Behavioral distinctiveness emerges because offenders tend to offend in areas that are familiar to them through their routine activities (e.g. they live or work in the area), and — given the wide range of potential variation in routine activities and awareness space — these areas tend not to overlap considerably with the awareness space of other offenders (e.g. Alston, 1994; Bernasco, 2010).

In terms of consistency in temporal behavior, research describes a subset of offenders for whom "financial need is effectively a constant" (Jacobs, Topalli, & Wright, 2003, p. 677) due to their excessive drinking and drug-taking and their preference for expensive items such as cars and clothing (Wright & Decker, 1994). For these individuals the only realistic option to maintain such an extravagant lifestyle is crime (Jacobs & Wright, 1999). Consequently, the motivation to offend is an almost constant presence amongst these individuals, which leads to a high frequency of offending and, therefore, short temporal proximity values. Furthermore, social status is vitally important amongst these offenders and many are willing to engage in violent behavior to maintain that status; particularly when they perceive it to be under threat (Jacobs et al., 2003). This motivation, when combined with the high level of intoxication these offenders often experience, means that they also engage in frequent violent offending as well as frequent property-related offending. Consistency in temporal behavior (i.e. short temporal proximity values), therefore, emerges to the extent that offenders are influenced by similar situational, affective and cognitive motivations to commit crime from one moment to the next. Indeed, given the relatively short time periods over which case

linkage research has sampled data (which do not often exceed five years), it is not unrealistic to expect some consistency in the factors that motivate offending.

Behavioral distinctiveness on the other hand emerges because offenders differ in the situational, affective and cognitive factors that motivate their offending, which subsequently leads to different temporal patterns of behavior. Indeed, there is evidence from the criminal career literature to support the notion that offenders differ in their temporal behavior. This literature has identified two distinct offending trajectories that differentiate between offenders in terms of the frequency and duration of their offending (e.g. Nagin, Farrington, & Moffitt, 1995; Piquero et al., 2007; Piquero, Sullivan, & Farrington, 2010). The very-low-rate chronics (also referred to as long-term, low-rate (LTLR) offenders) engage in a protracted period of offending that often spans many years where the offender offends at a relatively constant but low frequency level. Conversely, the high-adolescence-peaked offenders (also referred to as short-term, high rate (STHR) offenders) engage in a relatively short period of offending that is characterized by a markedly higher frequency of offending. As discussed by Piquero et al. (2007), these two distinct types of trajectory should be viewed as "clusters of similar individual trajectories" (p. 143), rather than as one fixed specific pattern. Thus, the literature has identified two basic types of offender who differ fundamentally in terms of their temporal behavior, but within these basic types there is further individual variation between offenders. Findings such as these are clear evidence that distinctiveness exists to some extent in temporal behavior and that the temporal proximity of crimes will vary from one offender to the next.

The Current Study

Although the behavioral case linkage literature has begun to provide tentative evidence to suggest that an offender's behavior might be used to identify linked crime series, this research can be criticized because the samples studied have been homogenous in terms of crime type (i.e. they have only contained one type of crime, e.g. only burglary). Consequently, it is not known whether offender behavior can be used to link crimes that are of different types (e.g. linking a burglary crime with a sexual crime). This issue is important because the majority of offenders (particularly those who commit the most crime and are, therefore, of the most interest to the police) tend to commit a variety of different types of crime rather than specializing in individual types (Farrington, Snyder, & Finnegan, 1988; Piquero et al., 2007). For example, Peterson and Braiker (as cited in Blumstein, Cohen, Roth, & Visher, 1986) found that 49% of the 624 prison inmates they sampled reported engaging in four or more different types of offence during the three-year period preceding their incarceration, and just 18% reported engaging in only one offence type during this period. It, therefore, seems that there is a need to develop reliable procedures for linking cross-crime series.

The current study, therefore, presents the first empirical test of whether it is possible to use the intercrime distance and temporal proximity to distinguish between linked and unlinked crimes that are from different offence types and categories. These two measures of offender behavior were chosen because they have received the most consistent empirical support within the case linkage literature. Furthermore, they are somewhat unique in terms of their applicability to a wide range of crimes. Other behaviors that have been examined in studies of behavioral case linkage, such as target

selection, property stolen and sexual behavior, are not applicable to all types of crime, which makes it relatively more difficult to utilize these behaviors in a study of cross-crime linkage. This is not to say, however, that a method might not be developed in the future to facilitate cross-crime linkage using these types of behavior; the issue is simply that it was logical to begin with those offender behaviors that are most supported by the evidence and that would be most easily applied in practice by police crime analysts.

Cross-crime linkage was examined at several levels, based on how UK police forces record crime (following definitions of crime that are set by the Home Office). Within the UK, there is a distinction between crime *types* (which refer to specific individual crimes, such as residential burglary) and crime *categories* (which refer to broader groups of crimes that contain several individual types; for example, the crime category 'robbery', which contains two specific types of robbery- personal and commercial[1]). Consequently, cross-crime linkage can be defined in terms of either crime *types* or crime *categories*. In terms of *types*, cross-crime linkage is defined as any situation in which two crimes of different specific types are linked (e.g. an attempt is made to link a personal robbery with a commercial robbery). Alternatively, cross-crime linkage in terms of *categories* is defined as any situation where two crimes from different Home Office categories are linked (e.g. a residential burglary is linked with a rape).

In the current study, cross-crime discrimination accuracy was examined at both the *type* and *category* level, and this performance was compared to discrimination

[1] The government department responsible for setting crime definitions in England and Wales (the Home Office) record 156 individual crime types, which are split into nine crime categories: violent offenses (containing 38 individual crime types), sexual offenses (containing 31 crime types), burglary offenses (containing seven crime types), drug offenses (containing four types), robbery (containing two types), theft/handling offenses (containing 16 types), fraud/forgery offenses (containing 16 types), criminal damage offenses (containing 11 types), and other offenses (containing 31 types).

accuracy within crime types (i.e. the 'traditional' way in which case linkage has been investigated). That is, when two crimes of the same specific type are linked using offender behavior (e.g. two residential burglary crimes are linked). These comparisons would demonstrate whether cross-crime discrimination accuracy could achieve a comparable level of accuracy to that observed in previous studies of within-crime linkage (Bennell & Canter, 2002; Bennell & Jones, 2005; Markson et al., 2010; Tonkin et al., 2008; Tonkin et al., 2011; Woodhams & Toye, 2007).

