BEHAVIOURAL CASE LINKAGE:

GENERALISABILITY, ECOLOGICAL VALIDITY, AND METHODOLOGY

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ABSTRACT

Thesis title: Behavioural Case Linkage: Generalisability, Ecological Validity, and Methodology

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Behavioural case linkage (BCL) is a procedure that can be used to identify linked crime series, which contain two or more crimes committed by the same person, thereby helping the police to detect and prosecute repeat offenders who are responsible for a disproportionate amount of crime. However, despite the potential benefits of BCL, there are also damaging consequences if crimes are incorrectly linked. Consequently, research has started to test if and how this procedure can work in the most efficient and reliable way. But, the extant literature has a number of important limitations, particularly in terms of (1) generalisability (i.e., there have been few attempts to replicate findings across geographical locations and time periods), (2) ecological validity (i.e., the methodology used to test BCL is not representative of how the procedure is used in practice), and (3) methodology (i.e., there is a lack of research to systematically compare the various methodological/statistical approaches to BCL). The primary aim of this thesis was to address these three important limitations. In terms of generalisability, this thesis has tested the extent to which previous BCL research on residential burglary, commercial robbery, and car theft can be replicated in new geographical locations and time periods. In terms of ecological validity, a number of new methodologies have been developed and tested that reduce the gap between research and practice in BCL by allowing both non-serial and unsolved offences (as well as solved, serial offences) to be included when testing the principles of BCL, and also for these principles to be tested with crime series that contain several different types of offence. In terms of methodology, novel methodological approaches have been compared with the 'traditional', status quo methodology for researching the BCL principles, thereby ensuring that the findings reported in this thesis can be compared with previous work. This thesis, therefore, has important implications for theory, research, and practice and the findings are discussed in the context of these. Future research directions are also outlined.

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2) Tonkin, M., Woodhams, J., Bull, R., Bond, J. W., & Palmer, E. J. (2011). Linking different types of crime using geographical and temporal proximity. *Criminal Justice and Behavior, 38*, 1069-1088. doi: 10.1177/0093854811418599

3) Tonkin, M., Woodhams, J., Bull, R., Bond, J. W., & Santtila, P. (2012). A comparison of logistic regression and classification tree analysis for behavioural case linkage. *Journal of Investigative Psychology and Offender Profiling*. Advance online publication. doi: 10.1002/jip.1367

4) Tonkin, M., Woodhams, J., Bull, R., & Bond, J. W. (2012). Linking solved and unsolved crimes using offender behaviour. *Forensic Science International*. Advance online publication. doi: 10.1016/j.forsciint.2012.05.017

5) Tonkin, M. (in press, a). Testing the theories underpinning crime linkage. In J. Woodhams & C. Bennell (Eds.), *Crime linkage: Theory, research and practice*. CRC Press.

6) Tonkin, M. (in press, b). Extending crime linkage to versatile offenders. In J. Woodhams & C. Bennell (Eds.), *Crime linkage: Theory, research and practice*. CRC Press.

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CHAPTER 1

THE PRACTICAL, THEORETICAL, AND EMPIRICAL BASES OF BEHAVIOURAL CASE LINKAGE[1]

1.1 An Introduction to Behavioural Case Linkage and its Benefits

One of the most compelling and well-supported findings in the psychological/ criminological literature 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 Kingdom (UK), for example, estimates suggest that 10% of offenders were responsible for over half of all reported crime in 2003/04 (Dodd, Nicholas, Povey, & Walker, 2004; Home Office, 2001). Findings such as these suggest that a cost-effective way for the police to tackle crime is to target repeat offenders because this approach will maximise the clear-up and prevention of crime whilst minimising the investigative resources used.

To target repeat offenders successfully, the police need to be able to identify *linked crime series*, which contain 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 (Grubin, Kelly, & Brunsdon, 2001). That is, if the same physical material is recovered at several different crime scenes, this allows the police to infer that

[1] As stated on pages 3 and 4, a version of this chapter has been published as Tonkin (in press, a).

the same person/s was involved. However, despite the impression that television programmes such as Crime Scene Investigation (CSI) and Silent Witness create, the availability of physical forensic evidence is surprisingly limited, with less than 1% of recorded crimes yielding searchable DNA profiles in the UK (House of Commons, 2005). The police cannot, therefore, rely completely on forensic approaches to linking crime; they must develop alternative approaches.

One potential alternative is to use offender crime scene behaviour, whereby crimes that are committed in a behaviourally similar way are judged to have been committed by the same person. Conversely, crimes that display many different behavioural features are judged to be the work of separate offenders. This procedure is known by several names, including linkage analysis and comparative case analysis (e.g., Bennell, Bloomfield, Snook, Taylor, & Barnes, 2010; Bennell & Canter, 2002), but the term behavioural case linkage (BCL) will be used throughout this thesis.

Academic and practical interest in BCL has grown significantly in recent years, with an increasing number of empirical studies being published (these are reviewed below and throughout this thesis) and information to suggest that BCL is not only being used during police investigations but also in some court proceedings (see Charron & Woodhams, 2010; Hazelwood & Warren, 2004; Labuschagne, 2012). Indeed, a number of specialist units and computer packages have been established around the world to support BCL in Canada, Japan, South Africa, Australia, New Zealand, the United States (US), and various European countries, including the UK (Hazelwood & Warren, 2004; Labuschagne, 2012; Snook, Luther, House, Bennell, & Taylor, 2012; Yokota, Fujita, Watanabe, Yoshimoto, & Wachi, 2007).

This interest is unsurprising given the potential benefits of identifying linked crime series. These include that BCL allows the evidence collected across several investigations to be pooled, which can increase the chances of catching and prosecuting the person responsible (Grubin et al., 2001). Not only does this help the police to meet government crime reduction targets, but it also increases public confidence in law enforcement. Second, when a collection of crimes is linked to a common offender these can be investigated together rather than separately, which is a more streamlined and cost-effective way of using police resources (Woodhams, Hollin et al., 2007). This is particularly important at a time when law enforcement agencies are being forced to make considerable reductions in their operational costs without compromising their ability to prevent and detect crime. However, the benefits of BCL depend on its reliability and accuracy. If there are errors in the linkage process this will lead to unhelpful lines of enquiry being pursued, which wastes both time and money, thereby making it more difficult to apprehend offenders (Grubin et al., 2001). Furthermore, incorrect BCL can cause unnecessary anxiety and fear of crime amongst the general public and can even result in individuals being falsely accused of crimes that they did not commit (Snook et al., 2012). Thus, there is a fine balance between the potential benefits of BCL and the damaging consequences if it goes wrong.

Given this fine balance and the growing use of BCL in practice, there is a clear need for empirical research that seeks to identify the most reliable and accurate ways of linking crime through offender behaviour. This thesis is primarily concerned with these issues; that is how and when can BCL be employed by the police in the most efficient, effective, and reliable way? And, importantly, how can research most successfully address these questions? Chapter 1 of this thesis will set the stage for subsequent empirical chapters by reviewing the theoretical assumptions of BCL and the prior research that has investigated whether these assumptions are supported using recorded crime data.

1.2 The Theoretical Assumptions of Behavioural Case Linkage

There is an extensive history of psychological theory and research into personality (see Cervone & Pervin, 2009). Fundamentally, this work rests on two basic assumptions (Mischel & Shoda, 1995; Mischel, Shoda, & Smith, 2004): (1) that there exist stable individual differences in human behaviour, emotion, and cognition; and (2) that these patterns can be measured and explained. The whole concept of personality is, therefore, based on the idea that humans have characteristic ways of thinking, feeling, and behaving that are relatively distinct from one person to the next and consistent within an individual over time.

These two assumptions of consistency and distinctiveness have been adopted by researchers as the underlying theoretical basis of BCL (e.g., Bennell, 2002; Woodhams, Bull, & Hollin, 2007). However, given the behavioural focus of this procedure, it is important to point out that it is *behavioural* consistency and distinctiveness that is necessary for BCL to work, rather than consistency/distinctiveness in the emotional or cognitive structures associated with offending[2]. Thus, offenders must behave in a relatively consistent way from one crime to the next if BCL is to work reliably and

[2] Although, consistency/distinctiveness in affect, cognition, and behaviour may be inter-related.

accurately. Without such behavioural consistency, there is no basis for using behavioural information to identify linked crime series. In addition, there must also be variation across individuals in the way that they commit crimes (referred to as behavioural distinctiveness or differentiation). Behavioural distinctiveness is necessary because if all offenders behaved in a similar way when committing crime there would be no opportunity to distinguish the crimes of one offender from those of another (Woodhams, Bull et al., 2007).

Crucially, however, it is not *absolute* behavioural consistency and distinctiveness that are required for BCL success, but *relative* consistency and distinctiveness (Bennell, Jones, & Melnyk, 2009). Thus, provided two crimes committed by the same person (linked crimes) are *more* behaviourally similar than two crimes committed by different people (unlinked crimes), BCL has the potential to work reliably and accurately. It does not matter if the absolute level of consistency/distinctiveness was low. Researchers are, therefore, seeking to identify a pattern of high behavioural similarity across linked crimes and low similarity across unlinked crimes, which would indicate the potential value of BCL.

By identifying these underlying assumptions, researchers made a significant step forward in both practical and academic terms because behavioural consistency and distinctiveness are testable. Consequently, it is possible to test the underlying theoretical assumptions of BCL and, therefore, whether BCL has the potential to work in practice[3].

---

[3] It is important to note the word "potential" because even if the assumptions of consistency and distinctiveness are supported using real world data, this does not necessarily mean that BCL will achieve a high level of accuracy during a live criminal investigation. There are many other factors that will determine whether the potential for BCL will actually be translated into practical success. For example, the resources that are available to law enforcement personnel (both in terms of time and statistical/ analytical software), the availability of behavioural evidence, and the ability of human decision-makers to identify and use

This thesis will now review and critique the empirical literature that has sought to test the underlying theory of BCL using recorded crime data.

1.3 Empirical Tests of Behavioural Consistency, Distinctiveness, and Discrimination Accuracy

The issue of consistency and distinctiveness in criminal behaviour is one that has been addressed at various levels (Canter, 2000; see Figure 1A). At the broadest level (level 1), research has questioned whether people are consistent in their decision to offend (i.e., persistence versus desistance in criminal behaviour; Blumstein, Farrington, & Moitra, 1985; Laub & Sampson, 2001; Moffitt, 1993). Consistency at level 1 is manifested as an individual who either persistently chooses to break the law or who persistently refuses to break it. At the next level (level 2), there is the issue of whether individuals specialise in certain types of offending behaviour over other types (i.e., offender specialisation versus versatility; Farrington & Lambert, 1994; Farrington, Snyder, & Finnegan, 1988; Soothill, Francis, Sanderson, & Ackerley, 2000). At a still finer level of analysis (level 3), is the extent to which offenders display similar patterns/themes in their offending behaviour (e.g., Salfati & Bateman, 2005; Sorochinski & Salfati, 2010; Wright, 2000; Yokota & Canter, 2004). For example, a sexual offender who repeatedly displays a tendency to behave in an excessively violent manner when offending would be considered consistent at level 3 (such as using sexually violent and threatening language, punching the victim, kicking the victim, and spitting on the victim). At the most refined level (level 4),

appropriate linkage strategies (see Chapters 5 and 6 for further discussion of these issues). Thus, this chapter is only concerned with the *potential* for BCL to work.

consistency can manifest as the offender displaying a single isolated behaviour repeatedly from one crime to the next (e.g., Bateman & Salfati, 2007; Harbort & Mokros, 2001; Sjöstedt, Långström, Sturidsson, & Grann, 2004). Thus, the distinction between levels 3 and 4 is that consistency at level 3 is examined across a group of behaviours that share a similar psychological meaning or function, but consistency at level 4 is examined in terms of single behaviours.

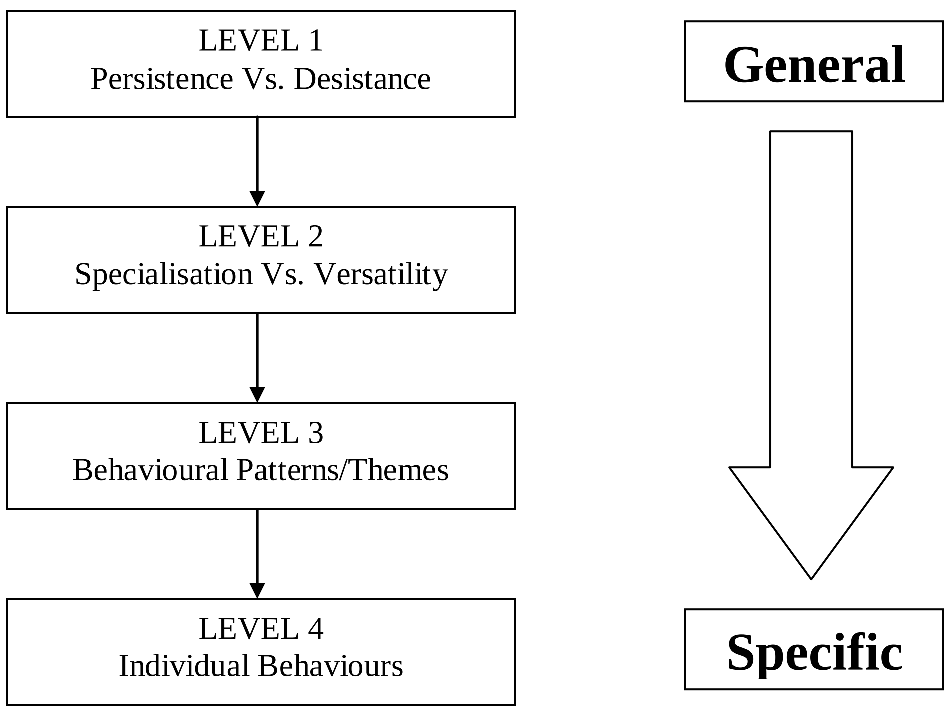

Figure 1A

The Different Levels of Behavioural Consistency and Distinctiveness (adapted from Canter, 2000)

However, not all levels of analysis are necessarily relevant to the practice of BCL (at least not directly). As discussed by Woodhams, Hollin et al. (2007), behavioural consistency and distinctiveness must be addressed at a level that gains the correct balance between being sufficiently refined to allow the police to distinguish between individual offenders, whilst not being so refined that noise in the data obscures meaningful patterns in offender behaviour. For example, an offender might be highly consistent in the type of offence s/he commits (e.g., s/he only commits burglaries), but without more detailed information on when, where, and how s/he behaves when offending it is unlikely that the police will be able to distinguish his/her crimes from the thousands of other burglaries committed in each UK police force every year (Home Office, 2012). Arguably, research that functions at levels 1 and 2 in Figure 1A is, therefore, too general to provide workable methods of linking crime. Likewise, it is also possible for research to examine behavioural consistency and distinctiveness at a level that is too refined (e.g., at the level of individual behaviours, see level 4 in Figure 1A)[4]. For example, an offender might tie the victim up using rope in one offence, but handcuff the victim in a second offence. At the level of individual behaviours, these two crimes might be classified as behaviourally inconsistent because different methods of restraining the victim were used. But, this may be inappropriate because victim restraint was evident in both offences, thereby demonstrating some degree of similarity in offender behaviour. One should expect slight behavioural variation such as this across a series of crimes due to situational factors and the inevitable noise that will exist in police data. In terms of the latter, the quality of behavioural evidence depends on numerous factors, including the victim's memory of

[4] However, it should be noted that the US Federal Bureau of Investigation (FBI), who have been involved in several high profile cases involving BCL (e.g., Hazelwood & Warren, 2004), have proposed the use of individual behaviours in some situations (see Douglas & Munn, 1992; Keppel & Walter, 1999).

events, the questions asked by the investigating police officer, and the reliability of data entry onto the police database[5]. Consequently, researchers have tended to look for consistency/distinctiveness in clusters of individual offence behaviours rather than behaviours in isolation (i.e., level 3 in Figure 1A) because this approach helps to counteract the influence of situational variation and low data quality (e.g., Bateman & Salfati, 2007).

Researchers have developed two distinct approaches in this regard. The first approach, pioneered by Grubin and Santtila and Salfati, uses statistical procedures such as multidimensional scaling and cluster analysis to form groups of behaviours that co-occur at crime scenes (referred to as the 'thematic approach' hereafter). The second approach, developed by Bennell (referred to as the 'Bennell methodology' hereafter), creates clusters of offence behaviour in an intuitive/non-statistical manner by combining behaviours that either serve a similar function during the offence (e.g., they facilitate entry into the property during a burglary) or that represent one 'type' of offender behaviour (e.g., spatial behaviour). The empirical research from each of these approaches will be examined in turn, starting with the thematic approach.

1.3.1 The Thematic Approach

[5] A police database contains a record of all offences committed within that particular police force area, and it would be within this database that a crime analyst would look for potentially linked crimes.

Grubin et al. (2001) were the first to explore a statistically-based approach to identifying behavioural themes[6]. Within their sample of serial rapes, they identified four offence domains, each of which represented a different aspect of rape behaviour (control; sex; escape; and style). Within each of these four offence domains, Grubin and colleagues used cluster analysis to identify four behavioural types, thus creating a total of 256 ($4 \times 4 \times 4 \times 4$) domain type combinations that could be used to describe a given offence in their sample. This allowed Grubin et al. (2001) to examine both single-domain consistency in offence behaviour (i.e., the extent to which an offender displayed the same domain type from one crime to the next, e.g., an offender who displayed control type 1 in all of his/her offences) and multi-domain consistency (i.e., the extent to which an offender displayed the same domain type combination from one offence to the next, e.g., an offender who displayed control type 1, sex type 2, escape type 4, and style type 3 in all of his/her offences). It was found that 83% of the serial offenders demonstrated single-domain consistency in at least one of the four domains throughout their series and 26% had at least two offences within their series that matched across all four domains. When compared with the level of consistency expected through chance, it was found that these percentages were significantly greater, thereby demonstrating support for the assumption of behavioural consistency. Interestingly, offenders were most consistent in their control behaviours (e.g., weapon use and the method of approaching the victim) and least consistent in style behaviours (i.e., those behaviours that are not necessary for the crime to be completed successfully, such as asking the victim personal questions and

[6] It should be noted that Grubin et al. (2001) actually used a combination of statistical and intuitive approaches to forming the behavioural themes in their study, but this research is discussed under the current sub-heading because their methodology bears greater resemblance to the studies of Salfati and of Santtila than it does to those of Bennell.

complimenting them during the assault). These are important findings because they suggest that BCL will be more successful if analysts focus selectively on certain types of offender behaviour over others (this issue is discussed in greater depth below).

Having demonstrated statistically significant levels of behavioural consistency, Grubin et al. (2001) tested whether these findings could be translated into a statistical methodology that would support BCL (thereby testing behavioural distinctiveness). For each offence in their sample they identified the 10% of cases that were most similar to that offence in terms of domain types (using a specially-designed statistical algorithm). With the exception of two offence series, the number of correct cases within the top 10% was significantly larger than the number that would be expected through chance. Furthermore, Grubin and colleagues demonstrated that the relatively large false positive rate (where an unlinked crime was incorrectly included within the top 10%) could be reduced to some extent by applying geographical and temporal 'filters', which gave greater weight to those crimes that were committed close together in space and time. Nevertheless, Grubin et al. (2001) concluded that their linking algorithm was not robust enough to be used during routine screening of large national databases. They called for further research and refinement of their methodology.

Since this initial study, a number of subsequent studies have adopted a statistical approach to identifying behavioural themes. In particular, Santtila and colleagues have used a variety of statistical approaches, including principal components analysis, multidimensional scaling, Mokken scaling, and discriminant function analysis (Santtila, Fritzon, & Tamelander, 2004; Santtila, Junkkila, & Sandnabba, 2005; Santtila, Korpela, & Häkkänen, 2004; Santtila et al., 2008). For example, Santtila et al. (2008) used

Mokken scaling (a non-parametric method similar to factor analysis) to identify seven behavioural themes amongst a sample of 116 Italian serial homicides. These behavioural themes were subsequently entered into a discriminant function analysis to produce a number of probability values for each crime, which indicated the predicted likelihood that the crime belonged to each series in the sample. It was found that 62.9% of the crimes were assigned to the correct series (only 6.2% would have been expected through chance). Similar (albeit slightly less successful) findings have been observed with samples of serial arson, rape, and car theft (Santtila, Fritzon et al., 2004; Santtila et al., 2005; Santtila, Korpela et al., 2004).

Another body of literature has been pioneered by Salfati and colleagues, who have utilised multidimensional scaling techniques to identify behavioural themes in offence behaviour (e.g., Horning & Salfati, 2008; Magyar & Salfati, 2007; Sorochinski & Salfati, 2010). These studies have found statistically significant levels of behavioural consistency in samples of serial rape and homicide. For example, in their sample of 19 US homicide offenders, Sorochinski and Salfati (2010) found that the level of consistency observed in planning behaviours, wounding, and victim-offender interaction was between 1.5 and 26.5 times greater than the level expected through chance. Not only do these findings support the assumption of behavioural consistency, but they further suggest that certain types of offender behaviour are more consistent than others (in Sorochinski and Salfati, 2010, for example, behaviours indicative of the victim-offender interaction were the most consistent and wounding behaviours were the least consistent).

But, while research from the thematic approach has made significant contributions to the BCL literature, there are important limitations that must be recognised. Specifically, if Salfati's methodology were to be applied in practice, an investigator would have to assign each crime to a behavioural theme based on how the offender behaved when offending. However, crime scenes rarely (if ever) contain behavioural characteristics that are associated with just one theme; typically, a crime scene will display several different thematic elements. Consequently, the investigator must set a threshold for judging when a crime has a sufficient number of characteristics to be assigned to a particular thematic category. As demonstrated by Salfati and Bateman (2005), the number of unclassifiable crimes can be quite large if the threshold is strict. For example, 60% of Salfati and Bateman's (2005) sample could not be classified according to their instrumental-expressive model of homicide when using the strictest threshold they tested[7]. Unclassifiable cases are problematic because this creates a potentially large number of crimes for which the Salfati method of BCL cannot be used.

Santtila and colleagues' approach overcomes this limitation because it assigns continuous scores that indicate the extent to which the different behavioural themes are present in a given crime. Their methodology does not, therefore, require the investigator to assign a crime to one behavioural theme over another. However, the disadvantage of their approach (and indeed many other approaches that use continuous measures of behavioural similarity/thematic emphasis) is that the investigator must set a decision threshold that tells him/her when two crimes are sufficiently similar to conclude that they are the work of the same person. As demonstrated by Bennell et al. (2009), the placement

[7] Salfati and Bateman (2005) tested three thresholds: (1) the crime was assigned to the thematic category for which it had the most crime scene behaviours (e.g., if 42% of the behaviours demonstrated at a homicide were expressive and only 40% instrumental, that crime would be labelled 'expressive'- this was the most lenient threshold); (2) the crime was only assigned to a thematic category when the proportion of behaviours in one theme was at least 1.5 times higher than the other theme; and (3) the crime was only assigned to a category when the proportion of behaviours in one theme was at least twice as high as that in the other theme (this was the strictest threshold, which led to 60% of the sample being deemed unclassifiable).

of this threshold can substantially affect discrimination accuracy (i.e., the success one has in predicting whether crimes are linked or unlinked). However, previous studies (including those of Santtila and colleagues) have failed to recognise this issue. Bennell and colleagues (2009) have, therefore, argued that research must use a method of analysis that can: (1) quantify the degree of discrimination accuracy in a way that is independent from specific decision thresholds; and (2) help law enforcement personnel to identify the threshold that maximises the number of correct linkage decisions. For these purposes, Bennell has proposed an analytical methodology using Receiver Operating Characteristic (ROC) analysis (e.g., Bennell, 2002; Bennell & Canter, 2002; Bennell & Jones, 2005). We will now review the steps involved in this methodology and the range of research that has adopted this approach.

1.3.2 The Bennell Methodology

Although slight variation exists in how Bennell's methodology has been applied, the general process is similar across studies (see Figure 1B).

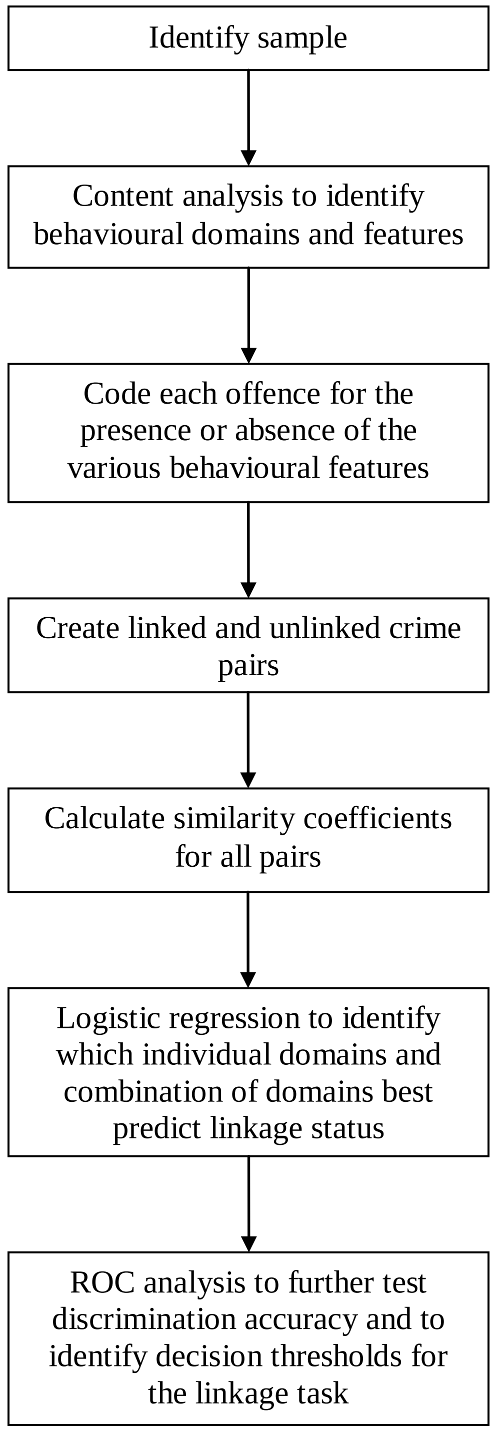

Figure 1B

The Bennell Methodology for Testing Behavioural Case Linkage

The process begins by identifying all offenders who have committed more than one offence during a given time period (e.g., all offenders who have committed two or more residential burglaries in the last three years). For each of these offenders, a number of crimes are selected for analysis (the number and method of selecting crimes has varied; see Bennell, 2002; Tonkin, Grant, & Bond, 2008; Woodhams & Toye, 2007).

Next, content analysis is used to identify relevant and available behavioural features from the police crime reports and/or court transcripts (depending on what information is available). These features are clustered into domains that contain behaviours that serve either a similar function during the offence or that represent one 'type' of offender behaviour. Each crime in the sample is then coded for the presence or absence of the identified behavioural features in a binary fashion.

The sample is then used to create a number of crime pairs, some of which contain two crimes committed by the same person (linked crime pairs) and some of which contain two crimes committed by different people (unlinked crime pairs). The method of forming these pairs has varied (e.g., Bennell, 2002; Tonkin et al., 2008). Various similarity coefficients are then calculated, which indicate the degree of behavioural, geographical, and temporal similarity between the two crimes in each pair. In terms of geographical and temporal similarity, the number of kilometres and the number of days separating the two crimes is calculated (referred to as inter-crime distance and temporal proximity, respectively). In terms of behavioural similarity, statistical coefficients are calculated to indicate the degree to which the two crimes share behavioural features, with these coefficients typically ranging from 0 (indicating no shared features) to 1 (indicating complete behavioural similarity). Traditionally, separate coefficients are calculated for each behavioural domain, but a combined coefficient that indicates the level of similarity across all behavioural features is often calculated as well. This allows researchers to examine both the combined and independent value of different types of offender behaviour for the purposes of BCL. It should be noted that different measures of behavioural similarity have been explored, but a coefficient called Jaccard's coefficient has been used most frequently (e.g., Bennell, Gauthier, Gauthier, Melnyk, & Musolino, 2010; Ellingwood, Mugford, Bennell, Melnyk, & Fritzon, in press).

These measures of behavioural, geographical, and temporal similarity are subsequently used to predict whether crime pairs are linked or unlinked (typically using binary logistic regression analysis). Direct logistic regression is used to indicate the potential value of each behavioural domain in isolation and stepwise logistic regression to indicate the combination of domains that maximises discrimination accuracy (Bennell & Canter, 2002). Statistically significant regression models are interpreted as evidence for relative behavioural consistency and distinctiveness in the crimes studied.

Finally, ROC analysis is used to provide an estimate of discrimination accuracy that is independent of decision thresholds (Bennell, 2002). In some studies, the crime pairs are split into training and test samples, where the models are developed on the training sample using logistic regression and applied to the test sample using ROC analysis (Bennell, 2002; Bennell & Canter, 2002; Bennell & Jones, 2005)[8]. The aim of this procedure is to reduce the potential bias that might arise from developing and testing linkage models on the same sample, thereby providing findings that have a realistic chance of generalising to future crimes (e.g., Bennell & Jones, 2005). However, not all studies have cross-validated their findings in this way (e.g., Tonkin et al., 2008;

[8] Section 2.2.3 provides a detailed description of this methodology.

Woodhams & Toye, 2007). The metric that is produced by ROC analysis, the Area Under the Curve (AUC), ranges from zero to one, with an AUC of 0.50 indicative of a chance level of discrimination accuracy[9]. Thus, the AUC is used to examine which domains (and combinations thereof) have the greatest potential to support BCL. Statistically significant AUC values that indicate moderate to high levels of discrimination accuracy are interpreted as evidence for relative behavioural consistency and distinctiveness.

One final step in Bennell's methodology is to identify decision thresholds that can be used to guide practitioners when they are conducting BCL in practice. Youden's index has been used for this purpose because it identifies the threshold that maximises the number of correct linkage decisions made (Bennell, 2002).

A number of studies have utilised Bennell's methodology since it was initially proposed (see Table 1A below). Overall, these studies have found evidence to suggest that relative behavioural consistency and distinctiveness exist in offender behaviour and can be used to facilitate statistically significant levels of discrimination accuracy when distinguishing between linked and unlinked crime pairs. These findings seem to hold across a variety of crime types, including residential and commercial burglary (e.g., Bennell & Jones, 2005), personal and commercial robbery (Burrell, Bull, & Bond, in press; Woodhams & Toye, 2007), car theft (e.g., Tonkin et al., 2008), arson (Ellingwood et al., in press), sexual assault (e.g., Bennell et al., 2009), and homicide (Melnyk, Bennell, Gauthier, & Gauthier, 2011).

However, as demonstrated in Table 1A, there is clear variation in consistency, distinctiveness, and discrimination accuracy across crime types and across behavioural

[9] Typically, AUCs between 0.50 and 0.70 are said to indicate low levels of accuracy, AUCs between 0.70 and 0.90 indicate moderate levels of accuracy, and AUCs between 0.90 and 1.00 indicate high levels of accuracy (Swets, 1988).

domains. In terms of behavioural domains, there is some evidence to suggest that those behaviours that are under the control of the offender, rather than dependent on the situational context, seem to demonstrate the most consistency and distinctiveness (Bennell & Canter, 2002). For example, inter-crime distance has consistently achieved superior discrimination accuracy in comparison with other behavioural domains, with moderate to high levels of accuracy observed in studies of serial rape, burglary, car theft, and robbery (see Table 1A). Arguably, this is because an offender has relatively greater control over the choice of offending location than over other aspects of offending behaviour, such as what items to steal during a burglary/robbery (which depend on what is available to steal) and how to enter a car/house (which depends to some extent on the behaviour of the owner, e.g., if s/he has left the property unlocked). This 'control' notion is given some credence when one considers that it is consistent with findings from the thematic approach to BCL research (Grubin et al., 2001; Salfati & Sorochinski, 2010) and also with studies on non-criminal behaviour (Funder & Colvin, 1991; Furr & Funder, 2004; Hettema & Hol, 1998; Hettema & van Bakel, 1997; Shoda, Mischel, & Wright, 1993).

Bennell and Jones (2005) do, however, discuss alternative explanations for the superiority of certain domains (such as inter-crime distance). For example, there is the issue of data quality. Geographical information is recorded by most police forces in a uniform manner (e.g., through postcodes or *x, y* coordinates) and it is also a relatively objective piece of information to record. This is in contrast to other types of behavioural information, such as how a burglar entered the property or whether a sexual offender was threatening, which are not necessarily recorded in a standardised manner and depend on the ability of the investigating officer to accurately reconstruct what happened during a particular crime (which may be difficult if the victim is traumatised, deceased, or there was no witness/victim present when the crime was committed- the latter is common in burglary and car theft crimes). In short, data quality may be superior for certain types of behavioural information than others, which would make the discovery of consistent and distinctive behavioural patterns more likely (see Bennell & Jones, 2005, for alternative explanations).

As mentioned above, there is also variation between crime types in terms of discrimination accuracy, but it is difficult to discern any reliable patterns from the findings in Table 1A. This may be due to the fact that different police force locations have been examined, which makes direct comparison between studies difficult. Indeed, there are a number of factors that might cause variation in discrimination accuracy between police forces, including data gathering and storage procedures and the distribution/type of potential targets (see Chapter 2 for further discussion of this issue).

Table 1A

A Summary of Research using the Bennell Methodology to Test Behavioural Case Linkage

	Country	**Area under the Curve (AUC)**
Burglary		
Bennell (2002)[a]		
- Inter-crime Distance		0.85**
- All Behaviours		0.63*

- Target - Entry - Property - Internal - Stepwise[b] (the stepwise model differed between datasets)	UK	0.59* 0.58* 0.57* 0.52* 0.82**
Bennell and Canter (2002)[c] - Inter-crime Distance - Target - Entry - Property - Stepwise (containing inter-crime distance and entry)	UK	 0.80** 0.68* 0.65* 0.63* 0.81**
Bennell and Jones (2005)[d] - Inter-crime Distance - Target - Entry - Property - Stepwise (the stepwise model differed between datasets)	UK	 Commercial: 0.84**; Residential: 0.90** Commercial: 0.61*; Residential: 0.58* Commercial: 0.57*; Residential: 0.59* Commercial: 0.55*; Residential: 0.59* Commercial: 0.85**; Residential: 0.90**

Markson, Woodhams, and Bond (2010)	UK	
- Inter-crime Distance		0.90**
- Temporal Proximity		0.86**
- All Behaviours		0.61*
- Target		0.54*
- Entry		0.54*
- Property		0.58*
- Stepwise (containing inter-crime distance and temporal proximity)		0.95***
Melnyk et al. (2011)[e]	UK	
- All Behaviours		0.62*
Commercial Robbery		
Woodhams and Toye (2007)	UK	
- Inter-crime Distance		0.89**
- Target		0.79**
- Planning		0.70*
- Control		0.90**
- Stepwise (containing inter-crime distance, planning, and		0.95***

control)		
Personal Robbery		
Burrell et al. (in press)[e] - Inter-crime Distance - Temporal Proximity - All Behaviours - Target Selection - Control - Property - Stepwise (containing inter-crime distance and target selection)	UK	 0.92*** 0.83** 0.64* 0.64* 0.56* 0.45* 0.90***
Rape/Sexual Assault		
Bennell et al. (2009) - All Behaviours	UK	 0.75**
Bennell, Gauthier et al. (2010)[f] - All Behaviours	UK	 0.81**
Woodhams (2008) - Control - Escape - Sex - Style	UK	 0.63* 0.73** 0.59* 0.31*

- Inter-crime Distance (Approach location) - Inter-crime Distance (Offence location) - Stepwise 1 (containing inter-crime distance (offence location, escape, and sex) - Stepwise 2 (containing control, escape, and sex)		0.99*** 0.99*** 1.00*** 0.82**
Woodhams and Labuschagne (2012) - All Behaviours (two crimes per offender) - All Behaviours (all crimes per offender)	South Africa	0.77** 0.88**
Winter et al. (in press)[g] - All Behaviours (Dimensional) - All behaviours (Multivariate)	UK	0.74** 0.84**
Car Theft		

Tonkin et al. (2008) - Inter-crime Distance - Inter-dump Distance - Target Selection - Target Acquisition - Disposal Behaviour	UK	 0.81** 0.77** 0.57* 0.56* 0.56*
Davies, Tonkin, Bull, and Bond (in press) - Inter-crime Distance - Inter-dump Distance - Temporal Proximity - Target Selection (Old) - Target Selection (New) - Target Acquisition - Disposal Behaviour - Age Difference - Value Difference - Stepwise (containing target selection (new), target acquisition, inter-crime distance, and temporal proximity)	UK	 0.91*** 0.88** 0.78** 0.62* 0.76** 0.64* 0.64* 0.62* 0.56* 0.93***
Homicide		

Melnyk et al. (2011)[f] - All Behaviours	US	 0.96***
Arson		
Ellingwood et al. (in press)[h] - All Behaviours - Instrumental Person (empirically-derived) - Instrumental Person (random) - Instrumental Object (empirically-derived) - Instrumental Object (random) - Expressive Person (empirically-derived) - Expressive Person (random) - Stepwise (containing instrumental object and instrumental person, both empirically-derived)	UK	 0.89** 0.77** 0.84** 0.82** 0.83** 0.72** 0.72** 0.84**

* Low predictive accuracy (AUC = 0.50 to 0.70); ** Moderate predictive accuracy (AUC = 0.70 to 0.90); *** High predictive accuracy (AUC = 0.90 to 1.00) (Swets, 1988).

[a] Bennell (2002) presents AUC statistics for a variety of UK police forces and for commercial and residential burglary separately. It is not possible, however, to succinctly summarise such detailed data in this table. Therefore, the combined mean statistics for the whole sample are presented here.

[b] Stepwise refers to the combination of behavioural domains identified through stepwise binary logistic regression analysis. Various domains were included within the stepwise models across Bennell's (2002) various datasets.

[c] This study refers to commercial burglary only.

[d] Bennell and Jones (2005) present AUC statistics separately for several different police districts. For the purposes of clarity, the mean statistics are collapsed by district to provide average scores for each domain across all districts.

[e] Burrell et al. (in press) present AUC statistics derived using Bennell's (2002) original methodology and using an altered methodology. Only those findings using the original methodology are presented in this table.

[f] Bennell et al. (2010) and Melnyk et al. (2011) present AUC statistics for two similarity coefficients over a range of experimental conditions. For the purposes of clarity, only the AUC statistic using Jaccard's coefficient with 100% of behaviours is presented, as this represents the variation of Bennell's methodology most commonly used in research.

[g] Winter et al. (in press) present AUC statistics based on serial data only and a combination of serial and non-serial rapes. Only those findings from the serial data are presented in this table because this reflects the methodology used in all previous research using Bennell's methodology.

[h] Ellingwood et al. (in press) present AUC statistics for two similarity coefficients, but for the purposes of clarity only the AUC statistics using Jaccard's coefficient are presented.

In summary, there is a growing body of work that has utilised ROC analysis to examine behavioural consistency, distinctiveness, and discrimination accuracy in recorded crime data. These studies support the underlying assumptions of BCL and suggest that consistency and distinctiveness exist at a level that has the potential to facilitate statistically significant discrimination accuracy in a variety of crime types (provided the correct behaviours are used). Bennell's methodology has, therefore, made a significant contribution to the literature on BCL for several reasons. First, it provides a psychometrically sound framework for testing the assumptions of BCL. Second, it provides an estimate of discrimination accuracy that is free from specific decision thresholds (Bennell et al., 2009). Third, it allows thresholds to be calculated that specify how similar two crimes must be before they should be considered linked, which is fundamental if BCL is to be applied in a practical context (Bennell, 2002). Fourth, it provides a methodology for testing consistency, distinctiveness, and discrimination accuracy that can be applied to a variety of offender behaviours (i.e., any behaviours that can be transformed into a continuous measure of behavioural similarity) and any crime type (Bennell, 2002). This makes it possible to compare different behavioural domains in terms of their potential BCL value (which is important from a practical perspective) and provides a consistent metric that allows different studies to be compared (which is important from a theoretical perspective because it helps to ensure that a unified and coherent body of research is produced). For these reasons, Bennell's methodology (particularly the use of ROC analysis) has become the most frequently used approach to BCL research at the time of writing.

Despite its growing popularity, however, there are many fundamental assumptions made when using this methodology that have potential to impact on the reliability of subsequent findings. While some of these issues are beginning to receive attention (e.g., Bennell et al., 2010; Ellingwood et al., in press; Winter et al., in press;

Woodhams & Labuschagne, 2012), there are many unanswered questions. Section 1.4 will describe these issues and, where possible, discuss research that is beginning to address them. But first, a body of research must be described that has taken a more practically-oriented approach to examining consistency, distinctiveness, and discrimination accuracy by developing and testing automated BCL systems.

1.3.3 Automated Behavioural Case Linkage Systems

A number of studies have developed and tested automated BCL systems, which are computerised programs that interface with police databases to extract and analyse offence information, thus producing an output that identifies potentially linked crimes and gives an associated degree of confidence (often as a percentage score). Due to the limits on space for this thesis (imposed by University regulations), it is not possible to provide a comprehensive review of all these systems; instead, several notable examples will be briefly described and the reader referred to more comprehensive sources.

At the National Research Institute of Police Science in Japan, Yokota and colleagues have developed the Behavioural Investigative Support System (BISS), which uses multiple features of offender behaviour to calculate similarity coefficients that are then used to create a prioritised list of known offenders (see Yokota et al., 2007; Yokota & Watanabe, 2002, for further details). This system has been successfully tested on burglary and sexual assault data. For example, Yokota and Watanabe (2002) extracted a target sample of 7,558 serial burglaries from a larger database containing 107,233 burglaries committed in Japan between 1993 and 1998 by 12,468 offenders. This target sample was submitted to the BISS to identify the degree of behavioural similarity between each target offence and the other offences within the larger database. These similarity coefficients were subsequently rank-ordered to determine whether the BISS had been able to successfully prioritise linked crimes. For 1,524 of the 7,558 target offences (20.16%) the highest ranked offence in the prioritised list was, indeed, committed by the same person. Furthermore, a linked crime was contained within the top 29 cases in the prioritised list for 50% of the target sample (3779 offences), which was a considerable achievement given that the prioritised list contained a total of 12,468 ranks. These findings suggest that the BISS may be able to reduce the time spent conducting BCL in practice. Nevertheless, there were notable instances where the BISS was unsuccessful, thereby leading to false positive and false negative errors[10].

Oatley, Ewart, and colleagues have also developed a decision support system that has a range of mapping and predictive capabilities, including the ability to identify potentially linked crimes using a variety of Bayesian and neural networks models (see Oatley & Ewart, 2003, for further details). Ewart, Oatley, and Burn (2005) tested the accuracy of three linkage algorithms contained within their decision support system[11]. Using a similar analytic strategy to Yokota and colleagues, they found that the algorithm combining behavioural, geographical, and temporal information was the most successful at identifying linked residential burglaries committed in the UK. Specifically, for 94% of the sample, the top 50 prioritised crimes produced using the combined algorithm contained a linked crime (compared to 62% for the behavioural algorithm and 53% for

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[10] A false positive error occurs when two crimes that were committed by different offenders are incorrectly labelled "linked", and a false negative error occurs when two linked crimes are labelled "unlinked".
[11] One algorithm utilised behavioural (MO) information only (this is the same algorithm used in the BISS), a second algorithm used geographical and temporal information (including temporal proximity, inter-crime distance, and the number of crimes committed), and a third algorithm combined the two approaches.

the geographical/temporal algorithm on their own). Likewise, a linked crime was within the top 30 crimes for 77% of the sample using the combined algorithm (the behavioural algorithm = 51% and the geographical/temporal algorithm = 52%). Given the size of the sample (n = 966 crimes), these findings are of potential practical value.

In summary, a range of studies have demonstrated that it is possible to develop complex computer packages that seem to perform well when tested in an experimental context. These findings further support the underlying theoretical assumptions of behavioural consistency and distinctiveness. As mentioned above, however, there are many other systems that cannot be reviewed here due to restricted space. The interested reader is referred to the work of Adderley and colleagues who have developed a BCL system that uses data mining techniques and neural networks (e.g., Adderley & Musgrove, 2003), Wang and colleagues who have proposed a system based on Shannon information theory (e.g., Wang & Lin, 2010), and the work of David Canter and colleagues who have developed a computerised system called the Interactive Offender Profiling System (IOPS), which can perform a range of decision support functions that are of relevance to law enforcement agencies, including BCL (e.g., Canter & Youngs, 2008).

1.3.4 A Summary of the Evidence on Behavioural Consistency, Distinctiveness, and Discrimination Accuracy

Within this chapter a range of empirical evidence relating to behavioural consistency, distinctiveness, and discrimination accuracy has been reviewed. Overall, there is evidence to suggest that many offenders demonstrate relative consistency and distinctiveness in their offending behaviour and that these patterns can be used to distinguish between linked and unlinked crimes to a level that is statistically significant. However, it is clear that certain types of offender behaviour show greater consistency/distinctiveness and, therefore, greater potential to support the practice of BCL than others. These findings have important practical implications because they suggest that law enforcement agencies should prioritise the use of certain behavioural features during BCL. Not only might this help to reduce the error rate associated with BCL (by helping analysts to avoid inappropriate linkage strategies), but it might save resources because law enforcement personnel could restrict the amount of behavioural evidence gathered/analysed during BCL (Bennell & Canter, 2002). However, the literature is not yet sufficiently developed for recommendations of this nature to be made.

Furthermore, it is important to note that some offenders do not behave in a consistent or distinctive manner when committing crime. Grubin et al. (2001), for example, reported that 17% of their sample was not consistent in any of the four sexual offence domains they examined. Furthermore, none of the studies using Bennell's methodology have reported AUC values that reach the theoretical maximum of 1.00 (thereby demonstrating errors in BCL). Also, automated BCL systems are associated with both false positive and false negative errors. One must, therefore, accept that there will always be a degree of error associated with BCL. The key question, though, is whether that degree of error is too large for it to be of practical use during a criminal investigation. The research reviewed in this chapter seems to suggest that BCL *does* have a potential practical value. But, there are a number of limitations associated with this research that must be addressed before reliable practical recommendations can be made to law enforcement agencies. The next section of this chapter will consider these limitations and the gaps that exist in the literature.

However, it is worth highlighting to the reader the research that has not been covered in this chapter due to the limitations of space. The following studies have adopted a miscellaneous range of approaches when examining behavioural consistency and/or distinctiveness, including the use of multidimensional scalogram analysis (MSA; see Canter et al., 1991; Mokros, 1999, cited in Canter, 2000), Bayesian analysis (Salo et al., 2012), fuzzy logic (Austin, 1996, cited in Grubin et al., 2001), and other approaches that do not fit neatly into a category (e.g., Bateman & Salfati, 2007; Beutler, Hinton, Crago, & Collier, 1995; Goodwill & Alison, 2006; Green, Booth, & Biderman, 1976; Guay, Proulx, Cusson, & Ouimet, 2001; Lundrigan, Czarnomski, & Wilson, 2010; Sjöstedt et al., 2004; Yokota-Sano & Watanabe, 1998).

