LINKING DIFFERENT TYPES OF CRIME USING GEOGRAPHICAL AND TEMPORAL PROXIMITY

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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

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, 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 or offenders (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 article.

BEHAVIORAL CASE LINKAGE

Behavioral case linkage is an investigative procedure that has received growing attention both practically and academically in the past 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). In addition, their behavior must 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 et al., 2008; Santtila, Junkkila, & Sandnabba, 2005). 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 or sexual assault, and homicide).

However, two behaviors in particular (spatial and temporal behavior) have demonstrated significant consistency and distinctiveness that often exceed 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 1.08 km and 22 days, compared to unlinked crimes, which were separated by an average of 16.25 km 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 2.994 km 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 area-under-the-curve (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 in 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 focus only on certain types of offender behavior while 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 while 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 in relatively restricted geographical areas (e.g., Lundrigan & Canter, 2001), they prefer short rather than long journeys to crime (e.g., Canter & Hammond, 2006; Sanntilla, 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) because of their excessive drinking and drug taking and their preference for expensive items, such as cars and clothing (Wright & Decker, 1994). For these individuals, crime is the only realistic option for maintaining such an extravagant lifestyle (Jacobs & Wright, 1999). Consequently, the motivation to offend is an almost constant presence, which leads to a high frequency of offending and, therefore, short temporal proximity values. Furthermore, social status is vitally important among these offenders, and many are willing to engage in violent behavior to maintain that status, particularly when they perceive it to be threatened (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 across which case linkage research has sampled data (which do not often exceed 5 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 offenders) engage in a protracted period of offending that often spans many years during which 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 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 contained only 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 specialize in individual types (Farrington, Snyder, & Finnegar, 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 offense during the 3-year period preceding their incarceration, and just 18% reported engaging in only one offense type during this period. It seems, therefore, 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 offense 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 use 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 on the basis of how United Kingdom police forces record crime (following definitions of crime that are set by the Home Office). Within the U.K., 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). 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 in which 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 the category level, and this performance was compared to discrimination 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, 2011; Woodhams & Toye, 2007).

**METHOD**

**SAMPLE**

To facilitate the current study, all offenders who had committed two or more types of violent, sexual, burglary, robbery, theft or handling, or criminal damage offenses between January 1, 2009, and December 31, 2009, were extracted from the force systems of a U.K. police force (with an area of 2,364 km²). This 1-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 U.K. Home Office. Crimes included in the categories of drugs offenses, fraud or 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 analyzed in this study are listed in the appendix. This resulted in a sample of 1,951 crimes committed by 537 offenders. A subsection of these data was extracted for analysis (as described below).

**DESIGN AND PROCEDURE**

A methodology was developed to investigate cross-crime linkage, which was 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 3 in an offender’s series paired with Crime 4 in his or her 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’s theorem to calculate the distance between the x- and 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 to address the key questions of this article.

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 whether 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?

### TABLE 1: A Summary of the Six Crime Pair Subsets Included in the Analyses

| Crime Pair Type | Description                                                                 | Example                                                                                     |
|----------------|------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------|
| Cross-category | 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 paired with a burglary in a dwelling also committed by Offender 1 |
| Linked         |                                                                                             | A burglary in a dwelling committed by Offender 1 paired with the theft of a motor vehicle committed by Offender 2 |
| Unlinked       | Pairs of crimes that contain two crimes from different Home Office categories that have been committed by different offenders |                                                                                              |
| Cross-type     | Pairs of crimes that contain two crimes from the same Home Office crime category that are of different specific crime types, which have been committed by the same offender | Personal robbery committed by Offender 1 paired with a commercial robbery also committed by Offender 1 |
| Linked         |                                                                                             | A shoplifting offense committed by Offender 1 paired with a theft from a vehicle committed by Offender 2 |
| Unlinked       | Pairs of crimes that contain two crimes from the same Home Office crime category that are of different specific crime types, which have been committed by different offenders |                                                                                              |
| Within-type    | 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 |
| Linked         |                                                                                             | Two burglaries in a dwelling committed by different offenders |
| Unlinked       | Pairs of crimes that contain two crimes committed by different offenders that are of the same specific crime type |                                                                                              |
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 data set (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 their being linked (using the method described by Bennell & Canter, 2002). These predicted probabilities were then used to conduct 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 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 to 0.70 are considered low, values of 0.70 to 0.90 are moderate, and values of 0.90 to 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 (copyright 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 while 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.
Nonparametric statistics were appropriate throughout the analyses because the distributions of intercrime distance and temporal proximity values departed 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 $\alpha = .008$) 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 in 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.