Method

The Sample

To facilitate the current study, all offenders who had committed two or more types of violent, sexual, burglary, robbery, theft/handling offenses, and criminal damage offenses between 01/01/2009 and 31/12/2009 were extracted from the force systems of a UK police force (with an area of 2,364KM^2). This one-year time period is consistent with that used in previous research on behavioral case linkage (Bennell & Canter, 2002).

Each crime included in the current sample was classed as 'detected' on the force systems, which typically means that the individual has confessed to the offense or that there is sufficient evidence from witnesses or forensics to incriminate (e.g. DNA or fingerprint evidence). However, it is worth noting that, although a crime may be classed as 'detected' by the police, this does not necessarily mean that a prosecution will result. Therefore, the burden of proof to satisfy the police to close the investigation might be seen as lower than that required in a court of law.

The crime categories used in the current study represent six out of the nine crime categories recognized by the UK Home Office. Crimes included under the categories of 'drugs offenses', 'fraud/forgery offenses' and 'other offenses' were excluded from this study because the crimes within these categories typically do not have definite offense locations and times, which makes it difficult to calculate meaningful intercrime distance and temporal proximity values. Furthermore, a small number of crime types were removed for similar reasons from the six crime categories studied here. The crime types that were included in this study are listed in Appendix A. This resulted in a sample of 1951 crimes committed by 537 offenders. A sub-section of these data was extracted for analysis (as described below).

Design and Procedure

A methodology was developed to investigate cross-crime linkage based on the predominant approach to researching behavioral case linkage that was originally proposed by Bennell (2002). Six groups of crime pairs were created, each containing a set of pairs with two crimes per pair (see Table 1). Each linked crime pair contained two offenses that had been randomly selected from the crimes committed by that offender during 2009. Consequently, the crimes in each linked pair were not necessarily contiguous in an offender's series (e.g. crime three in an offender's series paired with crime four in their series). One hundred crime pairs were randomly selected for each subset from the total pool of possible pairs (i.e. a total of 600 crime pairs were randomly selected across all six subsets). An equal number of pairs per subset was necessary to avoid violating the assumptions of some inferential statistical tests used in the subsequent analyses (Woodhams, 2008). An intercrime distance value (in kilometers) and a temporal

proximity value (in days) were then calculated for each crime pair. The intercrime distance values were calculated to the nearest meter using Pythagoras' theorem to calculate the distance between the *x, y* coordinates for each crime in the crime pair (Woodhams, 2008) and temporal proximity values were calculated as the number of days between the dates the crimes were recorded by the police. These figures were then compared statistically in order to address the key questions of this paper.

The rationale was that, by comparing the linked subsets with their unlinked counterparts (e.g. the Linked Cross-Category subset with the Unlinked Cross-Category subset), it would be possible to determine if linked and unlinked crimes can be discriminated from each other in an absolute sense across and within crimes. That is, is there the potential for discrimination accuracy to exceed chance across crime categories, across crime types, and within crime types?

Furthermore, by comparing the three linked crime subsets (Linked Cross-Category; Linked Cross-Type; and Linked Within-Type) it would be possible to determine the relative level of discrimination accuracy across and within crimes. That is, is it likely that discrimination accuracy will be greater across categories, across types, or within types?

[INSERT TABLE 1 HERE]

Data Analysis

In line with previous research into behavioral case linkage (e.g. Markson et al., 2010; Tonkin et al., 2008; Woodhams & Toye, 2007), the data analyses consisted of three

separate stages. Initially, the six crime pair subsets were compared statistically to determine whether they differed in terms of the intercrime distance and temporal proximity. These omnibus comparisons were followed by individual post-hoc comparisons to determine exactly where significant differences existed between the six crime pair subsets. These comparisons were conducted using the whole dataset (i.e. all 600 crime pairs).

Next, each subset was split into two halves to create development and test samples (e.g. 50 crime pairs from the Linked Cross-Category subset formed a development sample and the remaining 50 formed a test sample; 50 crime pairs from the Unlinked Cross-Category subset formed a development sample and the remaining 50 formed a test sample; and so on for all six subsets). This procedure allowed for the findings to be developed and tested on different samples (cross-validation), thereby increasing the wider applicability of these findings to future crimes committed in this jurisdiction (e.g. Bennell, 2002; Bennell & Canter, 2002). This is particularly important given that good model fit does not necessarily mean good predictive accuracy (Goldstein & Gigerenzer, 2009).

Using the development samples, six direct logistic regression analyses and three forward stepwise regression analyses were conducted to examine the independent and combined ability of the intercrime distance and temporal proximity to discriminate between linked and unlinked crime pairs (Bennell & Canter, 2002). Discrimination accuracy was examined at the cross-category, cross-type, and within-type levels and the variation in model performance across these different levels was examined visually.

Finally, the logistic regression models were used to produce predicted probabilities for each of the crime pairs in the test samples that indicated the predicted likelihood of them being linked (using the method described by Bennell & Canter, 2002). These predicted probabilities were then used to conduct Receiver Operating Characteristic (ROC) analysis that indicated how successfully the two linkage features were able to discriminate between linked and unlinked crimes that were across crime categories, across types and within types. To do this, ROC analysis provided a single measure of discrimination performance (the Area Under the Curve, AUC), which could range from 0 (indicating perfect inaccuracy in the discrimination task) to 1 (indicating perfect accuracy), with a value of 0.50 indicating a chance level of accuracy (Bennell & Jones, 2005). Typically, AUC values of 0.50-0.70 are considered low, values of 0.70-0.90 are moderate, and values of 0.90-1.00 are high (Swets, 1988). The AUC values for discrimination across categories, across types and within types were compared statistically using ROCKIT 1.1B2 (© University of Chicago).

Researchers of case linkage have discussed the need to estimate practical decision thresholds that might be used to guide the linking of crimes in practice (e.g. Bennell & Jones, 2005). These thresholds are designed to identify the particular point on a continuous measure of offender behavior that maximizes the number of correct linkage decisions, whilst minimizing the number of incorrect decisions (Bennell, 2002). Consistent with previous research, Youden's Index was used to identify these decision thresholds (see Bennell & Jones, 2005). A separate threshold was identified for the intercrime distance and temporal proximity at each level of analysis (cross-category, cross-type, within-type), thereby yielding a total of six decision thresholds.

Non-parametric statistics were appropriate throughout the analyses due to the distributions of intercrime distance and temporal proximity values departing significantly from normal ($p < .05$), as indicated by Kolmogorov-Smirnov tests.