1.4 The Limitations of Existing Research

Given that Bennell's methodology is currently the most common approach to BCL research (and will be utilised throughout this thesis), the limitations discussed in this section of the chapter will be organised in terms of Bennell's generic research process (see Figure 1C for a summary). However, many of the limitations discussed below are also relevant to research conducted using other methodological approaches. Where this is the case, it will be indicated.

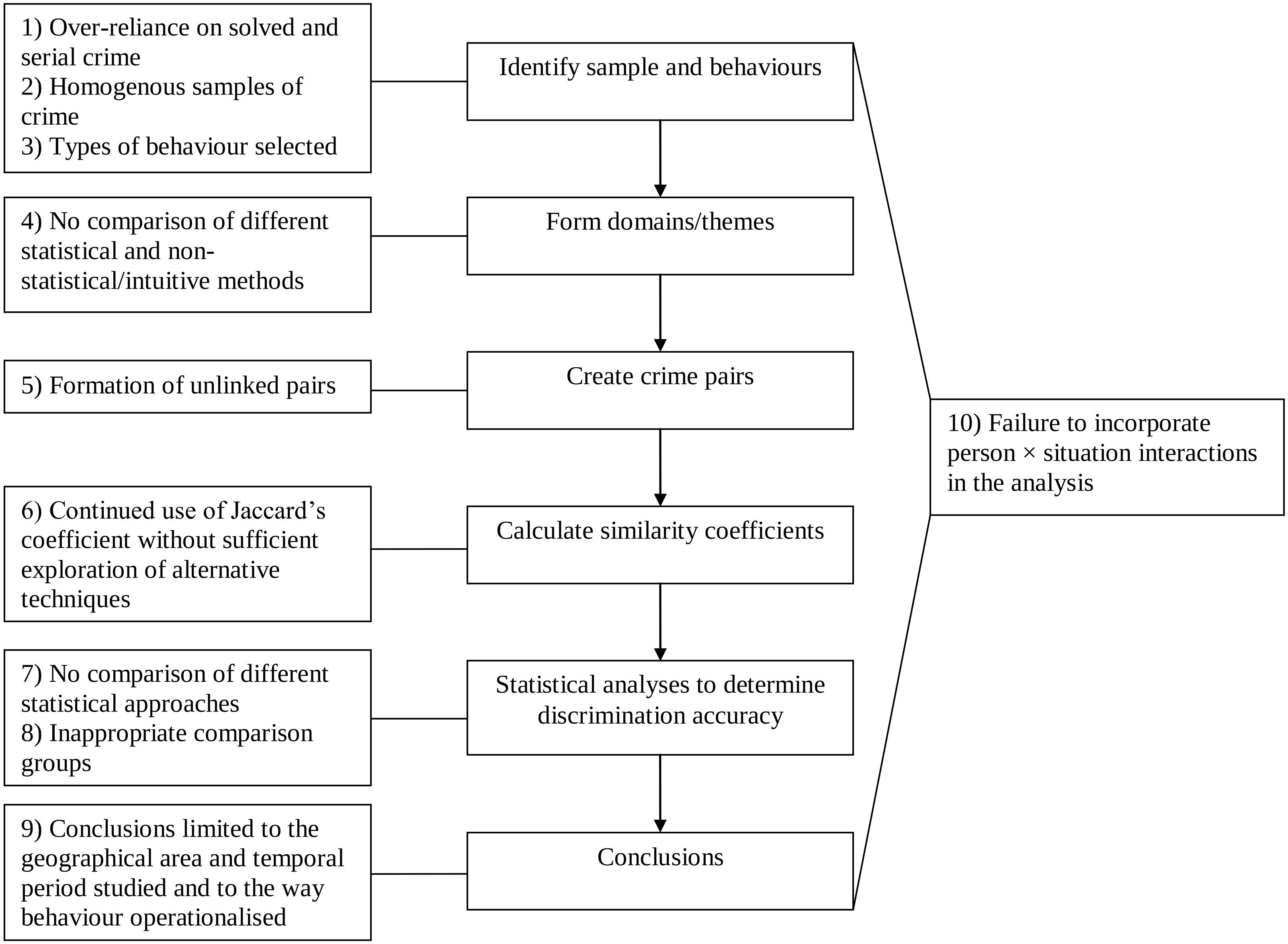

Figure 1C

Bennell's Generic Research Process and its Associated Limitations

The first stage for all research (regardless of methodology) is to select a sample of crimes for analysis. This stage is crucial because, unless the sample selected reflects the types of offence for which BCL is typically used in practice, the findings produced may not be relevant or useful. At best, inappropriate sample selection means that law enforcement agencies will not value BCL research; at worst, it risks misleading criminal investigations. Unfortunately, there are several aspects of sample selection that lead to questions regarding the validity of existing BCL findings. First, the vast majority of research has restricted its focus to samples of solved serial crime, which do not reflect the real life setting in which BCL is expected to perform (i.e., with both serial and non-serial offences that are unsolved; see Chapters 2 and 4; Bennell & Canter, 2002; Woodhams, Bull et al., 2007). Indeed, this is a limitation that spans the full range of methodologies discussed above, including the thematic approach (e.g., Santtila et al., 2005; Sorochinski & Salfati, 2010), Bennell's approach (e.g., Bennell & Canter, 2002; Tonkin et al., 2008; Woodhams & Toye, 2007), approaches that have tested automated BCL systems (e.g., Ewart et al., 2005; Yokota & Watanabe, 2002), and those that have adopted miscellaneous approaches to BCL research (e.g., Beutler et al., 1995; Canter et al., 1991; Goodwill & Alison, 2006; Sjöstedt et al., 2004). The use of solved crime is problematic because crime series may have been detected because they were committed in a highly consistent and/or distinctive manner (e.g., Bennell & Canter, 2002; Sorochinski & Salfati, 2010). Consequently, estimates of consistency, distinctiveness, and discrimination accuracy may be artificially inflated in samples of solved serial crime relative to what we might expect to see in live police investigations of unsolved serial crime (Bennell, 2002).

Fortunately, however, researchers have considered alternative methods of sample selection that might overcome this problem, including the use of unsolved crimes that have been linked as a series using physical evidence, such as DNA (Woodhams, Bull et al., 2007; Woodhams & Labuschagne, 2012), and by comparing series that were identified through behavioural similarity with those identified using physical evidence (Woodhams & Labuschagne, 2012). In terms of the latter, Woodhams and Labuschagne (2012) have recently demonstrated using a sample of serial sex offenders from South Africa that crime series identified through behavioural similarity are only marginally less consistent than those identified through physical evidence. These findings tentatively imply that findings from solved crime may be generalised to samples of unsolved crime. However, such findings must be replicated with different crime types and larger samples that allow more robust analyses to be conducted (Woodhams & Labuschagne, 2012). Indeed, this work is crucial if BCL research is to have a lasting impact on law enforcement practice. The current thesis will, therefore, explore behavioural consistency, distinctiveness, and discrimination accuracy using a sample that contains both solved and unsolved offences (see Chapter 4).

A second issue with sample selection is that, until recently, all previous studies of BCL have examined consistency, distinctiveness, and discrimination accuracy with samples of crime that are homogenous in terms of crime type (i.e., they contain only one type of crime, for example residential burglaries). This is despite the fact that many offenders (particularly the most prolific) do not restrict themselves to committing just one type of offence (see Chapter 4; Farrington et al., 1988; Piquero et al., 2007). Existing research does not, therefore, provide guidance for conducting BCL with series that contain several different types of crime. This is particularly problematic given recent evidence to suggest that law enforcement personnel are already attempting so-called cross-crime linkage (Burrell & Bull, 2011). This is a gap that must be filled if research wants to maximise its potential practical value. The current thesis will, therefore, explore the potential for cross-crime linkage using offender behaviour (see Chapter 4).

Having extracted a sample of crimes for analysis, the next stage of research is to identify those behaviours that might facilitate successful BCL. Some research has coded the data exactly as they are recorded on law enforcement databases (e.g., Bennell, 2002; Tonkin et al., 2008), which has the benefit of being ecologically valid, of immediate practical relevance, and simple. However, a full and complete psychological understanding of offenders it is not the primary aim of law enforcement. Consequently, law enforcement agencies may not categorise behaviour in the most *psychologically* appropriate way. For example, the police force studied by Tonkin et al. (2008) used a 12-category coding system to record the type of car stolen during a car theft (e.g., hatchback, saloon, estate, van, etc.). This system does not necessarily capture features such as engine size and anti-theft security measures, which may be of most relevance to a car thief when s/he is deciding whether to steal a car or not (e.g., Light, Nee, & Ingham, 1993; Spencer, 1992). Consequently, discrimination accuracy might be improved if the data were operationalised in a more appropriate manner. Indeed, Davies et al. (in press) recently demonstrated this point in their study of serial car theft. They found that a new target selection domain - consisting of whether the car theft was a car key burglary[12], whether the offender knew the victim, and whether an immobiliser was present - was able to achieve an AUC of 0.76, which was larger than that achieved using Tonkin et al.'s (2008) original target selection domain with the same data (AUC = 0.62). Furthermore, even when research has developed its own coding schemes for the purpose of BCL research (e.g., Woodhams, 2008), these studies

[12] A car key burglary is where the car keys are stolen during the course of a burglary and it appears that the primary purpose of breaking into the property was to steal a vehicle.

have still only tested one way of coding data. Thus, *all* of the extant BCL literature can be criticised for not exploring alternative ways of operationalising offender behaviour for the purposes of BCL analysis. Unless this issue is given greater attention, it will be difficult to make recommendations to prioritise the use of certain offence behaviours. Furthermore, researchers may risk inappropriately rejecting useful behavioural features.

The issues explored thus far have been concerned with how research currently selects offenders, crimes, and behaviours for analysis. The next stage of the research process is to cluster these crime scene behaviours into themes/domains. As discussed above, the thematic approach to BCL research uses statistical methods to cluster individual crime scene behaviours, whereas Bennell's methodology uses intuitive/non-statistical methods. At present, there has been no systematic attempt to compare these two research methodologies. Consequently, it is unclear which approach is the most appropriate, and it would seem illogical to advocate the use of one method over another until these issues have been thoroughly explored.

Having identified behavioural domains/themes, the next stage of BCL research is the formation of linked and unlinked crime pairs. In Bennell's methodology, the unlinked pairs act as a control group to which the linked pairs are compared in order to test the assumptions of behavioural consistency and distinctiveness. Thus, if the linked pairs are more behaviourally similar than the unlinked pairs this can be interpreted as evidence to support the underlying assumptions of BCL. The methodology used to form the unlinked pairs, therefore, has significant potential to influence the validity of BCL research. But, as explained by Woodhams (2008), there are both practical and statistical problems associated with the current method of forming the unlinked pairs, which involves randomly pairing crimes from the linked sample that are known to have been committed by different offenders. From a statistical perspective, this method means that the same crimes are used to form both the linked and unlinked crime pairs, which violates the assumption of statistical independence that is necessary for binary logistic regression analysis. (Although, it should be noted that ROC analysis overcomes this problem (Bennell, 2002)). From a practical perspective, the current method of forming the unlinked pairs leads to a sample consisting solely of serial offences (Bennell & Canter, 2002; Woodhams, 2008). This is problematic because in a real life setting law enforcement personnel would have to identify potentially linked crimes from a backdrop of both serial *and* non-serial crimes, which means that Bennell's approach to BCL research is not as realistic as it might be (Bennell, 2002; Tonkin, Santtila, & Bull, 2012; Woodhams & Labuschagne, 2012). This limitation also applies to research using different methodologies, which has excluded non-serial offences from their analyses too (e.g., Bateman & Salfati, 2007; Beutler et al., 1995; Lundrigan et al., 2010; Salfati & Bateman, 2005; Salo et al., 2012; Santtila, Fritzon et al., 2004; Santtila et al., 2005, 2008)[13]. Future research must, therefore, explore whether existing findings can be replicated using a more realistic approach that utilises an independent sample of serial and non-serial crimes to form the unlinked crime pairs (as suggested by Bennell, 2002). Research such as this will provide a much stronger evidence base from which to develop recommendations regarding BCL. The current thesis will, therefore, examine behavioural consistency, distinctiveness, and discrimination accuracy using a sample of serial and non-serial residential burglaries (see Chapter 2).

The next stage of BCL research is to calculate similarity coefficients that can be used to discriminate between linked and unlinked crimes. These coefficients are crucial because they form the basis of subsequent analyses that test discrimination accuracy and they may also form the basis of decision support tools that can support BCL in

[13] However, some studies have included both serial and non-serial offences in their tests of behavioural consistency, distinctiveness, and discrimination accuracy (e.g., Grubin et al., 2001; Woodhams, 2008; Yokota et al., 2007).

practice. In short, the statistical coefficient used by researchers and practitioners has the potential to impact considerably on the outcome of BCL (Bennell, Gauthier et al., 2010). However, despite the importance of this issue research has only recently begun to explore the variety of similarity coefficients that might potentially be used to quantify behavioural consistency/distinctiveness (see Bennell, Gauthier et al., 2010; Ellingwood et al., in press; Melnyk et al., 2011; Woodhams, Grant, & Price, 2007). But, this research is still at a very preliminary stage and there are a number of similarity coefficients yet to be explored (see Romesburg, 1984). Again, this issue must be addressed if researchers are to determine the most appropriate methodology for testing the underlying principles of BCL.

Once statistical measures of geographical, temporal, and behavioural similarity have been calculated, binary logistic regression analysis (or discriminant function analysis in the case of Santtila's methodology) is used to combine the various behavioural domains for the purposes of BCL. While logistic regression is suitable for this purpose, there are alternative statistical techniques that might be used at this stage of the research. Bennell, Woodhams, Beauregard, and Mugford (2011), for example, have recently suggested that classification tree analysis might enable more accurate, sensitive, and usable predictive models to be developed than those that are produced using logistic regression analysis (see Chapter 3). Furthermore, neural networks models and Bayesian analysis might also be useful given their success in previous studies of BCL (e.g., Adderley & Musgrove, 2003; Salo et al., 2012) and other similar areas of forensic psychology (e.g., Liu, Yang, Ramsay, Li, & Coid, 2011). It is, therefore, important to build a robust body of evidence on this issue before recommendations can be made and practical tools developed for the purposes of supporting BCL. The current thesis will build on the preliminary research of Bennell, Woodhams et al. (2011) by comparing binary logistic regression and classification tree analysis in terms of their ability to combine behavioural information for the purposes of BCL (see Chapter 3).

A further issue at this stage of the research process is that the vast majority of research (including research from the Bennell and thematic approaches, as well as research on automated BCL systems) has used chance as the benchmark for judging whether a particular statistical model/algorithm has the potential to support BCL. These studies assume that, if discrimination accuracy exceeds chance (e.g., an AUC of 0.50 or $p < 0.05$), it can be concluded that there is the potential for this model to support the linking of crime in practice. While this approach is justified from a statistical point of view and in terms of demonstrating support for the underlying principles of BCL, it is arguably more appropriate from a practical perspective to compare statistical models with the methods that are already available to law enforcement agencies (i.e., the discrimination accuracy achieved by law enforcement personnel who are responsible for conducting BCL in practice, such as crime analysts). Crime analysts often have considerable experience of crime, criminal behaviour and, specifically, BCL, so we might expect them to perform at a level that exceeds chance when linking crime. Thus, statistical models must be able to distinguish between linked and unlinked crimes at a level that is at least comparable to crime analysts if we are to conclude that they have a potential practical value. Despite the importance of this issue, there is only one study that has compared statistical approaches derived from research into BCL with human decision-making accuracy (Bennell, Bloomfield et al., 2010) and this study was associated with a number of limitations (see Chapter 5 for further details). Further work is, therefore, needed to examine the relative performance of statistical approaches and human decision-makers in mock BCL tasks. The current thesis will build on the preliminary work of Bennell, Bloomfield et al. (2010) by comparing students, crime analysts, and logistic regression models in terms of their ability to distinguish between linked and unlinked residential burglaries and commercial robberies (see Chapter 5).

The final stage in the BCL research process is to draw conclusions from the preceding analyses. However, it should be abundantly clear from the preceding discussion that any conclusions drawn from BCL research are necessarily limited to the methodology used, the sample selected, and the behaviours utilised. Furthermore, any findings are inherently tied to the geographical area and temporal period from which the data were sampled. This highlights the final limitation of existing research: the generalisability of findings. Unfortunately, this limitation can only be overcome by significant attempts to replicate existing research in new geographical areas and different temporal periods. Researchers should, however, adopt a systematic approach to this task, whereby geographical areas are specifically selected for study on the basis of factors that would be expected to impact BCL performance, such as population size, density and composition, and the availability of crime targets. Cross-national comparisons would, also, be particularly valuable. In the current thesis this issue was examined with a sample of residential burglaries from Finland and the findings compared with those previously obtained in the UK (see Chapter 2).

The limitations highlighted thus far are associated with particular components of BCL research, but there remains one final limitation that is associated with the whole approach to BCL research, rather than to one particular component. Specifically, Woodhams, Hollin, and Bull (2008a) have argued that the current approach to BCL research is yet to catch-up with the personality literature, which recognises that behaviour is the product of an interaction between the person and the situation (e.g., Mischel, 1999; Mischel & Shoda, 1995). They suggest that discrimination accuracy might be considerably improved if research were able to incorporate aspects of the person, the situation, and how they interact into BCL. Woodhams et al. (2008a) present a potential methodology for doing this (a linguistic computational program called Wordsmith©; Scott, 2004-2007), but the results using this procedure were somewhat limited. Nonetheless, the fundamental arguments they present are potentially very significant, and future research should attempt to develop ways of incorporating person × situation interactions in BCL research.

From the above critique, it is clear that there are many diverse limitations that threaten the validity of existing BCL research. However, it should also be clear that many of these limitations can be overcome (or at least addressed in some way). In summary, there seem to be three central concerns that researchers of BCL must address in the future:

1) Generalisability

The evidence for consistency, distinctiveness, and discrimination accuracy now extends across an impressive array of crimes, but the evidence that these findings are robust is sadly lacking. A primary concern is, therefore, to test whether existing findings can be reproduced in new geographical areas and different temporal periods. This work is essential if we are to build a robust body of evidence that can yield reliable practical recommendations regarding BCL.

2) Ecological validity

In several important respects, BCL research does not reflect the real life scenario in which linkage is conducted. This gap between research and practice must be addressed if the BCL literature is to have a lasting and valued impact on law enforcement practice.

3) Methodology

A fundamental limitation in the BCL literature is the lack of research comparing different methodological approaches, including how to develop domains/themes of offence behaviour, how to quantify consistency/distinctiveness, and how to combine different domains for the purpose of BCL. Unless research begins to address such gaps in the literature, existing findings will be limited in terms of their practical and theoretical value. From a practical perspective, researchers cannot make clear recommendations regarding BCL unless they have identified the most appropriate way of examining behavioural consistency, distinctiveness, and discrimination accuracy. From a theoretical perspective, the research literature will remain fragmented and there will be no methodological consensus until different statistical approaches have been systematically compared.

1.5 The Aims of this Thesis

The main aim of this thesis is to address the three fundamental limitations of BCL research that were highlighted above. While it is not possible in a project of this size to address all of the limitations highlighted in Section 1.4, an attempt will be made to at least partially address issues from each of the three groupings (generalisability; ecological validity; and methodology). By doing so, the current thesis hopes to move the BCL literature forward on at least these three key fronts.

In Chapter 2, a sample of residential burglaries from Finland will be used to investigate behavioural consistency, distinctiveness, and discrimination accuracy. This research will test whether the existing UK-based research can generalise to a country that is considerably different in terms of population demographics, crime patterns, and law enforcement practice. Furthermore, these data will be used to explore an important methodological issue by comparing Bennell's original approach to forming the unlinked crime pairs with an alternative methodology that uses an independent sample of crimes containing both serial and non-serial offences (as discussed above). Chapter 2 will, therefore, address the generalisability and ecological validity of existing research, whilst also exploring how methodological changes impact on the outcome of BCL research.

Chapter 3 will continue the exploration of methodology by comparing two different approaches to combining offence data for the purposes of BCL; the traditional approach of binary logistic regression analysis and a new approach, classification tree analysis. The sample of Finnish residential burglaries from Chapter 2 and a new sample of serial car thefts will be used for this purpose, thereby testing whether previous research can generalise across crime types and across geographical locations.

In Chapter 4, two studies will be reported that investigate for the first time whether aspects of offender behaviour can be used to support BCL across crime categories and crime types, as well as within crime types (the latter being the 'traditional' way in which BCL has been investigated). The first study will examine cross-crime linkage using a sample of solved offences and the second study will attempt to replicate these findings with a sample containing both solved and unsolved offences that have been linked via DNA evidence. This will provide one of the most ecologically valid tests of BCL conducted to date. Furthermore, it will provide law enforcement agencies with guidance on how to conduct BCL with versatile serial offenders, which (at present) is lacking.

The final empirical chapter, Chapter 5, will compare the discrimination accuracy of crime analysts who have extensive practical experience of BCL, university students who do not have such experience, and three logistic regression models that have been derived from previous research. These findings will help to determine whether existing BCL research truly has the potential to improve existing law enforcement practice. This chapter will also explore whether the findings generalise across different types of crime (residential burglary and commercial robbery) and whether simple training can improve human decision-making accuracy in (mock) linkage tasks.

The final chapter will draw together the theoretical and practical implications of this thesis, discuss the limitations of the new research presented herein, and delineate future research directions.

CHAPTER 2

BEHAVIOURAL CASE LINKAGE WITH RESIDENTIAL BURGLARY: TESTING RESEARCH CROSS-NATIONALLY AND EXPLORING METHODOLOGY[14]

2.1 Introduction

Chapter 1 introduced BCL as a growing area of applied research and an area of practical interest to the police. The extant research was reviewed and three central concerns identified:

1) Generalisability
2) Ecological validity
3) Methodology

These three central concerns summarise many of the limitations that exist within the BCL literature and are proposed as offering a potential roadmap for future research. The current chapter will, therefore, take some steps towards addressing each of these issues. But, first, some of the literature that is particularly pertinent to the issues addressed in this chapter will be reviewed.

2.1.1 Previous Behavioural Case Linkage Research with Residential Burglary

[14] As stated on pages 3 and 4, a version of this chapter has been published as Tonkin, Santtila, and Bull (2012).

A number of studies now exist that have examined BCL using residential burglary data (e.g., Bennell & Jones, 2005; Ewart et al., 2005; Goodwill & Alison, 2006; Markson et al., 2010). This research has found that certain offender behaviours demonstrate sufficient consistency and distinctiveness to allow linked crimes to be reliably distinguished from unlinked crimes. The kilometre-distance between offence locations (inter-crime distance) has been particularly successful in this task, with inter-crime distance outperforming target characteristics, entry behaviours, internal behaviours (such as offender search behaviour), and property stolen when differentiating between linked and unlinked burglaries. These findings have been shown to replicate in various locations within the UK (Bennell, 2002; Bennell & Jones, 2005; Markson et al., 2010).

The number of days separating burglaries (temporal proximity) has also been shown to reliably differentiate between linked and unlinked crimes (Markson et al., 2010). In Markson and colleagues' study, the temporal proximity achieved a higher level of discrimination accuracy than target, entry, internal, and property behaviours, and the combination of inter-crime distance and temporal proximity was able to facilitate the greatest level of discrimination accuracy (AUC = 0.95). These findings are corroborated by other UK studies that have utilised different methodologies (Ewart et al., 2005; Goodwill & Alison, 2006).

However, the extant BCL literature on burglary is restricted to samples from the UK, thus it is unclear whether these findings will generalise to other countries. Indeed, different countries can be expected to vary in terms of physical and social geography, the availability, type and distribution of potential targets, and approaches to policing and data recording/storage; all of which might impact on discrimination accuracy in the linkage task. Some of these differences are briefly reviewed below, with particular focus on differences between the UK and Finland that are relevant to burglary.

2.1.2 Cross-National Differences between the UK and Finland

The UK and Finland differ substantially in terms of population density, with Finland averaging approximately 16 persons per square kilometre compared to 255.60 persons per square kilometre in the UK[15]. Housing is, therefore, much more dispersed in Finland than the UK, which would be expected to impact considerably on offender spatial behaviour such as journey-to-crime and inter-crime distance.

There are also differences between the UK and Finland in terms of housing. The predominant type of residential accommodation in the UK is a house (80.00% of households in 2010), whereas in Finland the majority of housing is split across two types (43.60% are flats and 40.60% detached housing in 2010). The slightly wider variation in housing that is evident in Finland might impact on offender consistency and distinctiveness because there would be more scope for offenders to target different types of house and they may need to employ a wider range of entry behaviours. This would allow for between-offender differences in burglary behaviour to emerge more readily among Finnish than UK offenders. It might, therefore, be hypothesised that discrimination accuracy for target and entry behaviours would be enhanced in a Finnish compared to a UK sample.

Also, it is not unreasonable to suggest that police forces in Finland will differ from those in the UK in terms of how they record information about burglary crime. There may be additional behaviours recorded in Finland that are not recorded in the

[8] All statistics included in Section 2.1.2 were obtained from:
http://en.wikipedia.org/wiki/Finland
http://en.wikipedia.org/wiki/United_Kingdom
http://www.tilastokeskus.fi/tup/suoluk/suoluk_asuminen_en.html#dwellingunits
http://www.communities.gov.uk/documents/statistics/pdf/2084179.pdf

UK, for example, or the same behaviours may be recorded in different ways. Differences such as these have the potential to impact on discrimination accuracy.

2.1.3 Methodology in Behavioural Case Linkage Research

As discussed in Chapter 1, much of the research on BCL has followed a methodology originally proposed by Bennell (2002), and a number of recent studies have begun to explore how this methodology might be improved. For example, research has investigated the most appropriate statistical measures of consistency and distinctiveness (e.g., Bennell, Gauthier et al., 2010) and whether alternative approaches to forming the linked and unlinked pairs might be utilised. In terms of the latter, Woodhams (2008) has been argued that the current approach to forming the unlinked crime pairs in Bennell's methodology may be problematic for several reasons. First, such an approach will lead to the assumption of statistical independence becoming violated during logistic regression (Bennell, 2002; Woodhams, 2008). The impact of violating this assumption is that the confidence interval is spuriously inflated and the subsequent *p*-value of any statistical test diminished (Hopkins, 2001). Consequently, the statistical significance of certain offender behaviours may have been underestimated in previous research, thereby leading to them being rejected inappropriately.

Another issue is that the current methodology leads to a sample consisting solely of serial offences, which is not representative of the real life scenario in which BCL is expected to perform, where crime analysts must distinguish linked crimes from a backdrop of both serial and non-serial offences (Bennell & Canter, 2002; Woodhams, 2008). This leads one to question the applied value of existing BCL research.

2.1.4 Aims of the Current Chapter

The current chapter aimed to explore whether existing BCL findings for residential burglary in the UK would replicate cross-nationally with a sample of Finnish burglaries. Based on previous research, it was hypothesised that inter-crime distance and temporal proximity would achieve the highest levels of discrimination accuracy. However, it was also predicted that target and entry behaviours would perform more successfully than they have in previous UK-based research. The analyses were initially conducted using Bennell's (2002) original methodology to ensure comparability with previous research, but they were also conducted using an alternative methodology. This alternative formed the unlinked pairs from a statistically independent sample of serial and non-serial crimes. The findings produced using these two methodologies were compared to determine whether there was any impact on the conclusions of BCL research. Given the paucity of research in this area it was not possible to make specific predictions in this regard.

2.2 Method

2.2.1 Data

All data described in this chapter were provided by Professor Pekka Santtila, who is Professor of Applied Psychology at Åbo Akademi University, a senior lecturer in police psychology at the Police College of Finland, and lecturer in forensic and investigative psychology at the University of Turku.

To facilitate the replication aspect of this study, 234 solved residential burglary crimes committed by 117 serial burglars in the Greater Helsinki region of Finland[16] (between 1990 and 2001) were extracted from a dataset that had been established during a previous project (Laukkanen, Santtila, Jern, & Sandnabba, 2008; Santtila, Ritvanen, & Mokros, 2004). The 234 crimes represented a random selection of solved residential burglary crimes committed during this period. These data were originally collected to facilitate an investigation of offender and geographical profiling in Finland. Two offences were randomly selected from the series of each offender, which was necessary to prevent highly prolific offenders with unusually consistent or inconsistent offence behaviour having an undue influence on the findings (Bennell, 2002). This dataset is referred to as dataset one.

To facilitate the analysis of methodology, 508 serial and non-serial burglaries were extracted from the original dataset (Laukkanen et al., 2008; Santtila, Ritvanen et al., 2004). These 508 burglaries were referred to as dataset two. None of the crimes in dataset two were included in dataset one, so the two datasets can be considered statistically independent. Serial burglaries may be more common in jurisdictions than non-serial burglaries (Bennell & Canter, 2002; Goodwill & Alison, 2006). Consequently, the 508 crimes in dataset two contained a disproportionate number of serial to non-serial burglaries. In the absence of any published literature to suggest exactly how disproportionate serial and non-serial burglaries are in real life, a ratio of approximately 3:1 was used. It was hoped that this approach would enable a more ecologically valid test of behavioural consistency, distinctiveness, and discrimination accuracy.

[16] The greater Helsinki region of Finland covers an area of approximately 815 km^2 that contains the capital of Finland, Helsinki, and the neighbouring cities of Espoo and Vantaa.

For each of the crimes in these two datasets a range of behavioural data existed, including the location of the crime (*x, y* coordinates indicating the offence location to the nearest metre), the date the crime was committed (in many cases this was the mid-point between an "earliest crime date" and a "latest crime date" because the exact offence time was unknown, which is not unusual for burglary crime; Ratcliffe, 2002), the type of property burgled, the method of entry, the search behaviour, and the type and cost of the items stolen (see Appendix 1 for a full list of behavioural data included in this study).

Apart from the location and temporal information, the data were stored in a binary format (1 = present in the crime; 0 = absent). The use of binary data is consistent with previous BCL literature and is justified by findings suggesting that more complex coding schemes are unreliable with police data (Canter & Heritage, 1990). Satisfactory inter-rater reliability has been reported for the larger dataset from which the current data were selected (*Mdn* case-by-case $\kappa = 0.78$ and *Mdn* variable-by-variable $\kappa = 0.88$; Santtila, Ritvanen et al., 2004).

2.2.2 Procedure

The offence behaviours were first grouped into behavioural domains that contained behaviours that either served a similar function during the offence (e.g., they facilitated entry into the property), or that occurred at a similar stage of the offence (e.g., they occurred at the start of the offence when a burglar was selecting the target), or that represented one 'type' of offender behaviour (e.g., spatial behaviour) (see Appendix 1 for a full listing of which behaviours comprised each domain). Seven behavioural domains were created: (1) Target Characteristics (e.g., the type of property burgled);

(2) Entry Behaviours (e.g., the point and method of entry); (3) Internal Behaviours (e.g., search behaviour); (4) Property Stolen (e.g., cash, keys etc.); (5) Inter-crime Distance; (6) Temporal Proximity; (7) A combined behavioural domain, which included all behaviours in the target, entry, internal, and property domains. These domains were derived from previous BCL studies on burglary and the behaviours were placed into domains according to previous research (Bennell, 2002; Markson et al., 2010).

Pairs of crimes were then created from the two burglary datasets. Initially, 117 linked crime pairs were created from dataset one (one for each offender). Each pair contained two crimes committed by the same offender that were taken randomly from each offender’s series. One-hundred-and-seventeen unlinked crime pairs were then created from dataset one, with each pair containing two crimes committed by different offenders. Finally, a further set of 117 unlinked pairs were created from dataset two by randomly pairing two crimes that were known to have been committed by different offenders.

Having created these crime pairs, each group of pairs (linked dataset one; unlinked dataset one; and unlinked dataset two) was split into two halves to form a ‘training’ sample (containing 58 crime pairs per dataset) and a ‘test’ sample (containing 59 crime pairs per dataset). It should be noted that the larger number of pairs in the test samples is due to there being an uneven number of offenders. The training and test samples created from linked dataset one and unlinked dataset one were used to examine discrimination accuracy using Bennell’s (2002) original methodology. The training and test samples created from linked dataset one and unlinked dataset two were used to test discrimination accuracy using a new methodology that addresses statistical and practical issues associated with Bennell's (2002) existing approach (as discussed in Section 2.1.3).

The procedure of splitting data into training and test samples is known as split-half validation (Efron, 1982; Gong, 1986), and is discussed by Bennell and colleagues as a way of reducing the potential bias that might arise from developing and testing linkage models on the same sample (e.g., Bennell & Jones, 2005).

2.2.3 Data Analysis

The first stage of analysis was to calculate the degree of behavioural similarity between the linked and unlinked crime pairs. To achieve this, Jaccard's coefficient was used, which ranges from 0 (indicating no behavioural similarity) to 1.00 (indicating complete behavioural similarity). This coefficient has been favoured among BCL researchers because joint non-occurrences — when a given behaviour is absent from both crimes in a pair — do not contribute to the value of the Jaccard's coefficient (Bennell & Canter, 2002). This is preferable when working with police data, as the 'absence' of a particular behaviour from the crime report may not necessarily mean that the offender did not display that behaviour (Woodhams & Toye, 2007). Jaccard's coefficients were calculated for each crime pair in terms of target, entry, internal, and property behaviours separately, as well as for the combination of these behaviours. In addition to this, the kilometre-distance and number of days between the two crimes in each pair were calculated.

The potential value of these seven measures of offender behaviour for distinguishing between linked and unlinked crimes was assessed using logistic regression and ROC analysis (e.g., Bennell, 2002). In order to test the cross-national replicability of BCL research, seven direct logistic regression analyses were conducted on the linked and unlinked training samples from dataset one (one regression for each of the seven linkage features) with linkage status (linked versus unlinked) as the dependent variable and the linkage features as the independent variables. These analyses allowed the discrimination accuracy of each linkage feature to be judged independently from the others (Woodhams & Toye, 2007). A forward stepwise logistic regression was then conducted, where all linkage features were entered into the model, thus allowing the optimal combination of features to be identified (Bennell & Canter, 2002). However, the combined domain was not included in the stepwise analysis because this domain was comprised of a combination of behaviours from the target, entry, internal and property domains. Consequently, the inclusion of this variable in the same regression model as the other domains would risk violating the assumption of multicollinearity, which can lead to reduced *p*-values, incorrect regression coefficients and, ultimately, to incorrect conclusions (Field, 2005). Furthermore, the decision to exclude the combined domain was consistent with previous research (e.g., Bennell, 2002), which is important given that one of the primary aims of the current study was to replicate previous work.

Having developed regression models on the training samples from dataset one, these same models were used to produce predicted probabilities (ranging from 0 to 1) for each crime pair in the linked and unlinked test samples from dataset one (Bennell & Canter, 2002). These values indicated the predicted probability that the two crimes in each pair were linked (the higher the probability score, the more likely the model was to classify a crime pair as linked). To calculate these predicted probabilities, first, the log odds were calculated using Equation 1.

$$\text{Log odds} = \text{Constant} + (\text{logit change}_1 \times \text{similarity coefficient}_1) + (\text{logit change}_2 \times \text{similarity coefficient}_2) + \ldots + (\text{logit change}_n \times \text{similarity coefficient}_n) \tag{1}$$

In this equation the constant and logit change values were taken directly from the logistic regression analyses described above and the similarity coefficient represented the Jaccard's scores, inter-crime distance, or temporal proximity values in the corresponding test sample. These log odds were then transformed into odds by exponentiating them (see Equation 2).

$$\text{Odds} = e^{\text{Log odds}} \tag{2}$$

These odds were then transformed into a predicted probability value using Equation 3.

$$\text{p(linked)} = \text{odds}/(1+\text{odds}) \tag{3}$$

These predicted probabilities were then used as the test variables and linkage status (linked, unlinked) as the state variable to produce ROC curves for each of the seven single-feature behavioural domains and for the optimal combination of domains, as identified by the stepwise logistic regression.

As discussed in Chapter 1, the AUC provides a measure of discrimination accuracy, which can range from 0 (indicating perfect negative prediction) to 1 (indicating perfect positive prediction), with a value of 0.5 indicating a chance level of accuracy (Bennell & Jones, 2005). AUC values of 0.50 to 0.70 are described as a low level of discriminative accuracy, values of 0.70 to 0.90 are moderate, and values of 0.90 to 1.00 are high (Swets, 1988). The regression statistics and AUC values were compared visually with those obtained in previous UK-based burglary studies to allow the cross-national replicability of BCL findings to be examined. Cross-validation was examined by comparing the AUC values obtained for the training sample with those obtained for the test sample using a statistical package called ROCKIT 0.9B © (University of Chicago, Chicago, IL, United States). This package has been used in a number of previous studies of BCL (Bennell & Canter, 2002; Bennell & Jones, 2005; Woodhams & Toye, 2007).

To explore the impact of using a statistically independent sample of serial and non-serial burglaries to form the unlinked pairs, the same regression and ROC analyses were run using the linked pairs from dataset one and the unlinked pairs formed from dataset two. The regression statistics obtained from the first set of analyses were then compared visually with these analyses and the AUCs compared statistically using ROCKIT. Any differences suggested that the choice of methodology impacts on BCL findings.

2.3 Results

2.3.1 A Cross-National Replication of UK-Based Burglary Research on Behavioural Case Linkage

The results from seven direct logistic regression analyses using linked and unlinked pairs from dataset one are summarised in Table 2A. A degree of success was evident for all seven models of offence behaviour, although some models clearly outperformed others. The most successful single-feature models were for inter-crime distance, followed by the combined domain, then temporal proximity. These models all had highly significant model χ^2 values and Wald statistics ($p < 0.001$), with between 24% and 57% of the variability in linkage status explained individually by each of these three behavioural domains (Brace, Kemp, & Snelgar, 2003; Kinnear & Gray, 2000). Furthermore, all three models offered an improvement in predictive accuracy above the level one would expect through chance[17], with each model offering an approximate 21% to 26% improvement (see Table 2B). In contrast to these models, however, the target, entry, and internal models performed less favourably. These models explained between 11% and 25% of the variability in linkage status and offered an approximate 15% improvement in predictive accuracy above chance. The poorest performance was for the property domain, with just 5% to 6% of the variability accounted for by this model and a 6% improvement in predictive accuracy.

The signs of the logit change coefficients indicated that linked crimes were characterised by greater behavioural similarity in terms of combined, target, entry, internal, and property behaviours and shorter inter-crime distance and temporal proximity values than unlinked crimes.

To determine whether these individual domains could be combined to produce superior discriminative performance, a forward stepwise logistic regression was conducted. The stepwise regression proceeded through three steps before it converged on a final model. The final model (referred to as stepwise 1 in Tables 2A and 2B)

[17] Chance is calculated by assigning each crime pair to the predictive category (linked or unlinked) in which most cases fell (Field, 2009). In most instances, there was an equal number of linked versus unlinked crime pairs in the current sample, which led to a 50% chance level of predictive accuracy.

contained three domains (inter-crime distance, temporal proximity, and target characteristics), which accounted for between 56% and 75% of the variance in linkage status and facilitated an improvement in predictive accuracy of almost 30% above chance (see Tables 2A and 2B). These results indicate that stepwise model 1 was superior to any of the single-feature regression models in terms of discriminative performance.

Table 2A

Nine Logistic Regression Models for a Sample of Finnish Burglars: Bennell's (2002) Methodology

Model	Constant (*SE*) [a]	Logit Change (*SE*) [a]	χ^2 (df)	Wald (df)	R^2 (Cox & Snell-Nagelkerke)
Combined	-2.98 (0.651)	9.57 (2.03)	35.68 (1)***	22.13 (1)***	0.27 – 0.35
Target	-0.939 (0.286)	2.96 (0.705)	23.99 (1)***	17.61 (1)***	0.19 – 0.25
Entry	-1.17 (0.333)	3.14 (0.744)	22.37 (1)***	17.80 (1)***	0.18 – 0.23
Internal	-1.14 (0.389)	2.86 (0.865)	12.97 (1)***	10.93 (1)**	0.11 – 0.14
Property	-0.764 (0.385)	2.89 (1.27)	5.48 (1)*	5.14 (1)*	0.05 – 0.06
Inter-crime Distance	2.19 (0.512)	-0.320 (0.0628)	54.77 (1)***	25.95 (1)***	0.43 – 0.57
Temporal Proximity	1.01 (0.279)	-0.00148 (0.000325)	31.96 (1)***	20.59 (1)***	0.24 – 0.32
Stepwise 1	1.80 (0.690)		80.41 (3)***		0.56 – 0.75
Inter-crime		-0.242 (0.0679)		12.68 (1)***	
Temporal		-0.00219 (0.000717)		9.31 (1)**	
Target		4.65 (1.60)		8.44 (1)**	
Stepwise 2	2.77 (0.602)		67.62 (2)***		0.50 – 0.67
Inter-crime		-0.257 (0.0633)		16.51 (1)***	
Temporal		-0.00163		8.39 (1)**	

		(0.000562)			

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

[a] It should be noted that the constant and logit change values and their standard errors are reported to three significant figures throughout this thesis to provide the necessary level of precision should future researchers/practitioners choose to utilise these logistic regression models to derive linkage predictions.

It should be noted that a model combining inter-crime distance and temporal proximity was able to perform at a similar level to stepwise model 1 in terms of predictive accuracy and the percentage of variance explained (see stepwise 2 in Tables 2A and 2B below).

Table 2B

Predictive Accuracy of the Models (%): Bennell's (2002) Methodology

	Random	**Model**
Combined	50.00	75.90
Target	50.00	65.50
Entry	50.00	66.40
Internal	50.00	65.50
Property	50.00	56.00
Inter-crime Distance	58.60	79.80
Temporal Proximity	50.00	73.30
Stepwise 1	58.60	86.90
Stepwise 2	58.60	85.90

To facilitate further comparisons, nine empirical ROC curves were produced (one for each of the seven single-feature regression models and two for the stepwise regression models). The results are summarised in Table 2C.

The ROC results are largely consistent with those obtained from the logistic regression analyses, with inter-crime distance and temporal proximity achieving significantly larger AUC values than the other domains tested ($p < 0.05$, except for the comparison between temporal proximity and target behaviour, which was non-significant). Also, the stepwise models achieved significantly larger AUC values than all of the single-feature models ($p < 0.05$), except inter-crime distance and temporal proximity where the comparisons were non-significant.

To determine whether these findings could be successfully cross-validated, the ROC analyses were re-run using the training sample (see Table 2D) and compared statistically with those obtained using the test sample (see Table 2C). There were no statistically significant differences in terms of the AUC statistics ($p > 0.05$), which indicates that the findings have been successfully cross-validated.

Table 2C

Summary of the Receiver Operating Characteristic (ROC) Analyses with the Test Sample: Bennell's (2002) Methodology

Model	**AUC (*SE*)**	**95% Confidence Interval**	**Classification Category**
Combined	0.72 (0.05)***	0.63 – 0.81	Moderate
Target	0.73 (0.05)***	0.64 – 0.82	Moderate
Entry	0.66 (0.05)**	0.56 – 0.76	Low
Internal	0.66 (0.05)**	0.56 – 0.76	Low
Property	0.58 (0.05)	0.48 – 0.69	Low
Inter-crime Distance	0.84 (0.04)***	0.75 – 0.93	Moderate
Temporal Proximity	0.82 (0.04)***	0.74 – 0.90	Moderate
Stepwise 1	0.86 (0.04)***	0.78 – 0.93	Moderate
Stepwise 2	0.86 (0.04)***	0.79 – 0.94	Moderate

** $p < 0.01$; *** $p < 0.001$

Note. AUC = Area Under the Curve

Classification categories are according to Swets (1988), where an AUC value of 0.50 to 0.70 is low, 0.70 to 0.90 is moderate, and 0.90 to 1.00 is high.

Table 2D

Summary of the Receiver Operating Characteristic (ROC) Analyses with the Training Sample: Bennell's (2002) Methodology

Model	**AUC (*SE*)**	**95% Confidence Interval**	**Classification Category**
Combined	0.81 (0.04)***	0.73 – 0.90	Moderate

Target	0.74 (0.05)***	0.65 – 0.83	Moderate
Entry	0.74 (0.05)***	0.65 – 0.83	Moderate
Internal	0.68 (0.05)***	0.58 – 0.78	Low
Property	0.63 (0.05)*	0.53 – 0.73	Low
Inter-crime Distance	0.90 (0.03)***	0.84 – 0.96	High
Temporal Proximity	0.85 (0.04)***	0.78 – 0.92	Moderate
Stepwise 1	0.95 (0.02)***	0.91 – 0.99	High
Stepwise 2	0.93 (0.03)***	0.88 – 0.98	High

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Note. AUC = Area Under the Curve

Classification categories are according to Swets (1988), where an AUC value of 0.50 to 0.70 is low, 0.70 to 0.90 is moderate, and 0.90 to 1.00 is high.

2.3.2 The Impact of Methodological Variation in Behavioural Case Linkage Research

In this section, Bennell's (2002) original methodology was altered by forming the unlinked pairs from an independent sample of serial and non-serial burglaries (dataset two). This provided a more ecologically valid test of behavioural consistency, distinctiveness, and discrimination accuracy.

The findings from seven direct logistic regression analyses using linked pairs from dataset one and unlinked pairs from dataset two are summarised in Tables 2E and 2F. When these findings are compared with those obtained using Bennell's (2002) original methodology (as presented in Section 2.3.1 above), we see that there is a trend towards reduced discrimination accuracy when non-serial burglaries are included in the analyses, with less substantial model χ^2, Wald, and R^2 statistics for all domains except the target domain. But, the magnitude of these differences is small. Indeed, when the predictive accuracies from these two analyses are compared (Tables 2B and 2F) none of the domains differ by more than 5.20%.

A forward stepwise logistic regression was conducted to facilitate further comparisons. The stepwise regression proceeded through the same previous three steps before converging on a final model, which contained the same domains (target, inter-crime distance, and temporal proximity). The only difference was in terms of the performance of the stepwise models, whereby a slightly reduced performance was observed with dataset two compared to those presented in Section 2.3.1 with dataset one (as indicated by the model χ^2, Wald, and R^2 statistics). However, it should be noted that the predictive accuracies in Tables 2B and 2F indicate an improved rather than a reduced performance. The reason for this contradiction is probably due to the way in which these measures of model performance are calculated (Field, 2005).