**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 or 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 able to improve discrimination accuracy by only 2% above the level obtained for distance on its own (see Table 4), which—although statistically significant—is not of significant practical value.

**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 $\chi^2$ (df) | Wald (df) | Cox and Snell $R^2$ | Nagelkerke $R^2$ |
|-------------------------|---------------|------------|----------------------|-----------|---------------------|------------------|
| Intercrime distance (ICD) |               |            |                      |           |                     |                  |
| Across crime categories | 1.21 (0.33)   | -.15 (.03) | 31.15 (1)**          | 20.69 (1)** | .27                 | .36              |
| Across crime types      | 1.75 (0.37)   | -.30 (.07) | 61.91 (1)**          | 21.09 (1)** | .46                 | .62              |
| Within crime types      | 1.28 (0.33)   | -.14 (.03) | 35.80 (1)**          | 23.66 (1)** | .30                 | .40              |
| Temporal proximity (TP) |               |            |                      |           |                     |                  |
| Across crime categories | 0.61 (0.32)   | -.01 (.00) | 6.60 (1)*            | 5.87 (1)* | .06                 | .09              |
| Across crime types      | 0.71 (0.32)   | -.01 (.00) | 9.47 (1)**           | 8.38 (1)** | .09                 | .12              |
| Within crime types      | 0.72 (0.30)   | -.01 (.00) | 12.53 (1)**          | 10.57 (1)** | .12                 | .16              |
| Combined                |               |            |                      |           |                     |                  |
| Across crime categories | 1.86 (0.46)   | ICD: -.15 (.03) | 36.50 (2)**  | ICD: 19.53 (1)** | .31 | .41              |
| Across crime types      |               | TP: -.01 (.00) |                     | TP: 4.95 (1)* | .- | -                |
| Within crime types      |               |            |                      |           |                     |                  |

**Note.** Figures are not presented for the combined across-crime-types and within-crime-types models because the stepwise logistic regression analyses contained only the intercrime distance, so the figures are identical to the single-feature regression models.

*p < .05.  **p < .01.  ***p < .001.

**TABLE 4**: Predictive Accuracy of the Regression Models (in percentages)

|                      | Intercrime Distance |                      |                      |                      |                      |
|----------------------|---------------------|----------------------|----------------------|----------------------|----------------------|
|                      | Across Crime Categories | Across Crime Types | Across Crime Categories | Across Crime Types | Across Crime Categories | Across Crime Types |
|                       |                      |                      |                      |                      |                      |                      |
| Random               | 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                |

**Note.** Figures are not presented for the combined across-crime-types and within-crime-types models because the stepwise logistic regression analyses contained only the intercrime distance, so the figures are identical to the single-feature regression models.
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.

**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-types and the combined within-crime-types models because the stepwise analyses included only the intercrime distance in the final combined models, so the AUC values would be identical to the single-feature ROCs for the intercrime distance.

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 and 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 nonsignificant, $p > .05$). 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 with 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 with the intercrime distance on its own (both AUCs = 0.88). This supports the previously stated 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 than were 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, we constructed seven ROC curves using the development sample (see Table 6) and the AUC values obtained using the development and test samples were compared statistically (Bennell, 2002). There were no statistically significant differences between the AUC values obtained using either the development or the 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 U.K.

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 with the use of the intercrime distance and temporal proximity (see Table 7). With the use of these thresholds, it is possible to further quantify the relative benefits associated with using the intercrime distance compared with temporal proximity when distinguishing between linked and unlinked crime pairs. Consider as an example the across-crime-type thresholds presented in Table 7. With these thresholds, it is possible to correctly

| Case Linkage Feature | Across crime categories | Across crime types | Within crime types |
|----------------------|-------------------------|-------------------|-------------------|
|                      | Intercrime distance     | Temporal proximity| Intercrime distance | Temporal proximity | Intercrime distance | Temporal proximity |
|                      | .85 (.04)**             | .66 (.06)**       | .94 (.02)**        | .69 (.05)**        | .86 (.04)**         | .73 (.05)**         |
|                      | [.77, .92]              | [.55, .76]        | [.89, .98]         | [.59, .79]         | [.79, .94]          | [.63, .83]          |

**Note.** AUC = area under the curve. AUC values of 0.50 to 0.70 are considered low, values of 0.70 to 0.90 are considered moderate, and values of 0.90 to 1.00 are high (Swets, 1988).