Results

Statistical Comparisons

Two Friedman's ANOVA tests indicated significant differences across the six crime pair subsets in terms of intercrime distance, $\chi^2 (5) = 239.39$, $n = 100$, $p < .001$, and temporal proximity, $\chi^2 (5) = 70.32$, $n = 100$, $p < .001$. The results of post-hoc comparisons (Bonferroni corrected $\alpha = 0.008$) and effect size calculations are presented in Table 2. From this Table we can see that all three linked subsets contained shorter intercrime distance and temporal proximity values than their unlinked counterparts ($p < .001$ with medium to large effect sizes; Cohen, 1988). However, when the three linked subsets were compared there was only one statistically significant difference, with shorter temporal proximity values in the Linked Within-Type subset than the Linked Cross-Category subset ($p = .002$ with a small effect size; Cohen, 1988).

These findings suggest that discrimination accuracy using the intercrime distance and temporal proximity may function at a statistically significant level both within crime types and across crime types and categories. Furthermore, one might expect the level of discriminative accuracy to be somewhat comparable at the within type, across type and across category levels.

[INSERT TABLE 2 HERE]

Logistic Regression Analyses

The results of six direct logistic regression analyses are presented in Tables 3 and 4. All models achieved a statistically significant level of discrimination accuracy ($p < .05$), which indicates that discriminative accuracy using the intercrime distance and temporal proximity has the potential to function successfully across crime categories, across crime types and within crime types. Furthermore, there were not substantial differences in terms of model performance across the three different levels, which suggests that accuracy is comparable across and within crimes. But, it is clear that discrimination accuracy was greater when using the intercrime distance compared to the temporal proximity, regardless of whether the crimes were within or across categories/types.

The stepwise analyses that are reported in Tables 3 and 4 indicate that the combination of distance and time was not able to facilitate a substantial improvement in discrimination accuracy. Indeed, the intercrime distance was the only linkage feature included in the stepwise models for linkage across types and within types, with the addition of temporal proximity unable to statistically improve model performance. Furthermore, in the model for linkage across crime categories the addition of temporal proximity was only able to improve discrimination accuracy by 2% above the level obtained for distance on its own (see Table 4), which- although statistically significant- is not of significant practical value. It can, therefore, be concluded that the intercrime

distance should be used on its own (without the temporal proximity) to link across and within crime categories and crime types.

[INSERT TABLES 3 AND 4 HERE]

ROC Analyses

To further clarify discrimination accuracy across and within crimes, seven ROC curves were produced (see Table 5). ROC curves were not constructed for the Combined Across Crime Type and the Combined Within Crime Type models because the stepwise analyses only included the intercrime distance in the final combined models, so the AUC values would be identical to the single-feature ROCs for the intercrime distance.

[INSERT TABLE 5 HERE]

All of the AUC values were highly significant ($p < .01$), which suggests that both the intercrime distance and temporal proximity were able to achieve statistically significant levels of discrimination accuracy (both within and across crime types/categories). Furthermore, there were no statistically significant differences in discrimination accuracy using the intercrime distance across crime categories (AUC = 0.88), across crime types (AUC = 0.90), or within crime types (AUC = 0.91) (all comparisons were non-significant, $p > .05$). Also, there was no difference in terms of temporal proximity across categories (AUC = 0.67), across types (AUC = 0.74), or within types (AUC = 0.74), ($p > .05$). These findings suggest that a comparable level of

discrimination accuracy can be achieved when linking across crime types, across crime categories, and in the 'traditional' way, within crime types.

Table 5 also indicates that discrimination accuracy was superior generally for the intercrime distance compared to temporal proximity, with statistically larger AUC values across crime categories, across crime types and within types (comparisons at each level were significant at $p < .01$). Furthermore, the level of discrimination accuracy achieved when combining these two features to link crimes across categories was comparable to that achieved using the intercrime distance on its own (both AUCs = 0.88). This supports the above conclusion that the intercrime distance should be used on its own to link crimes (at least with the current sample and range of offender behaviors studied here).

As was noted earlier, the ROC analyses were conducted on a different sample to the logistic regression analyses, so the fact that the regression and ROC analyses converge on the same findings indicates that these results have been successfully cross-validated. However, to further test cross-validation seven ROC curves were constructed using the development sample (see Table 6) and the AUC values obtained using the development and test samples compared statistically (Bennell, 2002). There were no statistically significant differences between the AUC values obtained using either the development or test samples ($p > .05$). It can, therefore, be concluded that the current set of findings have been fully cross-validated and are applicable to future crimes committed within this jurisdiction of the UK.

[INSERT TABLE 6 HERE]

Estimating Practical Thresholds for Behavioral Case Linkage

Youden's Index was used to calculate six practical decision thresholds for linking across crime categories, across crime types, and within crime types using the intercrime distance and temporal proximity (see Table 7).

[INSERT TABLE 7 HERE]

Using these thresholds it is possible to further quantify the relative benefits associated with using the intercrime distance over temporal proximity when distinguishing between linked and unlinked crime pairs. Consider as an example the across crime type thresholds presented in Table 7. Using these thresholds it is possible to correctly identify (78 – 42) 36 additional unlinked crime pairs for every 100 unlinked pairs encountered when using the intercrime distance compared with using the temporal proximity at this level. Similar favorable comparisons can be drawn at the other two levels of analysis.

However, it is important to note that these thresholds are only presented for illustrative purposes and should not be considered suitable for use in practice. This issue is discussed in greater detail below.

Discussion

The current study represents the first empirical investigation of whether linked and unlinked crimes can be discriminated successfully across different types and categories of crime. It was found that both the intercrime distance and temporal proximity

achieved statistically significant levels of discrimination accuracy when differentiating between a wide variety of linked and unlinked crimes. Furthermore, the level of discrimination accuracy was comparable across the three levels of investigation, which suggests that there may be potential for a linkage tool to be developed that would facilitate behavioral case linkage across crime types and categories.

These findings are impressive given the wide array of crime types included in the current study, which spanned violent, sexual and property-related offenses. So, the fact that good discriminative accuracy could be achieved with such a diverse range of crimes is a good demonstration of the potential for cross-crime behavioral case linkage. Furthermore, discrimination accuracy was comparable to that observed in previous studies of within-crime linkage using the intercrime distance and temporal proximity with burglary, robbery, rape and auto theft crimes (Bennell & Canter, 2002; Bennell & Jones, 2005; Markson et al., 2010; Tonkin et al., 2008; Tonkin et al., 2011; Woodhams, 2008; Woodhams & Toye, 2007). While these findings must be tested under more realistic conditions (as discussed below) before we can draw conclusions about their ability to facilitate behavioral case linkage during live investigations, they do suggest that there is significant potential for the intercrime distance and temporal proximity to link a diverse range of crimes. Although, it seems that the intercrime distance demonstrates greater potential than the temporal proximity in this regard.