Table 2E

Nine Logistic Regression Models for a Sample of Finnish Burglars: New Methodology

Model	**Constant (*SE*)**	**Logit Change (*SE*)**	**χ^2 (df)**	**Wald (df)**	**R^2 (Cox & Snell-Nagelkerke)**
Combined	-2.52 (0.599)	7.80 (1.77)	27.88 (1)***	19.43 (1)***	0.21 – 0.29
Target	-0.975 (0.285)	3.18 (0.730)	26.79 (1)***	19.02 (1)***	0.21 – 0.28
Entry	-1.02 (0.329)	2.60 (0.688)	16.83 (1)***	14.33 (1)***	0.14 – 0.18
Internal	-1.09 (0.390)	2.69 (0.854)	11.55 (1)**	9.91 (1)**	0.10 – 0.13
Property	-0.545 (0.383)	1.99 (1.22)	2.73 (1)	2.64 (1)	0.02 – 0.03
Inter-crime	1.73 (0.445)	-0.247	36.23 (1)***	19.16 (1)***	0.34 – 0.46

Distance		(0.0565)			
Temporal Proximity	0.929 (0.273)	-0.00140 (0.000334)	28.97 (1)***	17.71 (1)***	0.22 – 0.30
Stepwise 1	2.13 (0.746)		68.02 (3)***		0.55 – 0.73
Inter-crime		-0.243 (0.0649)		14.00 (1)***	
Temporal		-0.00205 (0.000680)		9.08 (1)**	
Target		3.74 (1.36)		7.57 (1)**	
Stepwise 2	2.93 (0.649)		58.16 (2)***		0.49 – 0.66
Inter-crime		-0.228 (0.0596)		14.56 (1)***	
Temporal		-0.00203 (0.000608)		11.16 (1)**	

** $p < 0.01$; *** $p < 0.001$

Table 2F

Predictive Accuracy of the Models (%): New Methodology

	Random	**Model**
Combined	50.00	70.70
Target	50.00	67.20
Entry	50.00	66.40
Internal	50.00	61.20
Property	50.00	56.90
Inter-crime Distance	52.30	76.70
Temporal Proximity	50.00	74.10
Stepwise 1	52.30	87.20
Stepwise 2	52.30	87.20

The analyses thus far indicate that minor differences exist as a function of how the unlinked pairs are formed. To further examine this issue, nine empirical ROC curves were created as before (see Table 2G) and the findings compared with those produced using Bennell's (2002) original methodology (see Table 2C). There were no significant differences in terms of the AUC statistics produced in the two sets of analysis ($p > 0.05$)[18].

[18] It should be noted that the findings produced using the new methodology in this study were successfully cross-validated, as indicated by non-significant differences ($p > 0.05$) between the AUC statistics produced using the relevant training and test samples. However, the AUC statistics for the training sample are not presented due to the limits on space (as imposed by University regulations).

Table 2G

Summary of the Receiver Operating Characteristic (ROC) Analyses: New Methodology

Model	**AUC (*SE*)**	**95% Confidence Interval**	**Classification Category**
Combined	0.73 (0.05)***	0.64 – 0.82	Moderate
Target	0.71 (0.05)***	0.61 – 0.80	Moderate
Entry	0.66 (0.05)**	0.56 – 0.76	Low
Internal	0.72 (0.05)***	0.63 – 0.81	Moderate
Property	0.55 (0.05)	0.44 – 0.66	Low
Inter-crime Distance	0.85 (0.04)***	0.76 – 0.93	Moderate
Temporal Proximity	0.82 (0.04)***	0.74 – 0.90	Moderate
Stepwise 1	0.88 (0.04)***	0.81 – 0.95	Moderate
Stepwise 2	0.89 (0.03)***	0.82 – 0.96	Moderate

** $p < 0.01$; *** $p < 0.001$

Note. AUC = Area Under the Curve

Classification categories are according to Swets (1988), where an AUC value of 0.50 to 0.70 is low, 0.70 to 0.90 is moderate, and 0.90 to 1.00 is high.

2.4 Discussion

The analyses reported in this chapter addressed three key limitations of the BCL literature. First, the sole focus on samples of burglary from the UK was addressed by examining a sample of burglaries from Finland. There was evidence to suggest that a range of offender behaviours can be used to distinguish between linked and unlinked crimes, with the most successful being inter-crime distance, temporal proximity, and the combined domain. These findings are consistent with previous research that has shown the value of inter-crime distance and temporal proximity for linking burglary crimes committed in the UK (e.g., Bennell, 2002; Bennell & Canter, 2002; Ewart et al., 2005; Goodwill & Alison, 2006; Markson et al., 2010).

However, the magnitude of discrimination accuracy in the current study was larger for the combined, target, entry, and internal domains than in UK-based research. Most notably, the combined and target domains both achieved AUC values in excess of 0.70, which indicates a moderate degree of discrimination accuracy (Swets, 1988). In previous work the AUC values obtained in over ten UK police jurisdictions have never exceeded 0.69 for these domains (Mean combined AUC = 0.65; Mean target AUC = 0.60; Bennell, 2002; Bennell & Canter, 2002; Bennell & Jones, 2005; Markson et al., 2010). Likewise, the entry and internal domains (AUCs = 0.66) compare favourably to previous research on UK data (Mean Entry AUC = 0.58; Mean Internal AUC = 0.51). These findings suggest that a wider range of offender behaviours demonstrate the relative consistency and distinctiveness required to facilitate successful BCL in Finland compared to the UK.

There are several potential explanations for these differences. First, it is possible that Finnish burglars are more consistent and distinctive in their offence behaviour than burglars from the UK. This might be due to individual differences (such as the presence of particularly rigid and unique behavioural scripts for offending) and/or due to environmental differences (such as the availability and diversity of potential targets with which to offend against). In terms of the former, there is no theoretical basis to suggest that Finnish and UK burglars possess different characteristics that would be expected to impact on consistency and distinctiveness. In terms of the latter, one potential environmental factor was discussed earlier that might partially account for the observed differences. There is a wider variety of housing in Finland than in the UK, which could allow between-offender differences in burglary behaviour to emerge more readily among Finnish than UK offenders. A comparison between the current data and those from Markson et al. (2010) support this suggestion. In the current sample, 65% of the crimes in dataset one targeted detached housing or second floor apartments (two separate categories) and the remaining 35% were split across the other four categories of housing. This compares with 84% of crimes in Markson et al.'s (2010) sample that fell under one category of housing (i.e., the 'house' category). The wider variation in types of housing targeted by Finnish burglars might partially account for the superior discrimination accuracy observed in the current study for target characteristics.

Another explanation is that the UK and Finnish police may differ in terms of their data recording and storage practices. A comparison between the data available for the current and previous studies suggests that there may be some value in this explanation. The internal domain in this study, for example, included the number of offenders responsible for the crime and how the offender/s exited the crime scene. These variables were not included in previous research on UK data (Bennell, 2002). It is plausible that additional behaviours such as these led to the improved discrimination accuracy observed in the current study. It is also plausible that the behaviours were able to be operationalised in a more appropriate way in the current study compared with past research. For example, the target domain in this study included several variables related to the owner's occupancy, whereas in previous research occupancy has been defined simply in terms of one variable (e.g., Bennell, 2002; Markson et al., 2010) due to the way in which data is recorded by certain police forces in the UK. Differences such as these may also have contributed to the improved discrimination accuracy in the current study. If these explanations are valid, then it suggests that the UK police may be able to enhance BCL performance for residential burglary by altering the types and nature of information that is recorded on police databases.

However, it is difficult to tease out and test these potential explanations using the current set of data, which means that it is not possible to draw any definitive conclusions.

Despite the difficulty in definitively explaining these findings, the potential implications are clear. From a practical perspective, they suggest that the Finnish police may be able to use a wide range of offender behaviours to identify linked residential burglary crimes. But, it seems that they should prioritise inter-crime distance and temporal proximity in this process because, not only do these features facilitate the highest level of discrimination accuracy, but they are also the most simple and easy to use in practice. However, in the absence of data relating to these features, it seems that there is scope for the Finnish police to also rely on target, entry, and internal behaviours to link burglaries.

But, it is worth highlighting that the AUC values obtained in this study were below the theoretical maximum of 1.00, which indicates that a degree of error can be expected when linking burglary crimes in Finland using these behaviours.

From a theoretical point of view, the consistency and distinctiveness of inter-crime distance in this study provides support for several seminal theories of offender spatial behaviour, such as rational choice theory and crime pattern theory, which suggest that offenders seek to minimise the efforts and risks involved in offending (e.g., by returning to the same places that are familiar to them and by not travelling great distances to offend) (e.g., Brantingham & Brantingham, 1981; Clarke & Felson, 1993).

The consistency and distinctiveness of inter-crime distance and temporal proximity in this study also tie in with recent findings on the repeat and near-repeat phenomenon. According to these phenomena, becoming a victim of crime increases the subsequent risk of further victimisation, both at the same and also nearby geographical locations. However, the heightened risk of victimisation decays over time, such that the risk of becoming a victim of crime returns to pre-victimisation levels after approximately one month (e.g., Bowers & Johnson, 2004). Recent research has demonstrated that such repeat and near-repeat offences can often be attributed to the same prolific offender or the same group of offenders who are returning to a given geographical location to commit multiple crimes (e.g., Bernasco, 2008; Johnson, Summers, & Pease, 2009). Thus, two diverse research methodologies both indicate statistically significant levels of behavioural consistency in spatial and temporal offender behaviour. This increases confidence that the findings observed in the current study are reliable and valid.

Furthermore, these findings support previous BCL research in the UK that has shown offenders to commit crime in somewhat distinct, non-overlapping geographical areas (e.g., Bennell & Canter, 2002; Bennell & Jones, 2005; Tonkin et al., 2008; Woodhams & Toye, 2007). That is, the geographical locations that one offender chooses to offend in are somewhat different from the areas that a different offender may choose. A potential explanation for this finding comes from previous research using this dataset (Laukkanen et al., 2008), which has shown that Finnish burglars do not travel far from home to offend (a median of 3.88 km). Thus, it may be that the current sample chose to offend close to home and, by virtue of the fact that the offenders live in different areas, somewhat distinct, non-overlapping patterns of offender spatial behaviour emerged.

However, as noted above, the AUC values observed in the current study were below 1.00, so the offending “territories” of the burglars in this sample were not completely non-overlapping. Furthermore, the entire geographical area studied here was relatively large (815 km^2), so it is unclear whether these findings would be replicated on a smaller geographical scale (e.g., if an analyst were attempting to link burglaries within one particular neighbourhood of Helsinki[19]). But, we might be cautiously optimistic given that similar findings have been observed with burglars in the UK using study areas that are much smaller in size (112 to 230 km^2; Bennell & Jones, 2005).

The statistically significant levels of behavioural consistency, distinctiveness, and discrimination accuracy observed in the current study for target, entry, and internal behaviours also tie in with previous research using a very different methodological approach to studying offender behaviour. A range of studies utilising offender interviews and ethnographic methodologies have cited evidence to suggest that over time serial burglars develop "templates" or "cognitive scripts" that guide their target selection, entry, and search behaviour when committing burglaries (e.g., Brantingham & Brantingham, 1981; Nee & Meenaghan, 2006; Wright & Decker, 1994). These findings not only support the notion that burglars develop somewhat consistent scripts/templates that guide aspects of their offending behaviour, but also that these scripts/templates differ to some extent from one offender to the next[20]. However, it is clear that target, entry, and internal behaviours were not entirely heterogeneous in the current sample because the AUC values for these domains were substantially below the theoretical maximum of 1.00. This is logical when one considers that certain types of residential property may be more universally appealing to burglars than other types, and there are probably certain methods of entry and search behaviour that are more

[19] Helsinki is comprised of 59 neighbourhoods.
[20] If target, entry, and internal behaviours did not differ at least to some extent from one offender to the next, the AUC values achieved in the current study would not have exceeded chance (i.e., an AUC of 0.50).

likely to yield success than others. Consequently, one would predict a certain degree of homogeneity in target, entry, and internal burglary behaviour, thereby making it more difficult to distinguish between linked and unlinked crimes using these types of behaviour.

This chapter also compared two different approaches to forming the unlinked crime pairs in BCL research. The regression and ROC analyses revealed minor differences in discriminative accuracy across these two methodologies, but none of the differences were statistically significant. These findings are reassuring because they suggest that the practical and statistical problems associated with Bennell's (2002) methodology may not impact considerably on the findings of BCL research. Thus, researchers might continue to use Bennell's (2002) original approach to forming the unlinked crime pairs, as the additional effort associated with forming the unlinked pairs from an independent sample of serial and non-serial crimes may not be necessary. However, it is important that future research continue to explore this issue before any definitive recommendations are made.

Many of the limitations associated with previous BCL research (as outlined in Chapter 1) are also applicable to this study. First, the findings may not generalise beyond the geographical and temporal period studied here (although the use of split-half validation suggests that these findings may be applicable to other similar areas in Finland). Second, the current sample was restricted to solved crime, which may not be representative of real life police investigations, where BCL is conducted with unsolved crime (Bennell, 2002; also see Chapter 4 of this thesis). Nonetheless, the current study has contributed to the growing body of BCL literature by extending the evidence for burglary to a new country and by exploring new methodological issues in a systematic way.

CHAPTER 3

A COMPARISON OF LOGISTIC REGRESSION AND CLASSIFICATION TREE ANALYSIS FOR BEHAVIOURAL CASE LINKAGE[21]

3.1 Introduction

The previous chapter explored how changes to the method of forming the unlinked crime pairs impacted on the findings of BCL research. Such work forms part of a wider trend within the BCL literature, where researchers are beginning to explore a number of alterations that might be made to Bennell's (2002) original methodology. These include changes to the way in which behavioural similarity is measured (e.g., Ellingwood et al., in press; Melnyk et al., 2011; Woodhams, Grant et al., 2007), changes to the way in which samples are constructed for the purposes of analysis (e.g., Burrell et al., in press; Woodhams & Labuschagne, 2012; see also Chapter 2 of this thesis), and changes to the way in which offender behaviours are combined to distinguish between linked and unlinked crimes (e.g., Bennell, Woodhams et al., 2011; Winter et al., in press).

The current chapter seeks to continue the systematic exploration of methodology by replicating and extending the recent work of Bennell, Woodhams et al. (2011). In that study, Bennell and colleagues compared the traditionally used binary logistic regression with an alternative called classification tree analysis to determine which procedure could discriminate most successfully between linked and unlinked crimes. The current chapter, therefore, aims to address two of the three key limitations

[21] As stated on pages 3 and 4, a version of this chapter has been published as Tonkin, Woodhams, Bull, Bond, and Santtila (in press).

that were discussed in Chapter 1. First, it will seek to replicate Bennell, Woodhams et al.'s (2011) findings for residential burglary and extend these findings to a previously neglected crime type (car theft) and a new geographical location (Finland) (limitation number 1: generalisability). Second, it will explore the most appropriate statistical methodology for use in BCL research (limitation number 3: methodology). This chapter begins by discussing the use of binary logistic regression in BCL research.

3.1.1 The Use of Binary Logistic Regression in Behavioural Case Linkage Research

Binary logistic regression is an integral component of Bennell's (2002) methodology for investigating BCL. The widespread acceptance of this methodology (see Chapter 1 for a review) has, therefore, led to logistic regression becoming a common feature of many BCL studies.

As explained by Bennell (2002), logistic regression takes the place of a human decision-maker (e.g., a crime analyst or a police detective) in BCL research because it develops statistical models that predict whether crime pairs are linked or unlinked. These predictions can then be compared to the actual linkage status for each pair to determine whether the logistic model was able to successfully discriminate between linked and unlinked crimes.

But, there are a number of alternative statistical procedures that could be used to build predictive models instead of logistic regression, including discriminant function analysis, neural networks, and classification tree analysis (Bennell, 2002). However, logistic regression was selected by Bennell (2002) for several reasons. First, logistic regression is suitable for a wide variety of variables (continuous and categorical variables) and is resistant to violations of normality and homogeneity (Kinnear & Gray,

2009) that are common in BCL research. This makes it preferable to alternative procedures, such as discriminant function analysis, that have more stringent statistical assumptions. Second, unlike techniques such as neural networks and classification tree analysis, logistic regression is readily available in most statistical software packages, it is easy to use, and relatively well understood (e.g., see Field, 2009). Third, logistic regression is generally accepted as a diagnostic tool in a wide variety of academic disciplines, including clinical psychology, education, meteorology, and radiology (see Bennell, 2002).

However, since Bennell (2002) proposed his methodology, the use of classification tree analysis has increased and SPSS now offers a classification tree sub-routine. Classification tree analysis has, therefore, become a viable option for BCL researchers. The next section of this chapter will consider why classification tree analysis might offer a favourable alternative to logistic regression for the purposes of BCL research.

3.1.2 The Relative Merits of Classification Tree Analysis and Binary Logistic Regression

The relative merits of classification tree analysis over binary logistic regression have been discussed at length within the risk assessment literature for over a decade (e.g., Gardner, Lidz, Mulvey, & Shaw, 1996; Monahan et al., 2001; Rosenfeld & Lewis, 2005; Steadman et al., 2000). The current discussion draws heavily on this literature.

Researchers of risk assessment have argued that classification tree analysis is preferable to traditional main effects regression because it includes interaction effects between the different predictor variables that would otherwise be obscured or incomprehensible in a traditional regression approach (Rosenfeld & Lewis, 2005).

Researchers have also suggested that the findings produced using classification tree analysis are more user-friendly and acceptable to practitioners than those produced using logistic regression. First, classification tree analysis provides a predictive model that can be broken down into a series of simple yes/no questions, whereby subsequent questions depend on the answer given to the previous question (Gardner et al., 1996). This avoids the complex calculations that must be performed when utilising a logistic regression model to make predictions (Rosenfeld & Lewis, 2005). This means that classification trees may be preferable in situations where the decision-maker does not have an in-depth knowledge of statistics.

Second, predictive decisions derived from classification trees are more transparent than those from logistic regression models, with the various steps that lead to a prediction in tree-based models being far clearer than those in regression (Gardner et al., 1996). Arguably, this means that tree-based prediction is more suited to situations where a practitioner is required to justify and explain his/her decision-making processes to others, such as to an investigating officer or the courts. Furthermore, greater transparency is likely to reduce suspicion on the practitioner’s part because they can see exactly how a linkage decision was made, rather than a decision being proffered without any indication of how that decision was arrived at. Consequently, greater transparency may increase the likelihood of predictive models becoming adopted in practice (Woodhams, Bennell, & Beauregard, 2011).

Third, classification tree analysis does not assume that the same predictor variables apply to every case, whereas logistic regression does (Steadman et al., 2000). As explained by Monahan et al. (2001), classification tree analysis establishes a sequence of questions that starts with a common question that is asked of all cases and then, depending on the answer to this and subsequent questions, the cases are eventually categorised into a predictive category. Thus, the factors that are used to make predictive decisions with a decision tree can differ from one case to the next, even if the same final decision is reached. This contrasts with predictions that are based on a logistic regression model, where the same predictors are used for all cases (Monahan et al., 2001). Arguably, the greater flexibility offered by classification trees is more consistent with the attitudes of relevant practitioners, who tend to emphasise heterogeneity in offending behaviour (Steadman et al., 2000).

However, researchers have also noted some potential disadvantages of using classification trees relative to logistic regression. In particular, several studies have observed a tendency for the predictive models produced using classification tree analysis to be less robust when applied to new data than those produced using logistic regression (e.g., Rosenfeld & Lewis, 2005; Thomas et al., 2005). This phenomenon has been referred to as ‘shrinkage’ or ‘over-fitting of the data’ (e.g., Thomas et al., 2005). It occurs when complex models are produced by combining multiple predictive factors, which fit the training sample well but fail to generalise to new datasets (Liu et al., 2011). It, therefore, seems that some of the proposed advantages of classification tree analysis, where different predictive factors are used for different cases and where interaction effects are included in the predictive model, may sometimes lead to an overly-complex model that is not very robust. This could be a substantial problem when research is trying to build models that can be applied in future practical situations, as is the case in the BCL literature.

Nevertheless, despite the potential for over-fitting, Bennell, Woodhams et al. (2011) have recently suggested that classification tree analysis might enable more accurate, sensitive and usable predictive models to be developed for linking than those that are produced using logistic regression analysis. Indeed, when one inspects the BCL literature, there is evidence to suggest that behavioural consistency may be expressed differentially from one offender to the next, which would make the ‘one size fits all’ approach of logistic regression inappropriate (e.g., Grubin et al., 2001; Woodhams, 2008). For example, Grubin et al. (2001) analysed the behavioural consistency displayed by serial sex offenders in the UK and Canada. They found that behavioural consistency was evident in the crime scene behaviour of their sample, but the nature of such consistency was not the same for all offenders. That is, some offenders displayed consistency in their control behaviours, while others displayed consistency in their escape behaviours, and some were consistent in their sexual behaviours.

There is also an argument to suggest that tree-based linkage would be more usable in practice by police crime analysts than regression-based models (Bennell, Woodhams et al., 2011). While crime analysts receive extensive training in the use of practical tools such as Geographical Information Systems (GIS) and some may have completed university degrees that contain a basic level of statistical training (e.g., a BSc in Psychology), many crime analysts may not have the in-depth knowledge to understand the complex mathematical calculations of a logistic regression function. Consequently, some analysts may not understand how regression-based models have reached a particular linkage decision. This would make it very difficult for them to explain their decision-making processes to a senior investigating officer or to the courts (which they often have to do). Furthermore, even if they did understand the workings of logistic regression, it may be very difficult to explain this to a police officer who also may not have a detailed knowledge of statistics. Ultimately, this may prevent the uptake of regression models in practice (Woodhams et al., 2011). Tree-based models, however, are more simple and transparent, which would arguably make them more acceptable and usable by police crime analysts (Bennell, Woodhams et al., 2011).

Given the relative merits of classification tree analysis over logistic regression, Bennell, Woodhams et al. (2011) compared the ability of these two statistical procedures to build predictive models of offender behaviour that could discriminate between linked and unlinked offences.

3.1.3 The Bennell, Woodhams et al. (2011) Study

Bennell and colleagues analysed samples of residential burglary, commercial robbery, and rape. They found that an iterative approach to building classification trees (see Monahan et al., 2001; Steadman et al., 2000; and Section 3.2.3 below for further details) was able to discriminate between linked and unlinked offences at a level that was comparable to that using logistic regression. In their sample of adult serial stranger rapes, an AUC of 0.99 was achieved using classification tree analysis, which compared to an AUC of 0.98 using logistic regression. In their sample of serial commercial robberies, classification tree analysis achieved an AUC of 0.84, compared to an AUC of 0.90 using logistic regression. In their sample of serial residential burglaries, classification tree analysis achieved an AUC of 0.87, which compared to an AUC of 0.91 using logistic regression. While the logistic regression AUCs were marginally larger than the robbery and burglary tree-based models, the overlapping confidence intervals suggested that these AUC values were not significantly different (Melnyk et al., 2011).

Given the presumed superiority of classification trees over logistic regression models, in terms of being more user-friendly and transparent, Bennell, Woodhams et al.

(2011) concluded that classification tree analysis may be a useful alternative to logistic regression when it comes to building models that can assist crime analysts in the BCL task.

However, the level of shrinkage that occurred when Bennell and colleagues applied the classification trees from the training sample to the test sample in their study is unclear. This is important for evaluating model performance, as practitioners must be able to report the expected level of error that is involved in their linkage predictions. For example, one of the key components of Rule 702 of the Federal Rules of Evidence, which guides the acceptance of expert evidence in courts of law in the US, is that any theory or technique being presented in court must have a known or potential error rate. Thus, it is important that statistical approaches to BCL are shown to achieve relatively stable levels of discrimination accuracy from one sample to the next; otherwise it will be difficult to give an accurate estimate of the error rate. This is particularly important in the current context due to the significant shrinkage that has been observed when using classification trees to predict risk of re-offending (e.g., Liu et al., 2011; Rosenfeld & Lewis, 2005; Thomas et al., 2005). The extent to which classification tree analysis is able to produce robust and generalisable predictive models for the purposes of linking crime cannot, therefore, be fully evaluated unless the level of shrinkage is explicitly reported.

It is, also, important that we do not assume that the findings from one study will necessarily replicate with other crime types and in different geographical areas (as illustrated in Chapter 2). The current study, therefore, compared the ability of logistic regression analysis and classification tree analysis to build predictive models that can distinguish between linked and unlinked car thefts that were committed in the UK and between linked and unlinked residential burglaries that were committed in Finland.

Classification tree analysis has never been applied to car theft data before, nor has it been applied to residential burglaries outside of the UK.

3.2 Method

3.2.1 Samples

3.2.1.1 The Residential Burglary Data

The residential burglary data consisted of 160 residential burglaries committed by 80 serial burglars. These data were described in Section 2.2.1, so further details will not be re-iterated here. It should be noted that this sample is slightly smaller than that analysed in Chapter 2 because of missing geographical data. In the current study it was necessary to remove those crimes where data were missing because classification tree analysis requires a full dataset. The same geographical and behavioural information were used as in Chapter 2, but temporal information was not used for the reasons discussed below (see Section 3.2.2).

3.2.1.2 The Car Theft Data

The car theft data consisted of 376 vehicle theft crimes committed by 188 serial car thieves in Northamptonshire, UK, between January 2004 and May 2007. Two crimes per offender were randomly selected from the total number of offences that they had committed during this time period. These data were collected as part of a previous project (Tonkin, 2007), but were only used for preliminary analyses in that work. Thus, analyses using these data have not been previously published/made available.

For each car theft a range of behavioural data were recorded, including the location of the crime (an *x*, *y* coordinate to the nearest metre), the type of car that was stolen, the age of the vehicle, the time and day of the week that the vehicle was stolen (where an exact offence time was not available the mid-point between the earliest and latest crime dates/times was used), how the vehicle was entered and started, and the physical state in which the vehicle was recovered. Apart from the location information, the data were coded in a binary format because more complex coding schemes may be unreliable with police data (Canter & Heritage, 1990).

3.2.2 Procedure

First, a number of behavioural domains were created for each dataset. The behavioural domains created for the burglary data were identical to those described in Chapter 2, except for the exclusion of temporal proximity. Temporal proximity was not calculated in the current study because Bennell, Woodhams et al. (2011) used a specially-designed computer package to calculate inter-crime distance values and Jaccard's coefficients for all possible linked and unlinked crime pairs. This differs from the procedure used in Chapter 2, where a random subset of unlinked crime pairs was used in the analyses. Bennell's package, however, does not facilitate the calculation of temporal proximity and an alternative package had not been developed at the time of analysis. Given the large number of unlinked crime pairs that can be created from a sample of 160 crimes (12,640 pairs), it was not feasible to calculate the temporal proximity values manually.

Consequently, a decision had to be made to either replicate Bennell, Woodhams et al.'s (2011) methodology using all possible linked and unlinked crime pairs, thereby excluding temporal proximity from the analysis, or alter their methodology such that a sub-section of unlinked crime pairs were used, thus making the calculation of temporal proximity feasible. Given that a primary purpose of this study was to replicate Bennell, Woodhams et al. (2011), it was decided that all linked and unlinked crime pairs would be calculated and temporal proximity excluded from the analysis. But, the exclusion of temporal proximity is acknowledged as a limitation.

For the car theft data, five behavioural domains were created: (1) Target Selection Choices (e.g., the type and age of the vehicle stolen); (2) Target Acquisition Behaviour (e.g., the method and point of entry to the vehicle); (3) Disposal Behaviour (e.g., the condition of the vehicle when recovered); (4) Inter-crime Distance (in kilometres); (5) A combined behavioural domain, which included all behaviours in the target selection, target acquisition, and disposal domains. A full list of the behaviours that comprised each domain is given in Appendix 2.

Next, these data were used to create all possible linked and unlinked crime pairs for the two datasets. There were 80 linked residential burglary pairs and 12,640 unlinked residential burglary pairs, and there were 188 linked car theft pairs and 70,312 unlinked car theft pairs. Samples of this size were comfortably above the recommended minimum for the analyses reported in this chapter (Peduzzi, Concato, Kemper, Holford, & Feinstein, 1996; Perreault & Barksdale, 1980).

For each crime pair an inter-crime distance and a Jaccard's coefficient for each behavioural domain were calculated. In total, six similarity coefficients were calculated for each residential burglary pair (one inter-crime distance and five Jaccard's coefficients) and five coefficients were calculated for each car theft pair (one inter-crime distance and four Jaccard's coefficients). These coefficients formed the basis of the subsequent analyses.

Next, each dataset was randomly split in half to form a training sample and a test sample, which would allow for cross-validation of the predictive models (see Section 2.2.2).

3.2.3 Data Analyses

For each dataset binary logistic regression analysis and Iterative Classification Tree (ICT) analysis were conducted. Although the analyses were run separately for the burglary and car theft data, the same analytical procedure was followed for each dataset. This procedure is described below.

Logistic regression analysis was used to examine the independent and combined ability of the six burglary domains and the five car theft domains to distinguish between linked and unlinked crime pairs. These analyses were initially run on the training samples and subsequently applied to the corresponding test samples using the method described in Section 2.2.3. As in Chapter 2, separate direct logistic regression analyses were run for each behavioural domain, with the similarity coefficient (Jaccard's coefficient or inter-crime distance) entered as an independent variable and linkage status (linked versus unlinked) as the dichotomous dependent variable. Also, forward stepwise logistic regression analysis was used to determine the optimal combination of domains for linkage purposes. As explained in Chapter 2, the combined domain was not entered into the stepwise analyses (Field, 2005).

The logistic regression models were then used to produce predicted probability values for each crime in the test samples using the procedure described in Section 2.2.3.

These probability values were subsequently entered into ROC analyses to determine the ability of the logistic regression models to distinguish between linked and unlinked crime pairs.

To determine whether classification tree analysis could produce superior predictive models for the purposes of BCL, separate classification tree analyses were conducted on the burglary and car theft datasets. A summary of the analytical process is depicted in Figure 3A.

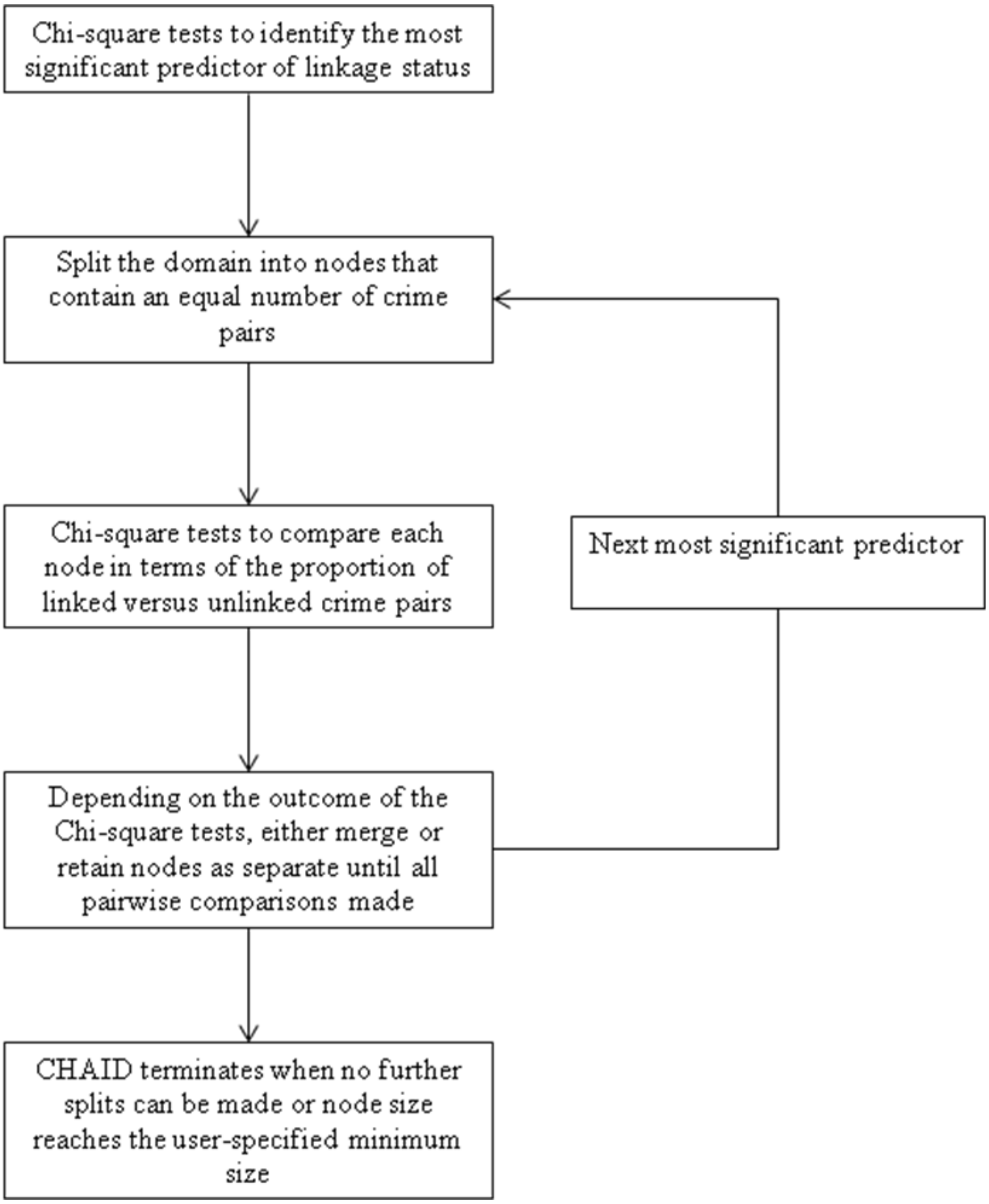

Figure 3A

The Analytical Process of Chi-Squared Automatic Interaction Detector (CHAID)

The CHAID algorithm initially conducted a series of Chi-square tests to identify the behavioural domain that was most significantly associated with linkage status (Steadman et al., 2000). Next, the algorithm split this domain into different categories (referred to hereafter as nodes) that contained a roughly even number of crime pairs (e.g., Node 1 = inter-crime distance ≤ 1.47 kilometres, containing 5000 crime pairs;

Node 2 = 1.47 kilometres < inter-crime distance ≤ 2.73 kilometres, containing 5000 crime pairs; and so on). At this stage of the analysis, the researcher can specify a maximum number of nodes to be created for each behavioural domain (which is referred to hereafter as the number of intervals). The researcher can also specify the minimum number of crime pairs to be included in each node. Each node was then compared with every other node in a pair-wise fashion using Chi-square analyses to determine whether there was a significant difference in the proportion of linked versus unlinked crime pairs in those two nodes (Perreault & Barksdale, 1980). If a significant difference was identified, the nodes were retained as separate; however, if there was no significant difference, the nodes were merged. In PASW version 18.0, the researcher can choose to use either the likelihood ratio or Pearson's χ^2 for these comparisons and s/he can set the level of significance to be used (e.g., $p < 0.05$, $p < 0.01$). This process of comparing nodes continued until all comparisons had been made and no further nodes could be merged. The aim was to identify consistent but distinctive groups of crime pairs. That is, in an ideal situation the crime pairs *within* a particular node would share a similar level of behavioural similarity (e.g., all crime pairs would have a similar inter-crime distance) and would be identical in terms of linkage status (e.g., all crime pairs would be classed as linked). But, when these crime pairs were compared with those from a different node, they would differ significantly in terms of behavioural similarity and linkage status (Steadman et al., 2000). It is worth pointing out, however, that perfect differentiation between nodes would be unlikely in practice; instead, it is much more likely that each node would overlap slightly with the other nodes in terms of behavioural similarity and linkage status (but of course the nodes would have to be statistically different, otherwise they would have been merged). Having completed this process for the most significant behavioural domain, the process was repeated for all domains that were statistically associated with linkage status to determine whether the nodes identified in the first iteration could be further split based on different types of behavioural similarity. If it were possible to further split a particular node, then that node would be described as a parent node and the nodes derived from the split would be described as child nodes (see Footnote 22 for further details). The CHAID process terminated when no further splits could be made or when the number of crime pairs in a particular node reached the minimum node size.

In conducting the CHAID analyses, the procedure described by Bennell, Woodhams et al. (2011) was followed using the Chi-Squared Automatic Interaction Detector (CHAID) software available in PASW version 18.0. The method was exhaustive CHAID. For the residential burglary data, tree depth was equal to five, the minimum node size for parent nodes was 20, and the minimum node size for child nodes was six[22]. The criterion for splitting nodes was set at $p < 0.05$ using the likelihood ratio. The number of intervals was set at 64, which is the maximum available in PASW version 18.0. Thus, the maximum number of nodes that could be created for a given behavioural domain was 64. For the car theft data, tree depth was equal to five, the minimum node size for parent nodes was 20, and the minimum node size for child nodes was five. The criterion for splitting nodes was set at $p < 0.05$ using the likelihood ratio. The number of intervals was set at 64. As explained by Bennell, Woodhams et al. (2011), Jaccard's coefficient is a relatively coarse-grained measure so it is appropriate to use the maximum number of possible intervals available in PASW version 18.0.

[22] Tree depth refers to the maximum number of levels of growth beneath the root node. For example, node 0 was the root node in Figure 3B and there were two levels of growth below node 0 in this tree. Each level of growth was added as the CHAID algorithm successfully split the sample (using Chi-square analysis) into sub-sets of crime pairs that were similar in terms of behavioural similarity and linkage status (as described above). Thus, the first level in Figure 3B was added because the sample was successfully split into nodes using the inter-crime distance. The second level was added because node 1 in Figure 3B was further split using the entry domain and node 4 was further split using the internal domain. Nodes 1 and 4 are, therefore, described as parent nodes and nodes 10 to 15 are described as child nodes.

Also, tree depth was set at five to ensure that all predictor variables within each dataset had the opportunity to be expressed within the tree (Bennell, Woodhams et al., 2011). The likelihood ratio was selected because it is more robust than the alternative method, Pearson's χ^2 (SPSS, n.d.).

Following the criteria established by Steadman et al. (2000) and Monahan et al. (2001), and subsequently used by Bennell, Woodhams et al. (2011), nodes containing less than twice, but more than half the base rate prevalence of linked pairs were deemed to be unclassifiable. These unclassifiable cases were separated from those that were successfully classified, and a further CHAID analysis was run on the unclassifiable cases in an attempt to classify further cases as either linked or unlinked. The same parameters described above were used in this analysis. This iterative process was repeated until no further cases could be classified.

The SPSS sub-routine for classification tree analysis was used to develop a tree on the training sample and then to automatically apply this tree to the test sample. These analyses produced a predicted probability value for each crime pair in the training and test samples, which were subsequently used to perform ROC analysis. This tested the discriminative accuracy of the classification tree models.

ROC curves were also constructed for the training samples, as well as the test samples, to determine whether the regression and classification tree models could be cross-validated. As discussed in Section 3.1.3, this is an integral part of testing model performance.

3.3 Results

3.3.1 Residential Burglary

Six direct and one stepwise logistic regression analysis were conducted using the residential burglary training sample to examine the ability of logistic regression to build predictive models that could distinguish between linked and unlinked crime pairs. These findings are reported in Table 3A. All logistic regression models were statistically significant ($p < 0.05$), but the most successful model (as measured by the model χ^2 values) was the stepwise model that combined inter-crime distance, entry behaviours, and internal behaviours. This was followed by the single-feature regression model for inter-crime distance. These seven regression models were then applied to the test sample to produce predicted probability values for the purposes of ROC analysis.

Table 3A

Binary Logistic Regression Models for Residential Burglary

Model	**Constant (*SE*)**	**Logit Change (*SE*)**	**χ^2 (df)**	**Wald (df)**	***R^2* (Cox & Snell-Nagelkerke)**
Combined	-7.30 (0.389)	7.87 (1.03)	50.97 (1)***	59.05 (1)***	0.01 – 0.11
Target	-5.60 (0.236)	1.78 (0.467)	12.32 (1)***	14.47 (1)***	0.00 – 0.03
Entry	-6.51 (0.316)	4.03 (0.544)	47.23 (1)***	54.84 (1)***	0.01 – 0.11
Internal	-6.68 (0.357)	4.27 (0.668)	36.43 (1)***	40.74 (1)***	0.01 – 0.08
Property	-5.76 (0.314)	2.61 (0.962)	6.53 (1)*	7.35 (1)**	0.00 – 0.02
Inter-crime Distance (ICD)	-2.43 (0.269)	-0.390 (0.0579)	96.47 (1)***	45.23 (1)***	0.02 – 0.21
Stepwise	-4.61 (0.490)		142.23 (3)***		0.02 – 0.31
ICD		-0.316 (0.0532)		35.27 (1)***	
Entry		2.69 (0.595)		20.36 (1)***	
Internal		2.60 (0.736)		12.44 (1)***	

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Classification tree analysis was also conducted on the residential burglary training sample and subsequently applied to the test sample. The classification trees produced by this analysis are depicted in Figures 3A and 3B. According to the criteria of Steadman et al. (2000) and Monahan et al. (2001), crime pairs were categorised as unclassifiable when the percentage of linked cases in a particular node fell between

0.30% and 1.20% for the training sample, and between 0.35% and 1.40% for the test sample. Consequently, cases within nodes 4, 6, and 8 of the training sample and within nodes 3, 4, 6, 8, and 14 of the test sample were deemed unclassifiable. This represented 2,604 crime pairs (20.47% of the total sample). A second CHAID analysis was run on these unclassifiable cases, but no further cases could be classified. The predicted probability values produced at iteration 1 were, therefore, used to conduct ROC analysis.

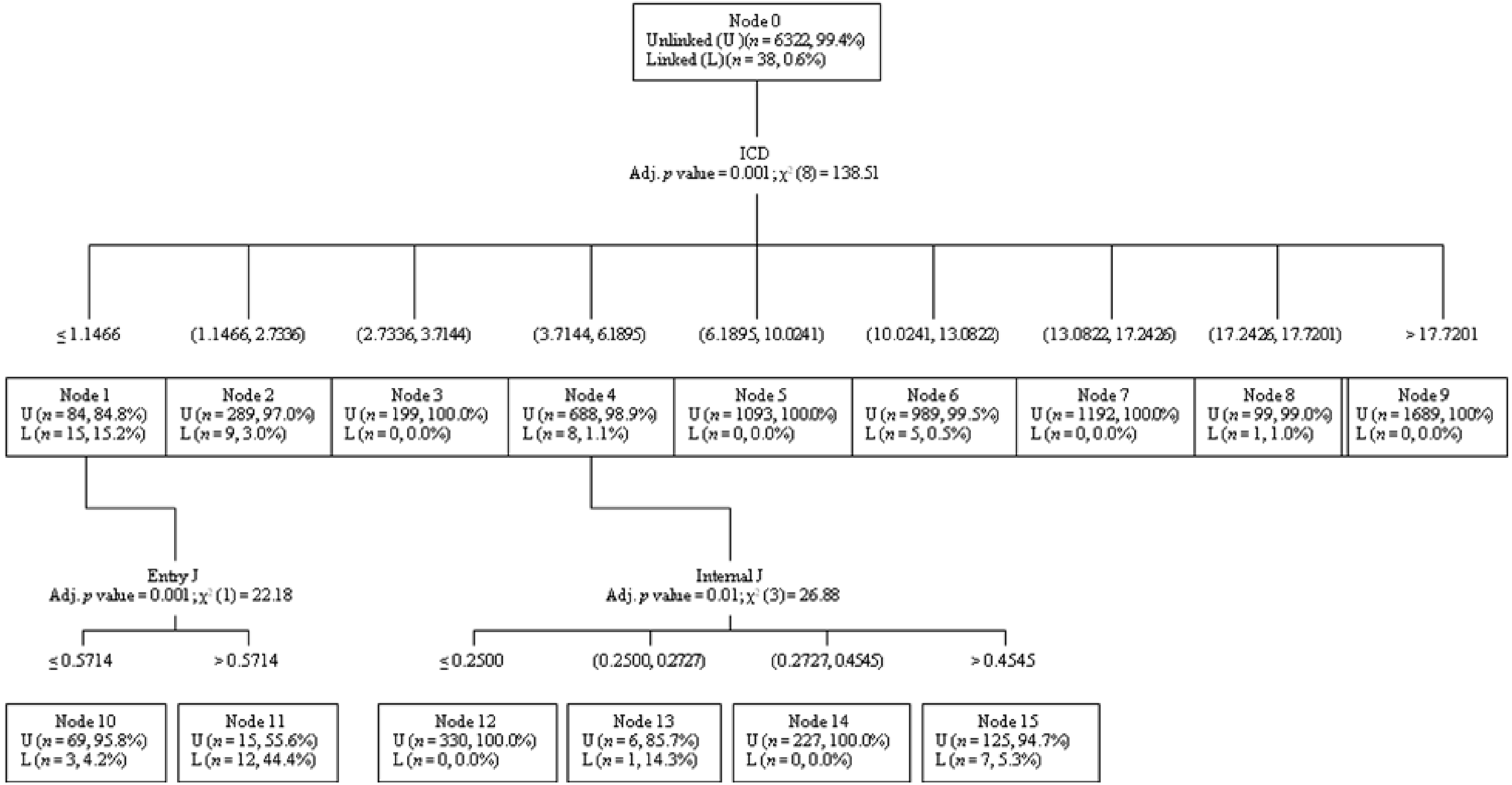

Figure 3B

Classification Tree for the Residential Burglary Training Sample (p < 0.05; parent nodes = 20; child nodes = 6)

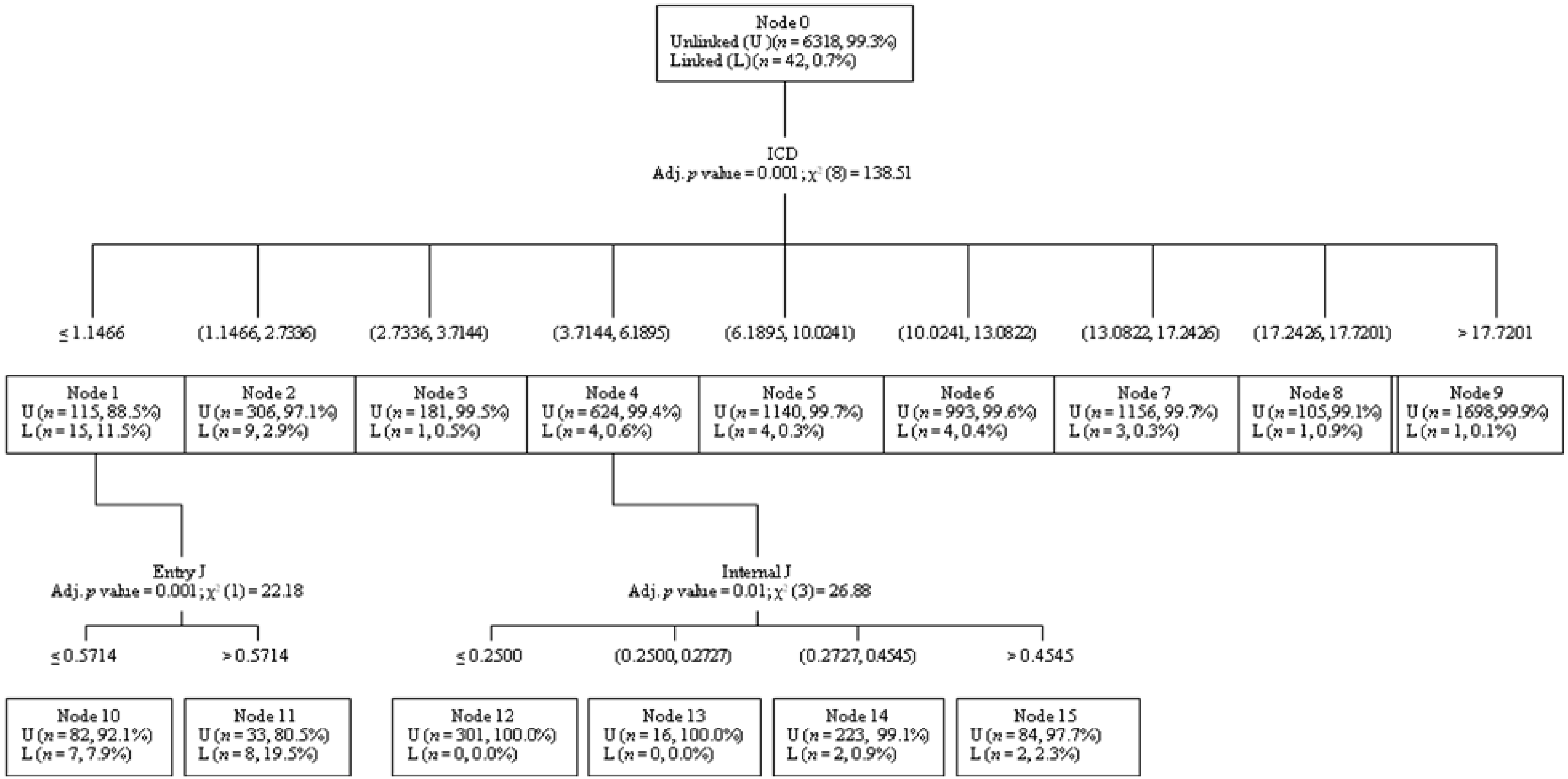

Figure 3C

Classification Tree for the Residential Burglary Test Sample (p < 0.05; parent nodes = 20; child nodes = 6)

Eight ROC curves were constructed using the predicted probability values in the test sample. Seven of these curves represented the logistic regression models reported in Table 3A and one represented the classification tree model depicted in Figure 3C. These analyses are reported in Table 3B. All models achieved statistically significant levels of discrimination accuracy with the test data ($p < 0.001$). The most successful model with the test data appeared to be the stepwise regression model (AUC = 0.87), which was superior to the classification tree model (AUC = 0.80). But, the difference in the AUC statistics was not statistically significant ($p > 0.05$).