**\( p < .01 \). **\( p < .001 \).
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 presented only for illustrative purposes and should not be considered suitable for use in practice. This issue is discussed in greater detail in the next section.

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 involving the intercrime distance and temporal proximity for burglary, robbery, rape, and auto theft crimes (Bennell & Canter, 2002; Bennell & Jones, 2005; Markson et al., 2010; Tonkin et al., 2008, 2011; Woodhams, 2008; Woodhams & Toye, 2007). Although these findings must be tested in more realistic conditions (as discussed later) before one 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. However, 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 with the use of Youden’s index. Nevertheless, these thresholds are presented for illustrative purposes and 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 or 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 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 km 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 km 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 km 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 work only in terms of probability.

For these reasons, we would argue that a more appropriate way of applying the current findings would be to use the intercrime distance to prioritize certain cases for analysis. So, in a situation in which 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, one would not assign any cases a potentially inappropriate linked or unlinked label; rather, some cases would merely be given greater priority over others, which might help to avoid linkage blindness.

These findings 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). However, the findings allow us to 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 finding provides support for several seminal models of offender spatial behavior that assume that 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, the findings 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 he or she encounters from one offense 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 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.

On the basis of 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. 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 nonsignificant trends in the hypothesized direction, with the median intercrime distance increasing in size from the within-type level (0.75 km) to the cross-type level (0.86 km) to the cross-category level (1.25 km) and the median temporal proximity increasing from 18 to 47 to 57 days as we moved 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 nonsignificant 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 offenses 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” offenses that could be used as the basis for distinguishing between similar and dissimilar offenses (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 composed 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 overestimate 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, Tonkin, Woodhams, Bond, and Bull (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 individual was not necessarily 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 in which 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 because these two behaviors have the most consistent empirical support in the case linkage literature and are the easiest to apply in practice, it is nevertheless important for future research to explore whether and how cross-crime linkage has the potential to function successfully using a wider range of offender behaviors.

Despite these limitations, 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 of crime.

APPENDIX
CRIMES INCLUDED IN THE ANALYSIS*

| Offense                                                                 | n   |
|------------------------------------------------------------------------|-----|
| 1. Violent offenses                                                    |     |
| Attempted murder                                                       | 1   |
| Wounding or carrying out an act endangering life                       | 17  |
| 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   |
| Public fear, alarm or distress (Public Order 1986)                     | 115 |
| Racially or religiously aggravated public fear, alarm or distress      | 19  |
| Child abduction                                                        | 1   |
| Assault without injury on a constable                                  | 48  |
| Assault without injury                                                 | 141 |
| Racially or religiously aggravated assault without injury              | 7   |

(continued)
## APPENDIX (continued)

| Offense                                                                 | n  |
|------------------------------------------------------------------------|----|
| **2. Sexual offenses**                                                 |    |
| Rape of a female aged 16 and older                                     | 3  |
| Rape of a female child younger than 16                                 | 7  |
| Rape of a female child younger than 13                                 | 2  |
| Exposure and voyeurism                                                 | 4  |
| **3. Burglary offenses**                                               |    |
| Burglary in a dwelling                                                 | 146|
| Attempt burglary dwelling                                              | 10 |
| Distraction burglary (including attempts)                              | 1  |
| Aggravated burglary in a dwelling                                      | 1  |
| Burglary other                                                         | 110|
| Attempt burglary, other                                                | 10 |
| **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 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 |
| 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, other                                                 | 90 |
| 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  |

*Note.* Many other crimes in each category were searched but were not found for that 1-year period (e.g., murder, manslaughter, infanticide, sexual activity involving children of various ages, possession of items to endanger life, soliciting for prostitution). A complete list of searched for but not found crimes is available from the corresponding author. TWOC = Taken Without Consent.

**NOTE**

The government department responsible for setting crime definitions in England and Wales (the Home Office) records 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 7 crime types), drug offenses (containing 4 types), robbery (containing 2 types), theft or handling offenses (containing 16 types), fraud or forgery offenses (containing 16 types), criminal damage offenses (containing 11 types), and other offenses (containing 31 types).
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