In terms of how these offender behaviors may be put into practice when linking crimes, practical decision thresholds were identified in the current study using Youden's Index. But, these thresholds are presented for illustrative purposes and so as to be consistent with previous research (e.g. Markson et al., 2010); we do not recommend that

they be used in practice. Indeed, Youden's Index is somewhat limited as a method for calculating decision thresholds because it does not take into account the prior probability that crimes are linked/unlinked and the various costs and benefits associated with correct and incorrect linkage decisions (Bennell, 2002). These are both important issues that should guide the selection of an appropriate decision threshold in practice. In addition to the limitations of Youden's Index, there is also an issue regarding the interpretation of decision thresholds more generally. That is, there is a tendency for thresholds to be applied in a rigid, 'black-and-white' manner. For example, two crimes that occurred 1.90 kilometers apart would be classed as unlinked according to the decision threshold developed at the across crime category level in this study, whereas two crimes that were 1.87 kilometers apart would be classed as linked. Thus, these two crime pairs would receive different linkage classifications when they are, in reality, only slightly different in terms of the intercrime distance (0.03 kilometers difference). We would argue that such a 'black-and-white' approach is inappropriate for use in practice, particularly since behavioral case linkage cannot give definite decisions regarding whether crimes are linked or not; it can only work in terms of probability.

For these reasons, we would argue that a more appropriate way of utilizing the current findings would be to use the intercrime distance to prioritize certain cases for analysis. So, in a situation where an analyst was tasked with finding all crimes within a police database that are linked to a particular crime (Crime X), we would suggest that the analyst calculate the intercrime distance between Crime X and these other crimes. These distances would then be put into ascending order (from smallest to largest), and the crimes with the smallest intercrime distances would be given priority for further analysis.

By following this method, no cases would be assigned a potentially inappropriate linked/unlinked label; rather, some cases would merely be given greater priority over others, which might help to avoid linkage blindness.

These findings also have theoretical implications, as well as practical ones. However, it should be noted that any suggestions made here are merely tentative and should be confirmed by more focused research. With this caution in mind, it can be said that the findings lend further support to the notion that offenders tend to commit their offenses in relatively restricted geographical areas and temporal periods that do not overlap significantly with those of other offenders (e.g. Bennell & Canter, 2002; Tonkin et al., 2008; Woodhams & Toye, 2007). But, they extend this conclusion beyond specific crime types, which suggests that the offenders in this sample offend in broadly the same geographical regions, regardless of crime type. This provides support for several seminal models of offender spatial behavior that assume generic psychological processes are involved in the production of criminal spatial behavior, irrespective of crime type (e.g. Brantingham & Brantingham, 1981, 1984; Clarke & Felson, 1993). However, they are inconsistent with research that has shown variation in spatial behavior as a function of crime type, such as Paulsen's (2006) study, which found variation in journey to crime, the size of the offense domain and the dispersion of offenses across different types of crime.

These findings are also relevant to the issue of situational similarity and behavioral consistency, which was originally discussed within the personality literature (e.g. Furr & Funder, 2004) and subsequently applied in relation to behavioral case linkage (Woodhams, Hollin, & Bull, 2008). In terms of case linkage, it has been

hypothesized that an offender's behavior will be most consistent when the situations that s/he encounters from one offence to the next are similar. As discussed by Woodhams et al. (2008), situational similarity in the criminal context can be defined in many ways; one of which is in terms of the type of crime being committed. Using such a definition, it would be predicted that crimes of the same type would elicit more similar offender behavior than crimes of different types. Based on this hypothesis, one would expect consistency to be greatest at the within-type level in the current study, followed by the cross-type level, and then the least consistent behavior would be observed at the cross-category level.

But, the findings from the current study do not support this hypothesis because consistency, distinctiveness and discrimination accuracy were comparable across all three levels of investigation. Nevertheless, there were non-significant trends in the hypothesized direction, with the Median intercrime distance increasing in size from the within-type level (0.75KM) to the cross-type level (0.86KM), to the cross-category level (1.25KM), and the Median temporal proximity increasing from 18 to 47 to 57 days as we move from the within-type to the cross-type to the cross-category level, respectively. This indicates a decreasing level of behavioral consistency from the within-type level up to the cross-category level. Nonetheless, the non-significant nature of these findings means that it can be concluded that there is little support for a substantive relationship between situational similarity and behavioral consistency in the current study. A similar conclusion was reached by Woodhams et al. (2008), who also found little evidence for a relationship between behavioral consistency and situational similarity.

However, these conclusions are based on a definition of situational similarity that functions at the level of crime types. This is potentially inconsistent with the notion of situational similarity as it is used in the personality literature, where similarity is defined in terms of psychological meaning rather than objective, physical characteristics of the situation (Shoda, 1999). Legal frameworks are not primarily designed to capture psychological similarities between offenses. Future work might, therefore, attempt to develop a psychologically-based classification of crimes that could replace the legal Home Office framework used in this study. This might be done in several different ways. First, existing psychological classification systems, such as that proposed by Youngs (2006), might be explored. Or the criminal career literature might be used, as this research has identified clusters of offences that co-occur frequently (e.g. Cohen, 1986). Alternatively, a new classificatory system might be developed using statistical methods for clustering data. Finally, offenders themselves might be asked to identify groups of 'psychologically similar' offences that could be used as the basis for distinguishing between similar and dissimilar offences (Grubin et al., 2001). Regardless of which approach is taken, a psychological approach to defining situational similarity will probably provide a more appropriate insight into the relationship between situational similarity and behavioral consistency.

Having considered the main findings and some of their implications, it is important to consider the limitations to these analyses. The current study suffered from many of the limitations associated with previous research in this area; most notably, that the current sample was comprised solely of solved crimes. Researchers of case linkage have discussed the fact that solved crimes may have been solved for the very reason that

they were committed in close geographical and/or temporal proximity, which would make the current empirical estimates of discrimination accuracy an over-estimate of the success one might realistically expect during real life police investigations (e.g. Bennell, 2002). Research that tests behavioral case linkage with unsolved crimes is, therefore, needed. Fortunately, work of this nature is ongoing (see Tonkin, Woodhams, Bull, & Bond, submitted; Woodhams & Labuschagne, in press).

Furthermore, it is important to begin testing statistical approaches to behavioral case linkage in a prospective manner during real life investigations. Although this may be difficult to organize and would require significant cooperation on behalf of the police, it is worthwhile given that research has suggested that large AUC values may not necessarily translate into significant predictive success when the base rate of the outcome variable is low (Szmukler, 2001).