Table 3B

Receiver Operating Characteristic (ROC) Analyses Representing the Discriminative Accuracy of Binary Logistic Regression and Classification Tree Models with Residential Burglary

Type of Analysis	**Domain**	**Training Sample**		**Test Sample**	
		AUC (*SE*)	**95% CI**	**AUC (*SE*)**	**95% CI**
Logistic Regression	Combined	0.80 (0.04)***	0.72 – 0.88	0.82 (0.04)***	0.76 – 0.89
	Target	0.64 (0.05)**	0.55 – 0.74	0.77 (0.04)***	0.69 – 0.85
	Entry	0.74 (0.05)***	0.65 – 0.83	0.70 (0.05)***	0.61 – 0.79
	Internal	0.73 (0.04)***	0.65 – 0.82	0.78 (0.03)***	0.72 – 0.84
	Property	0.64 (0.05)**	0.55 – 0.73	0.66 (0.05)***	0.57 – 0.75
	Inter-crime Distance (ICD)	0.88 (0.03)***	0.83 – 0.94	0.83 (0.03)***	0.76 – 0.89
	Stepwise (ICD, Entry, Internal)	0.92 (0.02)***	0.88 – 0.96	0.87 (0.03)***	0.81 – 0.92
ICT	---	0.96 (0.01)***	0.94 – 0.98	0.80 (0.04)***	0.71 – 0.88

** $p < 0.01$; *** $p < 0.001$

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).

Also reported in Table 3B are the AUC values that were obtained using the training sample. By comparing these AUC values with the equivalent values for the test sample, it is possible to determine whether discrimination accuracy is robust using these statistical models. All logistic regression models appeared to be robust and cross-validated (as indicated by the non-significant differences between the training and test AUC statistics; $p > 0.05$). However, the classification tree model achieved a significantly smaller AUC value in the test sample than the training sample ($p < 0.001$). These findings suggest that the classification tree model may not be as robust as the regression models when it comes to discriminating between linked and unlinked residential burglaries in this sample.

There are several different techniques that can be used to counteract over-fitting (Loh & Shih, 1997). For example, branches in the model that contain a relatively small number of cases can be removed (this technique is referred to as pruning) and alterations can be made to the model's growth limits, such as decreasing the maximum tree depth and increasing the minimum number of cases in the parent and child nodes (Liu et al., 2011). In an attempt to make the burglary classification tree more robust, the criterion for splitting nodes was made more stringent ($p < 0.001$) and the minimum number of cases allowed in the parent and child nodes was increased to 100 and 50, respectively. These analyses produced a tree that was much simpler than the initial tree, with the data split into nine nodes compared to the previous 15 nodes and with just inter-crime distance used to make predictive decisions (see Figures 3C and 3D). In total, 3,703 pairs (29.11% of the total sample) were deemed unclassifiable. The iterative process was unable to classify further cases, so the predicted probability values produced at iteration 1 were used to construct ROC curves. These analyses produced an AUC value of 0.93 ($SE = 0.02$, $p < 0.001$, 95% CI = 0.90 – 0.96) for the training sample and an AUC of 0.80 (*SE* = 0.04, $p < 0.001$, 95% CI = 0.72 – 0.89) for the test sample. The level of shrinkage reduced slightly (from 0.16 to 0.13), but was still statistically significant ($p < 0.05$) and was larger than the level of shrinkage observed with the majority of logistic regression models.

Having examined the relative accuracy of classification tree analysis and logistic regression with a sample of serial residential burglaries from Finland, the next section examined relative accuracy with a sample of serial car thefts from the UK.

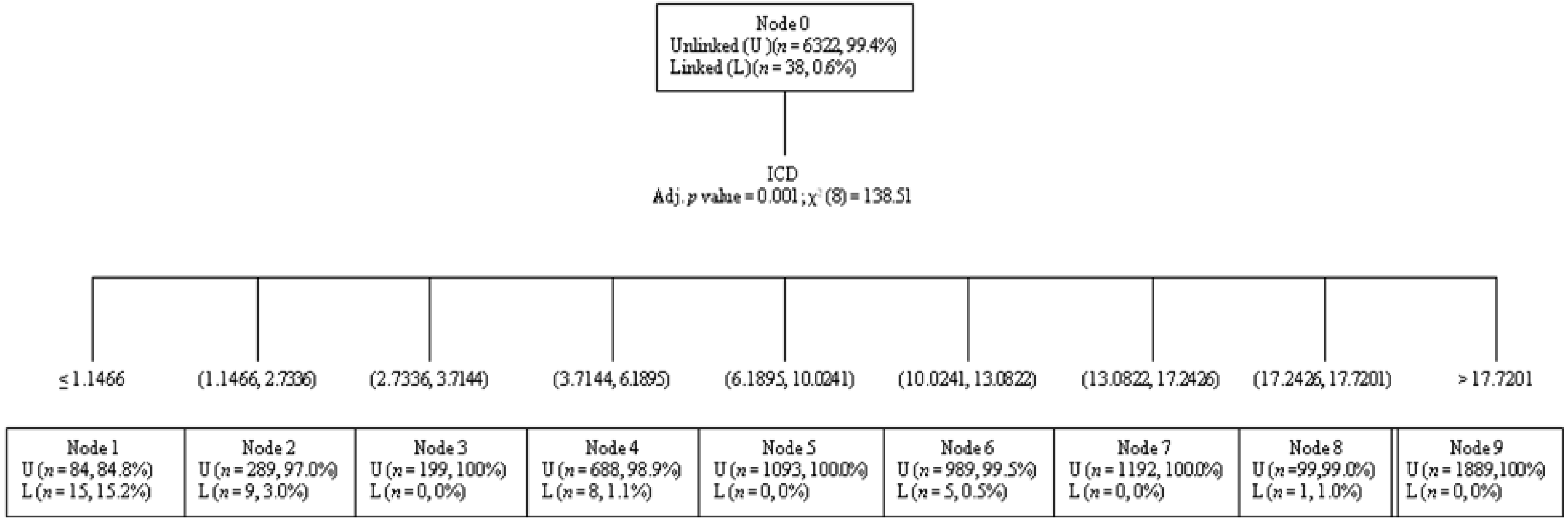

Figure 3D

Classification Tree for the Residential Burglary Training Sample (p < 0.001; parent nodes = 100; child nodes = 50)

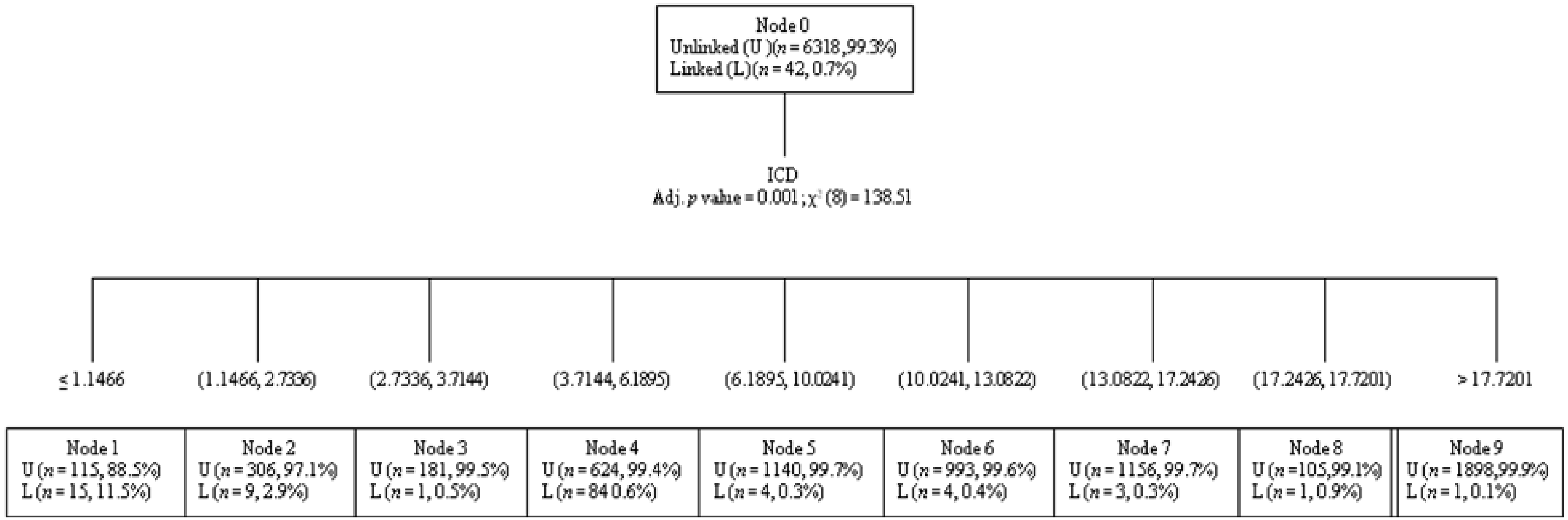

Figure 3E

Classification Tree for the Residential Burglary Test Sample (p < 0.001; parent nodes = 100; child nodes = 50)

3.3.2 Car Theft

Five direct and one stepwise logistic regression analysis were conducted using the car theft training sample (see Table 3C). All logistic regression models were statistically significant ($p < 0.01$), except the target acquisition model. The most successful model was the stepwise model, which combined inter-crime distance, target selection choices, and disposal behaviours. This was closely followed by the single-feature regression model for inter-crime distance.

Table 3C

Binary Logistic Regression Models for Car Theft

Model	Constant (*SE*)	Logit Change (*SE*)	χ^2 (df)	Wald (df)	R^2 (Cox & Snell-Nagelkerke)
Combined	-6.58 (0.201)	2.49 (0.590)	15.80 (1)***	17.80 (1)***	0.00 – 0.01
Target Selection (TS)	-6.31 (0.165)	1.49 (0.455)	9.68 (1)**	10.76 (1)**	0.00 – 0.01
Target Acquisition	-5.98 (0.109)	0.621 (0.476)	1.47 (1)	1.71 (1)	0.00 – 0.00
Disposal	-6.41 (0.199)	0.880 (0.293)	9.03 (1)**	8.99 (1)**	0.00 – 0.01
Inter-crime Distance (ICD)	-4.45 (0.148)	-0.156 (0.0194)	121.31 (1)***	64.44 (1)***	0.00 – 0.10
Stepwise	-5.16 (0.262)		133.64 (3)***		0.00 – 0.11
ICD		-0.150 (0.0191)		61.94 (1)***	
TS		0.969 (0.464)		4.37 (1)*	
Disposal		0.817 (0.299)		7.47 (1)**	

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Classification tree analysis was also conducted on the car theft training sample and subsequently applied to the test sample. The classification trees produced by this analysis are depicted in Figures 3E and 3F. Cases were categorised as unclassifiable when the percentage of linked cases in a particular node fell between 0.15% and 0.60% for both the training and test samples. Consequently, cases within nodes 3, 5, and 7 of the training sample and within nodes 2, 3, 7, and 8 of the test sample were deemed unclassifiable. This represented 22,758 crime pairs (32.28% of the total sample). A second CHAID analysis was run on these unclassifiable cases, but no further cases could be classified. The predicted probability values produced at iteration 1 were, therefore, used to conduct ROC analysis.

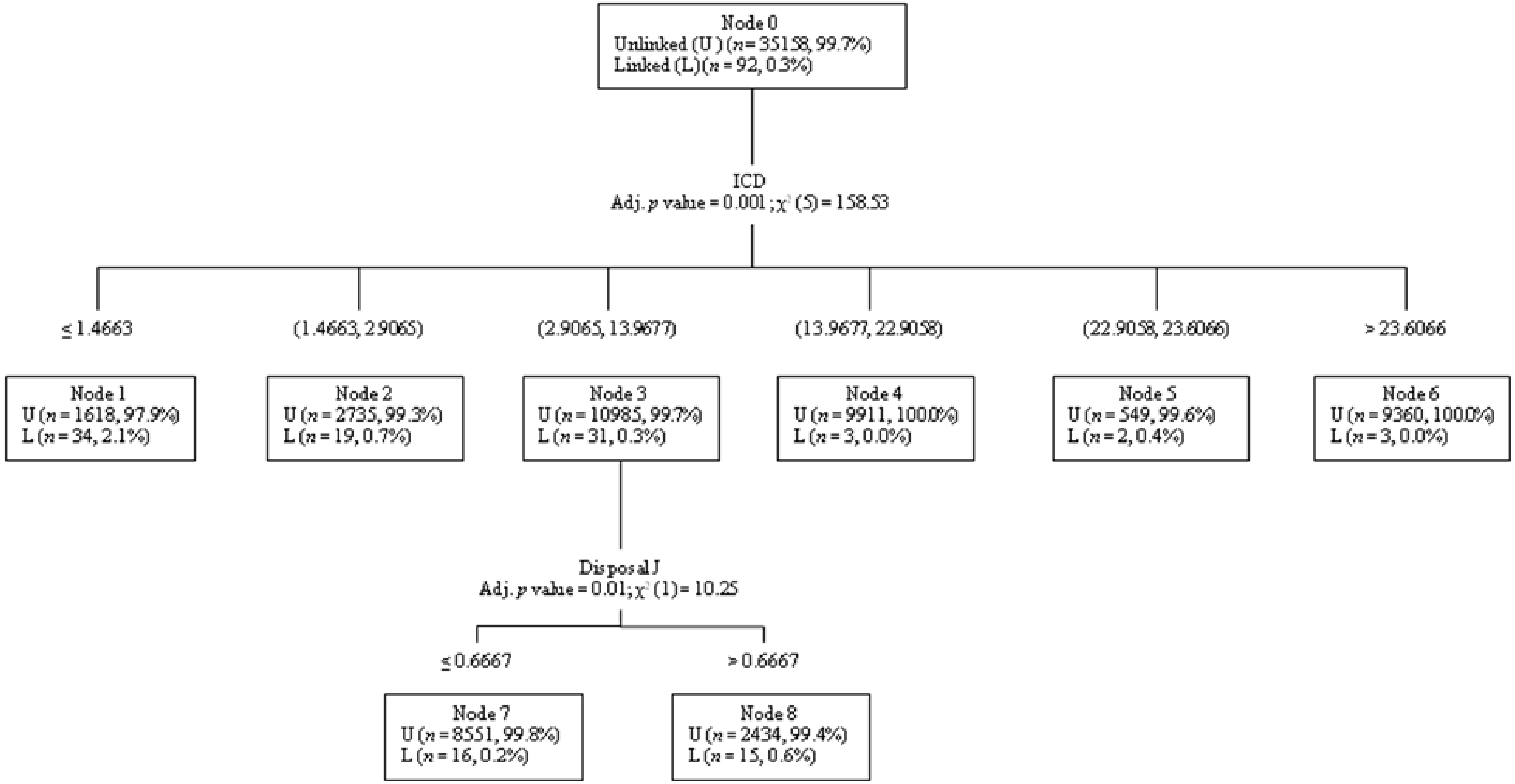

Figure 3F

Classification Tree for the Car Theft Training Sample ($p < 0.05$; parent nodes = 20; child nodes = 5)

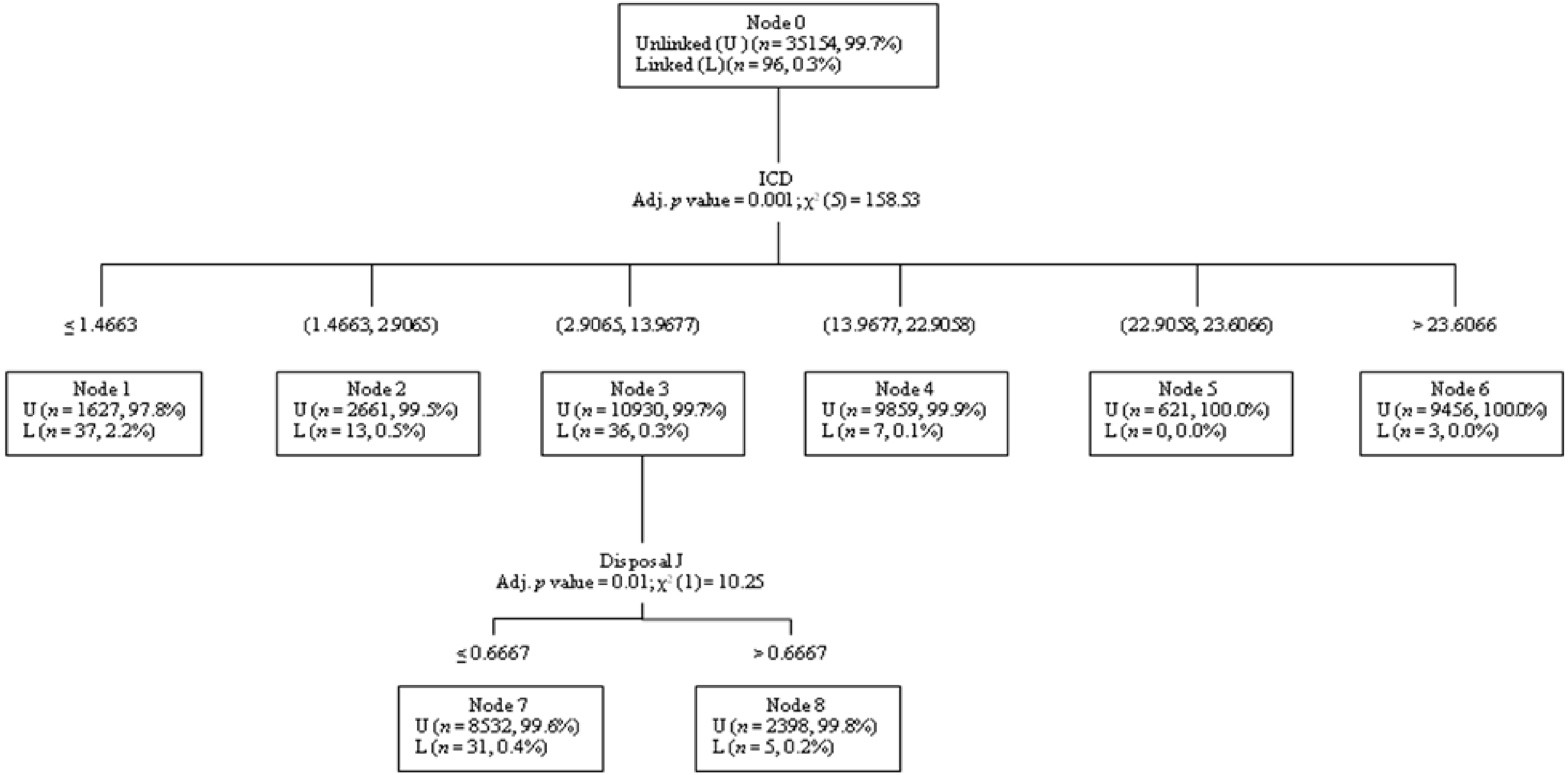

Figure 3G

Classification Tree for the Car Theft Test Sample (p < 0.05; parent nodes = 20; child nodes = 5)

Seven ROC curves were constructed using the predicted probability values in the test sample. Six of these curves represented the logistic regression models reported in Table 3C and one represented the classification tree model depicted in Figure 3G. The ROC analyses are reported in Table 3D. The most successful model with the test data was the single-feature regression model using inter-crime distance (AUC = 0.82). Somewhat unexpectedly this model outperformed the stepwise regression model (AUC = 0.80), which can be explained by the reduction in accuracy of the target selection and disposal domains when these regression models were applied from the training data to the test data. In contrast, inter-crime distance retained a stable level of predictive accuracy across both the training and test samples, thus allowing it to outperform the stepwise model when applied to the test data. The conclusion that can be drawn from these findings is that inter-crime distance is the most reliable logistic regression model with these car theft data. The inter-crime distance regression model also outperformed the classification tree model, which achieved an AUC value of 0.78 with the test data. But, this difference was not statistically significant ($p > 0.05$).

In contrast to the residential burglary findings, there was little evidence to suggest over-fitting with either the classification tree model or the logistic regression models, with the differences between training and test samples in terms of the AUC statistic non-significant ($p > 0.05$). Thus, unlike the burglary classification tree, it was not necessary to alter the growth limits for the car theft tree.

Table 3D

Receiver Operating Characteristic (ROC) Analyses Representing the Discriminative Accuracy of Logistic Regression and Classification Tree Models with Car Theft

Type of Analysis	**Domain**	**Training Sample**		**Test Sample**	
		AUC (*SE*)	**95% CI**	**AUC (*SE*)**	**95% CI**
Logistic Regression	Combined	0.61 (0.03)***	0.55 – 0.67	0.56 (0.03)*	0.50 – 0.62
	Target Selection (TS)	0.57 (0.03)*	0.51 – 0.63	0.54 (0.03)	0.49 – 0.60
	Target Acquisition	0.52 (0.03)	0.46 – 0.58	0.54 (0.03)	0.48 – 0.60
	Disposal Behaviour	0.58 (0.03)*	0.52 – 0.64	0.50 (0.03)	0.44 – 0.57
	Inter-crime Distance (ICD)	0.82 (0.02)***	0.78 – 0.86	0.82 (0.02)***	0.78 – 0.86
	Stepwise (ICD, TS, Disposal)	0.83 (0.02)***	0.79 – 0.87	0.80 (0.02)***	0.76 – 0.84
ICT	---	0.84 (0.02)***	0.80 – 0.88	0.78 (0.03)***	0.74 – 0.83

* $p < 0.05$; *** $p < 0.001$

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).

3.4 Discussion

The purpose of the current chapter was to build on the novel work of Bennell, Woodhams et al. (2011) by further comparing the ability of logistic regression analysis and classification tree analysis to discriminate between linked and unlinked residential burglaries and car thefts. In both datasets discrimination accuracy was found to be comparable between the regression and tree-based models; although there was a non-significant trend in favour of the most successful regression models. These findings are similar to those observed in the risk assessment literature (e.g., Gardner et al., 1996; Liu et al., 2011) and the wider medical literature (e.g., Austin, 2007), where comparable discrimination accuracy has been observed across various main effects and tree-based regression approaches. They are also similar to the findings of Bennell, Woodhams et al. (2011), who found comparable levels of discrimination accuracy when using logistic regression and classification tree analysis to distinguish between linked and unlinked burglaries, robberies, and rapes.

Given the greater transparency and usability of tree-based approaches, it might be tempting to conclude from these findings that classification tree analysis is a favourable alternative to logistic regression analysis. However, discrimination accuracy is only one component of good model performance; another key component is reliability. That is, will the model be able to discriminate successfully when it is applied to new cases that were not used in its development?

The reliability findings differ for the residential burglary and car theft data. There was significant shrinkage observed in the residential burglary sample when applying the classification tree model from the training to test sample, which suggests that this model may not fully generalise to new cases. This is a particular problem for BCL research, where the ultimate aim is to develop predictive models that can be used to guide future police investigations and where incorrect linkage decisions can significantly hinder an investigation (Grubin et al., 2001). Furthermore, it is difficult to provide an accurate estimate of the error rate one should expect when using the burglary ICT model to identify linked and unlinked crimes. Based on the 95% confidence intervals reported in Table 3B, the estimate of discrimination accuracy that an analyst might be expected to achieve using the ICT model to link residential burglary crimes in Finland would range from 0.71 to 0.98. This is not a very precise estimate, which may discourage the police and other law enforcement agencies from adopting these models in practice.

However, the findings are more encouraging when the best logistic regression model for the burglary data is examined (the stepwise model combining inter-crime distance, entry, and internal behaviours). This model did not demonstrate significant shrinkage from training to test, which suggests that it generalises to a greater extent than the ICT model. Furthermore, it is possible to give a rather more precise estimate of discrimination accuracy for this model, which would range from 0.81 to 0.96 from the figures reported in Table 3B. Overall, these findings suggest that logistic regression is favourable to classification tree analysis when constructing models for the purpose of linking residential burglaries in this sample.

These findings differ to those reported by Bennell, Woodhams et al. (2011), thus suggesting that we should be cautious before generalising their findings to other geographical locations. This further supports the notion discussed in Chapter 1 that replication studies should be an important component of future BCL research, as a multitude of social, demographic, geographical, and pragmatic issues have the potential to alter BCL findings.

The over-fitting that was observed in the current sample of residential burglaries is consistent with findings from the risk assessment literature, where complex predictive models have sometimes failed to replicate when applied to new datasets (e.g., Liu et al., 2011; Rosenfeld & Lewis, 2005; Thomas et al., 2005). It is particularly concerning that attempts to counteract over-fitting with these current data were unsuccessful. However, it is possible that the over-fitting was a result of using split-half validation, rather than necessarily an indication of model instability. Researchers have discussed the fact that split-half validation may not be the most robust method for testing the reliability of predictive models (Cohen, 1990) because it only splits the sample once for the purposes of cross-validation (i.e., into one training sample and one test sample). Consequently, there is a risk that the cross-validation findings are due to some peculiarity of how the data were split; it might be that the findings would change if the data were split differently (Grann & Långström, 2007). A more reliable procedure is, therefore, to create a number of different splits and to average across these splits (see Grann & Långström, 2007; Liu et al., 2011, for further details). Although it was important to replicate the methodology of Bennell, Woodhams et al. (2011) as closely as possible in this study, future research might consider adopting the multi-validation methods described by Liu et al. (2011) and Grann and Långström (2007) instead of the single-sample method used here.

Regarding the car theft models, both the classification tree model and the best logistic regression model (inter-crime distance) were reliable, with minimal shrinkage observed when discrimination accuracy was compared across the training and test samples. These findings are promising and suggest that classification tree analysis may offer an alternative to logistic regression when building predictive models that can discriminate between linked and unlinked car thefts.

However, the proportion of unclassifiable cases is an issue that requires discussion. The classification tree model was unable to classify 32% of the car theft crime pairs and 20% of the residential burglary pairs in this study. While these figures are somewhat comparable to those reported in previous research (Bennell, Woodhams et al., 2011; Steadman et al., 2000), they are not insubstantial numbers. Thus, if an analyst were to utilise these trees in practice, the current findings suggest that they would be unable to proffer recommendations to investigating officers for approximately one in five residential burglary crime pairs and one in three car theft pairs. This may limit the practical applicability of classification tree models.

But, it is important to note that the percentage of unclassifiable cases is entirely dependent on the criteria that are used to define what should and should not be classified. In this study the criteria described by Steadman et al. (2000) and Monahan et al. (2001) were adopted, so as to be consistent with Bennell, Woodhams et al. (2011) and the risk assessment literature. However, it is unclear how Steadman, Monahan, and colleagues developed these criteria and, therefore, whether they are appropriate for use in a policing context. This is an important issue because the most appropriate criteria for deciding whether cases can or cannot be classified may depend on the situation in which BCL is being used. For example, if the BCL analysis was to be presented as evidence in court, then the primary concern might be to reach a reliable predictive decision. In this situation it may be more appropriate to adopt a strict set of criteria for judging whether a case is classifiable or not. However, if the BCL analysis was to be used as an informal way of guiding an investigation, then the primary concern may be to provide some sort of predictive decision (whatever that may be). In this situation it may be appropriate to adopt less stringent criteria. Thus, it should be clear from this discussion that, while the large number of unclassifiable cases in this study is an important issue that should not be ignored, the practical impact of this issue will differ considerably depending on the context in which BCL is used during police investigations.

To summarise, while discrimination accuracy is relatively comparable across classification tree and logistic regression models, the classification tree models in this study demonstrated significant problems in terms of reliability or usability that the logistic regression models did not experience. Based on these findings, the use of classification tree analysis as an alternative to logistic regression cannot be supported in the area of BCL without further investigation.

Future work should explore multi-validation methods of cross-validation. Future work should also seek to compare the relative ability of logistic regression and classification tree analysis with datasets from different geographical locations to those studied thus far. This work will allow classification tree analysis and logistic regression to be tested under varying conditions, which will increase the likelihood that any conclusions drawn from this work will be applicable to a range of police forces and other investigative agencies.

Another important area for future research is to test the usability of classification tree models relative to logistic regression models. As discussed in the introduction, one of the key advantages of classification tree analysis over logistic regression is its potential ease of use and transparency (e.g., Steadman et al., 2000;

Woodhams et al., 2011). But, this should not be assumed; it should be explicitly tested with police crime analysts in mock linkage tasks, such as those employed by Bennell, Bloomfield et al. (2010) and Santtila, Korpela et al. (2004).

Finally, future work should attempt to examine the value of classification tree analysis using samples of unsolved crime, which better reflect the real life situation in which BCL is expected to perform (e.g., Woodhams & Labuschagne, 2012).

In conclusion, the research reported in this chapter has further contributed to the growing body of work that is beginning to systematically compare different methodological approaches to BCL research. It has also replicated existing research with a new crime type and in geographical areas that have not been investigated previously. Research such as this is necessary to build a comprehensive and robust literature upon which reliable and informed practical recommendations can be made to the police regarding the use of BCL.

CHAPTER 4

CROSS-CRIME LINKAGE USING SOLVED AND UNSOLVED CRIME[23]

4.1 Introduction

The research discussed thus far in this thesis has examined the potential value of BCL using samples of solved crime. This has been recognised as a significant limitation for some time by researchers (e.g., Bennell & Canter, 2002; Goodwill & Alison, 2006; Woodhams, Bull et al., 2007). Indeed, it might even be argued that the use of solved crime is *the* most significant limitation within the BCL literature, as it raises fundamental doubts about the ecological validity of existing research. That is, until unsolved crimes are included in studies of BCL, research can always be criticised for not replicating the real life situation in which BCL is conducted.

Previous research can also be criticised for focusing on samples of crime that are homogenous (i.e., they contain one type of crime, for example only residential burglary). This is despite the fact that many offenders (particularly the most prolific) do not restrict themselves to committing just one type of crime (e.g., Farrington et al., 1988; Piquero et al., 2007). Existing BCL research does not, therefore, provide guidance for dealing with series that contain several different types of crime. This is a gap that must be filled if research wants to maximise its potential value for law enforcement investigators and crime analysts.

[23] As stated on pages 3 and 4, versions of this chapter have been published as Tonkin, Woodhams, Bull, Bond, and Palmer (2011), Tonkin, Woodhams, Bull, and Bond (in press), and Tonkin (in press, b).

The current chapter, therefore, aimed to explore the ability of offender behaviour to distinguish between linked and unlinked crimes from different offence types and categories (cross-crime linkage). This issue was examined with a sample of solved offences (Study 1) and with a sample containing both solved and unsolved offences (Study 2). This research represents the first empirical test of cross-crime linkage, and it is one of the first times that BCL has been examined with unsolved crimes.

4.1.1 Why is it Important to be Able to Link Across Crime Types and Categories?

There are several reasons why law enforcement agencies might benefit from the ability to link across crime types and categories. First and foremost, as stated above, there is considerable evidence to suggest that many offenders are versatile in their offending. For example, Leitner and Kent (2009) report that 72.85% of the 3484 solved crime series held on the Baltimore County police database contain crimes of several different types, such as two burglaries and a car theft. Consequently, the police are regularly faced with apprehending versatile serial offenders, which necessitates a method for identifying linked crime series that contain several different types of crime.

Furthermore, it is not uncommon for police officers and crime analysts to be responsible for several different types of crime (Burrell & Bull, 2011). In rural forces this is particularly common because they do not have the resources to employ separate analysts for each crime type. But, this trend may become more widespread in the future given the current economic climate and the significant job losses amongst UK police forces (particularly amongst civilian members of the force, such as crime analysts)

(British Broadcasting Company, 2011; Daily Record, 2012; The Journal, 2011). Moreover, regardless of the economic climate, many forces are already required to combine several different types of crime for the purposes of investigation and analysis. For example, the term Serious Acquisitive Crime (SAC) has recently been coined to refer to a group of robbery, burglary, and vehicle related offences, with all UK police forces having strict Home Office targets in terms of reducing the number of SACs and prosecuting those offenders who are responsible (Department for Communities and Local Government, 2008). It might, therefore, benefit crime analysts if they had reliable techniques for linking across different types of crime, as this would allow them to deal with crime in a holistic way, rather than having to conduct analysis separately for each crime type.

4.1.2 Designing Research into Cross-Crime Linkage

Given the potential benefits of linking across crime types and categories, the next question is how might research begin to investigate whether cross-crime linkage has the potential to work reliably in practice?

The first issue is which types of offender behaviour have the potential to facilitate cross-crime linkage. As discussed in previous sections of this thesis, inter-crime distance and temporal proximity are two measures of offender behaviour that have shown substantial success when discriminating between linked and unlinked crime pairs that are from the same crime type (referred to as linkage within crime types; e.g., Davies et al., in press; Ewart et al., 2005; Goodwill & Alison, 2006; Markson et al., 2010; also see Chapter 2 of this thesis). It is, therefore, logical to suggest that they may also be able to facilitate cross-crime linkage.

In addition to the consistent empirical support for these two linkage features, inter-crime distance and temporal proximity can be calculated for a wide variety of crime types, which makes them well-suited to a study of cross-crime linkage. This is an advantage over other types of crime scene behaviour that have been included in previous studies of BCL within crime types, such as sexual behaviour, control behaviour, entry behaviour, and property stolen, which are only applicable to specific crime types. Thus, it is very difficult to include such behaviours in a study of cross-crime linkage, where the sample would contain a wide variety of property- and person-oriented crimes[24]. Inter-crime distance and temporal proximity are, therefore, well-suited to a study of cross-crime linkage because all that a researcher needs to calculate these measures is an offence location and an estimated offence time, which are features that the police routinely collect for most offences. Furthermore, these measures would be easy to calculate by crime analysts in practice, which gives inter-crime distance and temporal proximity high pragmatic value relative to other types of behaviour. In summary, it was logical to begin the preliminary investigation of cross-crime linkage using inter-crime distance and temporal proximity.

The next issue is how to define cross-crime linkage. According to definitions of crime set by the Home Office, 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 crime that contain several individual types; for example, the crime category ‘robbery’, which contains two specific types of robbery- personal and

[24] 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 behaviour. Please refer to Section 4.4 for a discussion of such potential methodologies.

commercial[25]). 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 BCL is conducted with two crimes of different specific types (e.g., a personal robbery and a commercial robbery). Alternatively, cross-crime linkage in terms of *categories* is defined as any situation in which BCL is conducted with two crimes from different Home Office categories (e.g., a residential burglary and a rape).

In the current chapter, cross-crime discrimination accuracy was examined at both the *type* and *category* level, and compared to discrimination accuracy within crime types (i.e., the 'traditional' way in which BCL has been investigated, where two crimes of the same specific type are paired for analysis, for example two residential burglary crimes are paired). These comparisons allowed investigation of whether cross-crime linkage (using inter-crime distance and temporal proximity) could achieve a comparable level of accuracy to that observed in previous studies of BCL within crime types (e.g., Bennell & Canter, 2002; Tonkin et al., 2008; Woodhams & Toye, 2007). The first study in the current chapter examined this issue with a sample of solved crimes.

4.2 Study 1

[25] At the time of writing, the Home Office record 156 individual crime types, which are split into nine crime categories: violent offences (containing 38 individual crime types), sexual offences (containing 31 crime types), burglary offences (containing seven crime types), drug offences (containing four types), robbery (containing two types), theft/handling offences (containing 16 types), fraud/forgery offences (containing 16 types), criminal damage offences (containing 11 types), and other offences (containing 31 types).

4.2.1 Method

4.2.1.1 The Data

To facilitate Study 1, all offenders who had committed two or more types of violent, sexual, burglary, robbery, theft/handling offences, and criminal damage offences between 01/01/2009 and 31/12/2009 were extracted from the force systems of Northamptonshire police force. This one-year time period is consistent with that used in previous research on BCL (Bennell & Canter, 2002). The location in which each offence occurred (stored as an *x, y* coordinate to the nearest metre) and the date on which each offence was reported to the police was extracted for analysis.

The crime categories used in the current study represent six out of the nine crime categories recognised by the UK Home Office. Crimes included under the categories of 'drug offences', 'fraud/forgery offences', and 'other offences' were excluded from this study because the crimes within these categories typically do not have definite offence locations and times, which makes it difficult to calculate meaningful inter-crime distance and temporal proximity values. Furthermore, a small number of crime types were removed from the other six crime categories for similar reasons. The crime types that were included in this study are listed in Appendix 3. 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).

4.2.1.2 Design and Procedure

A methodology was developed to investigate cross-crime linkage based on Bennell's (2002) methodology for linkage within crime types. Six groups of crime pairs were created, each containing a set of pairs with two crimes per pair (see Table 4A).

Table 4A

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

Crime Pair Type	Linkage Status	Description	Example
Cross-Category	Linked	This subset contained pairs of crime whereby the two crimes in each pair were from different Home Office crime categories and had 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 contained pairs of crime whereby the two crimes in each pair were from different Home Office crime categories and had 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 contained pairs of crime whereby the two crimes in each pair were from the same Home Office crime category but of different specific crime types. The two crimes in each	A personal robbery committed by offender 1 was paired with a commercial robbery also committed by offender 1.

		pair had been committed by the same offender.	
	Unlinked	This subset contained pairs of crime whereby the two crimes in each pair were from the same Home Office crime category but of different specific crime types. The two crimes in each pair had been committed by different offenders.	A shoplifting offence committed by offender 1 was paired with a theft from a vehicle committed by offender 2.
Within-Type	Linked	This subset contained pairs of crime whereby the two crimes in each pair were of the same specific crime type and had been committed by the same offender.	Two personal robbery crimes committed by offender 1 were paired.
	Unlinked	This subset contained pairs of crime whereby the two crimes in each pair were of the same specific crime type and had been committed by different offenders.	Two burglaries in a dwelling committed by different offenders were paired.

Each linked crime pair contained two offences that had been randomly selected from the crimes committed by that offender during 2009. 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)[26]. An inter-crime distance value (in kilometres) and a temporal proximity value (in days) were then calculated for each crime pair. These values were used to examine the potential for linking across crime categories, across crime types, and within crime types.

4.2.1.3 Data Analysis

Initially, each crime pair subset was split into two halves to create training and test samples (e.g., 50 crime pairs from the Linked Cross-Category subset formed a training sample and the remaining 50 formed a test sample; 50 crime pairs from the Unlinked Cross-Category subset formed a training sample and the remaining 50 formed a test sample; and so on for all six subsets). Six direct logistic regression analyses and three forward stepwise regression analyses were then conducted using the training samples in order to examine the independent and combined ability of inter-crime 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

[26] It was not possible to create all possible combinations of unlinked crime pairs with these data, as the statistical programme designed to do this was originally created for studies of BCL within crime types. Consequently, the programme was unable to create cross crime type and cross crime category pairs. A random sub-section of 100 unlinked pairs was, therefore, selected because it was feasible to calculate the inter-crime distance and temporal proximity manually for this volume of pairs. However, it should be noted that the existing statistical programme is currently being modified to allow such calculations.

levels was examined visually by comparing the Model χ^2 values, Wald statistics, and percentage accuracy.

The logistic regression models were used to produce predicted probabilities for each crime pair in the test samples (as described in Section 2.2.3). These predicted probabilities were then used to conduct ROC analysis that indicated how successfully the two linkage features (inter-crime distance and temporal proximity) were able to discriminate between linked and unlinked crimes that were across crime categories, across crime types, and within crime types. The level of discrimination accuracy achieved at these three levels of analysis with inter-crime distance and temporal proximity was compared statistically using ROCKIT 0.9B.

4.2.2 Results and Discussion

The results of six direct logistic regression analyses and three stepwise analyses are presented in Tables 4B and 4C. All models achieved a statistically significant level of discrimination accuracy ($p < 0.05$), which indicates that inter-crime distance and temporal proximity have the potential to function successfully as linkage features across crime categories, across crime types, and within crime types. Furthermore, model performance was relatively similar across all three levels, which suggests that accuracy is comparable across and within crime categories/types. But, it is clear that discrimination accuracy was greater when using inter-crime distance compared to the temporal proximity, regardless of whether the crimes were within or across categories/types.

The stepwise analyses indicated that the combination of inter-crime distance and temporal proximity was not able to facilitate a substantial improvement in discrimination accuracy. Indeed, inter-crime 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 stepwise 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 inter-crime distance on its own (see Table 4C), which- although statistically significant- is not of significant practical value. It can, therefore, be concluded with this sample that inter-crime distance should be given priority when linking across crime categories, across crime types, and within crime types.

Table 4B

Direct and Stepwise Logistic Regression Analyses for Inter-crime Distance and Temporal Proximity Across Crime Categories, Across Crime Types, and Within Crime Types (Solved Crime Only)

	Model	**Constant (SE)**	**Logit Change (SE)**	**Model χ^2 (df)**	**Wald (df)**	***R^2* (Cox & Snell-Nagelkerke)**
Inter-crime Distance	Across Crime Categories	1.21 (0.327)	-0.146 (0.0321)	31.15 (1)***	20.69 (1)***	0.27 – 0.36
	Across Crime Types	1.75 (0.373)	-0.303 (0.0661)	61.91 (1)***	21.09 (1)***	0.46 – 0.62
	Within Crime Types	1.28 (0.330)	-0.143 (0.0293)	35.80 (1)***	23.66 (1)***	0.30 – 0.40
Temporal	Across Crime Categories	0.607 (0.317)	-0.00663 (0.00274)	6.60 (1)*	5.87 (1)*	0.06 – 0.09
	Across	0.712 (0.315)	-0.00729	9.47 (1)**	8.38 (1)**	0.09 – 0.12

Proximity	Crime Types		(0.00252)			
	Within Crime Types	0.722 (0.296)	-0.00845 (0.00260)	12.53 (1)***	10.57 (1)**	0.12 – 0.16
Stepwise	Across Crime Categories	1.86 (0.463)	ICD: -0.148 (0.0335) TP: -0.00677 (0.00304)	36.50 (2)***	ICD: 19.53 (1)*** TP: 4.95 (1)*	0.31 – 0.41
	Across Crime Types	---	---	---	---	---
	Within Crime Types	---	---	---	---	---

$*p < 0.05$; $**p < 0.01$; $***p < 0.001$

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

Table 4C

Predictive Accuracy of the Regression Models (%) (Solved Crime Only)

	Inter-crime Distance			**Temporal Proximity**			**Stepwise**		
	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 regression analyses only contained inter-crime distance, so the figures were identical to the single-feature regression models.

To further clarify discrimination accuracy across and within crime types/categories, seven ROC curves were produced (see Table 4D). ROC curves were not constructed for the stepwise across crime types and the stepwise within crime types analyses because inter-crime distance was the only linkage feature included in the final models, so the AUC values would be identical to the single-feature ROCs for inter-crime distance.

All of the AUC values were highly significant ($p < 0.01$), which suggests that both inter-crime 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 inter-crime 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; $p > 0.05$). Also, there was no significant difference in terms of temporal proximity across categories (AUC = 0.67), across types (AUC = 0.74), or within types (AUC = 0.74) (all comparisons were non-significant; $p > 0.05$). 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 4D also indicates that discrimination accuracy was superior generally for inter-crime distance compared to temporal proximity, with statistically larger AUC values across crime categories, across crime types, and within types (all comparisons were significant at $p < 0.01$). Furthermore, the level of discrimination accuracy that was achieved when combining these two features to link crimes across categories was comparable to that achieved using inter-crime distance on its own (both AUCs = 0.88; $p > 0.05$). This supports the above conclusion that inter-crime distance should be given priority when linking crimes (at least with the current sample and range of offender behaviours studied here).

Table 4D

Receiver Operating Characteristic (ROC) Results Across Crime Categories, Across Crime Types, and Within Crime Types Using Inter-crime Distance and Temporal Proximity with the Test Samples (Solved Crime Only)

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

**$p < 0.01$; ***$p < 0.001$

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).

To test whether the findings could be successfully cross-validated, seven ROC curves were constructed using the training sample (see Table 4E) and the AUC values obtained using the training and test samples compared. There were no statistically significant differences (all comparisons $p > 0.05$). The current findings were, therefore, successfully cross-validated.

Table 4E

Receiver Operating Characteristic (ROC) Results Using the Training Samples (Solved Crime Only)

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

**$p < 0.01$; ***$p < 0.001$

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).

4.3 Study 2

Study 1 provides the first empirical demonstration that simple aspects of offender behaviour might be used to facilitate cross-crime linkage, and that the level of accuracy achieved is comparable to that observed when linking crimes of the same specific type (i.e., BCL within crime types).

However, the data sampled in Study 1 can be criticised because it does not contain unsolved offences, which is a significant departure from the real life setting in which BCL is expected to perform (Bennell & Canter, 2002; Woodhams, Bull et al., 2007). Specifically, there are two different scenarios in which a crime analyst would seek to link crimes (Woodhams, Bull et al., 2007). First, an analyst might proactively search for linked crimes among a police database. In this scenario it is most likely that the analyst would be attempting to link one unsolved crime with another unsolved crime. Alternatively, an analyst might be presented with an index offence (that has already been solved) and their task is to identify other, unsolved crimes that this offender may have committed (referred to as reactive BCL). In this scenario the analyst is attempting to link a solved crime with an unsolved crime. What is noticeable from these two scenarios is that there is no situation in which a crime analyst is required to link a solved crime with another solved crime (this would have little investigative value). However, this is exactly the situation tested in previous studies of BCL that have used samples of solved crime (e.g., Bateman & Salfati, 2007; Bennell & Jones, 2005; Goodwill & Alison, 2006; Santtila et al., 2005, 2008; Tonkin et al., 2008; Woodhams & Toye, 2007; Yokota et al., 2007). Consequently, it is questionable whether existing BCL research is applicable to real life police investigations.

This gap between research and practice becomes more concerning when one considers that solved crimes may be more behaviourally consistent and distinctive than unsolved crimes, which might explain why these crimes became solved in the first place (Bennell & Canter, 2002; Woodhams, Bull et al., 2007). For example, it is logical to suggest that two crimes committed in close geographical and temporal proximity would attract the attention of investigating officers, thus making it more likely that these two crimes would be linked to the same offender and, therefore, solved; whereas a third crime that was committed further from these two crimes in space and time may remain unsolved (Bennell, 2002). If this suggestion is correct, then research that is based solely on samples of solved crime may provide an unrealistic and inflated estimate of discrimination accuracy compared with what we would expect to see when BCL is used in real life with unsolved crime (Bennell & Canter, 2002). This is a significant problem for an area of research that ultimately hopes to yield reliable recommendations that can guide the linking of crimes in practice.

In response to this potential limitation, Woodhams and Labuschagne (2012) recently conducted a study to investigate the behavioural consistency and distinctiveness displayed by 22 serial sex offenders across 119 solved and unsolved sexual offences in South Africa[27]. They separated the sample into offence series that had first been identified as such by the South African Police via DNA matching (n = 9 series) and those that had first been identified as a series due to behavioural similarity (n = 9 series). Woodhams and Labuschagne (2012) hypothesised that if the degree of behavioural consistency and distinctiveness evident in the DNA-identified series was similar to that in the behaviour-identified series then it would be possible to apply the findings from previous research with solved crime to samples of unsolved crime. That is, it would suggest that existing BCL research is applicable to real life police investigations, despite its use of solved crime.

Woodhams and Labuschagne (2012) found that the DNA-identified series were marginally less consistent and distinctive than the behaviour-identified series (p = 0.049, with a small effect size; Cohen, 1988). The fact that this difference was small and only marginally statistically significant led the researchers to conclude that findings produced

[27] Jaccard's coefficient was used to measure behavioural consistency and distinctiveness in their study.

using samples of solved crime may be generalised to samples of unsolved crime and, therefore, that existing BCL findings may have real life practical value.

But, as the authors note themselves, future work must create larger samples that allow more robust analyses (such as ROC) to be conducted. It also cannot be assumed that Woodhams and Labuschagne's (2012) findings with sexual assault will necessarily apply to other types of crime, such as burglary, robbery, or car theft. Furthermore, there is a potential limitation of the methodology utilised by Woodhams and Labuschagne (2012) because its use depends on the researcher being able to determine how the offence series were initially identified by the police (i.e., whether the crimes were linked based on matching DNA or based on behavioural similarity). Unfortunately, it is not possible to identify how crimes were initially linked as a series in all police jurisdictions (Dr John Bond, personal communication; Dr Jessica Woodhams, personal communication), which means that an alternative methodology is needed in these situations.

One alternative is to use unsolved crimes that have been linked via DNA evidence (Sorochinski & Salfati, 2010; Woodhams, Bull et al., 2007). Such a sample would allow the researcher to determine with a degree of confidence which crimes were committed by the same offender (due to matching DNA being recovered at the different crime scenes), whilst allowing discrimination accuracy to be tested using a sample of crime that more closely reflects the real life scenario in which BCL would be expected to perform (i.e., with unsolved crime). Study 2, therefore, aimed to build on the findings of Study 1 by testing the potential for cross-crime linkage with a sample containing both solved and unsolved offences.

4.3.1 Method

4.3.1.1 The Data

One hundred and thirty-two offenders were identified who had committed two or more crimes between 2005 and 2009 in the Northamptonshire area. As with Study 1, crimes from six of the nine Home Office crime categories were included in this study (see Appendix 3 for a full listing of the crimes included in Study 2). The crimes identified for each offender contained at least one unsolved crime and all crimes were linked to each offender via DNA evidence. Two offences per offender were randomly selected from the crimes committed between 2005 and 2009 (thus replicating the methodology of Study 1). The sample, therefore, consisted of 264 crimes committed by 132 offenders. One-hundred and ninety-five (74%) of these offences were classed as unsolved and 69 were classed as solved (26%)[28]. The geographical location of each offence (stored as an *x, y* coordinate to the nearest metre) and the time and date the offence was reported to the police were recorded for each offence.

4.3.1.2 Design and Procedure

The methodology described in Study 1 was replicated in Study 2. For the sake of space, the description of this methodology is not repeated. However, it is worth noting that the sample in Study 2 was smaller than that in Study 1. Consequently, there were only 47

[28] For the purposes of this study, crimes that were classed as "detected" on Northamptonshire police databases were considered to be solved, whereas those classed as "undetected" were considered unsolved. A crime is classed as detected when there is sufficient evidence for the case to be submitted to the Crown Prosecution Service (the CPS are the government department responsible for prosecuting criminal offences in England and Wales). It should be noted that CPS policy does not allow a DNA match between a suspect and a crime scene to be submitted as evidence of guilt without corroborating evidence. Thus, it was possible in this study for two crimes to be linked via DNA evidence (and, therefore, considered to be committed by the same person), but for one of these crimes to be classed as solved (i.e., detected) and the other to be classed as unsolved (i.e., undetected).

linked and 47 unlinked crime pairs at the cross crime category level, there were 32 linked and 32 unlinked pairs at the cross crime type level, and 53 linked and 53 unlinked pairs at the within crime type level.

4.3.1.3 Data Analysis

The analyses reported in Study 1 were replicated in Study 2. To summarise, six direct logistic regression analyses and three stepwise analyses were conducted on the training samples. The logistic regression models were then applied to the test samples (as described in Section 2.2.3) to produce predicted probability values that were subsequently used to construct ROC curves. These curves indicated the level of discrimination accuracy achieved across crime categories, across crime types, and within crime types.

4.3.2 Results and Discussion

Six direct logistic regression analyses and three stepwise analyses were conducted using the training samples to determine the independent and combined ability of inter-crime distance and temporal proximity to link across crime categories, across crime types, and within crime types (see Tables 4F and 4G).

The findings reported in Tables 4F and 4G indicate that the same basic conclusions can be drawn in Study 2 as were drawn in Study 1. Specifically, inter-crime distance and temporal proximity show some evidence that they have the potential to link across crime categories, across crime types, and within crime types. Furthermore, the level of predictive accuracy is somewhat comparable across these three levels of analysis.

However, there was one instance of variation from Study 1 to Study 2. The model for temporal proximity across crime types was statistically significant in Study 1 ($p < 0.01$) but failed to reach statistical significance in Study 2. There are two potential explanations for this discrepancy. First, it might be that temporal proximity was simply less successful at the cross crime type level when tested with a sample that contained both solved and unsolved offences (compared to a sample that contained only solved offences). Alternatively, it may be that the smaller sample size in Study 2 resulted in diminished statistical power, thereby making it more difficult to detect significant findings (Cohen, 1988). Indeed, when the R^2 values and predictive accuracies reported in Studies 1 and 2 for temporal proximity across crime types are compared there is little difference, with the percentage of variance explained in Study 2 between 9 and 11% compared to between 9 and 12% in Study 1 and predictive accuracy reaching 59.40% in the current study compared to 62.00% previously. It might, therefore, be argued that, while the statistical significance of the findings in Study 2 differs from that in Study 1, discrimination accuracy itself is comparable. But, the ROC analyses provided a more comprehensive insight into this issue (Bennell, 2002; Hosmer & Lemeshow, 2000).

Table 4F

Direct and Stepwise Logistic Regression Analyses for Inter-crime Distance and Temporal Proximity Across Crime Categories, Across Crime Types, and Within Crime Types (Solved and Unsolved Crime)

	Model	**Constant (SE)**	**Logit Change (SE)**	**Model χ^2 (df)**	**Wald (df)**	***R^2* (Cox & Snell-Nagelkerke)**
Inter-crime Distance	Across Crime Categories	1.79 (0.570)	-0.310 (0.112)	27.07 (1)***	7.63 (1)**	0.43 – 0.58
	Across Crime Types	2.60 (0.917)	-0.252 (0.0780)	21.78 (1)***	10.39 (1)**	0.49 – 0.66
	Within Crime Types	1.76 (0.549)	-0.133 (0.0344)	21.48 (1)***	14.96 (1)***	0.33 – 0.44
	Across Crime Categories	0.816 (0.462)	-0.00193 (0.000886)	5.98 (1)*	4.75 (1)*	0.12 – 0.16

Temporal Proximity	Across Crime Types	0.727 (0.573)	-0.00192 (0.00120)	2.85 (1)	2.53 (1)	0.09 – 0.11
	Within Crime Types	1.10 (0.450)	-0.00269 (0.000934)	12.35 (1)***	8.31 (1)**	0.20 – 0.27
Stepwise	Across Crime Categories	3.30 (0.934)	ICD: -0.321 (0.111) TP: -0.00306 (0.00125)	34.75 (2)***	ICD: 8.31 (1)** TP: 5.96 (1)*	0.52 – 0.69
	Across Crime Types	---	---	---	---	---
	Within Crime Types	2.71 (0.761)	ICD: -0.125 (0.0359) TP: -0.00243 (0.00102)	28.62 (2)***	ICD: 12.05 (1)*** TP: 5.68 (1)*	0.41 – 0.55

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Note. Figures are not presented for the Combined Across Crime Types model because the stepwise logistic regression analysis only contained inter-crime distance, so the figures are identical to the single-feature regression model.

Table 4G

Predictive Accuracy of the Regression Models (%) (Solved and Unsolved Crime)

	Inter-crime Distance			**Temporal Proximity**			**Stepwise**		
	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
Model	79.20	84.40	75.90	64.60	59.40	66.70	85.40	---	77.80

Note. Figures are not presented for the Combined Across Crime Types model because the stepwise regression analysis only contained inter-crime distance, so the figures were identical to the single-feature regression model.

To further clarify discrimination accuracy across and within crimes, eight ROC curves were produced (see Table 4H). A ROC curve was not constructed for the stepwise model across crime types because the stepwise regression only included inter-crime distance in the model.

Table 4H

ROC Results for Behavioural Case Linkage Across Crime Categories, Across Crime Types, and Within Crime Types Using Inter-crime Distance and Temporal Proximity with the Test Samples (Solved and Unsolved Crime)

	Behavioural Case Linkage Feature	**AUC (*SE*)**	**95% Confidence Interval**
Across Crime Categories	Inter-crime Distance	0.83 (0.06)***	0.71 – 0.95
	Temporal Proximity	0.75 (0.07)**	0.61 – 0.89
	Stepwise	0.85 (0.06)***	0.73 – 0.96
Across Crime Types	Inter-crime Distance	0.73 (0.09)*	0.56 – 0.91
	Temporal Proximity	0.56 (0.11)	0.35 – 0.77
Within Crime Types	Inter-crime Distance	0.75 (0.07)**	0.62 – 0.89
	Temporal Proximity	0.80 (0.06)***	0.68 – 0.92
	Stepwise	0.81 (0.06)***	0.69 – 0.93

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

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).

All AUC values were statistically significant ($p < 0.05$), except for the temporal proximity across crime types. These findings support the notion that inter-crime distance has the potential to facilitate statistically significant discrimination accuracy across all three levels of analysis and temporal proximity has the potential across crime categories and within crime types. These findings are similar to those observed in Study 1, except for the diminished accuracy of temporal proximity across crime types, which has now been observed in both the regression and ROC analyses in this study.

However, while the same basic conclusions can be drawn across Studies 1 and 2, it is important to note that there were differences in the magnitude of discrimination accuracy (as indicated by the size of the AUC values). Most notably, inter-crime distance achieved a lower level of discrimination accuracy within crime types in Study 2 compared to Study 1. Also, the level of accuracy achieved using the temporal proximity was lower across crime types in Study 2. Both of these differences were confirmed statistically ($p < 0.05$). However, the other estimates of discrimination accuracy were comparable across the two studies ($p > 0.05$). These findings seem to suggest that the level of discrimination accuracy tends to be reduced in certain (but not all) cases when unsolved crimes are included in the analysis.

The final issue is whether the findings reported in Table 4H can be successfully cross-validated. Eight ROC curves were, therefore, constructed using the training samples (Table 4I) and the AUC values compared to those produced using the test samples. There were no statistically significant differences between the AUC statistics presented in Tables 4H and 4I ($p > 0.05$), thereby cross-validating the findings in Study 2.

However, it is important to note that the confidence intervals were relatively large in this study, which suggests that there may be an inflated risk of Type II error when comparing the AUC values achieved in Study 1 and Study 2, and when comparing the AUCs obtained with the training versus test samples in Study 2.

Table 4I

Receiver Operating Characteristic (ROC) Results Using the Training Samples (Solved and Unsolved Crime)

	Behavioural Case Linkage Feature	**AUC (*SE*)**	**95% Confidence Interval**
Across Crime Categories	Inter-crime Distance	0.93 (0.04)***	0.86 – 1.00
	Temporal Proximity	0.67 (0.08)	0.51 – 0.82
	Stepwise	0.94 (0.03)***	0.88 – 1.00
Across Crime Types	Inter-crime Distance	0.93 (0.05)***	0.84 – 1.00
	Temporal Proximity	0.60 (0.11)	0.38 – 0.81
Within Crime Types	Inter-crime Distance	0.84 (0.06)***	0.74 – 0.95
	Temporal Proximity	0.77 (0.06)***	0.64 – 0.89
	Stepwise	0.89 (0.04)***	0.81 – 0.98

***$p < 0.001$

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).

4.4 General Discussion

The research reported in this chapter is the first time that the potential for cross-crime linkage has been investigated, and only the second time that discrimination accuracy has been examined using unsolved offences. In summary, it was found that inter-crime distance and temporal proximity were able to facilitate statistically significant levels of discrimination accuracy when distinguishing across crime categories and across crime types. Furthermore, the level of cross-crime accuracy was generally comparable to that achieved when linking crimes of the same specific type (BCL within crime types). These basic findings were replicated with a sample containing just solved offences (Study 1) and with a sample containing both solved and unsolved offences (Study 2). It can, therefore, be concluded that there may be the potential for crime analysts to conduct cross-crime linkage in practice. Although, the findings indicate that inter-crime distance should be given priority over temporal proximity in this process.

However, it is important that researchers and practitioners of BCL are cautious when interpreting these findings. While the basic findings were replicated with both solved and unsolved crimes, there was a trend towards diminished discrimination accuracy and greater model instability when cross-crime linkage was examined with a more realistic sample (Study 2). Although it was difficult to determine whether these findings were a true indication of discrimination accuracy or simply an artefact of the sample size, it is important that researchers and practitioners assume the worst until it is proved otherwise. In short, they should assume that previous research may have somewhat over-estimated the potential value of BCL due to its reliance on samples of solved crime.

But, it is also important to recognise that discrimination accuracy did not *always* diminish from Study 1 to Study 2; there were several instances where accuracy was comparable. Thus, while researchers and practitioners should be cautious about interpreting previous research, they should not necessarily assume that the potential value of BCL has always been over-estimated. Indeed, the vast majority of statistical models in Study 2 achieved statistically significant levels of discrimination accuracy. Thus, while we should be careful to temper our enthusiasm for cross-crime linkage, we can be cautiously optimistic regarding the potential for this procedure to work reliably in practice.

Given this potential, the next issue to consider is how these offender behaviours may be put into practice by police crime analysts when linking crimes. The first option is to calculate decision thresholds that indicate the specific point at which two crimes are geographically and/or temporally close enough to be classed as linked. That is, when the inter-crime distance and/or temporal proximity value for a particular pair of crimes is below the threshold, the analyst can conclude that the two crimes were committed by the same person. Conversely, when the values exceed this threshold the analyst can conclude that the two crimes were committed by different offenders. It is worth noting that decision thresholds were calculated in this study using Youden's Index (see Bennell, 2002), but due to the limitations of space (imposed by University regulations) and also due to limitations with the methods used to form these thresholds (as discussed below) they were not presented in the analyses above[29]. However, the interested reader is referred to the published versions of this chapter, where the

[29] Likewise, decision thresholds were calculated for all analyses reported in this thesis, but were not reported for the same reasons.

thresholds and methods used to develop these thresholds are described in detail (see Tonkin, in press; Tonkin, Woodhams, Bull, Bond, & Palmer, 2011).

While decision thresholds that are derived from Youden's Index have been suggested as a way of guiding police crime analysts in practice (e.g., Bennell & Jones, 2005), the limitations of this method have been recognised for some time. In particular, Youden's Index does not take into account the prior probability that crimes are linked/unlinked, nor does it take into account the various costs and benefits associated with correct/incorrect linkage decisions (Bennell, 2002). These are both important issues that should guide the selection of an appropriate decision threshold in practice. Furthermore, there is a risk that decision thresholds will be applied in a rigid, 'black-and-white' manner. This might lead to a situation where two crime pairs are given different linkage classifications (one is classed as linked and the other classed as unlinked) despite the fact that they only differ very slightly in terms of behavioural, geographical, and/or temporal similarity. BCL is not at the stage (nor is it ever likely to be) where definitive predictive decisions can be made. Instead, it is more realistic to expect that BCL will work in terms of probability, and the best that research can hope for is to reduce the degree of uncertainty as much as possible (although it will never be completely eradicated). Consequently, it seems inappropriate to recommend the use of thresholds that promote a rigid and inflexible approach to linking crimes.

A more appropriate alternative might be to use inter-crime distance/temporal proximity to prioritise certain crimes for further analysis. For example, in a situation where an analyst is tasked with finding all crimes within a police database that are linked to a particular crime (Crime X), s/he could calculate inter-crime distance/ temporal proximity 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 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. This approach seems to avoid the rigid and inflexible approach of thresholds whilst also being consistent with the probabilistic nature of BCL.

Thus far this discussion has focused on the practical implications of the chapter's findings, but there are also theoretical insights that can be gleaned. 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 offences 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 offended in broadly the same geographical regions, regardless of crime type. This provides support for several seminal models of offender spatial behaviour, such as rational choice theory, routine activities theory and crime pattern theory, which assume that generic psychological processes are involved in the production of criminal spatial behaviour, irrespective of crime type (e.g., Brantingham & Brantingham, 1981; Clarke & Felson, 1993).

These findings are also relevant to the issue of situational similarity and behavioural consistency, which was originally discussed within the personality literature (e.g., Furr & Funder, 2004) and subsequently applied in relation to BCL (Woodhams et al., 2008a). In terms of BCL, it has been hypothesised that an offender's behaviour 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. (2008a), 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 behaviour 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 behaviour would be observed at the cross-category level. However, it should be noted that Woodhams and colleagues (2008) originally applied this argument to modus operandi behaviours rather than geographical and temporal behaviour.

The findings from the current study do not support the hypothesised relationship between situational similarity at the crime type level and consistency in geographical/temporal behaviours because consistency, distinctiveness, and discrimination accuracy were comparable across all three levels of investigation. It might, therefore, be concluded that there is little support for a substantive relationship between situational similarity and behavioural consistency in the current studies. A similar conclusion was reached by Woodhams et al. (2008a) in their study of modus operandi behaviours displayed by juvenile sexual offenders.

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 offences, so future work might 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; for example, existing psychological classification systems (e.g., see 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, or offenders 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; Woodhams et al., 2008a). 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 behavioural consistency.

Having considered the main findings and some of their implications, it is important to consider the limitations of the research reported in this chapter. The primary limitation of Study 2 was sample size, which made it somewhat difficult to interpret the findings. Nevertheless, the sample was similar in size to that utilised in previous BCL research (Bennell, 2002; Woodhams, 2008; Woodhams & Labuschagne, 2012). Moreover, the sample size could not have been increased because the full extent of Northamptonshire’s electronic crime records was searched to provide data for this study. To some extent this leads to questions about the feasibility of using unsolved but linked via DNA crimes to investigate BCL. Future work may have to consider combining several datasets from different police forces in order for this methodology to yield samples that are large enough to facilitate reliable analyses (see Chapter 6 for further discussion of ongoing work in this area).

At a more general level, however, it is unclear whether this methodology actually tests discrimination accuracy in a more ecologically valid way than the previous methodology that relies on solved crime. Although the inclusion of unsolved offences is clearly a step in the right direction, one has to question whether it is appropriate to include unsolved offences on the basis of DNA matching. In practice, police crime analysts would be less likely to conduct BCL when forensic evidence has been recovered, simply because forensic approaches to linkage are generally more reliable and have gained greater acceptance in court than behavioural approaches (Grubin et al., 2001). Potentially, this means that the crimes sampled in Study 2 (and in any future study using this methodology) were not necessarily representative of those that will be submitted to BCL in real life. Thus, the use of unsolved but linked via DNA crimes in BCL research may simply swap one threat to ecological validity with another. This highlights the difficulty faced by researchers of BCL when trying to reduce the gap between research and practice in order to provide more realistic findings.

Furthermore, the methodology used in Study 2 relied on scene-to-scene DNA matches as the basis for determining whether crime pairs were linked or unlinked. This is in contrast to Study 1 and previous research (e.g., Bennell & Canter, 2002; Markson et al., 2010), which used detection status to make these decisions. This is potentially a limitation if the offender's DNA was found at a crime scene for some reason other than that s/he committed the crime. For example, it may be that a suspect's DNA was left at the victim's house because s/he is a friend of the victim, rather than the perpetrator. In a situation such as this, a crime pair classed as linked in Study 2 would in fact be unlinked. This would introduce noise into the analyses. However, the pattern of findings observed in Study 2 does not suggest that noise has been systematically introduced as a result of the DNA-matching procedure. If this were the case, one would expect to see a significant reduction in discrimination accuracy across all statistical models tested in Study 2 compared with those tested in Study 1. In reality, the majority of statistical models achieved comparable levels of discrimination accuracy across the two studies.

The current set of findings should also be viewed as preliminary until future studies have replicated them. Given the variation in discrimination accuracy that has been observed across different geographical locations (e.g., Bennell & Jones, 2005; see also Chapter 2 of this thesis), future research should endeavour to test these findings across a diverse range of police jurisdictions.

Studies 1 and 2 were also limited in terms of the range of offender behaviours studied. BCL research has traditionally tested a much wider range of offender behaviours than those considered in this chapter. Although this decision was justified by these two behaviours having the most consistent empirical support in the BCL 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 using a wider range of offender behaviours. This may, however, require a slightly different methodology to that utilised in the current study. For example, researchers might focus on certain types of crime that share particular behavioural features, such as robbery, rape, and murder, which all contain elements of victim-offender interaction, control, and escape behaviours (e.g., the use of a weapon, methods of victim restraint, and attempts to conceal one's identity from the victim). Indeed, a research study investigating the potential to link across rapes and robberies using such behaviour is already underway at the University of Birmingham, UK. This may help to overcome the obvious difficulty posed by studying a diverse range of crimes that contain often very different types of offender behaviour. Alternatively, future work might consider developing behavioural themes from offender crime scene behaviour that would subsequently be used to examine discrimination accuracy across crime categories/types. These themes could be developed statistically using techniques such as multidimensional scaling and cluster analysis (e.g., Bateman & Salfati, 2007; Santtila et al., 2008) or researchers might consider using theoretical models that are designed to apply to a wide variety of crime types, such as the Narrative Action System (NAS) model (Canter & Youngs, 2009; Youngs & Canter, 2009). Regardless of the approach used, research such as this is important because investigators will otherwise have no guidance in situations where geographical and temporal behaviour are either unreliable or absent (e.g., where a victim has been drugged or knocked unconscious and is unable to recall where and when the offence took place).

Despite these limitations, the current chapter represents a significant development in the BCL literature. These studies are the first empirical demonstration of the potential for cross-crime linkage, which is important because many serial offenders are versatile in their offending and cross-crime linkage is a key part of helping the police to deal effectively with these problematic offenders. However, significant replication and extension of this preliminary research is needed before these findings can be applied with confidence in practice.

CHAPTER 5

BEHAVIOURAL CASE LINKAGE: STUDENTS, CRIME ANALYSTS, AND STATISTICS

5.1 Introduction

Throughout this thesis and previous research, chance has been used as the benchmark for judging whether a particular statistical model has the potential to support BCL. The assumption is that, when discrimination accuracy exceeds chance (e.g., an AUC of 0.50 or $p < 0.05$), it can be concluded that there is the potential for this model to support the linking of crime in practice[30]. While this approach is justified from a statistical point of view, it is arguably more appropriate from a practical perspective to compare statistical models with the methods that are already available to the police (i.e., the discrimination accuracy achieved by law enforcement personnel who are responsible for conducting BCL in practice, such as crime analysts). Crime analysts often have considerable experience of crime, criminal behaviour and, specifically, BCL, so we might expect them to perform at a level that exceeds chance when linking crime. Thus, statistical models must be able to distinguish between linked and unlinked crimes at a level that is at least comparable to crime analysts if we are to conclude that such models have a potential practical value. The current chapter will examine this issue by comparing the

[30] However, given the interpretative guidelines of Swets (1988), it is probably unlikely that a researcher would attribute practical value to a statistical model unless it achieved an AUC greater than 0.70.

discrimination accuracy of crime analysts, university students, and three logistic regression models in a mock linkage task.

5.1.1 Clinical Versus Actuarial Approaches to Decision-Making

To some extent, the current study is a contribution to the literature on clinical versus actuarial decision-making because the aim was to examine the relative accuracy of humans compared to statistical models in a mock BCL task. It is, therefore, logical to begin with a discussion of this literature in forensic and non-forensic contexts.

The debate regarding clinical versus actuarial approaches to decision-making has a long tradition in psychological and medical research (e.g., Dawes, Faust, & Meehl, 1989; Grove & Meehl, 1996; Meehl, 1954). Generally speaking, clinical approaches to decision-making involve a particular decision-maker combining various pieces of information using informal and subjective methods in order to reach a conclusion, whereas actuarial approaches (also referred to as statistical or mechanical methods) involve the application of some algorithm or equation to a set of data in order to reach a conclusion (Grove, Zald, Lebow, Snitz, & Nelson, 2000).

Overall, this body of work appears to reach the resounding conclusion that actuarial approaches to decision-making are often superior to clinical approaches. For example, 64 out of the 136 studies (47%) included in Grove and Meehl's (1996) meta-analysis demonstrated superior performance for actuarial methods over clinical methods, which compared to just eight studies (6%) that favoured the clinical approach. These findings led Grove and Meehl (1996) to conclude that "[e]mprical research provides no clear, replicated, robust examples" (p. 298) of clinical approaches outperforming actuarial approaches to decision-making.

Within forensic contexts, a similar pattern of findings has emerged. For example, five out of the six meta-analyses identified by Singh and Fazel (2010) in their meta-review demonstrated the superiority of actuarial over clinical approaches to the prediction of reoffending[31]. Furthermore, Bennell, Jones, and Taylor (2011) recently demonstrated that a statistical prediction rule was able to outperform human decision-makers when determining whether suicide notes were genuine or false, even when the decision-makers received training in how to successfully distinguish between genuine and falsified notes.

Bennell, Bloomfield et al. (2010) provide a cogent explanation for the superior performance of actuarial methods in decision-making tasks. They suggest that humans are limited in terms of their information-processing capabilities, which subsequently leads them to rely on heuristics when making decisions (i.e., decision-making rules that simplify the complexity of the real world). According to the literature on decision-making, heuristics often contain a range of errors and biases that ultimately lead to mistakes in the decision-making process (Bennell, Bloomfield et al., 2010; Dawes et al., 1989; Grove & Meehl, 1996; Kahneman & Tversky, 1973). Actuarial methods on the other hand do not rely on such heuristics.

But, Bennell, Bloomfield et al. (2010) also highlight a range of research that supports the use of heuristics in certain situations. Specifically, they draw attention to

[31] However, it should be noted that structured clinical judgement (SCJ) – which combines actuarial and clinical methods – is currently the recommended approach to risk assessment in the UK (Department of Health, 2007; National Institute for Health and Clinical Excellence, 2005).

the literature on geographical profiling[32], where the superiority of actuarial approaches has been questioned (e.g., Bennell, Taylor, & Snook, 2007). In a series of studies, Bennell and colleagues have demonstrated that students who are told to adopt an 'error minimisation' heuristic, whereby they predict the offender's home location to be situated roughly in the geographical centre of a series of crimes, can perform as successfully as complicated statistical algorithms in mock geographical profiling tasks (e.g., Bennell, Snook, Taylor, Corey, & Keyton, 2007; Snook, Canter, & Bennell, 2002; Snook, Taylor, & Bennell, 2004; Taylor, Snook, & Bennell, 2009). The success of the error minimisation heuristic in this context appears to be due to the fact that it successfully captures real world patterns in offender behaviour (Bennell, Bloomfield et al., 2010). Thus, the superiority of actuarial methods should not be assumed; instead, human decision-makers can be expected to achieve highly accurate levels of decision-making accuracy, provided they rely on heuristics that are a reasonable approximation to reality (referred to as ecologically rational heuristics; Martignon & Hoffrage, 1999). What, then, is the likelihood that humans are able to identify and successfully use ecologically rational heuristics in the context of BCL?

5.1.2 Human Performance in the Behavioural Case Linkage Task

There are four studies that have examined the performance of humans in mock BCL tasks (Bennell, Bloomfield et al., 2010; Canter et al., 1991; Pakkanen, Zappalà, Grönroos, & Santtila, in press; Santtila, Korpela et al., 2004). The first of these studies

[32] Geographical profiling is an investigative methodology that uses the locations of a linked series of crimes to make a prediction about where the offender is most likely to live (Paulsen, 2006; Rossmo, 2000).

was conducted by Canter et al. (1991), who studied 32 police detectives from across the UK in terms of their ability to identify four linked series of sexual assaults. The officers were provided with a short description of each of the 12 offences and were asked to indicate the linked crimes. The majority of officers performed at a chance level of accuracy (i.e., they identified three out of 12 correct links[33]), which indicates that a number of linkage errors were made by the participants. But, there was significant between-participant variation in BCL performance; for example, three officers achieved an accuracy score of eight out of 12, indicating just one mistake in their decision-making[34], whereas a different three officers performed below the chance level of accuracy, with one officer failing to identify any of the correct links. The poor performance of some officers was attributed to their reliance on inappropriate linkage features and their inability to combine the relevant information in a useful way (Canter et al., 1991).

The second study to examine human performance in the linkage task was reported by Santtila, Korpela et al. (2004). They compared the performance of various participant groups in a mock linkage task where participants were asked to identify series of linked car thefts. Consistent with Canter et al. (1991), there was wide variation in linkage accuracy both across and within the different groups of participants.

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[33] Each offender had committed three crimes (A, B, C), so there were three correct links that could be identified for each offender: (1) A-B; (2) A-C; (3) B-C. This makes a total of 12 correct links that could be identified in Canter et al.'s (1991) experimental task (3 links × 4 offenders).

[34] As explained by Canter et al. (1991), a score of eight indicates just one mistake in decision-making because the task is not open-ended (i.e., once three series have been correctly identified, the fourth follows logically). Thus, it is not possible to achieve scores of 11, 10, or 9 out of 12 in this task; either a score of 12 is achieved (indicating no mistakes) or a score of 8 is achieved (indicating one mistake). For example, a participant makes the following links: A1-B1-C1, A2-B2-C2, A3-B3-C4, A4-B4-C3. In this example, the letters refer to the three different crimes and the numbers refer to the four different offenders (e.g., A1 refers to crime A, committed by offender 1). There are a total of eight correct links for this participant: (1) A1-B1; (2) A1-C1; (3) B1-C1; (4) A2-B2; (5) A2-C2; (6) B2-C2; (7) A3-B3; (8) A4-B4; and four incorrect links: (1) A3-C4; (2) B3-C4; (3) A4-C3; (4) B4-C3. Notice, however, that the four incorrect links are a consequence of one single mistake (incorrectly assigning crime C3 to the fourth offender, thereby leading to crime C4 mistakenly being linked to the third offender).

Interestingly, there was a trend towards increased accuracy amongst the more experienced participants, with the most accurate performance observed for the experienced car crime investigators (59% accuracy), followed by investigators who were experienced in the investigation of other crime types (43% accuracy), then novice police investigators (41%), and finally participants with no police experience performed worst in the linkage task (28%). Furthermore, it seemed that linkage success was associated with using a small number of specific offences features (such as vehicle type and the time and location of theft), whereas inaccuracy was associated with using a larger number of features, including features such as what property was stolen and whether the vehicle was damaged/vandalised. These findings further support the notion that successful BCL performance relies on the ability to identify appropriate linkage features, and it seems that many of the participants in Santtila and colleagues' study struggled to do this (although some clearly did not struggle).

In the third study the primary aim was not to test human performance in the linkage task; however accuracy scores were reported for a sample of 17 university students (Pakkanen et al., in press). In that study, the participants were given short case summaries that described the behavioural details of 10 Italian homicides (committed by five offenders). On average, each participant made three correct linkage decisions out of a total of 10. Interestingly, there was variation in accuracy from one series to the next[35], thereby suggesting that some linkage decisions are easier to make than others. But, it is unclear whether there were individual differences in accuracy between the participants. The authors compare these findings to previous studies that have developed statistical methods of linking homicide offences, concluding that statistical

[35] Only 41% of participants made a correct linkage decision for series 2, whereas 76% of participants made a correct decision for series 4.

approaches based on discriminant function analysis and Bayesian analysis are more efficient at linking crimes. However, these comparisons are questionable because the crimes presented to participants were a small sub-section of the samples that were used to test the statistical methods of linking, and it is unclear whether these sub-sections were representative of the larger sample.

From these three studies we can conclude that many participants (but not all) found it difficult to identify and successfully use ecologically rational heuristics when linking crime. However, it is unclear whether the inconsistent performance of participants could have been improved through simple training or by providing them with a statistical support tool.

The fourth study to investigate human BCL performance provides some insight into these issues (Bennell, Bloomfield et al., 2010). In that study Bennell and colleagues compared students, police professionals, and a logistic regression model in terms of their ability to distinguish between linked and unlinked commercial burglaries. Participants were presented with a series of burglary pairs and asked to indicate how likely it was that the two burglaries in each pair had been committed by the same person. To assist them in their decision-making, participants were provided with a range of geographical and behavioural information for each crime. Furthermore, half of the participants received brief training in the BCL task, which amounted to a short paragraph indicating that inter-crime distance was the most useful offence feature for distinguishing between linked and unlinked commercial burglaries.

It was found that simple training led to statistically significant improvements in the linkage performance of both students and police professionals. But, despite these improvements, the logistic regression model achieved a higher level of discrimination accuracy than the human participants. The regression model achieved an AUC of 0.87 in the discrimination task, which was statistically larger than trained and untrained students (AUCs = 0.79 and 0.70, respectively) and trained and untrained police professionals (AUCs = 0.71 and 0.64, respectively). The superior performance of the statistical model in this study was attributed to the human participants relying on inappropriate linkage strategies. For example, despite training to the contrary participants continued to rely, at least partially, on target, entry, and property behaviours when linking crime (as indicated by self-report), which were not the most useful behavioural features in this task. Conversely, the logistic regression model relied solely on inter-crime distance when linking crime, which was the most ecologically rational strategy with these data.

These findings indicate that statistical tools may be able to improve the performance of police professionals when distinguishing between linked and unlinked offences. As such, there may be value in research beginning to explore how statistical tools might be developed and implemented during real life police investigations. However, it is important to recognise that there were several limitations to the research described above, which question the seemingly superior performance of statistical tools over human participants.

5.1.3 The Limitations of Previous Research

First, the extent and nature of BCL experience amongst the police participants is unclear. Two out of the three studies that tested police participants gave no indication whatsoever as to whether the participants had real life investigative experience of BCL

(Canter et al., 1991; Santtila, Korpela et al., 2004) and the third study did not ask participants whether they had BCL experience with the specific crime type studied (Bennell, Bloomfield et al., 2010). It is, therefore, unclear whether the participants in these studies had *relevant* practical experience and knowledge of BCL. Indeed, Bennell indicates that many of the police professionals sampled in his study had “almost no linkage experience” (Bennell, personal communication). This casts doubt over the conclusion that statistical tools can outperform human decision-makers who are experienced in the BCL task. Several studies have shown improved performance on well-known cognitive tasks as a result of experience/familiarity (see Cox & Griggs, 1982; Edwards, Brice, Craig, & Penri-Jones, 1996), thus the police professionals in these studies may have performed at a comparable level to the statistical tool (or possibly better) if they had extensive practical experience of conducting BCL. Thus, we cannot conclude that statistical models have a potential practical value until we compare these models with an appropriate baseline of police accuracy that includes only those participants who have relevant practical experience of BCL.

A second limitation is that the crimes used in these four studies were from a geographical area that was unfamiliar to the participants (because the participants were typically drawn from several different countries or different locations within a particular country). As explained by Bennell and colleagues (2010), this may have disadvantaged the participants if they were using their own locally-derived linkage strategies that were inappropriate to the geographical location studied. It may also have created an unfair advantage in favour of the logistic regression model in Bennell, Bloomfield et al. (2010), which *was* developed on data from the same geographical area that was used to construct the questionnaire. A fairer comparison would be to compare human participants with a logistic regression model that was developed on data from a completely different geographical area. This would ensure that the human participants and the logistic regression model were equally disadvantaged in terms of 'local knowledge'.

A third limitation of Bennell, Bloomfield et al. (2010) was that they did not provide participants with temporal information about each offence. Over 50% of the police professionals in their study commented on this omission, suggesting that it is a behavioural feature that they would normally use when linking crime (Bennell, Bloomfield et al., 2010). Arguably, the police professionals would have been more successful when linking crime if they had been provided with temporal information (especially as this type of information has often been found by prior research to be of use when discriminating between linked and unlinked crime pairs; e.g., Markson et al., 2010; Chapter 2 of this thesis).

In summary, there are key limitations that should be addressed before it can be concluded that statistical tools have the potential to improve upon the performance of relevant police professionals in the BCL task.

5.1.4 The Current Study

The current study attempted to build on the findings of these four initial studies (Bennell, Bloomfield et al., 2010; Canter et al., 1991; Pakkanen et al., in press; Santtila, Korpela et al., 2004). Crime analysts with relevant BCL experience, undergraduate psychology students without BCL experience, and three logistic regression models (Markson et al., 2010; stepwise model 2 in Table 2A of the current thesis; Woodhams

& Toye, 2007) were compared in terms of their ability to discriminate between linked and unlinked residential burglaries and commercial robberies. Human BCL performance has never been examined with these types of crime.

The methodology of Bennell, Bloomfield et al. (2010) was followed, with several important alterations. First, participants were asked to report not only the number of years experience with BCL but also the frequency with which they were involved in this task and the crime types with which they had analytical experience (these latter two questions were not asked in previous research). This helped to ensure that the sample of crime analysts examined in the current study had *truly relevant* practical experience of BCL. Ultimately, this provided a more appropriate police baseline with which to compare the statistical linkage models. Second, two out of the three logistic regression models included in this study were developed on crimes from a totally different geographical area to the crimes presented in the questionnaire. The optimal model[36] developed by Woodhams and Toye (2007) was used in this study to predict whether commercial robbery crime pairs were linked or not. This model was developed using data from a police force in the UK that is substantially different from the geographical area in which crimes were sampled in the present study (Northamptonshire, UK)[37]. Ideally, a robbery model developed using Northamptonshire data would also have been included for comparison purposes, but this was not possible because Woodhams and Toye (2007) is the only study to have examined BCL with

[36] Woodhams and Toye (2007) tested a variety of logistic regression models in their study, but the most accurate performance was achieved using a combination of inter-crime distance, planning, and control behaviours.

[37] For confidentiality reasons, the police force studied by Woodhams and Toye's (2007) cannot be named. However, this force is not classed within the Home Office's list of 'most similar forces' for Northamptonshire. Furthermore, the geographical area studied by Woodhams and Toye (2007) is about half the size of Northamptonshire and has a substantially larger population density (678 persons per square kilometre compared to 291 persons per square kilometre in Northamptonshire). Thus, Woodhams and Toye's (2007) logistic regression model was developed in a geographical area that was considerably different to the location from which the crimes were sampled in the current study.

commercial robbery. However, residential burglary has been studied far more extensively within the BCL literature, so it was possible to include both a local model (developed on Northamptonshire data by Markson et al., 2010[38]) and a non-local model (developed in Finland- see Chapter 2[39]). This methodology helped to eliminate the potentially unfair advantage that was given to the logistic regression model in Bennell, Bloomfield et al.'s (2010) study. Third, participants in the current study were provided with temporal information, as well as geographical and behavioural information. This helped to ensure that participants had all of the information available to them that they would normally use when conducting BCL.

Based on previous research it was hypothesised that the logistic regression models would outperform the human participants in the mock linkage tasks, even when these participants received simple training in how to maximise discrimination accuracy.

5.2 Method

5.2.1 Participants

One hundred and thirty-seven participants took part in this study (100 students and 37 crime analysts[40]). The 100 students had a mean age of 19.30 years (*SD* = 2.38) and the

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[38] Markson et al. (2010) tested a variety of logistic regression models in their study, but the most accurate performance was achieved using a combination of inter-crime distance and temporal proximity.

[39] As described in Chapter 2, a variety of logistic regression models were tested with data from Finland, but the most accurate performance was achieved using a combination of inter-crime distance and temporal proximity. It should be noted that the model developed using Bennell's (2002) original methodology was used in this study, rather than the model developed using the new methodology.

[40] It should be noted that the term "crime analyst" is used to refer to participants who had relevant practical experience of BCL (as described below).

vast majority (*n* = 88) were female. All students were undergraduate psychology students at the University of Birmingham, UK, who participated in return for course credit. None of the student participants reported experience of crime analysis, BCL, or police work. The 37 crime analysts had a mean age of 36.81 years (*SD* = 8.78) and the majority (*n* = 29) were female. The analysts were predominantly from the UK (*n* = 29), but analysts from the US (*n* = 7) and Austria (*n* = 1) also participated. In terms of practical experience, the crime analysts reported an average of 9.67 years (*SD* = 6.85) experience of police work, 7.55 years (*SD* = 4.08) experience of crime analysis, and 7.09 years (*SD* = 4.31) experience of BCL. The majority of analysts indicated that they were involved in BCL on at least a monthly basis (*n* = 9 on a daily basis; *n* = 9 on a weekly basis; *n* = 15 on a monthly basis), but two participants indicated that they were involved on a yearly basis and one on a less than yearly basis (also, one participant did not respond to this question).

Approximately half of the participants (*n* = 49 students and *n* = 17 crime analysts) received a questionnaire depicting residential burglary crimes and the remaining participants received a questionnaire depicting commercial robberies (*n* = 51 students and *n* = 20 crime analysts). Participants were randomly allocated to either the residential burglary task or to the commercial robbery task. With the exception of five participants, all crime analysts reported previous analytical experience with the crime type that they were asked to conduct BCL with in this study. Approximately half of the participants (Residential Burglary: *n* = 25 students and *n* = 10 crime analysts; Commercial Robbery: *n* = 26 students and *n* = 12 crime analysts) received training information describing the most successful approach to linking crime (based on previous research- see Section 5.2.2 below), while the remaining participants did not receive such information (Residential Burglary: n = 24 students and n = 7 crime analysts; Commercial Robbery: n = 25 students and n = 8 crime analysts). Participants were randomly allocated to these training versus no training conditions. There were no statistically significant differences between the trained versus untrained participants[41] in terms of age, gender, the frequency with which BCL was engaged in, and the number of year's experience of crime analysis, BCL, or police work. The participants in the training versus no training conditions can, therefore, be considered equivalent in terms of demographic characteristics, some of which might be expected to impact on BCL accuracy in this study.

5.2.2 Materials

There were eight different versions of the questionnaire, with each version containing a set of demographic questions, 15 crime pairs[42] (two crimes per pair) with a range of geographical, temporal, and behavioural information for each offence, and base rate information that indicated the number of linked crime pairs in the questionnaire (there were three linked and 12 unlinked crime pairs in each questionnaire). Exemplar questionnaires are presented in Appendices 4 and 5. The eight versions were a function of variation in the type of crime included in the questionnaire (residential burglary versus commercial robbery), whether the participants received training information or

[41] It should be noted that two sets of comparisons were conducted: (1) trained versus untrained students; and (2) trained versus untrained crime analysts.
[42] Larger questionnaires that contained 30 crime pairs were trialled, however the length of completion time was too long (approximately three hours). It was thought that this would discourage participation (particularly among crime analysts who often have high case loads and were not receiving payment in return for their participation in the current study). Thus, the questionnaires were shortened to 15 crime pairs.

not (training versus no training), and the order in which the crime pairs were presented (random order 1 versus random order 2).

The crimes included in these questionnaires were a random selection of residential burglaries and commercial robberies that were committed within Northamptonshire police force boundaries between 01/01/2009 and 31/12/2010. These data were collected explicitly for the purpose of conducting this study. The location of the crime (*x, y* coordinates to the nearest metre), the date the crime was reported to the police, and free text descriptions of offender behaviour were extracted from Northamptonshire police databases for each offence. This information was used to construct the burglary and robbery questionnaires.

The burglary and robbery questionnaires presented participants with the following behavioural information: 1) A map (size = 16cm X 17cm) indicating the location of all 30 offences, with a corresponding number to identify each of the 15 crime pairs; 2) The straight-line kilometre distance between the two offences in each pair (inter-crime distance); 3) The number of days separating the two offences in each pair (temporal proximity); 4) The characteristics of the property targeted in each offence (target characteristics); and 5) The items that were stolen during the offence (property stolen). The burglary questionnaire also presented participants with information on how the offender entered the property (entry behaviours) and the behaviour of the offender once inside the property (internal behaviours), whereas the robbery questionnaire presented participants with information regarding the level of planning that was evident in the offender’s behaviour, such as bringing a bag with which to carry away stolen goods (planning behaviours) and any attempts that were made to control the victim or the offending situation, such as using violent or threatening behaviour (control behaviours).