A further limitation is that the crimes included in this sample were classed as 'detected' by the police, which (as discussed earlier) means that the offender may not necessarily have been convicted in a court of law. This potentially introduces a degree of error to the data, as certain cases included in this sample as linked crimes may in fact have been committed by different offenders. Error such as this would introduce "noise" into the data, thus decreasing the likelihood of good discrimination accuracy. Although this is clearly a limitation, this is less problematic than a situation where the empirical success of case linkage was inflated and recommendations were made to implement an inappropriate practice.

The current set of findings should also be viewed as preliminary until future studies have replicated them. Given the variation in case linkage performance that has

been observed across different geographical locations (e.g. Bennell, 2002; Bennell & Jones, 2005), future research should endeavor to test these findings across a diverse range of police jurisdictions.

The current study was also limited in terms of the range of offender behaviors studied. Case linkage research has traditionally tested a much wider range of offender behaviors than those considered in the current study. Although this decision was justified by these two behaviors having the most consistent empirical support in the case linkage literature and being the easiest to apply in practice, it is nevertheless important for future research to explore if and how cross-crime linkage has the potential to function successfully using a wider range of offender behaviors.

Despite these limitations, though, the current study is a significant development in the linkage literature. This study demonstrates for the first time that a moderate to high degree of discrimination accuracy can be achieved when distinguishing between a diverse range of linked and unlinked crimes. This is important because a significant amount of research has highlighted the versatility in offending behavior that seems to characterize the majority of offenders, particularly the most prolific offenders (Farrington et al., 1988; Piquero et al., 2007). Therefore, the shift in focus that this study represents — from research that is crime-specific to research that crosses crime types and categories — is important because it may help the police to deal more effectively with those versatile offenders who are responsible for the vast majority crime.

References

Alston, J. D. (1994). *The serial rapist's spatial pattern of target selection* (Unpublished Masters' thesis). Simon Fraser University, Vancouver, Canada.

Bateman, A. L., & Salfati, C. G. (2007). An examination of behavioral consistency using individual behaviors or groups of behaviors in serial homicide. *Behavioral Sciences and the Law, 25*, 527-544. doi: 10.1002/bsl.742

Bennell, C. (2002). *Behavioural consistency and discrimination in serial burglary* (Unpublished doctoral dissertation). University of Liverpool, Liverpool, UK.

Bennell, C., & Canter, D. V. (2002). Linking commercial burglaries by modus operandi: Tests using regression and ROC analysis. *Science and Justice, 42*, 153-164. doi: 10.1016/S1355-0306(02)71820-0

Bennell, C., & Jones, N. J. (2005). Between a ROC and a hard place: A method for linking serial burglaries by modus operandi. *Journal of Investigative Psychology and Offender Profiling, 2*, 23-41. doi: 10.1002/jip.21

Bernasco, W. (2010). A sentimental journey to crime: Effects of residential history on crime location choice. *Criminology, 48*, 389-416. doi: 10.1111/j.1745-9125.2010.00190.x

Bernasco, W., & Kooistra, T. (2010). Effects of residential history on commercial robbers' crime location choices. *European Journal of Criminology, 7*, 251-265. doi: 10.1177/1477370810363372

Blumstein, A., Cohen, J., Roth, J. A., & Visher, C. A. (1986). *Criminal careers and "career criminals", Volume II*. Washington, DC: National Academy Press.

Brantingham, P. J., & Brantingham, P. L. (1981). *Environmental criminology*. Beverly Hills, CA: Sage.

Brantingham, P. J., & Brantingham, P. L. (1984). *Patterns in crime*. New York, NY: Macmillan.

Canter, D., & Hammond, L. (2006). A comparison of the efficacy of different decay functions in geographical profiling for a sample of US serial killers. *Journal of Investigative Psychology and Offender Profiling, 3*, 91-103. doi: 10.1002/jip.45

Clarke, R. V., & Felson, M. (1993). *Routine activity and rational choice*. New Brunswick, NJ: Transaction.

Cohen, J. (1986). Research on criminal careers: Individual frequency rates and offense seriousness. In A. Blumstein, J. Cohen, J. A. Roth, & C. A. Visher (Eds.), *Criminal careers and "career criminals", Volume II*. Washington, DC: National Academy Press.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Hillsdale, NJ: Erlbaum.

Ewart, B. W., Oatley, G. C., & Burn, K. (2005). Matching crimes using burglars' modus operandi: A test of three models. *International Journal of Police Science and Management, 7*, 160-174. Retrieved from http://www.vathek.com/ijpsm/contents.php?vi=7.3

Farrington, D. P., Snyder, H. N., & Finnegan, T. A. (1988). Specialization in juvenile court careers. *Criminology, 26*, 461-487. doi: 10.1111/j.1745-9125.1988.tb00851.x

Felson, M. (1986). Linking criminals' choices, routine activities, informal control, and criminal outcomes. In D. Cornish & R. V. Clarke (Eds.), *The reasoning criminal: Rational choice perspectives on offending* (pp. 119-128). New York, NY: Springer-Verlag.

Felson, M. (1994). *Crime and everyday life: Insights and implications for society*. Thousand Oaks, CA: Pine Forge Press.

Furr, R. M., & Funder, D. C. (2004). Situational similarity and behavioral consistency: Subjective, objective, variable-centred, and person-centred approaches. *Journal of Research in Personality, 38*, 421-447. doi: 10.1016/j.jrp.2003.10.001

Goldstein, D. G., & Gigerenzer, G. (2009). Fast and frugal forecasting. *International Journal of Forecasting, 25*, 760-772. doi: 10.1016/j.ijforecast.2009.05.010

Goodwill, A. M., & Alison, L. J. (2006). The development of a filter model for prioritizing suspects in burglary offenses. *Psychology, Crime & Law, 12*, 395-416. doi: 10.1080/10683160500056945

Grubin, D., Kelly, P., & Brunsdon, C. (2001). *Linking serious sexual assaults through behaviour* (Home Office Research Study 215). London: Home Office Research, Development and Statistics Directorate.

House of Commons (2005). *Forensic science on trial: Seventh report of session 2004-05*. London: The Stationery Office Limited.

Jacobs, B. A., Topalli, V., & Wright, R. (2003). Carjacking, streetlife and offender motivation. *The British Journal of Criminology, 43*, 673-688. doi: 10.1093/bjc/43.4.673

Jacobs, B. A., & Wright, R. (1999). Stick-up, street culture, and offender motivation. *Criminology, 37*, 149-173. doi: 10.1111/j.1745-9125.1999.tb00482.x

Kershaw, C., Nicholas, S., & Walker, A. (2008). *Crime in England and Wales 2007/08: Findings from the British Crime Survey and police recorded crime*. London: Home Office.