Those participants who received a ‘training’ version of the burglary/robbery questionnaires were given a short paragraph that indicated the most reliable information to use when conducting BCL. In the burglary questionnaire this paragraph told participants that inter-crime distance and temporal proximity were the most reliable methods for linking offences and that the other types of behavioural information were not very useful in this task. These instructions were based on previous research with residential burglary in Northamptonshire (Markson et al., 2010). In the robbery questionnaire participants were told that inter-crime distance, and information about planning and control behaviours were most useful for linking offences but that information about the property stolen and target characteristics were less useful in this task. These instructions were based on previous BCL research with commercial robbery (Woodhams & Toye, 2007). These paragraphs were not included in the ‘no training’ versions of the questionnaire.

Where possible, the behavioural information was presented exactly as it appeared on the police database (i.e., using the same wording and phrases). This was to ensure that the information presented to analysts was as close as possible to what they would receive in a real life investigative setting when conducting BCL.

Using this information, participants were asked to indicate for each of the 15 crime pairs whether they believed the two crimes were committed by the same person or by different people (a binary decision)[43]. They were also asked to indicate on an 11-point scale how likely it was that the two crimes had been committed by the same

[43] Bennell, Bloomfield et al. (2010) did not include a binary decision, but this is important to allow linkage performance to be examined using percentage accuracy as well as ROC analysis (see Section 5.2.4).

person (0 = Not at all likely; 10 = Very likely). Having made these decisions, participants were then asked to indicate for each crime pair the extent to which they relied on the different types of geographical, temporal, and behavioural information that were provided to them (0 = Not at all; 10 = Very much). A section for any further comments was available at the end of each questionnaire.

5.2.3 Procedure

5.2.3.1 The Human Participants

The student participants were recruited through internal advertisements within the University of Birmingham, UK, and the crime analysts were recruited through personal contacts and through postings via the listservs of several national and international crime analyst organisations.

The advertisement invited potential participants to contact the author via e-mail in order to obtain the information sheet, consent form, and questionnaire. Upon receipt of this e-mail, each participant was randomly assigned to one of the eight groups and sent the corresponding questionnaire. The questionnaire was designed for completion in Microsoft Word and could be returned to the author via e-mail when complete. Completed questionnaires were checked for omissions and once any issues had been clarified the responses were entered into PASW version 18.0 for analysis.

5.2.3.2 The Logistic Regression Models

An important aim of this study was to examine the relative performance of statistical models in the BCL task. Three logistic regression models were used for this purpose (two residential burglary models and one commercial robbery model). In terms of residential burglary, the optimal model developed by Markson et al. (2010) and the stepwise model that was developed on Finnish data in Chapter 2 of the current thesis (see stepwise model 2 in Table 2A) were applied to each of the 15 crime pairs in the residential burglary questionnaire. Both of these regression models utilised inter-crime distance and temporal proximity to predict whether crimes were linked or unlinked. In terms of commercial robbery, the optimal model developed by Woodhams and Toye (2007) was applied to the 15 robbery crime pairs. This model utilised inter-crime distance and similarity in planning and control behaviours to link crime pairs. Following the procedure described in Section 2.2.3, the regression models were used to produce a predicted probability value for each of the 15 crime pairs, which indicated the likelihood that the two crimes had been committed by the same person (ranging from 0 to 1.00). The logistic regression models took the following form:

Residential Burglary Models

Markson et al. (2010)

Log odds = 3.10 + (0.000232 × inter-crime distance[44]) + (-0.0129 × temporal proximity)

[44] The relevant inter-crime distance and temporal proximity values for each pair were inserted into the equations.

Stepwise Model 2 (Table 2A)

Log odds = 2.77 + (-0.257 × inter-crime distance) + (-0.00163 × temporal proximity)

Commercial Robbery Model

Woodhams and Toye (2007)

Log odds = -1.57 + (2.11 × Jaccard's coefficient for planning behaviours[45]) + (6.68 × Jaccard's coefficient for control behaviours) + (-0.07[46] × inter-crime distance)

It is important to note that none of the crimes included in the burglary and robbery questionnaires were used to develop the above models. Thus, the accuracy of the regression models in this study was not artificially inflated, as it might have been if crimes from the original construction sample had been used in the questionnaires (Bennell, Bloomfield et al., 2010).

5.2.4 Measuring Decision-Making Accuracy

Consistent with the methodology of Bennell, Bloomfield et al. (2010), ROC analysis was used to examine decision-making accuracy in the current study. The predicted

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[45] To utilise the commercial robbery model, the coding dictionary described by Woodhams and Toye (2007) was used to code for the presence or absence of control and planning behaviours. One planning variable (face covered by unspecified means) was added to this coding dictionary and five control variables (gun, hammer, golf club, brick, and piece of wood) were added to account for different offence information being available with Northamptonshire data compared to the data of Woodhams and Toye (2007). For each of the 15 commercial robbery crime pairs, these binary codes were used to calculate a Jaccard's coefficient for planning behaviours and a Jaccard's coefficient for control behaviours, which were inserted into the equation. A second rater (Dr. Jessica Woodhams) independently coded a random selection of 20% of the data to test inter-rater reliability. A Cohen's Kappa of 0.84 was obtained, which represents a very good level of agreement (Landis & Koch, 1977). The percentage level of agreement was 97.29%.

[46] It was not possible to obtain the logit change value to three significant figures from the developers of this logistic regression equation.

probability values that were produced by the logistic regression models were used to construct ROC curves that indicated the level of discrimination accuracy achieved when using statistical models to distinguish between the 15 linked and unlinked crime pairs. Separate curves were constructed for each of the three logistic regression models described above. The decision-making accuracy of human participants was measured using the likelihood ratings provided by participants in response to the question "How likely is it that these two crimes were committed by the same person?" (0 = Not at all likely; 10 = Very likely). These responses were converted into decimal numbers (ranging from 0.00 to 1.00) that could be used to construct ROC curves. Separate curves were constructed for each participant, which allowed an average to be calculated for trained versus untrained crime analysts and trained versus untrained students (burglary and robbery figures were calculated separately).

A novel feature of this study was the inclusion of a dichotomous decision question, which asked participants to make an outright decision regarding whether the two crimes in each pair were committed by the same person or not. These responses were used to calculate the percentage accuracy of human participants. The percentage accuracy of the logistic regression models was calculated by organising the predicted probability values produced by each model from largest to smallest, with the top three crime pairs assigned to the linked category and the remaining 12 assigned to the unlinked category (reflecting how many linked and unlinked pairs there were in each task).

5.3 Results

5.3.1 Decision-Making Accuracy

Individual AUC values and percentage accuracy scores were calculated for each participant and the mean calculated for trained versus untrained students and for trained versus untrained crime analysts. Also, an AUC value and percentage accuracy score were calculated for each of the three logistic regression models. These findings are summarised in Table 5A.

Table 5A

Decision-Making Accuracy for Three Logistic Regression Models and Trained Versus Untrained Students and Crime Analysts

		Residential Burglary				Commercial Robbery			
		Mean AUC (*SD/SE*)	**Min AUC – Max AUC**	**Mean % Accuracy (*SD*)**	**Min % - Max %**	**Mean AUC (*SD/SE*)**	**Min AUC – Max AUC**	**Mean % Accuracy (*SD*)**	**Min % - Max %**
Students	Trained	0.89 (0.14)	0.40 – 1.00	84.00 (11.39)%	46.67 – 100.00%	0.90 (0.12)	0.47 – 1.00	84.87 (14.79)%	40.00 – 100.00%
	Untrained	0.77 (0.16)	0.49 – 1.00	78.06 (13.97)%	53.33 – 100.00%	0.90 (0.10)	0.68 – 1.00	85.60 (11.33)%	60.00 – 100.00%
Police	Trained	0.80 (0.16)	0.47 – 0.94	84.00 (9.53)%	66.67 – 100.00%	0.97 (0.07)	0.78 – 1.00	94.44 (5.57)%	86.67 – 100.00%
	Untrained	0.91 (0.08)	0.81 – 1.00	85.71 (12.43)%	66.67 – 100.00%	0.99 (0.03)	0.92 – 1.00	94.17 (9.72)%	73.33 – 100.00%

Markson et al. (2010)	1.00 (0.00)	---	100.00%	---	---	---	---	---
Stepwise Model 2	0.92 (0.09)	---	86.67%	---	---	---	---	---
Woodhams & Toye (2007)	---	---	---	---	0.92 (0.08)	---	86.67%	---

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).

To determine whether the logistic regression models achieved a higher level of discrimination accuracy than human participants (as measured by the AUC[47]), a series of one-sample t-tests were conducted. Both residential burglary models achieved a statistically larger AUC value than did the crime analysts, *t*s > -2.26, $p < 0.05$, $r = 0.76$ (Markson et al., 2010), $r = 0.49$ (stepwise model 2), and a statistically larger AUC value than did the students, *t*s > -3.84, $p < 0.01$, $r = 0.73$ (Markson et al., 2010), $r = 0.48$ (stepwise model 2). Woodhams and Toye's (2007) commercial robbery model achieved a statistically *smaller* AUC value than did the crime analysts, $t = 4.23$, $p < 0.001$, $r = 0.70$, but there was no statistically significant difference when compared with the students, $t = -1.09$, $p > 0.05$, $r = 0.15$.

To explore the impact of professional experience and training on decision-making accuracy, two 2 (Experience: student and crime analyst) × 2 (Training: trained and untrained) ANOVAs were conducted with AUC values as the dependent variable (one ANOVA for residential burglary and one for commercial robbery). The order in which the crime pairs were presented to participants in the burglary task (random order 1 versus random order 2) did not impact significantly on their decision-making accuracy (as measured by the AUC), $t = -0.57$, $p > 0.05$, $r = 0.07$. However, order of presentation did impact significantly on decision-making accuracy in the robbery task, $t = -2.74$, $p < 0.01$, $r = 0.33$. Order of presentation was not, therefore, entered as a covariate in the burglary ANOVA, but it was entered as a covariate in the robbery ANOVA. In terms of residential burglary, there were no significant main effects for experience, $F(1, 62) = 0.29$, $p > 0.05$, *partial* $\eta^2 = 0.01$, or training, $F(1, 62) = 0.02$, $p > 0.05$, *partial* $\eta^2 = 0.00$. But, there was a significant two-way interaction between

[47] The above analyses were repeated using percentage accuracy as the dependent variable rather than AUC values, but these findings are not reported here because they were similar to those produced using the AUC.

experience and training, $F(1, 62) = 7.32$, $p < 0.01$, *partial* $\eta^2 = 0.11$, which indicated that training was associated with increased discrimination accuracy amongst students but decreased accuracy amongst crime analysts. In terms of commercial robbery, there was a significant main effect of experience, $F(1, 66) = 8.42$, $p < 0.01$, *partial* $\eta^2 = 0.11$, with crime analysts achieving higher AUC values than students. But, there was no significant main effect of training, $F(1, 66) = 0.41$, $p > 0.05$, *partial* $\eta^2 = 0.01$, and no significant two-way interaction between experience and training, $F(1, 66) = 0.37$, $p > 0.05$, *partial* $\eta^2 = 0.01$.

5.3.2 What Types of Behavioural Information Did Participants Report Using When Linking Crime?

In an attempt to understand the above findings, the extent to which trained and untrained students and crime analysts reported relying on different types of behavioural information when linking residential burglaries (Figure 5A) and commercial robberies (Figure 5B) was examined.

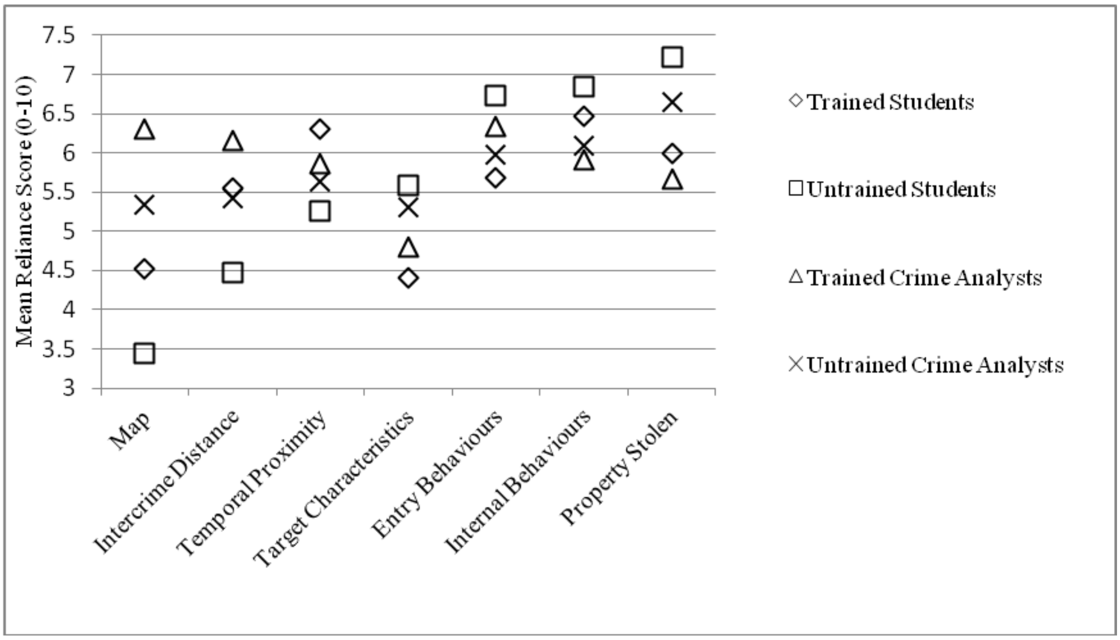

Figure 5A

Residential Burglary: Mean Reliance Scores for Trained and Untrained Students and Crime Analysts

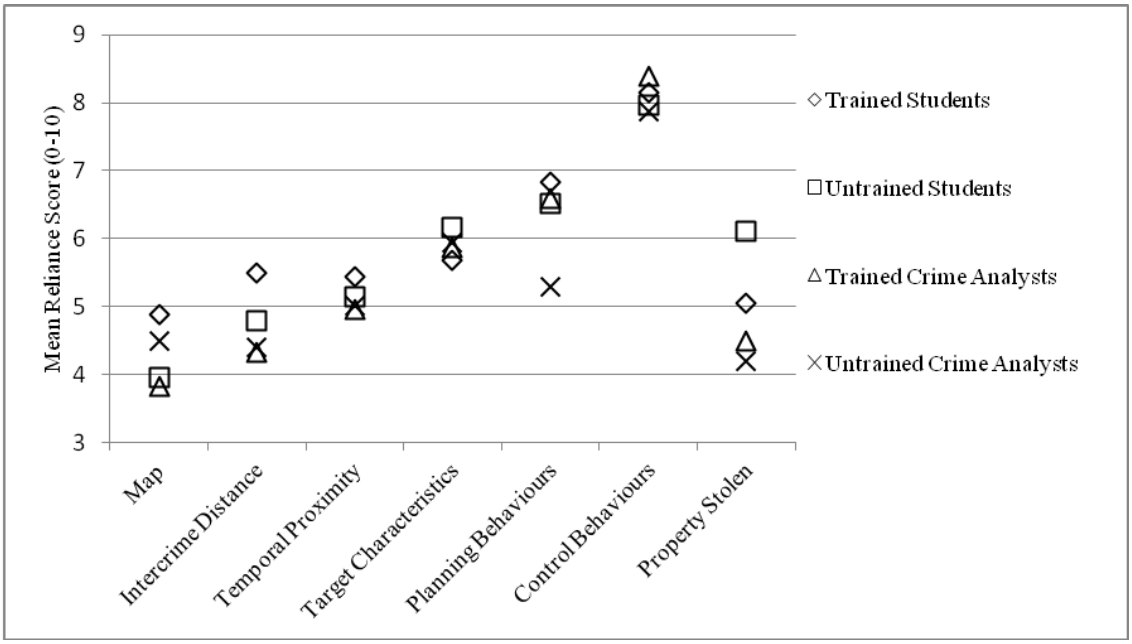

Figure 5B

Commercial Robbery: Mean Reliance Scores for Trained and Untrained Students and Crime Analysts

To determine whether there were significant differences in the reliance scores for residential burglary, a 7 (Information Type: map, inter-crime distance, temporal proximity, target characteristics, entry behaviours, internal behaviours, and property stolen) × 2 (Experience: student and crime analyst) × 2 (Training: trained and untrained) mixed ANOVA was conducted with reliance scores as the dependent variable. There were no significant main effects for experience, $F(1, 60) = 1.32$, $p > 0.05$, *partial* $\eta^2 = 0.02$, or training, $F(1, 60) = 0.01$, $p > 0.05$, *partial* $\eta^2 = 0.00$, but there was a significant main effect for information type, F(2.56, 153.74[48]) = 12.88, $p < 0.001$, *partial* $\eta^2 = 0.18$. There was also a significant two-way interaction between information type and experience, $F(2.56, 153.74) = 6.07$, $p < 0.01$, *partial* $\eta^2 = 0.09$, and between information type and training, $F(2.56, 153.74) = 6.12$, $p < 0.01$, *partial* $\eta^2 = 0.09$. No further two-way or three-way interactions were significant.

To further explore the main effect of information type for residential burglary, mean reliance scores and paired-samples t-tests were computed (Bonferroni corrected alpha = 0.002). In summary, participants reported relying on property stolen information ($M = 6.46$, $SD = 1.28$), internal behaviours ($M = 6.46$, $SD = 1.01$), entry behaviours ($M = 6.20$, $SD = 0.95$) and temporal proximity ($M = 5.76$, $SD = 1.62$) to a statistically greater extent than inter-crime distance ($M = 5.22$, $SD = 1.48$), target characteristics ($M = 5.00$, $SD = 1.28$) and the map ($M = 4.50$, $SD = 1.97$) (all ts > 3.29, $p < 0.002$, $r > 0.37$).

To further explore the significant two-way interaction between information type and professional experience for residential burglary, independent-samples t-tests were

[48] Mauchly's test indicated that the assumption of sphericity had been violated, $\chi^2(20) = 208.15$, $p < 0.001$, so the Greenhouse-Geisser correction was applied to all tests involving information type. It should be noted that these tests remained significant regardless of whether the Greenhouse-Geisser correction or the Huynh-Feldt correction was used.

computed to compare crime analysts and students in terms of their self-reported reliance scores (Bonferroni corrected alpha = 0.007). Crime analysts reported greater reliance on the map (M = 5.90, SD = 1.19) than students (M = 3.99, SD = 1.95), t = 4.73, $p < 0.001$, r = 0.57. All other comparisons did not reach the adjusted alpha level, ts < -2.45, $p > 0.01$.

To further explore the significant two-way interaction between information type and training for residential burglary, independent-samples t-tests were computed to compare participants in the training versus no training conditions in terms of their self-reported reliance scores (Bonferroni corrected alpha = 0.007). Those who received training reported greater reliance on inter-crime distance (M = 5.73, SD = 1.33) than those who did not receive training (M = 4.69, SD = 1.41), t = -3.06, p = 0.003, r = 0.57. Also, those who received training reported less reliance on target, entry, and property behaviours (M (SD) = 4.52 (1.29), 5.86 (0.89), and 5.90 (1.33), respectively) than those who did not receive training (M (SD) = 5.53 (1.09), 6.56 (0.92), and 7.09 (0.85), respectively), ts > 3.09, $p < 0.003$, $r > 0.36$. All other comparisons did not reach the adjusted alpha level, ts < -2.45, $p > 0.01$.

To determine whether there were significant differences in the reliance scores for commercial robbery, a 7 (Information Type: map, inter-crime distance, temporal proximity, target characteristics, planning behaviours, control behaviours, and property stolen) × 2 (Experience: student and crime analyst) × 2 (Training: trained and untrained) mixed ANOVA was conducted with reliance scores as the dependent variable. There were no significant main effects for experience, $F(1, 64) = 2.90$, $p > 0.05$, *partial* $\eta^2 = 0.04$, or training, $F(1, 64) = 0.37$, $p > 0.05$, *partial* $\eta^2 = 0.01$, but there was a significant main effect for information type, $F(3.81, 243.61$[49]$) = 53.47$, $p < 0.001$, *partial* $\eta^2 = 0.46$. There were no significant two-way or three-way interactions.

To further explore the main effect of information type for commercial robbery, mean reliance scores and paired-samples t-tests were computed (Bonferroni corrected alpha = 0.002). In summary, participants reported relying on control behaviours ($M = 8.11$, $SD = 0.89$), planning behaviours ($M = 6.51$, $SD = 1.42$) and target characteristics ($M = 5.88$, $SD = 1.35$) to a statistically greater extent than property stolen information ($M = 5.20$, $SD = 1.81$), temporal proximity ($M = 5.17$, $SD = 1.65$), inter-crime distance ($M = 4.93$, $SD = 1.69$) and the map ($M = 4.35$, $SD = 1.99$) (ts > 3.41, $p < 0.002$, $r > 0.37$).

In summary, there was no relationship between the types of behavioural information used when linking crime in either the residential burglary or commercial robbery tasks and professional experience or training. However, certain types of behavioural information were favoured over others when linking crimes in both tasks. In the residential burglary task there were two-way interactions between the type of information used when linking crime and experience and training, but there were no such interactions in the commercial robbery task. There was no three-way interaction in either the residential burglary task or the commercial robbery task.

5.4 Discussion

[49] Mauchly's test indicated that the assumption of sphericity had been violated, $\chi^2(20) = 105.42$, $p < 0.001$, so the Greenhouse-Geisser correction was applied to all tests involving information type. It should be noted that these tests remained significant regardless of whether the Greenhouse-Geisser correction or the Huynh-Feldt correction was used.

Previous BCL research has judged the potential practical value of statistical linkage models by comparing the discrimination accuracy achieved using these models with chance (e.g., an AUC of 0.50). But, it is more appropriate from a practical point of view to compare statistical models with human crime analysts who have relevant practical experience of BCL. The current study, therefore, compared crime analysts who have practical experience of BCL, undergraduate psychology students without such experience, and three logistic regression models (Markson et al., 2010; stepwise model 2 in Table 2A of the current thesis; Woodhams & Toye, 2007) in terms of their ability to discriminate between linked and unlinked residential burglaries and linked and unlinked commercial robberies.

5.4.1 Decision-Making Accuracy: Humans versus Statistics

Both residential burglary models achieved statistically greater discrimination accuracy than students and crime analysts in the burglary task, but crime analysts outperformed the statistical model in the commercial robbery task. However, we should be cautious when interpreting these statistically significant differences because the number of linkage decisions made in each questionnaire was relatively small (n = 15) in order to reduce the completion time for each questionnaire and, therefore, to encourage participation in the current study. Consequently, a single mistake in the linkage task equated to a drop of 7.50% in percentage accuracy (and an equivalent drop in the AUC). Therefore, statistically significant differences do not necessarily equate to practically significant findings in this study. As an illustration of this point, consider the statistically superior performance of the crime analysts over the statistical model in the robbery task, which amounted to just one additional correct linkage decision. Thus, the most appropriate conclusion that can be drawn from these data is that the statistical models performed at a comparable level to crime analysts and students in the mock BCL tasks.

These findings are somewhat inconsistent with the literature on clinical versus actuarial decision-making, which has shown that actuarial approaches often outperform clinical approaches in a variety of decision-making settings, including BCL (Bennell, Bloomfield et al., 2010; Bennell, Jones et al., 2011; Grove & Meehl, 1996; Singh & Fazel, 2010). However, as discussed in this chapter's introduction, human decision-makers can achieve a high level of accuracy provided they rely on ecologically rational heuristics (e.g., Bennell, Bloomfield et al., 2010; Martignon & Hoffrage, 1999; Snook et al., 2002, 2004). Thus, it seems that the students and crime analysts in this study were able to identify and successfully use ecologically rational heuristics in the BCL task. This is surprising since previous studies have indicated that students and police professionals often seemed to find it difficult to identify such strategies (Bennell, Bloomfield et al., 2010; Canter et al., 1991; Santtila, Korpela et al., 2004). There are several potential explanations for this discrepancy. First and foremost, an explicit attempt was made in the current study to sample crime analysts who had *relevant* practical experience of BCL, which was not the case in previous studies. Indeed, when one compares the current sample with that of Bennell and colleagues the crime analysts in this study reported a greater level of linkage experience (approximately seven years experience compared to less than two in Bennell, Bloomfield et al., 2010). Furthermore, the current sample reported frequent BCL experience with the crime type that they conducted linkage with in this study, whereas Bennell reports that their sample was very heterogeneous and many of their participants had “almost no linkage experience” (Bennell, personal communication). These differences might explain the superior discrimination accuracy of analysts in this study.

However, these ‘experience’ differences cannot explain the high level of accuracy achieved by the student participants in this study. It is, therefore, necessary to consider alternative explanations. One such explanation is that participants were required to link fewer crime pairs in the current study (n = 15 crime pairs) than in Bennell, Bloomfield et al. (2010) (n = 38 crime pairs), which may have led to less fatigue and, therefore, superior discrimination accuracy. But, this is not a convincing argument because the time it took to complete the current questionnaire (based on pilot trials) was longer than the 45 minutes that Bennell and colleagues report for completion of their questionnaire. An alternative explanation is that the crimes included in the current questionnaires were simply easier to link than those included in previous research due either to chance or the geographical location from which they were sampled. But again, this is not a convincing argument because the crimes were sampled randomly and there is little evidence from previous research that residential burglaries can be linked more accurately in Northamptonshire than other locations in the UK and Finland (see Chapters 1 and 2 for a review of this research).

Regardless of how these results can be explained, it is an important finding that crime analysts were able to achieve a high level of discrimination accuracy, even when they were linking crimes from a geographical area with which they were unfamiliar. Law enforcement agencies across the UK and abroad devote significant resources to supporting BCL and there is growing evidence (based on the current study and on Burrell & Bull, 2011) that BCL is frequently used by crime analysts. Thus, it is reassuring that analysts appear able to make these decisions accurately. However, it is important that the overall success of human participants in the present study is not used to mask the variation in discrimination accuracy between participants (see Table 5A). Indeed, while the majority of participants performed very successfully, some participants performed at a level that was below chance (e.g., some participants achieved AUCs of 0.40 and percentage accuracy scores of 40%). This is consistent with previous research, which has found large individual differences in mock BCL accuracy (Bennell, Bloomfield et al., 2010; Canter et al., 1991; Santtila, Korpela et al., 2004). Consequently, statistical BCL support tools may be of value in a practical setting because they can provide a consistent and standardised method for linking crime, which might help to reduce such individual variation. Furthermore, if the current trend towards using BCL as evidence in court continues (e.g., Labuschagne, 2012), the development of a consistent and standardised approach to linkage that is based on empirical evidence would certainly be of value (see Chapter 6 for further discussion).

It should also be borne in mind that the mock BCL task reported in the present study is a simplified version of the task that an analyst would face in practice. In the current questionnaire the linkage decisions were broken down into a series of pair-wise decisions, but in reality analysts would often be faced with a database containing many offences from which they would have to identify potentially linked crimes. Thus, a more realistic decision-making scenario would have been to present the participants with a list of 30 crimes, rather than breaking them into 15 pair-wise comparisons. In this more realistic scenario the decision-maker would be faced with a far greater number of linkage decisions (a sample of 30 crimes yields a total of 435 individual pair-wise comparisons- crime 1 paired with crime 2, crime 1 paired with crime 3, and so on-, which is clearly larger than the 15 pairs presented in the current study). The number of decision alternatives is a commonly used definition of task complexity (e.g., Payne, 1976), so by presenting the participants with pair-wise decisions cognitive load was substantially reduced in the current study. This may have eliminated one of the potential advantages that statistical tools have over humans, which is that statistical tools are able to process large quantities of information in a quick and efficient way, whereas humans are notoriously limited in terms of their information processing capacities (e.g., Cowan, 2005; Neath, 1998; Newell & Simon, 1972; Simon, 1981). Future research should, therefore, investigate the relative performance of human participants and statistics in mock BCL tasks where cognitive load is high. It might be hypothesised that human performance will deteriorate relative to that of statistical tools under such conditions.

Another aspect of the present study that potentially made it easier for the participants to link crime was the inclusion of base rate information (although it is clear that some participants either forgot or chose not to consider this information when making their linkage decisions because some participants indicated that seven out of the 15 crime pairs were linked, despite being told that only three were linked[50]). Base rate information may not necessarily be available to crime analysts when conducting BCL in practice (Bennell, Bloomfield et al., 2010), so future research should explore whether discrimination accuracy deteriorates in such situations.

Furthermore, the behavioural information for each crime was segregated into seven different types. Arguably, this may have provided the participants with a logical and structured way of processing the information that they would otherwise not have

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[50] Interestingly, Bennell, Bloomfield et al. (2010) also report a similar finding in their study.

used. Future research should vary the way in which the crime information is presented to participants to determine if this impacts on discrimination accuracy. For example, participants could be presented with a prose paragraph describing the circumstances of each crime. Given that task complexity is inherently tied to the mode in which decision-making information is presented (see Campbell, 1988, for a review), one might predict deterioration in discrimination accuracy when the crime information is presented in that manner.

In summary, while the discrimination accuracy of participants in this study is unexpected and impressive, it is important to understand that such accuracy may not exist in the more complicated and cognitively demanding environment of the real world. Furthermore, the variation in discrimination accuracy across participants in this study suggests that a consistent and standardised approach to BCL (such as that offered by statistical tools) might be of value in a practical setting.

5.4.2 The Relationship between Professional Experience and Decision-Making Accuracy

The relationship between professional experience and decision-making accuracy in the current study differed depending on crime type. In the residential burglary task there was no relationship, with crime analysts and students performing at a comparable level (although there was a non-significant trend in favour of the crime analysts). This is perhaps unsurprising because the students and analysts reported similar decision-making strategies in the burglary task. Indeed, the only statistically significant difference was that the analysts relied more heavily on the map; they did not differ in their use of features such as inter-crime distance and temporal proximity, which have been shown to be associated with moderate to high discrimination accuracy in the BCL task (e.g., Markson et al., 2010; Chapter 2 of this thesis). In the commercial robbery task, however, crime analysts statistically outperformed the students. These findings contradict those of Bennell, Bloomfield et al. (2010), who found that students outperformed police professionals in the BCL task. However, the relatively greater BCL experience reported in the current sample of crime analysts compared with the police professionals sampled by Bennell, Bloomfield et al. (2010) may explain this discrepancy.

The robbery findings are somewhat consistent with the findings of Santtila, Korpela et al. (2004), who found that linkage accuracy increased as a function of relevant police experience. Furthermore, the robbery findings are consistent with a wealth of literature from cognitive psychology, which has demonstrated a relationship between experience and various characteristics of task performance. For example, research suggests that experienced individuals are able to process task-relevant information more quickly than their ‘non-experienced’ counterparts (referred to as automaticity; Palmeri, Wong, & Gauthier, 2004), they can recognise task-relevant information more effectively (Savelsbergh, van der Kamp, Williams, & Ward, 2005), they have greater domain-relevant memory and recall (Chase & Ericsson, 1982), and demonstrate superior skill when organising task information into meaningful chunks, patterns or themes (Chase & Simon, 1973). From this wider psychological perspective, the superior performance of the crime analysts in the robbery task is understandable; however it is less clear why such a difference was not observed in the burglary task.

Again, though, the practical significance of these differences should not be overestimated.

Nevertheless, it is important to offer some explanation for why the findings may have differed depending on crime type, particularly since the participants who engaged in the commercial robbery task were comparable to those who engaged in the residential burglary task in terms police, crime analysis, and BCL experience. To explain these findings, consideration is needed of how these two types of crime differ in nature. One of the primary differences is that residential burglary typically occurs in the absence of a specific victim (i.e., the homeowner is often absent or unaware that a crime is being committed), whereas commercial robbery by definition involves stealing property in the presence of a specific person. Consequently, much of the behavioural detail that the police record during residential burglary offences (such as search behaviour and entry behaviour) must be inferred from the evidence left at a crime scene. When investigating commercial robbery, however, the police often have a more direct way of reconstructing how an offender behaved during the crime (e.g., through victim and/or witness statements and sometimes even CCTV evidence). Consequently, the description of offender behaviour is often more detailed and accurate for robbery offences than burglary (i.e., the quantity and quality of the data is better). Indeed, an examination of the data used in the current study (and a comparison of the exemplar questionnaires in Appendices 4 and 5) certainly supports this suggestion. This is important because as data quality deteriorates it becomes increasingly difficult to achieve successful BCL due to the fact that noise begins to obscure any consistent and distinctive behavioural patterns (e.g., Bennell & Jones, 2005). Thus, data quality puts a limit on the accuracy that can be achieved during BCL, and no amount of additional professional experience can overcome this limit. Arguably, the students and crime analysts had reached this limit in the residential burglary task, thereby preventing experience from exerting a beneficial effect on BCL accuracy. But, due to greater data quality, this limit may have been higher in the commercial robbery task, thus allowing the marginally beneficial effect of experience to be demonstrated.

5.4.3 The Relationship between Training and Decision-Making Accuracy

Overall, there was no statistical relationship between the brief training and decision-making accuracy in both the burglary and robbery tasks. These findings contradict those of Bennell, Bloomfield et al. (2010), who found that training increased discrimination accuracy. Most likely, this is because there was a ceiling effect in the current study, such that the participants were already performing at a very high level (even without training), so there was little scope for training to exert an effect on accuracy. This is logical when one considers that the participants were spontaneously able to identify and use appropriate BCL strategies prior to training, such as temporal proximity, and planning and control behaviours (as discussed above).

Alternatively, the lack of a statistical relationship between brief training and decision-making accuracy may be because the participants chose to ignore the training instructions. Indeed, there are several reasons why the instructions might have been ignored by the participants in this study. Specifically, the participants were not told how the training instructions had been derived; they were simply told that they came from “research”. Without any way of scrutinising the source of these instructions, the participants may have chosen to reject them. It is also possible that the participants did not perceive a need to be trained in how to conduct BCL, thereby leading them to reject the training. While it is unclear why the student participants would have had such a perception (due to their lack of relevant practical experience), the crime analysts reported considerable experience of BCL and the vast majority indicated that BCL was a core part of their day-to-day job. It might, therefore, be understandable if the crime analysts had chosen to reject the brief training instructions in favour of their personal experiences. Indeed, similar findings have been observed in other forensic settings where attempts have been made to alter the professional practice of experienced police officers (e.g., Memon, Holley, Milne, Koehnken, & Bull, 1994). Future research should, therefore, explore whether alternative modes of training delivery have a stronger effect on decision-making. In particular, more extensive, face-to-face delivery methods that explain the empirical basis of training guidelines should be examined, as this would more closely replicate existing BCL training that is offered by academics and practitioners.

It is also possible that the training instructions were not appropriate for the crimes tested in this study, which might explain the lack of a training effect. Indeed, Bennell, Jones et al. (2011) report a similar finding in their study that looked at whether training could improve the ability of humans to distinguish between genuine and falsified suicide notes. In that study one group of participants received very explicit training in how to perform the task, but despite this training they performed almost as poorly as participants who received no training whatsoever. This was attributed to the fact that the very explicit training instructions did not apply to the suicide notes that participants were asked to consider in the study. But, this explanation does not seem to fit the findings in the current study because, when the full range of statistical models developed in Chapter 2 and by Markson et al. (2010) and Woodhams and Toye (2007) were applied to these data, the training recommendations were supported[51].

5.4.4 What Types of Behavioural Information did Participants Report using when Linking Crime?

It is clear that the participants in this study reported using certain types of behavioural information more than others when linking residential burglaries and commercial robberies (regardless of training or experience). In terms of residential burglary, the participants reported relying on property stolen, internal behaviours, entry behaviours, and temporal proximity to a statistically greater extent than inter-crime distance, target characteristics, and the map. In terms of commercial robbery, the participants reported relying on control behaviours, planning behaviours, and target characteristics to a statistically greater extent than property stolen, temporal proximity, inter-crime distance, and the map. It is, therefore, surprising that the participants in this study were able to achieve such high levels of discrimination accuracy because logistic regression models using burglary features such as property stolen, internal behaviours, and entry behaviours have not facilitated AUC values above 0.66 in previous empirical research (see Chapter 2; Bennell, 2002; Bennell & Jones, 2005; Markson et al., 2010) and regression models using target characteristics have not facilitated an AUC above 0.79 in research on commercial robbery (Woodhams & Toye, 2007). These values are below the AUCs of 0.92 achieved by participants in the current study. Furthermore, when the

[51] That is, the AUC values for the optimal models were larger than the AUC values achieved with the types of behavioural information that participants were told to ignore (i.e., target and property stolen in the robbery questionnaire and target, entry, internal, and property in the burglary questionnaire). Due to the limitations of space, these AUC values are not reported in this thesis.

statistical models for these features were applied to the data in this study none of the models achieved an AUC above 0.75. This raises the following question: How were the participants in this study able to achieve such high levels of discrimination accuracy (AUC $\geq$ 0.92) using these features?

One suggestion is that the human participants were utilising the behavioural information in a more appropriate way than the logistic regression models. This is certainly plausible because, as discussed in Chapter 1, a logistic regression model is based on a very specific method of coding offender behaviour. Thus, if that particular coding scheme was inappropriate for the purposes of linking crime, the level of accuracy achieved would be low. However, the level of accuracy might be improved by coding the offender behaviour in a different way. It is, therefore, possible that the participants were using the target, entry, internal, and property information in a manner that was more suited to the linking of crimes than the regression models. To explore this suggestion, future research should ask participants not only whether they relied on the linkage features, but crucially *how* they used these features during the task. This may help to identify novel ways of processing crime information that could be incorporated into existing statistical tools.

However, 'general' psychological research suggests that people have limited insight concerning their cognitive processing (e.g., Dhami & Ayton, 2001; Dhami & Harries, 2001; Reilly & Doherty, 1992). Thus, it is possible that the reliance ratings provided in this study were not a true reflection of how the participants actually linked crime. Consequently, participants may have relied less than they thought on features such as property stolen, internal behaviours, entry behaviours, and target characteristics and more on features such as inter-crime distance and temporal proximity, which could explain why they were able to achieve such high levels of discrimination accuracy in this study. Thus, if researchers of BCL want to further their understanding of decision-making processes in the BCL task it might be fruitful to adopt the approach of Dhami and colleagues (e.g., Dhami & Ayton, 2001; Dhami & Harries, 2001). In Dhami et al.'s research a variety of simple decision-making heuristics (such as the Matching Heuristic and Franklin's Rule) are used to predict participant decision-making. The heuristic that predicts participant decision-making most accurately is judged to be the best approximation of their decision-making strategy. Thus, decision strategies are inferred using measures of model fit (such as R^2) rather than being obtained directly via participant self-report.

5.4.5 Limitations of this Study

With regard to the number of participants, it should be noted that the current sample compares favourably to that studied by Bennell, Bloomfield et al. (2010) (31 police professionals and 40 students), Canter et al. (1991) (n = 32 police officers), Santtila, Korpela et al. (2004) (n = 33 participants), and Pakkanen et al. (in press) (n = 17 students). Nevertheless, there are limits on the extent to which these findings might be applied to different crime types, other geographical locations, and other law enforcement personnel.

Also, the mock tasks used in this study were clearly a simplified version of BCL as it would function during a live criminal investigation (as discussed above). Future research could vary whether participants receive base rate information and how the crime information is presented in order to determine whether the high levels of discrimination accuracy observed in the present study are resistant to such changes.

A further limitation is that the questionnaire did not present participants with all of the information that they would normally have available when linking crime (despite including temporal information). For example, one participant suggested that CCTV evidence/physical descriptions are important when attempting to identify linked commercial robbery crimes, and another participant commented that the map was not of a sufficient resolution to offer any practical value. Future research should ensure that as much of the information that would normally be used to link crime is available to participants because this will probably make the estimates of human discrimination accuracy more reliable.

5.4.6 Conclusions

The main aim of the present study was to compare crime analysts, undergraduate students, and logistic regression models in a mock linkage task. All three of these approaches demonstrated a high level of discrimination accuracy. This is reassuring given the significant resources already devoted to BCL and the frequency with which it is now being used during live police investigations in the UK and abroad. There would also seem to be support for developing statistical linkage tools that can assist crime analysts because, while the majority of participants performed very well in this study, some individuals performed poorly. Thus, a consistent and standardised approach to BCL might help to reduce such variation in discrimination accuracy and it will certainly be of value if the police are seeking to present BCL as evidence in court.

Furthermore, statistical tools are unique in their ability to process large quantities of information in a quick and efficient manner. These advantages may help to reduce the time that analysts spend conducting BCL in practice, which would be of significant value in the current economic/political climate where police budgets and jobs are being drastically cut.

CHAPTER 6

CONCLUSIONS, IMPLICATIONS, AND FUTURE DIRECTIONS

6.1 Introduction

The primary aim of this thesis was to move the BCL literature forward on three key fronts: 1) Generalisability; 2) Ecological Validity; and 3) Methodology. This final chapter will, therefore, begin by reviewing the central findings of this thesis in terms of these three issues, thereby demonstrating the contribution of this research to the BCL literature.

6.2 The Contribution of this Thesis to Issues of Generalisability

It is commonly said that "replication is the cornerstone of good science" (e.g., see Roediger, 2012). Indeed, this sentiment is particularly true in applied areas of research, such as this, where the ultimate aim is to provide recommendations that can be used in future practical contexts. However, as discussed in Chapter 1, there have been few attempts to replicate the findings of BCL research across different geographical locations and time periods. Consequently, one of the main aims of this thesis was to test the generalisability of previous BCL research.

For several reasons the research reported in this thesis has achieved that aim. First, behavioural consistency, distinctiveness, and discrimination accuracy were examined using a sample of residential burglaries committed in Finland (see Chapter 2). This was the first time that these issues had been explored with a sample of burglaries from outside of the UK. While the central findings from previous research were supported, it was found that a wider range of offender behaviours have the potential to support BCL with residential burglary in Finland compared with the UK.

Second, the discrimination accuracy of logistic regression and classification tree analysis was examined using both residential burglaries from Finland and car thefts from the UK, thereby testing whether previous research would generalise across crime types and across geographical locations (see Chapter 3). It was found that the two approaches achieved relatively comparable levels of discrimination accuracy, but in both datasets the classification tree models demonstrated significant problems in terms of reliability or usability that the logistic regression models did not experience (i.e., shrinkage in discrimination accuracy from training to test was observed and a large number of cases were left unclassifiable by the tree-based models).

Third, the research reported in Chapter 5 tested whether three logistic regression models (derived from previous research) could be successfully applied to a new set of residential burglaries and commercial robberies. This was the first attempt to replicate Woodhams and Toye's (2007) findings for commercial robbery. It is interesting to note that a high level of discrimination accuracy was achieved using their stepwise regression model with these new data, despite Woodhams and Toye's (2007) model having been developed in a geographical location that was very different from the location sampled in this thesis (see footnote 37 for more details). Furthermore, stepwise model 2 also achieved a high level of discrimination accuracy when applied to the current UK dataset, despite this model having originally been developed on data from an entirely different country (Finland). Markson et al.'s (2010) model was also successfully applied to a new sample of residential burglaries. The regression models tested in Chapter 5 were, therefore, shown to generalise across geographical locations and time periods.

In summary, this thesis has helped to build a more robust evidence base for BCL by testing the generalisability of previous research on residential burglary, commercial robbery, and car theft. This is important if reliable practical and theoretical recommendations are to be made from this work.

6.3 The Contribution of this Thesis to Issues of Ecological Validity

A fundamental limitation of linkage research is that there is a gap between how research tests BCL and the real life scenario in which this procedure is used. Consequently, there are several threats to ecological validity that must be addressed if the BCL literature is to have a lasting and valuable impact on law enforcement practice.

The current thesis has taken some important steps towards reducing this gap. Most importantly, Bennell's (2002) original methodology has been extended in this thesis to include not just solved, serial offences, but non-serial and unsolved offences as well. This represents a much closer approximation to the real life scenario in which BCL is conducted. Consequently, the findings derived from this thesis provide a more solid foundation upon which to develop theoretical and practical insights into behavioural consistency, distinctiveness, and discrimination accuracy. These insights are discussed in more detail below.

This thesis has also developed a methodology that allows series containing several different types of crime to be included in BCL research. This is important because previous research has restricted itself to samples that are homogenous in terms of crime type, despite tentative evidence to suggest that law enforcement personnel (at least in certain areas of the UK) attempt both within- *and* cross-crime BCL (Burrell & Bull, 2011). The research reported in this thesis has, therefore, examined behavioural consistency, distinctiveness, and discrimination accuracy in a way that is more closely attuned to law enforcement practice.

Finally, the research reported in Chapter 5 compared the discrimination accuracy of statistical models with that achieved by human decision-makers, including crime analysts who had extensive and relevant practical experience of BCL. This enabled the potential practical value of BCL research to be tested in a more ecologically valid manner.

In summary, this thesis has developed and tested a number of new methodologies that seek to reduce the gap between research and practice in the BCL literature. Consequently, one can be somewhat more confident in the practical and theoretical implications that are derived from this research.

6.4 The Contribution of this Thesis to Issues of Methodology

As discussed in Chapter 1, the lack of research comparing different methodological approaches limits the practical and theoretical value of existing BCL research. The current thesis has addressed this issue in a number of ways. First, two different methodological approaches to forming the unlinked crime pairs were systematically compared in Chapter 2. Second, binary logistic regression and classification tree analysis were compared in terms of their ability to build statistical linkage models (see Chapter 3). Third, a completely new methodology was designed and tested in Chapter 4 that allowed behavioural consistency, distinctiveness, and discrimination accuracy to be examined across crime categories and across crime types, as well as within crime types (the latter being the ‘traditional’ way in which these issues have been examined). Fourth, a new methodology was explored that allowed both solved and unsolved offences to be included in BCL research. Importantly, these new methodological/statistical approaches have been explicitly compared with the ‘traditional’, status quo, methodology, thereby ensuring that the findings reported in this thesis can be compared with previous research. This has helped to build an evidence base for BCL that is more coherent and synthesised, which ultimately makes it easier to draw theoretical and practical conclusions from this work.

The implications of this thesis will now be discussed. However, it is important to note that – as with any new area of research – there are clearly caveats to these implications, which are discussed later in the chapter.

6.5 The Theoretical Implications

Various theoretical implications have been discussed throughout the current thesis, so this section will merely reiterate and extend certain implications. It should also be noted that some of the ideas expressed here are similar to those that have been discussed by other researchers of BCL (see e.g., Woodhams & Bennell, 2012; Woodhams, Hollin et al., 2007).

In considering the theoretical implications of this thesis, it is useful to place this project within its wider theoretical context, which consists of at least four bodies of literature: (1) the literature on personality psychology; (2) the criminal career literature; (3) the theories and research from environmental criminology; and (4) the street culture literature.

6.5.1 Personality Psychology

For almost 100 years psychologists have sought to identify stable individual differences in the way that people think, feel, and behave. Indeed, the whole notion of personality rests on the existence of such consistent and distinctive patterns (Cervone & Pervin, 2009; Mischel & Shoda, 1995; Mischel et al., 2004). Thus, the fundamental assumptions of personality psychology are the same as those adopted in the current thesis (and by other researchers of BCL). But, the research reported in this thesis is different because it has extended the notions of consistency and distinctiveness to a new domain of human behaviour – the criminal domain – whereas the personality literature has overwhelmingly focused on these issues within non-criminal behaviour. Thus, the assumptions of consistency and distinctiveness that were originally proposed for non-criminal behaviour have been shown in this thesis to apply to criminal behaviour as well.

These findings suggest that many theories that were originally designed to describe non-criminal psychological processes may also be relevant to the understanding of criminal behaviour. Indeed, this notion has been supported recently by a number of studies that have found evidence to suggest that offences such as robbery, sexual assault, and child sexual abuse demonstrate behavioural characteristics that are consistent with the circumplex model of interpersonal behaviour, which was originally designed to describe non-criminal interpersonal processes (see Alison & Stein, 2001; Bennell, Alison, Stein, Alison, & Canter, 2001; Porter & Alison, 2004, 2006). Future researchers who are seeking to describe and explain offending behaviour may, therefore, benefit from grounding their work in theoretical models that were originally developed to explain non-criminal behaviour.

Despite the potential overlap between criminal and non-criminal behaviour, however, the evidence for behavioural consistency and distinctiveness in this thesis could be deemed as somewhat surprising given the data and methodology adopted. According to recent personality theory (i.e., the Cognitive-Affective Personality System (CAPS); Mischel, 1999; Mischel & Shoda, 1995), the human personality system is comprised of numerous 'if-then' situation-behaviour profiles that specify how an individual will behave given a specific situation (i.e., *if* presented with situation X, *then* exhibit behaviour Y). Each individual is predicted to have their own, somewhat unique, collection of 'if-then' profiles and these profiles are presumed to remain relatively stable over time. Thus, the modern-day conception of behavioural consistency and distinctiveness is based on the interaction between situation and person variables, and a logical prediction from this theory is that it will not be possible to identify meaningful patterns of behavioural consistency and distinctiveness without considering both the person and the situation. However, statistically significant levels of behavioural consistency and distinctiveness were observed in this thesis (and have been observed in other studies of BCL) using a methodology that does not account for the interaction between person and situation variables. Thus, by focusing on different types of individual (i.e., serial offenders rather than university students) in rather unique situations (i.e., criminal events), this thesis has demonstrated that behavioural consistency and distinctiveness can be observed without explicit consideration of the situation. This is despite the assertion of some personality psychologists that this should not be possible (e.g., Mischel & Peake, 1982).

One potential explanation for these findings may lie with the notion of situational similarity. A logical prediction from the CAPS theory is that situations which activate similar cognitive-affective components of the personality system (i.e., situations that are psychologically similar) lead to greater cross-situational consistency in behaviour than those situations that are not similar (Mischel, 1999). Thus, many previous studies of behavioural consistency from the personality literature have failed to find substantial consistency because they have attempted to correlate behaviour over a broad range of highly diverse situations that are not psychologically similar (see Funder & Colvin, 1991). The BCL literature, however, has examined consistency in a very specific type of situation (i.e., during criminal events). Furthermore, many studies have even restricted their analyses to consistency within a specific type of offence (e.g., residential burglary). Consequently, the level of situational similarity may be high in studies of BCL, which might explain why statistically significant levels of behavioural consistency have been observed (Woodhams, Hollin et al., 2007; Woodhams et al., 2008a).

This explanation certainly holds some credence when applied to studies of BCL within crime types that have examined consistency and distinctiveness across crimes of the same type (e.g., Chapter 2 of this thesis), where it might be logical to assume that a degree of situational similarity exists. But, the current thesis also found evidence for consistency and distinctiveness across diverse criminal events that one might not necessarily assume to have a significant degree of situational similarity (i.e., across crime types and crime categories, such as across burglary and violent offences - see Chapter 4). These findings might lead one to question the assumed relationship between situational similarity and behavioural consistency (at least in the criminal domain). Indeed, similar questions were raised by Woodhams et al. (2008a), who found little relationship between situational similarity and behavioural consistency in their sample of juvenile sexual offenders. Furthermore, these findings add to the growing body of work on offender behavioural consistency that has failed to find a relationship between consistency and other proposed moderators, such as expertise/experience (Santtila et al., 2008; Tonkin et al., 2008; Yokota & Canter, 2004)[52], temporal proximity (Markson et al., 2010; Tonkin et al., 2008; Woodhams et al., 2008a), and age of the offender (Woodhams, Hollin, & Bull, 2008b). Future research must, therefore, attempt to explain why modern views within the personality literature do not seem to replicate in the criminal domain.

One possibility is that police recorded crime data contain too much noise to identify the moderating effects of situational similarity, age, expertise, and temporal proximity. Another possibility is that these moderating variables have not been studied in an appropriate manner in the BCL literature. As discussed in Chapter 4, for example, it may be inappropriate to define situational similarity in terms of legal definitions of crime (such as those proposed by the Home Office and used in Chapter 4 of this thesis). Instead, future research might attempt to identify the *psychologically active* components of offending situations that determine whether two criminal events will be

[52] However, some studies have found evidence to suggest that expertise/experience in offending does increase behavioural consistency (Beutler et al., 1995; Woodhams & Labuschagne, 2012; Yokota & Watanabe, 2002).

perceived as similar by the offender. One way in which this might be achieved is by looking at the underlying motivation for the offence. That is, when the offender is motivated by the same need, two criminal events might be classed as psychologically similar, whereas when the motivation for offending is different the situations can be classed as dissimilar. This may be a more appropriate methodology for testing the hypothesised relationship between situational similarity and behavioural consistency. But, it remains to be seen whether police records currently contain sufficient detail to facilitate such research or whether interviews with serial offenders are needed instead.

Another surprising aspect of the research reported in this thesis was that statistically significant levels of consistency and distinctiveness were observed using 'third-hand' records of offender behaviour, such as victim statements, eyewitness accounts, and/or police reports. These data stand in contrast to the direct, 'first-hand' records of behaviour that have often been used by personality psychologists to study consistency and distinctiveness (e.g., Shoda, Mischel, & Wright, 1989, 1993, 1994). While it is clearly important to study behaviour using direct observational methods where possible (see Baumeister, Vohs, & Funder, 2007), this is sometimes neither practical nor ethical (e.g., during natural or human-induced emergencies, or where the behaviour of interest has already occurred, or where the researcher has limited time and money available). Thus, the findings reported in this thesis suggest that indirect, non-observational methods can yield reliable and valid insights into the consistency and distinctiveness of human behaviour. These findings might, therefore, open up a wider range of data collection methods for use in personality psychology research.

In summary, this thesis has extended the notions of behavioural consistency and distinctiveness to a new domain of human behaviour (the criminal domain), thereby demonstrating that these phenomena can be identified using indirect, non-observational methods that do not incorporate aspects of the situation. However, it is clearly important for future research to explore how situational aspects can be incorporated into BCL analysis (see Section 6.8 for further discussion of this issue).

6.5.2 The Criminal Career Literature

The criminal career approach is fundamentally concerned with issues of stability and change in offending behaviour over time, thus it is essentially a longitudinal approach to criminology that seeks to go beyond the cross-sectional analysis of behaviour (Farrington, 1992). In this respect, the criminal career approach is similar to the BCL literature, which also seeks to examine patterns of offender behavioural consistency *across time*. But, the timescale of criminal career research tends to be much larger than that of BCL, with the former tending to study offending across the life course (e.g., Piquero et al., 2007) whereas the latter is typically concerned with a small subset of offending behaviour that lasts just several months or sometimes years (e.g., Bennell & Canter, 2002; Tonkin et al., 2008). (Although, there is no reason why BCL research should be restricted in this way; indeed, if future BCL research were to take a more longitudinal approach to the study of behavioural consistency and distinctiveness, this may yield interesting theoretical insights). Furthermore, BCL research tends to take a more molecular view of criminal behaviour than the criminal career approach. That is, criminal career researchers tend to focus on the number and types of crime committed during the life course (leading to studies of persistence versus desistance and specialisation versus versatility in offending behaviour), whereas researchers of BCL tend to focus on *how* crimes were committed (i.e., what behaviours were evident at the crime scene). Despite these differences, this thesis has yielded some interesting insights that tie in with the criminal career literature.

It is a common finding in the criminal career literature that offenders tend to display versatility across the life course in their offending behaviour (e.g., Farrington et al., 1988; Piquero et al., 2007). These findings have been further confirmed in the current thesis because a significant number of the offenders sampled in Study 1 of Chapter 4 were convicted of at least two different types of crime during the one-year study period. Thus, it has been demonstrated in this thesis that versatility in offending behaviour can occur not just across the whole life course, but also when a short sub-section of the criminal career is examined. Putting aside the obvious differences in methodology and data that exist between the current research and the criminal career literature, these findings suggest that if short-term specialisation in offending were to exist (as suggested by several researchers; e.g., McGloin, Sullivan, Piquero, & Pratt, 2007; Shover, 1996; Sullivan, McGloin, Pratt, & Piquero, 2006) such specialisation may be in the order of months or weeks, rather than years. This supports the recent call for criminal career research to aggregate over shorter time periods (Sullivan et al., 2006). Based on the current findings, it would be interesting if future criminal career research could provide more precise estimates of the length of short-term specialisation by examining how the 'Diversity Index' (the measure used by some criminal career researchers to quantify specialisation/versatility; e.g., McGloin et al., 2007; Sullivan et al., 2006) varies over increasing periods of time aggregation (e.g., at two weeks, one month, three months, six months, and so on).

Criminal career researchers have also identified individual differences between offenders in terms of the frequency and duration of their offending (Nagin, Farrington, & Moffitt, 1995; Nagin & Land, 1993; Piquero et al., 2007; Piquero, Sullivan, & Farrington, 2010). For example, researchers have identified several distinct trajectories of offending behaviour, including *high-rate chronic* offenders (who engage in a protracted period of high frequency offending), *low-rate chronics* (who engage in a protracted period of low frequency offending), and *adolescence-limited* offenders (who engage in a relatively short period of high frequency offending, which normally occurs between the ages of 12 and 19 years). Furthermore, some criminal career researchers have argued that these trajectories should be viewed as "clusters of similar individual trajectories" rather than as one fixed specific pattern (Piquero et al., 2007, p. 143). Thus, the criminal career literature has identified meaningful individual differences between offenders in terms of their temporal offending behaviour. The discrimination accuracy achieved using the temporal proximity in this thesis further supports the notion of between-offender differences in temporal behaviour. That is, it would not have been possible to distinguish between linked and unlinked crimes using the temporal proximity if there were not individual differences in such behaviour.

These findings are particularly noteworthy when one considers the relatively short time period typically used to sample offenders in the BCL literature with volume crime (e.g., Bennell and Canter, 2002, and Study 1 in Chapter 4 of this thesis sampled crimes over just a one-year period). Consequently, the samples studied in some BCL research with volume crime may have been predominantly comprised of high-rate chronic offenders (and possibly adolescence-limited offenders as well, depending on the age of criminal responsibility in the country sampled). Low-rate chronics on the other hand may have been excluded from these samples because they had not committed two or more offences during the short study periods used in such research. Thus, even when certain offending trajectories are effectively excluded from BCL research with volume crime (thereby reducing the potential for between-offender variation), it is still possible to identify meaningful individual differences in the temporal behaviour of offenders.

6.5.3 Environmental Criminology

Environmental criminology is a framework for understanding the spatial and temporal aspects of crime (e.g., Brantingham & Brantingham, 1981). Contained within this framework are a range of seminal theories that describe and explain the various factors that guide criminal spatial behaviour, including theories such as rational choice theory, routine activities theory, and crime pattern theory (e.g., Brantingham & Brantingham, 1981; Clarke & Felson, 1993). Given the focus on spatial and temporal behaviour in this thesis, the theories of environmental criminology are clearly relevant.

A central finding of this thesis was that offenders tend to commit their crimes in relatively distinct, non-overlapping geographical areas. Thus, the offenders sampled throughout this thesis tended to return to the same (or similar) geographical locations from one crime to the next. These findings are consistent with a number of theories from environmental criminology, which suggest that offenders will seek to minimise the efforts and risks involved in offending (e.g., Brantingham & Brantingham, 1981; Clarke & Felson, 1993). Rational choice theory, for example, suggests that offending is the outcome of a logical decision-making process that weighs the perceived rewards of committing crime against the perceived efforts, costs, and risks. Thus, a logical prediction from this theory is that offenders will return to similar geographical locations to commit crime because this minimises the costs and effort associated with offending. As explained by Johnson and colleagues in their optimal foraging theory (e.g., Johnson, Bowers, Birks, & Pease, 2008; Johnson et al., 2009), the perceived risks are less and the expected rewards greater when returning to a previously-visited offending area (compared with an area in which the offender has not committed crime) because the offender knows about levels of natural surveillance in the area, as well as about access and escape routes. Furthermore, in the case of burglary offences there is a greater likelihood that offender will be familiar with the internal and external layout of the properties when offending in a previously-visited area compared with an unvisited area, and s/he may have greater knowledge of the items that are available to steal (Bowers & Johnson, 2004).

In short, the success of inter-crime distance as a linkage feature in this thesis is consistent with key theories from environmental criminology. These findings underscore the notion that offenders do not navigate through their spatial environment in a random manner; instead, the locations in which they choose to offend are meaningful and may reveal important insights about the offender (e.g., Brantingham & Brantingham, 1981). This is a fundamental tenet of environmental criminology and of the various practical applications in crime analysis that have developed from this literature, such as geographical profiling.

6.5.4 Street Culture

Throughout this thesis, linked crimes have been separated by fewer days than unlinked crimes. These findings suggest that many of the offenders sampled during this research engaged in relatively high frequency offending (at least when compared with the number of days between randomly paired crimes that were committed by different offenders). Indeed, this fits with the suggestion above that BCL samples will contain predominately high-rate chronic offenders. Furthermore, these findings fit with a body of research on street culture, which has highlighted a subset of offenders who engage in a lifestyle of self-indulgence and ‘partying’, where drinking and drug-taking are common and social status is conferred on those who can afford expensive luxury items, such as cars, clothing, and jewellery (e.g., Copes, 2003; Wright, Brookman, & Bennett, 2006; Wright & Decker, 1994, 1997). For these offenders, “financial need is effectively a constant” (Jacobs, Topalli, & Wright, 2003, p. 677) and crime is the only realistic way of maintaining such a lifestyle (Jacobs & Wright, 1999). Given this context, a relatively high frequency of offending is understandable and explicable.

6.5.5 Drawing Together Criminal Career Research, Environmental Criminology, and Street Culture

Thus far the theoretical implications have been explored by examining several bodies of literature in isolation, but the discussion above suggests that three of these literatures might be drawn together to explain some of the central findings of this thesis.

To reiterate, three important findings of this thesis are that (1) many serial offenders appear to display versatility in their offending behaviour (i.e., they do not restrict themselves to committing just one type of crime), (2) serial offenders often return to the same or similar geographical locations to commit crime, and (3) serial offenders tend to commit their crimes in closer temporal proximity than one would expect by chance.

Using the theories discussed above, one might hypothesise that many of the offenders sampled throughout this thesis are high rate chronic or adolescence-limited offenders who are motivated by a need to gain quick and easy cash that will allow them to maintain the extravagant lifestyle of street culture within which they are embedded. Naturally, this hypothesis can only be inferred from the behavioural patterns observed in this research and more focused research involving offender interviews is needed to test this notion. But, such a hypothesis fits with the three findings highlighted above.

First, the need for quick and easy cash can be satisfied via a number of criminal means, including both violent and property-related offences (e.g., commercial and personal robbery, burglary, theft etc.). Moreover, several researchers have highlighted the importance of physical aggression in and of itself as a means of maintaining social status amongst those engaged in street culture, rather than simply as a means of obtaining money to buy status-enhancing items (e.g., Copes & Hochstetler, 2003; Wright et al., 2006). Thus, considerable versatility in offending behaviour would be predicted amongst those engaged in street culture (i.e., these individuals might be expected to engage in a variety of property and person-oriented crimes, including burglary, car theft, robbery, and physical violence).

Second, the street culture literature emphasises the largely spontaneous nature of offending and the relative lack of pre-offence planning (e.g., Wright et al., 2006; Wright & Decker, 1994). Furthermore, theories such as rational choice theory and routine activities theory from environmental criminology suggest that offenders will seek to minimise the effort associated with offending, which often leads them to offend in the areas that they frequent regularly. In short, one would expect those involved in street culture to commit their offences in the same or similar geographical locations from one offence to the next.

Third, both the criminal career and street culture literatures identify individuals who engage in high frequency offending. As mentioned above, these offenders spend considerable sums of money and thus a frequent pattern of offending can be the only realistic option for maintaining such an extravagant lifestyle (e.g., Copes, 2003; Jacobs et al., 2003; Jacobs & Wright, 1999). It is, therefore, logical to predict that the crimes committed by offenders engaged in the street culture lifestyle would occur closer together in time than would be expected by chance.

In summary, it is suggested here that many of the offenders sampled throughout this thesis are those individuals described as high rate chronic and adolescence-limited offenders in the criminal career literature. Furthermore, a potential explanation for their criminal behaviour can be drawn from the street culture literature, which describes a subset of individuals who are motivated to offend by their desire for quick and easy cash that can be used to maintain their lifestyle of drinking and drug-taking. This hypothesis fits with the central behavioural patterns observed throughout this thesis.

However, it is important to recognise that this hypothesis is clearly a generalised statement about the offenders in this thesis and may not apply to all offenders. Furthermore, this suggestion may not apply to previous BCL research. For example, it is probably unlikely that such an explanation would apply to serial homicide or sexual offenders. But, given that much of the street culture literature has focused on offences such as robbery, burglary, and car theft, the proposed explanation may apply successfully to previous BCL research with these crime types (e.g., Bennell & Jones, 2005; Burrell et al., in press; Davies et al., in press; Markson et al., 2010; Tonkin et al., 2008; Woodhams & Toye, 2007).

6.6 The Practical Implications

The statistically significant levels of behavioural consistency, distinctiveness, and discrimination accuracy observed in this thesis suggest that BCL may be a viable investigative procedure. This is reassuring given the significant resources already devoted to BCL, its growing use in practice, and the potentially serious consequences of linkage decisions (e.g., Burrell & Bull, 2011; Grubin et al., 2001; Snook et al., 2012).

These findings might, therefore, be used to develop a statistical tool that can support BCL during live criminal investigations. This tool would contain a number of logistic regression models that have been developed by previous research[53], including models that permit BCL across crime categories and crime types, models that allow linkage within crime types for a variety of offences (e.g., models for residential burglary, models for commercial robbery, and so on), and possibly models for a range of geographical locations. The tool would also permit the user to specify his/her own model parameters. Such diversity in the regression models would help to ensure that the tool has widespread value and appeal.

[53] The tool would contain the Beta and constant values developed in previous research, which are the core components of a logistic regression model in terms of producing BCL predictions.

Depending on the particular regression model used, the analyst would load the relevant geographical, temporal, and/or behavioural information into the tool and a probability value would be calculated (using the logistic regression equation and steps described in Section 2.2.3). This value would indicate the predicted likelihood that the crimes were committed by the same person, ranging from 0 (very unlikely to be linked) to 1.00 (very likely to be linked). Such a tool could be used to support BCL involving just a small number of offences (e.g., where an analyst is presented with two offences and asked to determine whether they have been committed by the same person; so-called reactive BCL), but it could also be used to support proactive BCL where the analyst has a large database of crimes and s/he is actively searching for linked crimes amongst this database (Woodhams, Bull et al., 2007). In the latter scenario, the tool would calculate a predicted probability value for every pair-wise combination of crimes in the database (i.e., crime 1 paired with crime 2, crime 1 paired with crime 3, and so on). These values would subsequently be organised from highest to lowest value, thereby providing the analyst with a prioritised list of potentially linked crimes for consideration. This would give law enforcement agencies an empirically-based method for screening large databases of crime that would otherwise be quite unmanageable for the individual analyst.

As discussed in Chapter 5, there are a number of potential benefits that such statistical BCL tools can offer law enforcement agencies. First, they represent a consistent and standardised method for conducting BCL. Unlike human approaches, a statistical tool will always reach the same linkage decision if it is given the same input and it will not be influenced by extraneous variables that are unrelated to the actual linkage status of the crimes, such as fatigue or recent case exposure (Faust, 1989).

Indeed, there is a growing body of evidence to suggest that human decision-making (particularly in forensic contexts) is subject to a range of biases that affect perception and judgement (see Dror & Cole, 2010; Rainbow, Almond, & Alison, 2011). These biases include confirmation bias, belief persistence and selective information searching, where human decision-makers have a tendency to seek out and appraise information in a manner that supports their preconceived hypotheses, rather than evaluating that information in an unbiased and balanced manner (e.g., Ross & Anderson, 1982; Snyder & Swann, 1978). This may cause problems in the context of BCL, for example, if an investigating police officer were to convey his expectations regarding linkage before the analyst was able to conduct his or her BCL analysis. With prior expectations instilled in the analyst's mind, it may prove very difficult to appraise the crime scene information in a balanced manner. Another potential bias that can impact decision-making is the clustering illusion (Gilovich, Vallone, & Tversky, 1985), whereby humans have a tendency to seek out patterns in data, even when such patterns do not exist. In the context of BCL, the clustering illusion may lead to false positive errors, where unlinked crimes are mistakenly classed as linked. Thus, while an awareness of such biases may help decision-makers to avoid these errors, statistical tools might further help to reduce the influence of such biases in BCL.

Second, statistical tools such as the one described above would be based on peer-reviewed psychological research. Not only is this important in terms of ensuring that BCL adheres to the principles of evidence-based practice, but it is also crucial if BCL is to be used as similar fact evidence in court (e.g., Hazelwood & Warren, 2004; Labuschagne, 2012). Indeed, a key component of judging the admissibility of expert evidence in a variety of countries is whether that evidence is based on theory/findings that have been tested, supported, and subjected to peer review (Meyer, 2007; Woodhams, Hollin et al., 2007). Thus, statistical tools may enhance the evidential value of BCL and help to avoid the significant costs that are incurred when expert evidence is sought but ultimately rejected by the court (see Meyer, 2007, for historical case examples where BCL has been rejected in court due to a lack of perceived reliability and questions regarding its scientific status).

Third, statistical tools provide a quantifiable approach to BCL that can be broken down into a series of steps and fully explained to lay persons. Human decision-making, however, is notably more difficult to explain (e.g., Dhami & Ayton, 2001; Dhami & Harries, 2001; Reilly & Doherty, 1992). This is important because law enforcement personnel must frequently explain their decision-making processes to investigating police officers and occasionally the courts. Statistical tools might, therefore, make this task easier.

Fourth, statistical tools can process large quantities of information in a more quick and efficient manner than can humans. Statistical tools might, therefore, reduce the time that it takes to conduct BCL, which is particularly important at a time when many law enforcement agencies are being forced to make considerable reductions in their operational costs without compromising their ability to prevent and detect crime.

However, it is important to note that, while statistical tools have a number of advantages in comparison with human approaches to BCL, these tools function in a relatively simplistic way and cannot yet take into account the situational circumstances of crime (Woodhams et al., 2008a). Furthermore, statistical tools are based on aggregate data. Consequently, while these tools may provide appropriate conclusions for many offenders, they will not be successful in 100% of cases. Thus, statistical tools such as the one proposed here should not be seen as a replacement for crime analysts, but instead they should be seen as a decision-making aid that can help law enforcement personnel to conduct BCL in a more efficient, reliable, and evidence-based way. These recommendations are, therefore, consistent with the notion of structured clinical judgement, which combines the use of both clinical and actuarial approaches to decision-making and has been successfully employed in other areas of forensic psychology in the UK, such as risk assessment (Department of Health, 2007; National Institute for Health and Clinical Excellence, 2005).

A further practical implication that should be discussed is whether the findings reported in this thesis can be used to help law enforcement agencies to prioritise the use of certain behaviours when linking crime. Based on the current findings, law enforcement personnel might prioritise inter-crime distance, closely followed by temporal proximity, when linking across crime categories, across crime types, and within crime types for residential burglary and car theft. Not only do these measures achieve moderate to high levels of discrimination accuracy, but they are also quick and easy to calculate and law enforcement agencies routinely have this information available during their investigations (unlike other forms of behavioural evidence that might be used to link crime, such as entry and internal behaviours).

However, this recommendation does not mean that the police should stop collecting other types of behavioural information. First, the potential for cross-crime linkage with behaviours other than inter-crime distance and temporal proximity was not examined in this thesis. It is entirely plausible that these alternative behavioural approaches will facilitate greater discrimination accuracy than geographical and temporal behaviour. Second, it has been demonstrated by Davies et al. (in press) that discrimination accuracy can vary depending on how offender behaviour is operationalised for the purpose of BCL (as discussed in Chapter 1). Thus far, this issue has not been explored to an extent that would allow researchers or practitioners to definitively reject *any* domains of behaviour from the linkage process. Furthermore, even when this work has been conducted, researchers and law enforcement agencies must remain cautious because BCL research is typically conducted at the aggregate level and the findings will not necessarily apply to every offender. Consequently, if the police were to stop collecting certain types of behavioural information they may miss the opportunity to detect some offenders. However, decreasing police budgets may dictate that law enforcement agencies reduce the amount of behavioural information gathered during the course of criminal investigations. If this is the case, it is strongly recommended that a thorough cost-benefit analysis is conducted before implementing such a policy to provide an estimate of how this will affect the ability to link and detect crime.

One final issue that is worthy of discussion is whether law enforcement agencies should develop their own, area-specific regression equations or whether they can achieve acceptable levels of discrimination accuracy using equations that have been developed in different geographical locations. In an ideal world, each law enforcement agency would develop their own equations, but the reality is that police resources are becoming scarcer in many places and it is highly unlikely that this is a feasible option for most law enforcement agencies. The findings reported in Chapter 5 tentatively suggest that it is possible to achieve high levels of discrimination accuracy using 'non-local' regression equations to discriminate between linked and unlinked crimes. Specifically, stepwise model 2 and Woodhams and Toye's (2007) stepwise regression model achieved AUCs of 0.92 when applied to crime pairs that were from very different geographical areas to those originally used to develop the models. While these findings must be replicated before solid practical recommendations are made, they suggest that law enforcement agencies that do not have the resources to develop their own, area-specific, regression models may be able to utilise non-local regression models when conducting BCL. But, to limit the risk of such a strategy law enforcement agencies might select regression equations that have been developed in areas that are similar to their own in terms of land use, population density, geographic features, crime patterns, and other demographic characteristics. The Home Office's list of 'most similar forces' might be used to guide these decisions in England and Wales.

6.7 Implications for Researchers of Behavioural Case Linkage

In addition to the theoretical and practical implications, this thesis has a number of methodological implications for researchers of BCL. First, it might be suggested that researchers should continue to use Bennell's (2002) original approach to forming the unlinked pairs, which involves randomly pairing two crimes from the linked subset that are known to have been committed by different offenders. While this approach has a number of potential limitations (see Chapter 2), the findings produced using this methodology were little different to those produced using an alternative methodology that formed the unlinked pairs from an independent sample of crimes containing both serial and non-serial offences. Thus, the additional effort that this new methodology entails (for both the researcher and potentially for the law enforcement agency facilitating the research) does not seem justified. However, these findings naturally need replication before a definitive conclusion can be drawn.

A second implication is that future researchers should continue to use binary logistic regression in favour of classification tree analysis (at least until further research has been conducted). The shrinkage that occurred in discrimination accuracy from training to test and the large number of unclassifiable cases observed with the tree-based models in this thesis justifies this recommendation.

Third, it is very important that future research continue to explore the potential for cross-crime linkage. Versatile serial offenders are common and they have a disproportionate impact on crime rates and public safety (e.g., Farrington et al., 1988; Leitner & Kent, 2009; Piquero et al., 2007), so future BCL research must continue to explore how these individuals can be successfully detected and prosecuted. Some suggestions for future research were discussed in Chapter 4 and these are reiterated in Section 6.8.

Fourth, researchers must continue to include unsolved offences in their analyses of behavioural consistency, distinctiveness, and discrimination accuracy, as this will help to ensure that BCL research is ecologically valid and that the recommendations drawn from this work are applicable to practice. The methodology described in the current thesis (using unsolved offences that have been linked via DNA evidence) is one way of achieving this aim. However, future research may have to consider either sampling from larger, probably metropolitan, police forces and/or combining datasets from several locations to ensure that sample size is sufficient to facilitate reliable analyses. While sample size was acceptable for the study of cross-crime linkage reported in Chapter 4, a further study by the author of solved and unsolved residential burglaries was excluded from this thesis due to concerns regarding sample size. This decision seems justified when one considers that recent BCL findings have been questioned on the basis of sample size (see Bennell, Gauthier et al., 2010; Melnyk et al., 2011).

Fifth, researchers who are interested in studying human decision-making in the BCL task should make explicit attempts to determine the extent and nature of previous linkage experience amongst the police participants in their research (e.g., by asking the participants to report the number of years experience with BCL, the frequency with which they conduct BCL, and the crime types with which they have had analytical/linkage experience). This is important because the whole point of comparing statistical tools with police participants is to determine whether these tools are able to outperform the methods that are currently available to law enforcement agencies when linking crime. Thus, if the participants included in this research are not the individuals who are responsible for BCL in practice, then these comparisons will not address the ultimate issue of whether statistical decision aids can improve upon existing methods of BCL.

6.8 Future Research Directions

As stated in Chapter 1, a project of this size cannot address all limitations/gaps in the literature. Consequently, a number of future research directions remain to be investigated. This section of the thesis will highlight some of the most important future directions, including those where work is either in the planning stages or has already begun.

Further research is clearly needed with samples containing unsolved offences. But, as discussed above, this work may have to combine several datasets to yield samples of sufficient size to support reliable statistical analysis. Fortunately, work of this nature is currently being planned by Dr. Woodhams, who has recently had a bid for funding accepted to develop an international network of BCL researchers (including the author of this thesis). One of the primary aims of this network will be to collate a sample of solved and unsolved serial sex offences and sexual homicides from across Europe, South Africa, Canada, and North America. This work will be the most ecologically valid and statistically sound test to date of behavioural consistency, distinctiveness, and discrimination accuracy conducted with these crime types.

The potential for cross-crime linkage is also an important avenue for future research. As discussed in Chapter 4, this research should examine whether behaviours other than inter-crime distance and temporal proximity can be used to facilitate cross-crime linkage. This may, however, require a slightly different methodology to that utilised in the current thesis. For example, researchers might focus on certain types of crime that share particular behavioural features, such as robbery, rape, and murder, which all often contain elements of victim-offender interaction, control, and escape behaviours (e.g., the use of a weapon, methods of victim restraint, and attempts to conceal one's identity from the victim). This may help to overcome the obvious difficulty posed by studying a diverse range of crimes that contain often very different types of offender behaviour. Research of this nature is already under way at the University of Birmingham, UK. Alternatively, future work might consider developing behavioural themes from offender crime scene behaviour that would subsequently be used to examine discrimination accuracy across crime categories/types. These themes could be developed statistically using techniques such as multidimensional scaling and cluster analysis (e.g., Bateman & Salfati, 2007; Santtila et al., 2008; Sorochinski & Salfati, 2010) or researchers might consider using theoretical models that are designed to apply to a wide variety of crime types, such as the Narrative Action System (NAS) model (Canter & Youngs, 2009; Youngs & Canter, 2009). Regardless of the approach used, research such as this is important because investigators will otherwise have no guidance in situations where geographical and temporal behaviour is either unreliable or absent (e.g., where a victim has been drugged or knocked unconscious and is unable to recall where and when the offence took place).

There are also important methodological issues that require further investigation. First, future research should conduct a comparison of statistical versus non-statistical/intuitive methods of forming the behavioural domains in BCL research. This issue was discussed in Chapter 1, but was only explored in a preliminary manner in this thesis. In a study conducted by the author (that was not presented within this thesis due University regulations regarding thesis length), the level of discrimination accuracy achieved using Bennell’s (2002) approach to domain formation was compared with an alternative approach that was based on factor analysis. In short, both approaches achieved a comparable level of discrimination accuracy with a sample of residential burglaries from Finland. Further research is needed to compare Bennell’s (2002) non-statistical approach to domain formation with approaches that are based on statistical clustering techniques such as Multidimensional Scaling, factor analysis, or Mokken scaling.

Second, researchers should explore alternative statistics for quantifying behavioural similarity in BCL research because the limitations of Jaccard’s coefficient have been recognised for some time (e.g., Bennell & Canter, 2002). This issue was also explored in a study conducted by the author, but it was not possible to report these findings due to the limits of space. In this study the level of discrimination accuracy achieved using Jaccard's coefficient was compared with that achieved using an alternative measure of behavioural similarity called the simple matching coefficient. In short, Jaccard's coefficient and the simple matching coefficient achieved comparable levels of discrimination accuracy with a sample of residential burglaries from the UK. Future research should endeavour to conduct a comprehensive comparison of the different similarity coefficients that are suitable for binary data (see Romesburg, 1984).

A third methodological issue is the continued use of binary logistic regression analysis without sufficient exploration of alternative techniques. While this issue was addressed to some extent in the current thesis by comparing logistic regression and classification tree analysis, there are a number of alternative approaches that remain to be fully explored, such as neural networks models and Bayesian analysis (e.g., Adderley & Musgrove, 2003; Salo et al., 2012). Future research should conduct a comprehensive comparison of these different approaches.

A fourth issue was raised when deciding whether to include the study of solved and unsolved residential burglaries in this thesis (as discussed above). This study was excluded partly on the basis of small sample size, but the process of making this decision highlighted a gap in the literature. That is, research has yet to examine the minimum sample size needed to facilitate reliable estimates of behavioural consistency, distinctiveness, and discrimination accuracy in BCL research. A simulation study is, therefore, needed to determine how measures of effect size, confidence intervals, and the overall size of the AUC change as a function of sample size. This research should use a variety of datasets containing different types of crime from different geographical locations to ensure that the findings are robust.

All of the work described above is important because it will help to determine the most appropriate methodology for investigating BCL, thereby ensuring that the theoretical and practical conclusions drawn from this research are valid.

One of the central tenets of this thesis is that replication should form a fundamental part of future BCL research. While the findings reported in this thesis have helped to build a more robust evidence base for BCL, there is a significant amount of work still required. First, there are certain types of crime for which behavioural consistency, distinctiveness, and discrimination accuracy have yet to be examined (e.g., metal theft, group rape, and prostitute homicide). Fortunately, future research is currently being planned by the author of this thesis and others to investigate the potential for BCL with these crime types. A second important part of future replication work is to explore whether existing findings generalise cross-nationally. The author of this thesis is currently in talks with law enforcement agencies and researchers from the US and Australia, which will help to address this issue. In the US there has been no BCL research on property-related offences and in Australia there has been no BCL research whatsoever. These are important gaps to fill if academics are to maximise the potential impact of BCL research.

Future researchers must also expand their endeavours beyond simply testing the assumptions of BCL. This is important because there are a multitude of factors beyond behavioural consistency and distinctiveness that will impact on whether BCL is able to function successfully in practice (e.g., the range and quality of information available for BCL, the decision-making ability of law enforcement personnel, their motivation to use statistical tools and/or follow guidelines, the usability of such tools, the extent to which these tools are able to integrate with complex police databases, the resources that are available to law enforcement personnel, and so on). By focusing on the theoretical assumptions of BCL, existing research provides very little insight into whether these more practically-oriented issues can be overcome. One way in which future research might address these issues is by comparing the linkage performance[54] of crime analysts who have access to a statistical BCL tool with those analysts who do not have access to such a tool (i.e., a control-group design). Alternatively, a pre/post design might be utilised, whereby linkage performance is measured prior to receiving the tool and subsequently compared to performance post-tool. While there are a number of difficulties associated with these suggestions (not least the significant level of cooperation required between researchers and law enforcement agencies), research such as this is crucial if the BCL literature is to be successfully translated into practice.

Fortunately, research of this nature is already underway. The current author has recently conducted a series of analyses using logistic regression, classification tree analysis, ROC analysis, and several measures of behavioural similarity to determine whether offender behaviour can be used to discriminate between linked and unlinked residential burglaries in a UK police force. These analyses have yielded a number of logistic regression equations that achieved high levels of discrimination accuracy. He is currently (with others) using these findings to develop a statistical BCL tool, which will subsequently be trialled by the police force in question to determine whether it has the potential to assist the linking of residential burglaries. Such research is an important

[54] Throughout the BCL literature there has been a heavy focus on discrimination accuracy (often measured using the AUC), but it is important that future research adopt a wider definition of 'performance' in studies such as this. Most importantly, the time taken to conduct BCL should be considered alongside accuracy because one of the proposed benefits of statistical tools is that they can process large quantities of information in a more quick and efficient manner than humans.

step towards translating existing BCL research into workable methods of linking crime that can assist crime analysts during live investigations.

Another area that must receive empirical attention is the issue of decision thresholds. As mentioned above, researchers have emphasised the importance of identifying decision thresholds that can guide the use of BCL in practice (e.g., Bennell, 2002; Bennell & Jones, 2005). Youden's Index has been proposed as a potential method for calculating these thresholds, but this method does not take into account the prior probability that crimes are linked/unlinked nor does it account for the various costs and benefits associated with correct/incorrect BCL decisions (Bennell, 2002). These are both important issues that should guide the selection of an appropriate decision threshold in practice. Future research must, therefore, attempt to develop decision thresholds that are sensitive to these issues. The prior probability that crimes are linked/unlinked would be fairly straightforward to calculate using a database of solved cases, but it would be much more difficult to estimate the various costs and benefits associated with correct/incorrect linkage decisions. For example, how does one quantify the financial and personal costs associated with incorrectly linking an offence and thereby misleading a police investigation? Nevertheless, this is an important topic for research to explore because decision thresholds are an important part of translating BCL research into practice.

Finally, this thesis has not considered how research might incorporate aspects of the person, the situation, and how they interact into BCL. While the research reported in this thesis suggests that useful practical methods of linking crime can be developed without doing this, it is nevertheless important to explore whether discrimination accuracy can be improved by considering some situational variables. Fortunately, research of this nature is currently ongoing amongst researchers from Belgium and the UK (Winter & Taylor, in press).

6.9 Concluding Remarks

The research reported within this thesis has made an important contribution to the literature on BCL. Importantly, the generalisability of previous research has been tested, thereby helping to build a more robust evidence base for BCL. A number of new methodologies have been developed and tested that increase the ecological validity of BCL research. And important methodological issues have been systematically explored, which shed light on the most appropriate way of researching BCL. This thesis has, therefore, yielded a range of theoretical, practical, and methodological findings that can be used to guide researchers and practitioners. However, this is still a newly emerging area of research and there are many unanswered questions, none of which will be addressed unless researchers and practitioners develop close and cooperative working relationships. But, if this is possible, there is significant potential for BCL research to make an important contribution to law enforcement policy and practice around the world.

APPENDICES

Appendix 1: Content Dictionary of Offence Behaviours and Behavioural Domains used in Chapter 2 (Residential Burglary in Finland)

Target Characteristics

A detached house

1st floor of a multi-storey building

2nd floor or above of a multi-storey building

A studio flat

A terraced or semi-detached house

Other target

Owners present

Owners temporarily away (i.e., less than 24 hours)

Owners away 1-3 days

Owners away 3+ days

Target has safeguards present (alarm, security light, dog etc.)

Target in an urban city area

Entry Behaviours

Door

Back door

Balcony door

Window

Mailbox

Open or unlocked door

Manual force

Breaking glass

Climbing (above street level)

Lock

Key

Tool

Crowbar

Hook

Sharp weapon

Garden tool

Screwdriver or spike

Brick or stone

Tool brought to the scene

Tool used from the scene or the immediate vicinity

Internal Behaviours

Interrupted

Interrupted by a guard or the owner

Fingerprints, footprints, or DNA left at the scene

Tools used in the burglary left at the scene

1 offender

2 offenders

3+ offenders

Tidy search

Untidy search

Only first room entered was searched

Whole target searched

Drawers/cabinets opened and searched

Drawers pulled out and contents possibly thrown on floor

Inner doors opened using force

Property piled up to be carried away

Stolen items hidden close by

Stolen items abandoned

Used facilities (consumed food/drink, used toilet/shower, defecated/urinated)

Exit by car

Exit on foot

Property Stolen

Cash

Credit or bank cards, cheques, bank book, shares

Firearms, ammunition, explosives

Sharp weapons (not cutlery)

Watches, wristwatches

Small-size consumer electrical items

Large electrical equipment, musical instruments that need to be carried with both hands

Tapes, CD's LP's, videotapes

Jewellery

Fake jewellery (costume)

Prescription medication

Tobacco products/smoking tools

Cosmetic, hygiene products

Alcohol

Plates, cups, cutlery and other utensils

Food

Clothes

Purses, hand bags, suitcases, backpacks

Wallet

Keys (home, car)

Identity documents (e.g., passport, driving licence, library card etc.)

Spectacles, sunglasses or other optical items

Antique or art objects

Construction tools or materials

Porcelain, crystal glass, silverware

Games or sports equipment

Vehicle

Items stolen could be carried by one person

Stolen items worth less than 170 Euros

Stolen items worth up to 1700 Euros

Stolen items worth more than 8400 Euros

Combined

Contains all behaviours listed above under target characteristics, entry behaviours, internal behaviours, and property stolen

Inter-crime Distance

The distance in kilometres between two crime sites

Temporal Proximity

The number of days between two crime dates

Appendix 2: Content Dictionary of Offence Behaviours and Behavioural Domains used in Chapter 3 (Car Theft in the UK)

Target Selection Choices

Hatchback

Saloon

Estate

Van

Coupe

Convertible

Sports car

Jeep/Landrover

Pickup

Camper van/Caravanette

MPV/People carrier

Other vehicle

New vehicle (0 - 3 years old)

Middle-aged vehicle (3 – 9 years old)

Old vehicle (9 - 15 years old)

Very old vehicle (15+ years old)

Car theft occurred between 0600 - 1359

Car theft occurred between 1400 - 1759

Car theft occurred between 1800 - 2259

Car theft occurred between 2300 - 0559

Car theft occurred on a Monday

Car theft occurred on a Tuesday

Car theft occurred on a Wednesday

Car theft occurred on a Thursday

Car theft occurred on a Friday

Car theft occurred on a Saturday

Car theft occurred on a Sunday

Target Acquisition Behaviour

Keys were used to enter the vehicle

The door locks were forced to gain entry to the vehicle

The door locks were removed to gain entry to the vehicle

The vehicle windows were smashed to gain entry

The vehicle windows were bent to gain entry

The vehicle windows were removed to gain entry

Keys were used to start the vehicle's engine

The cowling was removed and the ignition tampered with to start the vehicle's engine

The ignition barrel was either tampered with or removed to start the vehicle's engine

Disposal Behaviour

Property stolen from the vehicle was loose (e.g., cash, sports equipment)

Property stolen from the vehicle was attached (e.g., the stereo system, wheels)

No property was stolen from the vehicle

The vehicle was recovered after the theft intact

The vehicle was recovered after the theft with light damage

The vehicle was recovered after the theft with serious damage

The vehicle was recovered in a written-off condition

The vehicle was recovered burnt out

Combined

Contains all behaviours listed above under target selection choice, target acquisition behaviour, and disposal behaviour

Inter-crime Distance

The distance in kilometres between two crime sites

Appendix 3: List of Crime Types Searched for and Included in Chapter 4 Studies 1 and 2

	Study 1	Study 2
	n	***n***
Violent Offences		
Murder	0	0
Attempted murder	1	0
Conspiracy to murder	0	0
Threats to kill	0	0
Manslaughter	0	0
Infanticide	0	0
Causing death by dangerous driving	0	0
Causing death by careless driving under the influence of drink or drugs	0	0
Death by careless or inconsiderate driving	0	0
Cause/allow death of child or vulnerable person	0	0
Causing death by driving: unlicensed drivers etc.	0	0
Wounding or carrying out an act endangering life	17	0
Use of substance or object to endanger life	0	0
Possession of items to endanger life	0	0
Endangering railway passengers	0	0
Endangering life at sea	0	0

Inflicting grievous bodily harm without intent	13	1
Actual bodily harm and other injury (includes minor wounding)	233	2
Racially or religiously aggravated inflicting grievous bodily harm without intent	1	0
Racially or religiously aggravated actual bodily harm and other injury	5	0
Poisoning or female genital mutilation	0	0
Harassment (Harassment Act 1997)	0	0
Racially or religiously aggravated harassment	0	0
Public fear, alarm or distress (Public Order 1986)	115	0
Racially or religiously aggravated public fear, alarm or distress	19	0
Possession of firearms with intent	0	0
Possession of other weapons	0	0
Possession of articles with blade or point	0	0
Abandoning child under 2 years	0	0
Child abduction	1	0
Causing death by aggravated vehicle taking	0	0
Assault without injury on a constable	48	0
Assault without injury	141	0
Racially or religiously aggravated assault without injury	7	0

Sexual Offences

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

Exposure and voyeurism	4	0
Soliciting for prostitution from motor vehicle	0	0
Soliciting for prostitution	0	0
Burglary Offences		
Burglary in a dwelling	146	83
Attempt burglary dwelling	10	1
Distraction burglary (incl. attempts)	1	0
Aggravated burglary in a dwelling	1	1
Burglary other	110	47
Attempt burglary- other	10	5
Aggravated burglary other	0	0
Robbery Offences		
Robbery of business property	13	1
Robbery of personal property	96	1
Theft/Handling Offences		
Aggravated vehicle taking	6	8
Theft from person	8	0
Theft in dwelling (other than automatic machine/meter)	29	2
Theft by an employee	2	0
Theft of mail	0	0
Theft or unauthorized taking of pedal cycle	35	0

Theft from vehicle	41	23
Shoplifting	394	6
Theft from automatic machine or meter	2	1
Theft/TWOC of motor vehicle	36	58
Attempt theft/TWOC of motor vehicle	0	0
Other theft	55	3
Interfering with a motor vehicle	15	8
Criminal Damage Offences		
Arson endangering life	2	0
Arson not endangering life	8	0
Criminal damage- to dwellings	138	5
Criminal damage- to other buildings	81	6
Criminal damage- to vehicles	0	2
Criminal damage- other	90	0
Racially or religiously aggravated criminal damage to a dwelling	0	0
Racially or religiously aggravated criminal damage to a building other than a dwelling	3	0
Racially or religiously aggravated criminal damage to a vehicle	1	0
Racially or religiously aggravated other criminal damage	1	0
Threat or possession with intent to commit criminal damage	0	0

Appendix 4: Exemplar Residential Burglary Questionnaire with Training Information from Chapter 5

Please note that the map presented in the appendix was reduced slightly in size to fit the margins required for this thesis.