Labuschagne, G. N. (2006). The use of a linkage analysis as evidence in the conviction of the Newcastle serial murderer, South Africa. *Journal of Investigative Psychology and Offender Profiling, 3*, 183-191. doi: 10.1002/jip.51

Laub, J. H. (2004). The life course of criminology in the United States: The American Society of Criminology 2003 presidential address. *Criminology, 42*, 1-26. doi: 10.1111/j.1745-9125.2004.tb00511.x

Lundrigan, S., & Canter, D. (2001). Spatial patterns of serial murder: An analysis of disposal site location choice. *Behavioral Sciences and the Law, 19*, 595-610. doi: 10.1002/bsl.431

Markson, L., Woodhams, J., & Bond, J. W. (2010). Linking serial residential burglary: Comparing the utility of *modus operandi* behaviours, geographical proximity, and temporal proximity. *Journal of Investigative Psychology and Offender Profiling, 7*, 91-107. doi: 10.1002/jip.120

Nagin, D. S., Farrington, D. P., & Moffitt, T. E. (1995). Life-course trajectories of different types of offenders. *Criminology, 33*, 111-139. doi: 10.1111/j.1745-9125.1195.tb01173.x

Office of the Legislative Auditor (2001). *Chronic offenders*. St Paul's, MN: The Program Evaluation Division, Office of the Legislative Auditor.

Paulsen, D. J. (2006). Connecting the dots: Assessing the accuracy of geographic profiling software. *Policing: An International Journal of Police Strategies and Management, 29*, 306-334. doi: 10.1108/13639510610667682

Piquero, A. R., Farrington, D. P., & Blumstein, A. (2007). *Key issues in criminal career research: New analyses of the Cambridge study in delinquent development*. New York, NY: Cambridge University Press.

Piquero, A. R., Sullivan, C. J., & Farrington, D. P. (2010). Assessing differences between short-term, high-rate offenders and long-term, low-rate offenders. *Criminal Justice and Behavior, 37*, 1309-1329. doi: 10.1177/0093854810382356

Santtila, P., Junkkila, J., & Sandnabba, N. K. (2005). Behavioural linking of stranger rapes. *Journal of Investigative Psychology and Offender Profiling, 2*, 87-103. doi: 10.1002/jip.26

Santtila, P., Laukkanen, M., & Zappalá, A. (2007). Crime behaviours and distance travelled in homicides and rapes. *Journal of Investigative Psychology and Offender Profiling, 4*, 1-15. doi: 10.1002/jip.56

Santtila, P., Pakkanen, T., Zappalá, A., Bosco, D., Valkama, M., & Mokros, A. (2008). Behavioural crime linking in serial homicide. *Psychology, Crime & Law, 14*, 245-265. doi: 10.1080/10683160701739679

Sarangi, S., & Youngs, D. (2006). Spatial patterns of Indian serial burglars with relevance to geographical profiling. *Journal of Investigative Psychology and Offender Profiling, 3*, 105-115. doi: 10.1002/jip.38

Shoda, Y. (1999). A unified framework for the study of behavioral consistency: Bridging person X situation interaction and the consistency paradox. *European Journal of Personality, 13*, 361-387. doi: 10.1002/(SICI)1099-0984(199909/10)13:5<361::AID-PER361>3.0.CO;2-I

Swets, J. A. (1988). Measuring the accuracy of diagnostic systems. *Science, 240*, 1285-1293. doi: 10.1126/science.3287615

Szmukler, G. (2001). Violence risk prediction in practice. *The British Journal of Psychiatry, 178*, 84-85. Retrieved from http://bjp.rcpsych.org/cgi/reprint/178/1/84

Tonkin, M., Grant, T., & Bond, J. W. (2008). To link or not to link: A test of the case linkage principles using serial car theft data. *Journal of Investigative Psychology and Offender Profiling, 5*, 59-77. doi: 10.1002/jip.74

Tonkin, M., Santtila, P., & Bull, R. (2011). The linking of burglary crimes using offender behavior: Testing research cross-nationally and in more realistic settings. *Legal and Criminological Psychology*. Advance online publication. doi: 10.1111/j.2044-8333.2010.02007.x

Tonkin, M., Woodhams, J., Bull, R., & Bond, J. W. (submitted). Linking solved and unsolved crimes using offender behavior.

Woodhams, J. (2008). *Juvenile sex offending: An investigative perspective* (Unpublished doctoral dissertation). University of Leicester, Leicester, UK.

Woodhams, J., Hollin, C. R., & Bull, R. (2007). The psychology of linking crimes: A review of the evidence. *Legal and Criminological Psychology, 12*, 233-249. doi: 10.1348/135532506X118631

Woodhams, J., Hollin, C., & Bull, R. (2008). Incorporating context in linking crimes: An exploratory study of situational similarity and if-then contingencies. *Journal of Investigative Psychology and Offender Profiling, 5*, 1-23. doi: 10.1002/jip.75

Woodhams, J., & Labuschagne, G. (in press). A test of case linkage principles with solved and unsolved serial rapes. *Journal of Police and Criminal Psychology*.

Woodhams, J., & Toye, K. (2007). An empirical test of the assumptions of case linkage and offender profiling with serial commercial robberies. *Psychology, Public Policy, and Law, 13*, 59-85. doi: 10.1037/1076-8971.13.1.59

Wright, R. T., & Decker, S. H. (1994). *Burglars on the job*. Boston, MA: Northeastern

University Press.

Youngs, D. (2006). How does crime pay? The differentiation of criminal specialisms by fundamental incentive. *Journal of Investigative Psychology and Offender Profiling, 3*, 1-19. doi: 10.1002/jip.44

Appendix A- List of Crime Types Searched for and Included in the Current Study

	n
1) Violent Offenses	
Murder	0
Attempted murder	1
Conspiracy to murder	0
Threats to kill	0
Manslaughter	0
Infanticide	0
Causing death by dangerous driving	0
Causing death by careless driving under the influence of drink or drugs	0
Death by careless or inconsiderate driving	0
Cause/allow death of child or vulnerable person	0
Causing death by driving: unlicensed drivers etc.	0
Wounding or carrying out an act endangering life	17
Use of substance or object to endanger life	0
Possession of items to endanger life	0
Endangering railway passengers	0
Endangering life at sea	0
Inflicting grievous bodily harm without intent	13

Actual bodily harm and other injury (includes minor wounding)	233
Racially or religiously aggravated inflicting grievous bodily harm without intent	1
Racially or religiously aggravated actual bodily harm and other injury	5
Poisoning or female genital mutilation	0
Harassment (Harassment Act 1997)	0
Racially or religiously aggravated harassment	0
Public fear, alarm or distress (Public Order 1986)	115
Racially or religiously aggravated public fear, alarm or distress	19
Possession of firearms with intent	0
Possession of other weapons	0
Possession of articles with blade or point	0
Abandoning child under 2 years	0
Child abduction	1
Causing death by aggravated vehicle taking	0
Assault without injury on a constable	48
Assault without injury	141
Racially or religiously aggravated assault without injury	7

2) Sexual Offenses

Sexual assault on a male aged 13 and over	0
Sexual assault on a male child under 13	0

Rape of a female aged 16 and over	3
Rape of a female child under 16	7
Rape of a female child under 13	2
Rape of a male aged 16 and over	0
Rape of a male child under 16	0
Rape of a male child under 13	0
Sexual assault on a female aged 13 and over	0
Sexual assault on a female child under 13	0
Sexual activity involving a child under 13	0
Causing sexual activity without consent	0
Sexual activity involving a child under 16	0
Incest or familial sexual offenses	0
Exploitation of prostitution	0
Abduction of female	0
Soliciting for the purpose of prostitution	0
Sexual activity etc.- with a person with a mental disorder	0
Trafficking for sexual exploitation	0
Abuse of position of trust of a sexual nature	0
Gross indecency with a child	0
Sexual grooming	0
Other miscellaneous sexual offenses	0
Unnatural sexual offenses	0
Exposure and voyeurism	4

Soliciting for prostitution from motor vehicle	0
Soliciting for prostitution	0

3) Burglary Offenses

Burglary in a dwelling	146
Attempt burglary dwelling	10
Distraction burglary (incl. attempts)	1
Aggravated burglary in a dwelling	1
Burglary other	110
Attempt burglary- other	10
Aggravated burglary other	0

4) Robbery Offenses

Robbery of business property	13
Robbery of personal property	96

5) Theft/Handling Offenses

Aggravated vehicle taking	6
Theft from person	8
Theft in dwelling (other than automatic machine/meter)	29

Theft by an employee	2
Theft of mail	0
Theft or unauthorized taking of pedal cycle	35
Theft from vehicle	41
Shoplifting	394
Theft from automatic machine or meter	2
Theft/TWOC of motor vehicle	36
Attempt theft/TWOC of motor vehicle	0
Other theft	55
Interfering with a motor vehicle	15

6) Criminal Damage Offenses

Arson endangering life	2
Arson not endangering life	8
Criminal damage- to dwellings	138
Criminal damage- to other buildings	81
Criminal damage- to vehicles	0
Criminal damage- other	90
Racially or religiously aggravated criminal damage to a dwelling	0
Racially or religiously aggravated criminal damage to a building other than a dwelling	3
Racially or religiously aggravated criminal damage to a vehicle	1

Racially or religiously aggravated other criminal damage	1
Threat or possession with intent to commit criminal damage	0

Tables

Table 1

A Summary of the Six Crime Pair Subsets Included in the Analyses

Crime Pair Type	Linkage Status	Description	Example
Cross-Category	Linked	This subset contains pairs of crimes that contain two crimes from different Home Office crime categories that have been committed by the same offender.	A personal robbery committed by offender 1 was paired with a burglary in a dwelling also committed by offender 1.
	Unlinked	This subset contains pairs of crimes that contain two crimes from different Home Office categories that have been committed by different offenders.	A burglary in a dwelling committed by offender 1 was paired with the theft of a motor vehicle committed by offender 2.
Cross-Type	Linked	This subset contains pairs of crimes that contain two crimes from the same Home Office crime category that are of different specific crime types. These two crimes have been committed by the	Personal robbery committed by offender 1 was paired with a commercial robbery also committed by offender 1.

		same offender.	
	Unlinked	This subset contains pairs of crimes that contain two crimes from the same Home Office crime category that are of different specific crime types. These two crimes have been committed by different offenders.	A shoplifting offense committed by offender 1 was paired with a theft from a vehicle committed by offender 2.
Within-Type	Linked	This subset contains pairs of crimes that contain two crimes committed by the same offender that are of the same specific crime type.	Two personal robbery crimes committed by offender 1 were paired.
	Unlinked	This subset contains pairs of crimes that contain two crimes committed by different offenders that are of the same specific crime type.	Two burglaries in a dwelling committed by different offenders were paired.

Table 2

Post-Hoc Comparisons of the Six Crime Pair Subsets in terms of the Intercrime Distance and Temporal Proximity

Intercrime Distance				**Temporal Proximity**			
Median (KM) Crime Pair Subset 1	Median (KM) Crime Pair Subset 2	*Z*	*r*	Median (Days) Crime Pair Subset 1	Median (Days) Crime Pair Subset 1	*Z*	*r*
LCrCat = 1.25	UCrCat = 15.42	6.93*	0.69	LCrCat = 57.00	UCrCat = 110.00	4.04*	0.40
LCrTyp = 0.86	UCrTyp = 17.63	8.29*	0.83	LCrTyp = 47.00	UCrTyp = 100.50	4.77*	0.48
LWi = 0.75	UWi = 15.67	7.34*	0.73	LWi = 18.00	UWi = 83.50	4.40*	0.44
LCrCat = 1.25	LCrTyp = 0.86	-2.14	-0.21	LCrCat = 57.00	LCrTyp = 47.00	-0.43	-0.04
LCrCat = 1.25	LWi = 0.75	-2.14	-0.21	LCrCat = 57.00	LWi = 18.00	-3.12*	-0.31
LCrTyp = 0.86	LWi = 0.75	-0.01	-0.00	LCrTyp = 47.00	LWi = 18.00	-1.72	-0.17

Note. * = Significant at the adjusted alpha level ($\alpha = 0.008$); All $n = 100$

LCrCat = Linked Cross-Category pairs; UCrCat = Unlinked Cross-Category pairs; LCrTyp = Linked Cross-Type pairs; UCrTyp = Unlinked Cross-Type pairs; LWi = Linked Within-Type pairs; UWi = Unlinked Within-Type pairs.

Table 3

Direct and Stepwise Logistic Regression Analyses for Intercrime Distance and Temporal Proximity Across and Within Crime Types and Categories

	Model	**Constant (SE)**	**Logit (SE)**	**Model χ^2 (df)**	**Wald (df)**	**Cox and Snell R^2**	**Nagelkerke R^2**
Intercrime Distance	Across Crime Categories	1.21 (0.33)	-0.15 (0.03)	31.15 (1)***	20.69 (1)***	0.27	0.36
	Across Crime Types	1.75 (0.37)	-0.30 (0.07)	61.91 (1)***	21.09 (1)***	0.46	0.62
	Within Crime Types	1.28 (0.33)	-0.14 (0.03)	35.80 (1)***	23.66 (1)***	0.30	0.40
	Across Crime Categories	0.61 (0.32)	-0.01 (0.00)	6.60 (1)*	5.87 (1)*	0.06	0.09

Temporal Proximity	Across Crime Types	0.71 (0.32)	-0.01 (0.00)	9.47 (1)**	8.38 (1)**	0.09	0.12
	Within Crime Types	0.72 (0.30)	-0.01 (0.00)	12.53 (1)***	10.57 (1)**	0.12	0.16
Combined	Across Crime Categories	1.86 (0.46)	ICD: -0.15 (0.03) TP: -0.01 (0.00)	36.50 (2)***	ICD: 19.53 (1)*** TP: 4.95 (1)*	0.31	0.41
	Across Crime Types	---	---	---	---	---	---
	Within Crime Types	---	---	---	---	---	---

Note. *$p < .05$; **$p < .01$; ***$p < .001$

Figures are not presented for the Combined Across Crime Types and Within Crime Types models because the stepwise logistic regression analyses only contained the intercrime distance, so the figures are identical to the single-feature regression models.

Table 4

Predictive Accuracy of the Regression Models (%)

	Intercrime Distance			**Temporal Proximity**			**Combined**		
	Across Crime Categories	Across Crime Types	Within Crime Types	Across Crime Categories	Across Crime Types	Within Crime Types	Across Crime Categories	Across Crime Types	Within Crime Types
Random	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00
Model	74.00	82.00	76.00	61.00	62.00	66.00	76.00	---	---

Note. Figures are not presented for the Combined Across Crime Types and Within Crime Types models because the stepwise logistic regression analyses only contained the intercrime distance, so the figures are identical to the single-feature regression models.

Table 5

ROC Results for Behavioral Case Linkage Across and Within Crime Types and Categories Using the Intercrime Distance and Temporal Proximity

	Case Linkage Feature	**AUC (SE)**	**95% Confidence Interval**
Across Crime Categories	Intercrime Distance	0.88 (0.03)***	0.82 - 0.95
	Temporal Proximity	0.67 (0.05)**	0.57 - 0.78
	Combined	0.88 (0.04)***	0.82 - 0.95
Across Crime Types	Intercrime Distance	0.90 (0.03)***	0.84 - 0.97
	Temporal Proximity	0.74 (0.05)***	0.64 - 0.83
Within Crime Types	Intercrime Distance	0.91 (0.03)***	0.84 - 0.97
	Temporal Proximity	0.74 (0.05)***	0.64 - 0.84

Note. **$p < .01$; ***$p < .001$

AUC values of 0.50-0.70 are considered low, values of 0.70-0.90 are considered moderate, and values of 0.90-1.00 are high (Swets, 1988).

Table 6

ROC Results Using the Development Sample

	Case Linkage Feature	**AUC (SE)**	**95% Confidence Interval**
Across Crime Categories	Intercrime Distance	0.85 (0.04)***	0.77 - 0.92
	Temporal Proximity	0.66 (0.06)**	0.55 - 0.76
	Combined	0.84 (0.04)***	0.77 - 0.92
Across Crime Types	Intercrime Distance	0.94 (0.02)***	0.89 - 0.98
	Temporal Proximity	0.69 (0.05)**	0.59 - 0.79
Within Crime Types	Intercrime Distance	0.86 (0.04)***	0.79 - 0.94
	Temporal Proximity	0.73 (0.05)***	0.63 - 0.83

Note. **$p < .01$; ***$p < .001$

AUC values of 0.50-0.70 are considered low, values of 0.70-0.90 are considered moderate, and values of 0.90-1.00 are high (Swets, 1988).

Table 7

Potential Decision Thresholds for Behavioral Case Linkage and their Associated Proportion of Hits and Correct Rejections

	Intercrime Distance	**Temporal Proximity**
Across Crime Categories	<1.88KM *p*H = 0.70; *p*CR = 0.96	<120.50 days *p*H = 0.80; *p*CR = 0.50
Across Crime Types	<10.61KM *p*H = 0.96; *p*CR = 0.78	<132.00 days *p*H = 0.94; *p*CR = 0.42
Within Crime Types	<2.19KM *p*H = 0.86; *p*CR = 0.90	<26.50 days *p*H = 0.62; *p*CR = 0.82

Note. *p*H = probability of obtaining a hit at this decision threshold (i.e. correctly identifying a linked crime pair); *p*CR = probability of obtaining a correct rejection at this decision threshold (i.e. correctly identifying an unlinked crime pair)

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Mr. Tonkin is a doctoral student at the University of Leicester, UK. His doctoral research focuses on the development of statistical approaches to linking crime using offender crime scene behavior. He has published several papers on this topic and has also published in the areas of geographical and offender profiling, offence paralleling behavior, and the social climate of prisons and forensic psychiatric hospitals.

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Dr. Woodhams is a Forensic Psychologist employed at the University of Birmingham, UK. Jessica started her career as a crime analyst, during which time she conducted linkage analysis on stranger sex offences and robberies. Since becoming an academic she has conducted several studies testing the principles of linkage analysis with different crime types, and she has written several book chapters on this topic.

Prof. Ray Bull

Prof. Bull is Professor of Forensic Psychology at the University of Leicester, UK. In 2010 he was "Elected by acclaim" an Honorary Fellow of the British Psychological Society "for the contribution made to the discipline of psychology". In 2008 he received from the European Association of Psychology and Law the "Award for Life-time Contribution to Psychology and Law".

Dr. John W. Bond

Dr. Bond is a Fellow in the Department of Chemistry at the University of Leicester, UK. His research interests centre on the use of forensic science to detect crime, principally through data analysis and the development of new techniques to enhance fingerprints. John has published over forty research papers and has patents related to new ways of visualizing fingerprints. One patent was included in Time Magazine's top 50 inventions of 2008.

Dr. Emma J. Palmer

Dr. Palmer is reader in forensic psychology at the University of Leicester, UK. Her research interests include the design and evaluation of interventions with offenders, risk/need assessment, and the role of parenting and social cognition in the development of offending. She is co-editor with Clive Hollin of a book titled Offending Behaviour Programmes: Development, Applications, and Controversies (2006, Wiley).