DEMOGRAPHIC QUESTIONS

1) **What is your age (in years)?**

   ....

2) **What is your gender?**

   [ ] Male   [ ] Female

3) **In which country do you work/study?**

   ....

4) **What is your job title?**

....

....

5) **How many years' experience do you have in crime analysis, linkage analysis, and police work?**

   If you do not have experience in any of these three areas, please write "N/A" on each line

   i) Crime analysis

   .... years

PLEASE TURN OVER

ii) Linkage analysis

Linkage analysis is when someone uses information about when, where and how crimes were committed to judge whether they have been committed by the same or by different people. Linkage analysis is also referred to as comparative case analysis and behavioural case linkage.

.... years

iii) Police work

.... years

6) If you have linkage analysis experience, please indicate, on average, how regularly you are involved in this activity by placing an X in the appropriate box.

[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Daily	Weekly	Monthly	Yearly	Less than yearly	Not applicable

7) If you have any experience in crime analysis, linkage analysis, or police work, please indicate the types of offence for which you have regular experience ('Regular experience' means that you deal with that particular type of offence at least once a month).

If you do not have any relevant experience, please write "N/A".

....

....

....

....

INSTRUCTIONS

You will be presented with a number of offence pairs. Each offence pair contains two offences that were committed in the United Kingdom, and for each offence a range of information is listed. Your task is to decide whether the two offences in each pair have been committed by the same person or whether they have been committed by different people.

You do not have to use all of the offence information listed when making your decision. You can use as much or as little as you like.

You should also indicate how confident you are that the same offender committed the two offences in each pair, and to what extent you relied on the different types of information presented to you.

If you feel you are at all familiar with any of the crimes presented below, then you should indicate which crimes and which offence pairs you are familiar with in the space provided at the end of the questionnaire.

PLEASE TURN OVER

IMPORTANT INFORMATION TO HELP WITH THE RESIDENTIAL BURGLARY TASK

Fifteen residential burglary pairs are presented below. Each burglary is plotted on the map below.

Residential burglary is when a person or persons have entered a place of residence without the owner's consent with the intention of stealing property.

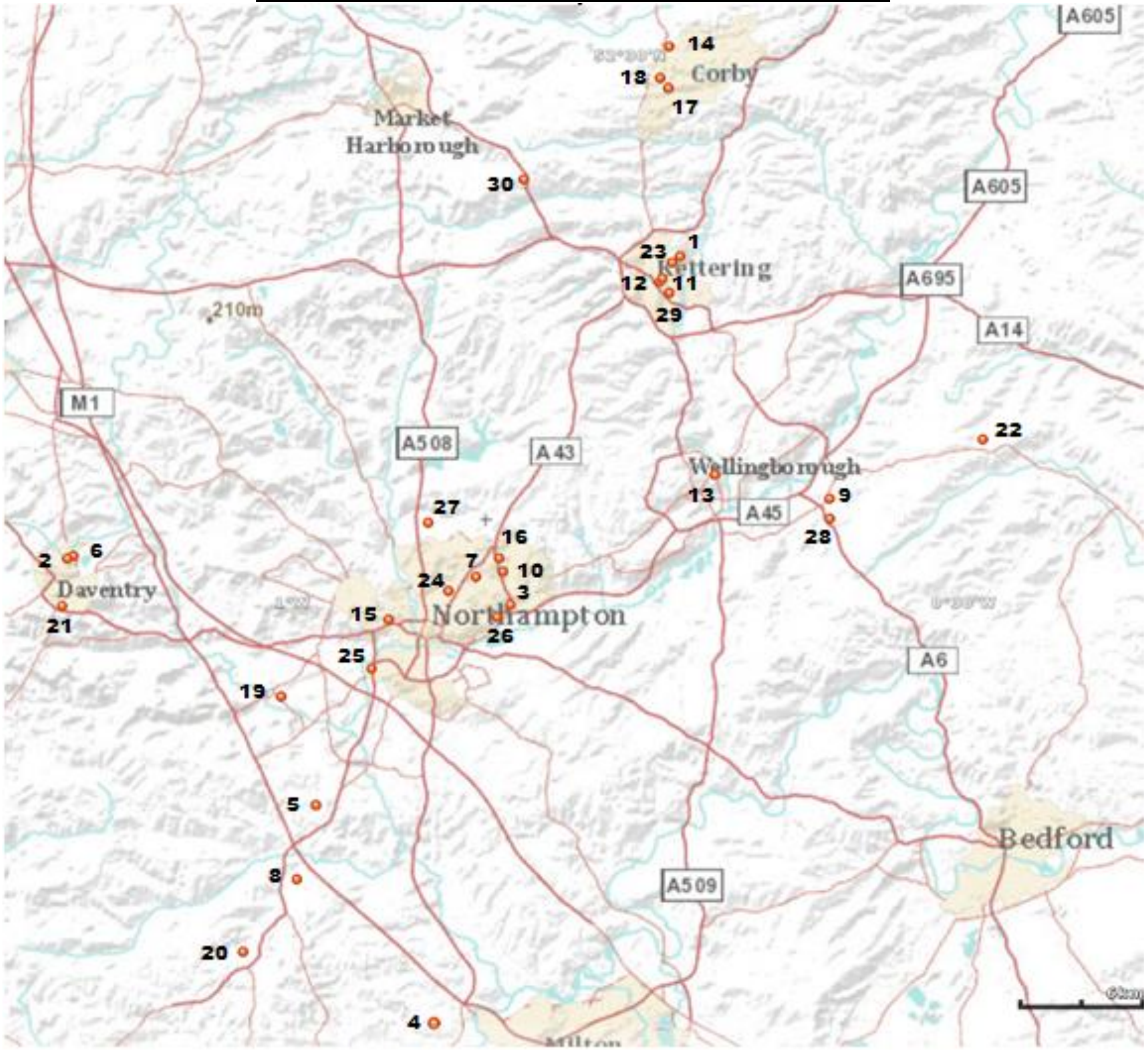
For three of these pairs they contain two crimes that were committed by the same person. The remaining 12 pairs contain two crimes that were committed by different people.

When deciding whether two offences have been committed by the same offender, previous research has indicated that **some types of offence information are more useful than others**.

This research has suggested that **offences committed by the same offender can be most successfully identified using the kilometre distance and number of days between them**. That is, the closer two offences are to one another geographically and the shorter the number of days separating them, the more likely it is that the same offender committed them.

Other types of offence information, such as the type of property stolen and who or what type of building/car was targeted, are not very useful when identifying crimes that have been committed by the same person.

A MAP DEPICTING THE RESIDENTIAL BURGLARY LOCATIONS



RESIDENTIAL BURGLARY OFFENCE PAIRS

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 1

Residential Burglary 1

Distance:
Burglary 1 occurred 34.88 kilometres (21.67 miles) away from burglary 2

Time:
There were approximately 113 days separating burglary 1 and burglary 2

Target Characteristics:
The target was a terraced house
The house was occupied at the time of the burglary

Entry Behaviours:
The burglar entered the property via an insecure front window

Behaviour inside the Property:
The burglar conducted a tidy search of the property

Property Stolen:
Attempt made to steal a car

Residential Burglary 2

Distance:
Burglary 2 occurred 34.88 kilometres (21.67 miles) away from burglary 1

Time:
There were approximately 113 days separating burglary 1 and burglary 2

Target Characteristics:
The target was a detached house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar entered the property by forcing a ground floor rear window with an unknown implement

Behaviour inside the Property:
The burglar conducted an untidy search of the entire house

Property Stolen:
Television
DVDs
Computer games console

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 1

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 2

Residential Burglary 3

Distance:
Burglary 3 occurred 21.72 kilometres (13.50 miles) away from burglary 4

Time:
There were approximately 300 days separating burglary 3 and burglary 4

Target Characteristics:
The target was a terraced house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar entered the rear garden by unbolting the gate. The garden shed door was forced with an unknown implement. The house was entered by forcing the rear dining room door probably using bodily pressure

Behaviour inside the Property:
Most of the property did not appear to have been searched, but there was a tidy search of the upstairs bedroom

Property Stolen:
Cash

Residential Burglary 4

Distance:
Burglary 4 occurred 21.72 kilometres (13.50 miles) away from burglary 3

Time:
There were approximately 300 days separating burglary 3 and burglary 4

Target Characteristics:
The target was an end terrace house
The house was occupied at the time of the burglary

Entry Behaviours:
The burglar gained access to the rear garden of the premises by lifting the trellis work from the top of the garden fence panel. The offender then lifted and propped up the fence panel with the trellis work. The offender then entered the property via an insecure garage door and an internal door to property

Behaviour inside the Property:
The burglar conducted a tidy search of the property

Property Stolen:
Cash
Laptop computer
Driving licence
Non-payment card/loyalty card
Passport
Payment card (debit/credit card)
Ladies handbag
2 sets of car and house keys
Mobile telephone
2 vehicles

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 2

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 3

Residential Burglary 5

Distance:
Burglary 5 occurred 17.55 kilometres (10.91 miles) away from burglary 6

Time:
There were approximately 277 days separating burglary 5 and burglary 6

Target Characteristics:
The target was a detached house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry by breaking a single-glazed kitchen window by unknown means and climbing through the window

Behaviour inside the Property:
The burglar completed an untidy search throughout the property

Property Stolen:
Laptop computer
A brooch (jewellery)
Earrings
Necklace
Other jewellery
A ring

Residential Burglary 6

Distance:
Burglary 6 occurred 17.55 kilometres (10.91 miles) away from burglary 5

Time:
There were approximately 277 days separating burglary 5 and burglary 6

Target Characteristics:
The target was an end terrace house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry through the ground floor kitchen window. The window frame was forced with an unknown object causing damage

Behaviour inside the Property:
The burglar conducted a tidy search of the property

Property Stolen:
Cash
Computer games console
Wallet

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 3

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 4

Residential Burglary 7

Distance:
Burglary 7 occurred 18.08 kilometres (11.24 miles) away from burglary 8

Time:
There were approximately 74 days separating burglary 7 and burglary 8

Target Characteristics:
The target was an end terrace house
The house was unoccupied at the time of the burglary

Entry Behaviours:
The burglar gained entry by forcing a ground floor double glazed window with an unknown instrument

Behaviour inside the Property:
The burglar conducted a tidy search of the living room only

Property Stolen:
DVD player
DVDs
Games for a computer console
Personal computer (base/tower unit)

Residential Burglary 8

Distance:
Burglary 8 occurred 18.08 kilometres (11.24 miles) away from burglary 7

Time:
There were approximately 74 days separating burglary 7 and burglary 8

Target Characteristics:
The target was a semi-detached house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry by forcing a downstairs dining room window

Behaviour inside the Property:
The burglar conducted a tidy search of the property

Property Stolen:
Cash
Jacket/Coat
Car keys
Vehicle
Umbrella
Spectacles/Sun glasses

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 4

1) Do you think these two crimes were...

[ ] Committed by the same person

[ ] Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 5

Residential Burglary 9

Distance:
Burglary 9 occurred 17.07 kilometres (10.61 miles) away from burglary 10

Time:
There were approximately 378 days separating burglary 9 and burglary 10

Target Characteristics:
The target was a detached house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry by climbing on to the roof of the conservatory and climbing through an upstairs window without causing damage to the window

Behaviour inside the Property:
The burglar conducted an untidy search of 2 upstairs bedrooms

Property Stolen:
Portable transmitter radio (walkie talkie)
Cash
Safe
Computer components
Computer games console
Games for the computer console
A joystick/controller for the computer console
Laptop computer
Other computer equipment (not components)
Batteries (not vehicle)
Business/work papers
Passport
Bracelet
Necklace
Other jewellery
Ring

Residential Burglary 10

Distance:
Burglary 10 occurred 17.07 kilometres (10.61 miles) away from burglary 9

Time:
There were approximately 378 days separating burglary 9 and burglary 10

Target Characteristics:
The target was a terraced house
The house was occupied at the time of the burglary

Entry Behaviours:
The burglar gained entry through an insecure (i.e. unlocked) ground floor front door

Behaviour inside the Property:
The burglar conducted a tidy search of the property

Property Stolen:
Cash
Handbag
Mobile telephone

Property Stolen (continued):
Watch
Miscellaneous household items
A camcorder (hand-held video camera)
Camera
Mobile telephone
Electric/Cordless drill
Satellite Navigation System (Sat Nav)

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 5

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 6

Residential Burglary 11

Distance:
Burglary 11 occurred 0.25 kilometres (0.15 miles) away from burglary 12

Time:
Burglary 11 and burglary 12 were committed on the same day

Target Characteristics:
The target was a terraced house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry to the ground floor of the property using unknown means

Behaviour inside the Property:
The burglar conducted a tidy search of the ground floor

Property Stolen:
Television
Cigarettes
Driving licence
Non-payment card/loyalty card
Payment card (debit/credit card)
Wallet

Residential Burglary 12

Distance:
Burglary 12 occurred 0.25 kilometres (0.15 miles) away from burglary 11

Time:
Burglary 11 and burglary 12 were committed on the same day

Target Characteristics:
The target was a detached house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry by smashing a rear ground floor window with a brick

Behaviour inside the Property:
The burglar conducted a tidy search of the property

Property Stolen:
Cigarette lighter
Cigarettes
Other documents (not identification or loyalty cards)
Watch
Car and door keys

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 6

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 7

Residential Burglary 13

Distance:
Burglary 13 occurred 21.90 kilometres (13.61 miles) away from burglary 14

Time:
There were approximately 151 days separating burglary 13 and burglary 14

Target Characteristics:
The target was a semi-detached house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry through a rear wooden door by removing one of the panes of glass using an unknown instrument. The door was then opened using the key that was hanging on the inside of the door

Behaviour inside the Property:
The burglar conducted an untidy search upstairs and downstairs
The burglar was seen leaving in a silver vehicle

Property Stolen:
Other audio-visual equipment
Television
Jumper (clothing)
Laptop computer
Other computer equipment (not components)
Other garden equipment
Holdall bag
Watch
Keys
Camera
Mobile telephone

Residential Burglary 14

Distance:
Burglary 14 occurred 21.90 kilometres (13.61 miles) away from burglary 13

Time:
There were approximately 151 days separating burglary 13 and burglary 14

Target Characteristics:
The target was a semi-detached house
The house was occupied at the time of the burglary

Entry Behaviours:
The burglar gained entry by forcing the rear patio doors using unknown means
The shed had also been entered using unknown means that caused damage to the lock

Behaviour inside the Property:
The burglar conducted an untidy search of the downstairs of the property
The stolen items had been put in the victim's car and an attempt to steal the car was made

Property Stolen:
CD player (not a car stereo)
DVD player
Satellite box
Leather jacket
Computer games console
Games for the computer console
Laptop computer
Printer
Other documents (not identification or loyalty cards)
Payment card (debit/credit card)
Handbag
Purse
Keys

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 7

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 8

Residential Burglary 15

Distance:
Burglary 15 occurred 6.53 kilometres (4.06 miles) away from burglary 16

Time:
There were approximately 331 days separating burglary 15 and burglary 16

Target Characteristics:
The target was a bungalow
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry by smashing the kitchen window using an unknown instrument

Behaviour inside the Property:
The burglar conducted an untidy search of the property

Property Stolen:
Computer games console
Games for the computer console
Food/drink products (not alcohol)
Other consumables (not food/drink)
Purse
Rucksack bag
Watch
Back door key

Residential Burglary 16

Distance:
Burglary 16 occurred 6.53 kilometres (4.06 miles) away from burglary 15

Time:
There were approximately 331 days separating burglary 15 and burglary 16

Target Characteristics:
The target was a terraced house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry by throwing a brick through the front door window

Behaviour inside the Property:
The burglar conducted an untidy search of the property

Property Stolen:
Other audio-visual equipment
Television
Digital photo frame
Other furniture and carpets (not antique)
Clock
Glassware
Other miscellaneous household items

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 8

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 9

Residential Burglary 17

Distance:
Burglary 17 occurred 0.65 kilometres (0.40 miles) away from burglary 18

Time:
There were approximately 9 days separating burglary 17 and burglary 18

Target Characteristics:
The target was an end terrace house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry by forcing a rear door, using a brick to smash the plastic and pop open the door

Behaviour inside the Property:
The burglar conducted an untidy search of the property, mainly through the lounge and kitchen and then throughout the rest of the property

Property Stolen:
Alcohol
Computer games console
Payment card (debit/credit card)
Holdall bag
Wallet
Keys

Residential Burglary 18

Distance:
Burglary 18 occurred 0.65 kilometres (0.40 miles) away from burglary 17

Time:
There were approximately 9 days separating burglary 17 and burglary 18

Target Characteristics:
The target was an end terrace house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry through an insecure small rear kitchen window.
The burglar leaned through to open a larger rear kitchen window

Behaviour inside the Property:
The burglar conducted an untidy search of the property

Property Stolen:
Computer games console
Games for the computer console
Bracelet
Earrings
Pendant/locket
A ring
Camera
Mobile telephone

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 9

1) Do you think these two crimes were...

[ ] Committed by the same person

[ ] Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 10

Residential Burglary 19

Distance:
Burglary 19 occurred 13.11 kilometres (8.15 miles) away from burglary 20

Time:
There were approximately 5 days separating burglary 19 and burglary 20

Target Characteristics:
The target was a detached house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry by opening the letterbox to reach in and get the door keys off nearby coat hooks

Behaviour inside the Property:
The burglar conducted an untidy search of the upstairs rooms and a tidy search of the downstairs rooms
The burglar put the door key back on the hook as s/he left

Property Stolen:
MP3 player/iPod
Cash box/tin
Computer games console
Laptop computer
A personal organiser (e.g. a Blackberry)
Bank statements/Paying-in book
Birth certificate
Other documents (not identification or loyalty cards)
Vehicle registration documents (log book)
Holdall bag
Laptop bag
Suitcase
Jewellery box

Residential Burglary 20

Distance:
Burglary 20 occurred 13.11 kilometres (8.15 miles) away from burglary 19

Time:
There were approximately 5 days separating burglary 19 and burglary 20

Target Characteristics:
The target was a detached house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry to the back garden by forcing the rear side gate, causing damage to one of the wooden panels. The burglar then removed the whole patio door from its frame using an unknown instrument

Behaviour inside the Property:
The burglar conducted an untidy search of all the rooms

Property Stolen:
Laptop computer
Other computer equipment (not components)
Other weapon
Jewellery box
Other jewellery
Watch
Satellite Navigation System (Sat Nav)

Property Stolen (Continued):
Other jewellery
Keys
Home telephone
Mobile telephone

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 10

1) Do you think these two crimes were...

[ ] Committed by the same person

[ ] Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 11

Residential Burglary 21

Distance:
Burglary 21 occurred 47.29 kilometres (29.39 miles) away from burglary 22

Time:
There were approximately 104 days separating burglary 21 and burglary 22

Target Characteristics:
The target was a detached house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry by forcing the kitchen window with an unknown instrument

Behaviour inside the Property:
The burglar conducted a tidy search downstairs, but subjected the main bedroom upstairs to an untidy search

Property Stolen:
MP3 player/iPod
Television
Cash
Garden fencing
Keys
Household ornaments
A camcorder (hand-held video camera)
Satellite Navigation System (Sat Nav)

Residential Burglary 22

Distance:
Burglary 22 occurred 47.29 kilometres (29.39 miles) away from burglary 21

Time:
There were approximately 104 days separating burglary 21 and burglary 22

Target Characteristics:
The target was a detached house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry by forcing a side double-glazed door using an unknown instrument

Behaviour inside the Property:
The burglar conducted an untidy search of the property

Property Stolen:
MP3 player/iPod
Speaker/Headphones/Earphones
Laptop computer
Other computer equipment (not components)
Bracelet

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 11

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 12

Residential Burglary 23

Distance:
Burglary 23 occurred 20.15 kilometres (12.52 miles) away from burglary 24

Time:
There were approximately 668 days separating burglary 23 and burglary 24

Target Characteristics:
The target was an end terrace house
The house was occupied at the time of the burglary

Entry Behaviours:
The burglar gained entry by smashing the ground floor kitchen window using a brick. The burglar then opened the window and climbed through

Behaviour inside the Property:
The victim hears the window smash and comes downstairs, disturbing the burglar who leaves by unlocking the front door from the inside
Cannot tell whether a tidy/untidy search was conducted

Property Stolen:
Nothing reported stolen

Residential Burglary 24

Distance:
Burglary 24 occurred 20.15 kilometres (12.52 miles) away from burglary 23

Time:
There were approximately 668 days separating burglary 23 and burglary 24

Target Characteristics:
The target was an end terrace house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry by forcing a ground floor rear door by removing the handle and disabling the lock mechanism using an unknown instrument. The lock was pushed through and entry gained

Behaviour inside the Property:
The burglar conducted a tidy search of the property

Property Stolen:
Computer games console

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 12

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 13

Residential Burglary 25

Distance:
Burglary 25 occurred 6.96 kilometres (4.32 miles) away from burglary 26

Time:
There were approximately 109 days separating burglary 25 and burglary 26

Target Characteristics:
The target was a detached house
The house was occupied at the time of the burglary

Entry Behaviours:
The burglar gained entry to the garage using unknown means, then entered the property via an internal door

Behaviour inside the Property:
The burglar conducted a tidy search of the property
The victim is awoken by sounds on the driveway, he looks out to see his car reversing down the driveway, with the burglar giving him an obscene sign. The burglar drives off in a calm manner. A police car pursuit ensues, with the burglar driving dangerously. The burglar abandons the car and is pursued by dogs

Property Stolen:
Other clothing and linen
Payment card (debit/credit card)
Car keys
Other medical equipment
Mobile telephone
Vehicle (recovered later)

Residential Burglary 26

Distance:
Burglary 26 occurred 6.96 kilometres (4.32 miles) away from burglary 25

Time:
There were approximately 109 days separating burglary 25 and burglary 26

Target Characteristics:
The target was a detached house
The house was occupied at the time of the burglary

Entry Behaviours:
The burglar knocked on the victim’s door claiming to be collecting for a cancer charity. Having gained entry the burglar asks to use the bathroom. This is a distraction burglary

Behaviour inside the Property:
Cash was taken from the victim’s wallet, which was on the table, as the burglar came back from the toilet.

Property Stolen:
Cash

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 13

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 14

Residential Burglary 27

Distance:
Burglary 27 occurred 20.43 kilometres (12.69 miles) away from burglary 28

Time:
There were approximately 152 days separating burglary 27 and burglary 28

Target Characteristics:
The target was a semi-detached house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry through a kitchen window using unknown means

Behaviour inside the Property:
The burglar conducted a tidy search on the ground floor. The upstairs was not searched
The burglar wrote on the walls of the property

Property Stolen:
MP3 player/iPod
Laptop computer
Other documents (not identification or loyalty cards)
Passport
Handbag
Other medical equipment
Camera
Mobile telephone
Telephone box
Satellite Navigation System (Sat Nav)

Residential Burglary 28

Distance:
Burglary 28 occurred 20.43 kilometres (12.69 miles) away from burglary 27

Time:
There were approximately 152 days separating burglary 27 and burglary 28

Target Characteristics:
The target was an end terrace house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry to the rear secure garden by climbing the gate, then an unknown instrument used to smash a window. The burglar then reached in to open the window and climbed through

Behaviour inside the Property:
The burglar conducted a tidy search of all floors of the property

Property Stolen:
MP3 player/iPod
Laptop computer
Payment card (debit/credit card)
A ring
A camcorder (hand-held video camera)

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 14

1) Do you think these two crimes were...

[ ] Committed by the same person

[ ] Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0 1 2 3 4 5 6 7 8 9 10
Not at all likely — Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0 1 2 3 4 5 6 7 8 9 10
Not at all — Very much

4) To what extent did you base your decision on the distance information?

0 1 2 3 4 5 6 7 8 9 10
Not at all — Very much

5) To what extent did you base your decision on the time information?

0 1 2 3 4 5 6 7 8 9 10
Not at all — Very much

6) To what extent did you base your decision on the target information?

0 1 2 3 4 5 6 7 8 9 10
Not at all — Very much

7) To what extent did you base your decision on the entry information?

0 1 2 3 4 5 6 7 8 9 10
Not at all — Very much

8) To what extent did you base your decision on the behaviour inside the property?

0 1 2 3 4 5 6 7 8 9 10
Not at all — Very much

9) To what extent did you base your decision on the property stolen?

0 1 2 3 4 5 6 7 8 9 10
Not at all — Very much

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 15

Residential Burglary 29

Distance:
Burglary 29 occurred 9.41 kilometres (5.85 miles) away from burglary 30

Time:
There were approximately 404 days separating burglary 29 and burglary 30

Target Characteristics:
The target was a semi-detached house
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry by breaking the lock on the door using unknown means

Behaviour inside the Property:
The burglar conducted an untidy search of the property

Property Stolen:
Computer games console
Games for the computer console
Laptop computer
Camera

Residential Burglary 30

Distance:
Burglary 30 occurred 9.41 kilometres (5.85 miles) away from burglary 29

Time:
There were approximately 404 days separating burglary 29 and burglary 30

Target Characteristics:
The target was a bungalow
It is unknown whether the owners were at home when the house was burgled

Entry Behaviours:
The burglar gained entry to the rear garden through an insecure gate and attempts to jemmy open a rear ground floor wooden door, but fails. The burglar then smashes the glass panel in the door and gains entry to the property

Behaviour inside the Property:
The burglar conducted an untidy search of the property

Property Stolen:
Other antiques
Other jewellery

RESIDENTIAL BURGLARY OFFENCE PAIR NUMBER 15

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on the entry information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the behaviour inside the property?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

If you have any comments about this study, please provide them in the space below.

....

....

....

....

....

....

....

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....

....

....

....

If you would be interested in taking part in another similar study, please provide your contact details here (e.g. an e-mail address):

....

We understand that becoming a victim of crime and reading about crimes can be distressing. So, if you feel distressed by any of the issues raised in this questionnaire, please contact the:

Victim Supportline on 0845 3030 900 or via e-mail at supportline@victimsupport.org.uk

Or visit their website at http://www.victimsupport.org.uk/

Many thanks for taking part

Appendix 5: Exemplar Commercial Robbery Questionnaire with Training Information from Chapter 5

Please note that the map presented in the appendix was reduced slightly in size to fit the margins required for this thesis.

DEMOGRAPHIC QUESTIONS

1) **What is your age (in years)?**

....

2) **What is your gender?**

[ ] Male   [ ] Female

3) **In which country do you work/study?**

....

4) **What is your job title?**

....

....

5) **How many years' experience do you have in crime analysis, linkage analysis, and police work?**

If you do not have experience in any of these three areas, please write "N/A" on each line

iv) Crime analysis

.... years

PLEASE TURN OVER

v) Linkage analysis

Linkage analysis is when someone uses information about when, where and how crimes were committed to judge whether they have been committed by the same or by different people. Linkage analysis is also referred to as comparative case analysis and behavioural case linkage.

.... years

vi) Police work

.... years

6) If you have linkage analysis experience, please indicate, on average, how regularly you are involved in this activity by placing an X in the appropriate box.

[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Daily	Weekly	Monthly	Yearly	Less than yearly	Not applicable

7) If you have any experience in crime analysis, linkage analysis, or police work, please indicate the types of offence for which you have regular experience ('Regular experience' means that you deal with that particular type of offence at least once a month).

If you do not have any relevant experience, please write "N/A".

....

....

....

....

INSTRUCTIONS

You will be presented with a number of offence pairs. Each offence pair contains two offences that were committed in the United Kingdom, and for each offence a range of information is listed. Your task is to decide whether the two offences in each pair have been committed by the same person or whether they have been committed by different people.

You do not have to use all of the offence information listed when making your decision. You can use as much or as little as you like.

You should also indicate how confident you are that the same offender committed the two offences in each pair, and to what extent you relied on the different types of information presented to you.

If you feel you are at all familiar with any of the crimes presented below, then you should indicate which crimes and which offence pairs you are familiar with in the space provided at the end of the questionnaire.

PLEASE TURN OVER

IMPORTANT INFORMATION TO HELP WITH THE COMMERCIAL ROBBERY TASK

Fifteen commercial robbery pairs are presented below. Each robbery is plotted on the map below.

Commercial robbery is when a person or persons have taken property belonging to a business or commercial entity without their consent using force or the threat of force. This includes failed attempts to take property.

For three of these pairs they contain two crimes that were committed by the same person. The remaining 12 pairs contain two crimes that were committed by different people.

When deciding whether two offences have been committed by the same offender, previous research has indicated that **some types of offence information are more useful than others**.

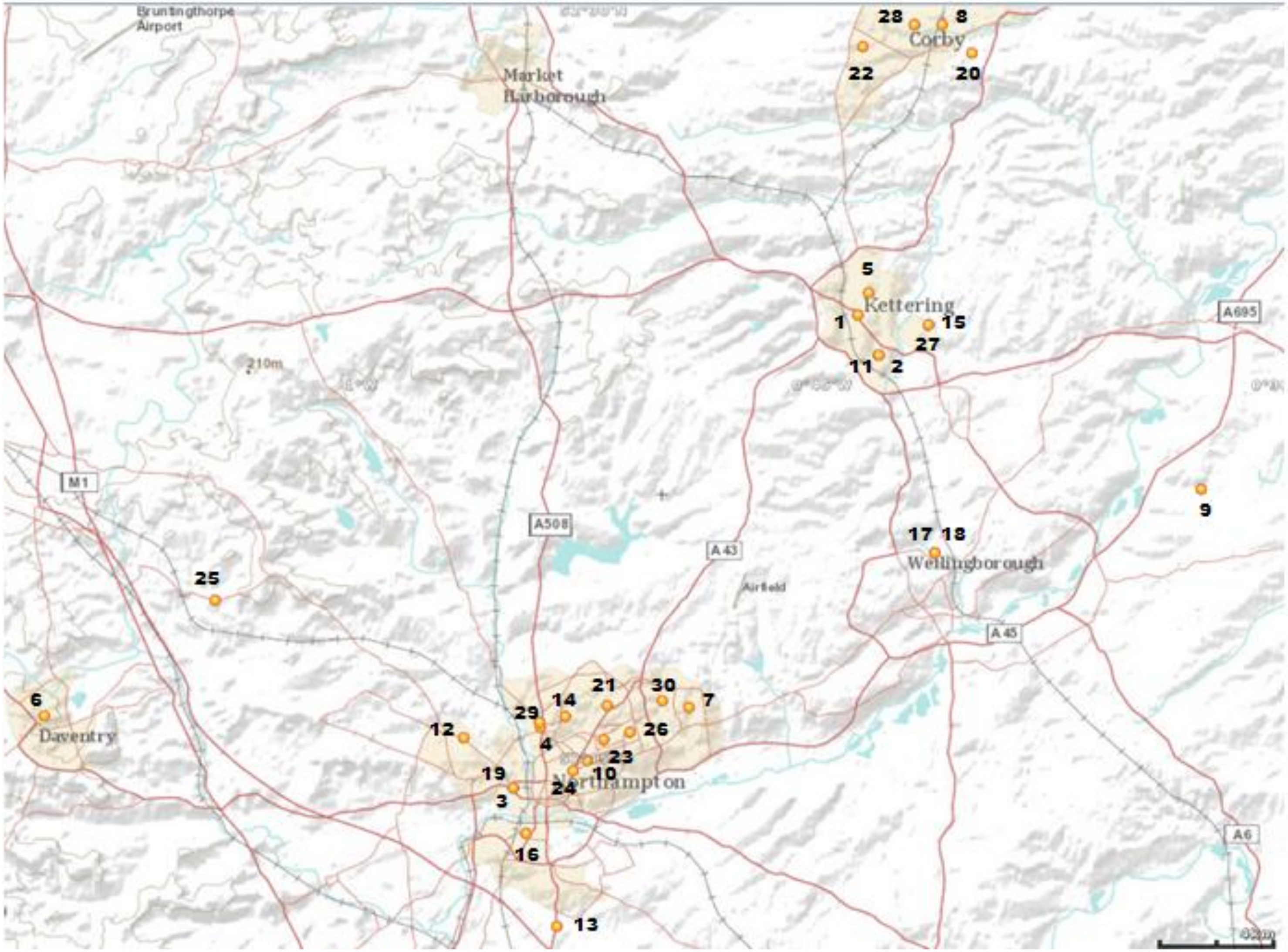
This research has suggested that three types of information are the most useful. First, **offences committed by the same offender can be successfully identified using the kilometre distance between them**. That is, the closer two offences are to one another geographically, the more likely it is that the same offender committed them.

Second, **offences committed by the same offender can be successfully identified by looking for similarities in the way an offender controls the victim/s, such as what weapon was used and whether the victim/s were subjected to violence during the offences.**

Third, **offences committed by the same offender can be successfully identified by looking for evidence that the offender has planned the offence, such as wearing a disguise and gloves, stealing CCTV (closed-circuit television) footage, and bringing a bag or a vehicle to carry the stolen goods away in.**

But, the type of property stolen during the robbery and what type of business was targeted are less useful when identifying crimes that have been committed by the same person.

A MAP DEPICTING THE COMMERCIAL ROBBERY LOCATIONS



COMMERCIAL ROBBERY OFFENCE PAIRS

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 1

Commercial Robbery 1	**Commercial Robbery 2**
Distance: Robbery 1 occurred 1.68 kilometres (1.04 miles) away from robbery 2	Distance: Robbery 2 occurred 1.68 kilometres (1.04 miles) away from robbery 1
Time: There were approximately 144 days separating robbery 1 and robbery 2	Time: There were approximately 144 days separating robbery 1 and robbery 2
Target Characteristics: The target of the robbery was a licensed premises The robbery occurred at approximately 10:00AM on a Thursday.	Target Characteristics: The target of the robbery was a shop The robbery occurred at approximately 18:00 on a Sunday
Planning: There is no evidence that the offenders covered their faces The offenders pretended to be the police and had brought what appeared to be a warrant card The CCTV hard drive was removed	Planning: One offender, possibly both, were wearing balaclavas The offenders ran out of the shop
Control Behaviours: Four offenders took part in the robbery All staff were taken to the manager’s office where they were restrained with cable ties Physical force was used on the manager to obtain the code for the safe, which caused swelling and bruising to the face All telephone cables were removed from the walls and mobile phones taken from staff	Control Behaviours: Two offenders took part in the robbery One offender holds a knife to the victim’s throat and says “Give us the money” They instruct the victim to open both tills in the shop
Property Stolen: Cash was stolen from the safe Mobile telephones	Property Stolen: Cash was stolen from both tills

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 1

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 2

Commercial Robbery 3

Distance:
Robbery 3 occurred 2.44 kilometres (1.51 miles) away from robbery 4

Time:
There were approximately 9 days separating robbery 3 and robbery 4

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 17:00 on a Wednesday

Planning:
There is no evidence that the offender covered their face

Control Behaviours:
A lone offender committed the robbery
The offender approached the till and said "Hand over all the money in the till" and threatened to harm the shop assistant if they rang the security bell while holding a kitchen knife close to the victim's body

Property Stolen:
Cash was stolen from the till
Jacket/Coat
Trousers/Jeans

Commercial Robbery 4

Distance:
Robbery 4 occurred 2.44 kilometres (1.51 miles) away from robbery 3

Time:
There were approximately 9 days separating robbery 3 and robbery 4

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 18:00 on a Friday

Planning:
The offender entered with a covered face
The offender left on foot

Control Behaviours:
A lone offender committed the robbery
The offender approached the cashier and demanded money by holding a large bladed knife to the cashier's throat and saying "Open the fucking till"
The offender warned the victim "Don't press no fucking buttons"
Another employee then entered and the offender chased this employee outside
Slight injuries were caused to the cashier

Property Stolen:
No items were stolen

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 2

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 3

Commercial Robbery 5

Distance:
Robbery 5 occurred 34.39 kilometres (21.37 miles) away from robbery 6

Time:
There were approximately 220 days separating robbery 5 and robbery 6

Target Characteristics:
The target of the robbery was a pizza delivery van
The robbery occurred at approximately 19:00 on a Monday

Planning:
There is no evidence that the offenders covered their faces
The offenders left the area on foot

Control Behaviours:
Four offenders took part in the robbery
The victim was approached by the offenders, threatened with violence and pushed against a wall
The offenders stated "Give us your pizzas we won't take your money"
The offenders then went in to the pizza shop and tried to exchange the pizzas but were refused service

Property Stolen:
Pizzas were stolen from the pizza delivery man
Hat
Sportswear
Training shoes

Commercial Robbery 6

Distance:
Robbery 6 occurred 34.39 kilometres (21.37 miles) away from robbery 5

Time:
There were approximately 220 days separating robbery 5 and robbery 6

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 07:00AM on a Friday

Planning:
There is no evidence that the offenders covered their faces

Control Behaviours:
An unknown number of offenders took part in the robbery
The offenders threatened staff that they would be stabbed if they did not comply with the offenders' wishes (no knife and was seen)
Staff were then ushered in to a rear store room where a member of staff was instructed to open the safe and hand over the cash

Property Stolen:
Cash was stolen from the safe
Clothing
Stamps

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 3

1) Do you think these two crimes were...

[ ] Committed by the same person

[ ] Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 4

Commercial Robbery 7

Distance:
Robbery 7 occurred 27.19 kilometres (16.90 miles) away from robbery 8

Time:
There were approximately 370 days separating robbery 7 and robbery 8

Target Characteristics:
The target of the robbery was a delivery van driver for a takeaway restaurant
The robbery occurred at approximately 02:00AM on a Saturday

Planning:
There is no evidence that the offender covered his face

Control Behaviours:
The robbery was committed by a lone offender
When the takeaway was delivered the offender pulled out a large kitchen knife from his right pocket and placed it to the victim's throat saying "Give me the stuff". The delivery man gave the offender the delivery and was told to get in the van and leave

Property Stolen:
Alcohol
Cigarettes

Commercial Robbery 8

Distance:
Robbery 8 occurred 27.19 kilometres (16.90 miles) away from robbery 7

Time:
There were approximately 370 days separating robbery 7 and robbery 8

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 21:00 on a Saturday

Planning:
There is no evidence that the offender covered his face

Control Behaviours:
The robbery was committed by a lone offender
The offender approached the checkout with various items and produced a knife from his right pocket, holding it up and moving it from left to right in front of the checkout assistant
The assistant asked the offender to put the knife away, which he did.
Security were called and when they arrived the offender left the scene without paying.
When the offender was asked to return the items he replied "Fuck off. I have a knife and I will fucking stab you"
The security guard followed the offender outside the shop, at which point the offender produced the knife from his right pocket holding it up and holding it up and shouting "Fuck off"

Property Stolen:
Confectionary

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 4

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 5

Commercial Robbery 9

Distance:
Robbery 9 occurred 24.85 kilometres (15.44 miles) away from robbery 10

Time:
There were approximately 411 days separating robbery 9 and robbery 10

Target Characteristics:
The target of the robbery was an office
The robbery occurred at approximately 13:00 on a Thursday

Planning:
There is no evidence that the offender covered their face
The offender ran off on foot

Control Behaviours:
The robbery was committed by a lone offender
The offender threatened the single staff member with two kitchen knives
When leaving the scene, the offender said "Follow me and I will stab you"

Property Stolen:
Cash
Cash till drawer

Commercial Robbery 10

Distance:
Robbery 10 occurred 24.85 kilometres (15.44 miles) away from robbery 9

Time:
There were approximately 411 days separating robbery 9 and robbery 10

Target Characteristics:
The target of the robbery was a taxi driver
The robbery occurred at approximately 22:00 on a Tuesday

Planning:
There is no evidence that the offenders covered their faces

Control Behaviours:
The robbery was committed by three offenders
The offenders booked a taxi. When they arrived at their destination they produced an eight-inch serrated knife. They held it against the driver's throat saying "Give us all your money".
The driver grabbed the blade causing cuts to his hand that were treated in hospital

Property Stolen:
No items were stolen

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 5

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 6

Commercial Robbery 11	Commercial Robbery 12
Distance: Robbery 11 occurred 20.97 kilometres (13.03 miles) away from robbery 12	Distance: Robbery 12 occurred 20.97 kilometres (13.03 miles) away from robbery 11
Time: There were approximately 288 days separating robbery 11 and robbery 12	Time: There were approximately 288 days separating robbery 11 and robbery 12
Target Characteristics: The target of the robbery was a shop The robbery occurred at approximately 12:00 on a Sunday afternoon	Target Characteristics: The target of the robbery was a shop The robbery occurred at approximately 15:00 on a Monday
Planning: The offenders entered wearing facial disguises The offenders fled on foot	Planning: There is no evidence that the offenders covered their faces The offenders waited for the manager to come out of a shop near to his place of work, then forced him to drive back to work where the robbery occurred The offenders were driven away from the crime scene in a white van
Control Behaviours: The robbery was committed by two offenders One offender carrying a gun demanded that the victim open the till and hand over money The victim refused and a struggle took place with the victim trying to stop the offenders getting in to the till. During the struggle the victim's mobile phone was taken The offenders then started throwing goods at the victim before they were disturbed by customers entering the shop	Control Behaviours: The robbery was committed by two offenders who both claimed to have guns (only one gun was seen) The offenders entered the victim's vehicle and instructed him to drive to his place of work When they arrived one of the offenders threatened the security guard with the firearm The victim was forced to let the offenders in to his place of work and one offender said "Where is the money? Where is the safe?" Due to the shop security systems the manager was unable to open the safe
Property Stolen: Mobile telephone	Property Stolen: The manager's mobile telephone was stolen when he could not open the safe

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 6

1) Do you think these two crimes were...

[ ] Committed by the same person

[ ] Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 7

Commercial Robbery 13

Distance:
Robbery 13 occurred 7.85 kilometres (4.88 miles) away from robbery 14

Time:
There were approximately 78 days separating robbery 13 and robbery 14

Target Characteristics:
The target of the robbery was a petrol station/garage
The robbery occurred at approximately 03:00 on a Wednesday

Planning:
There is no evidence that the offenders covered their faces

Control Behaviours:
Three offenders took part in the robbery
Upon entry to the property the offenders assaulted the sole member of staff by punches to the head and face resulting in swelling to the top of the head, bruising to the face and a slight loss of consciousness
The offenders were disturbed by a second member of staff

Property Stolen:
Cash was stolen from the till

Commercial Robbery 14

Distance:
Robbery 14 occurred 7.85 kilometres (4.88 miles) away from robbery 13

Time:
There were approximately 78 days separating robbery 13 and robbery 14

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 22:00 on a Monday

Planning:
There is no evidence that the offenders covered their faces
The offenders ran off on foot

Control Behaviours:
Two offenders took part in the robbery
The victim was preparing to close the store when the offenders entered and refused to let him leave
One of the offenders kicked the victim shouting "Give me vodka". The victim gave the offenders the goods because he feared further violence
The kick caused reddening to the upper thigh but no medical assistance was requested

Property Stolen:
Alcohol

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 7

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 8

Commercial Robbery 15

Distance:
Robbery 15 occurred 24.12 kilometres (14.98 miles) away from robbery 16

Time:
There were approximately 376 days separating robbery 15 and robbery 16

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 21:00 on a Saturday

Planning:
The offender wore a piece of cloth over his face
The offender left the scene in a red Vauxhall Corsa

Control Behaviours:
The robbery was committed by a lone offender
The offender entered the shop with a double-barrelled firearm
The offender threatened staff to open the till and shouted “Get down on the floor”
The offender was challenged by a member of staff
The offender then left and returned almost immediately with a baton
At some point during the offence a minor injury was inflicted to the head of an employee using the butt of the gun, which caused a small bump

Property Stolen:
Footwear
Shirt
Sportswear
Trousers/Jeans

Commercial Robbery 16

Distance:
Robbery 16 occurred 24.12 kilometres (14.98 miles) away from robbery 15

Time:
There were approximately 376 days separating robbery 15 and robbery 16

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 06:00 on a Friday

Planning:
There is no evidence that the offenders covered their faces

Control Behaviours:
Four offenders took part in the robbery
One offender was carrying a hammer and demanded that the cashier leave the till and go into the stock area. The same demand was made of the cleaner
Two offenders remained with the cashier, cleaner and baker in the stock room while the manager was forced to unlock the cash office and give the offenders the keys to the safe
At the end of the offence all four members of staff were locked in the cash office

Property Stolen:
Cash was stolen from the safe

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 8

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 9

Commercial Robbery 17

Distance:
Robbery 17 and robbery 18 occurred in the same place

Time:
There were approximately 8 days separating robbery 17 and robbery 18

Target Characteristics:
The target of the robbery was an office
The robbery occurred at approximately 10:00 on a Saturday

Planning:
There is no evidence that the offenders covered their faces

Control Behaviours:
Five offenders took part in the robbery, one of which was armed with a golf club
As the offenders were leaving a member of staff challenged them and was assaulted

Property Stolen:
Food/drink products (not alcohol)

Commercial Robbery 18

Distance:
Robbery 17 and robbery 18 occurred in the same place

Time:
There were approximately 8 days separating robbery 17 and robbery 18

Target Characteristics:
The target of the robbery was an office
The robbery occurred at approximately 22:00 on a Sunday

Planning:
There is no evidence that the offenders covered their faces

Control Behaviours:
Six offenders took part in the robbery
Three offenders were armed with golf clubs
One of the victims was threatened with a golf club. The offenders then smashed his car up, causing glass shards from the car to become lodged in the victim’s face (cuts and bleeding)
The offenders then assaulted a second victim with a punch to the face causing no injury
A third victim was hit on the head with a brick causing two large gashes
No speech was used by the offenders throughout the offence

Property Stolen:
Items were stolen but their exact nature was not specified

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 9

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 10

Commercial Robbery 19

Distance:
Robbery 19 occurred 32.15 kilometres (19.97 miles) away from robbery 20

Time:
There were approximately 390 days separating robbery 19 and robbery 20

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 14:00 on a Sunday

Planning:
There is no evidence that the offenders covered their faces
The offenders approached the shop on foot and left the scene on foot

Control Behaviours:
An unknown number of offenders took part in the robbery
One of the offenders approached the cashier and pushed her out of the way to gain access to the till

Property Stolen:
Cash was stolen from the till

Commercial Robbery 20

Distance:
Robbery 20 occurred 32.15 kilometres (19.97 miles) away from robbery 19

Time:
There were approximately 390 days separating robbery 19 and robbery 20

Target Characteristics:
The target of the robbery was a petrol station/garage
The robbery occurred at approximately 23:00 on a Tuesday

Planning:
There is no evidence that the offenders covered their faces
Both offenders wore latex gloves
The offenders stole the CCTV and used a curtain they had brought along with them to carry the stolen goods out of the garage
The offenders left the scene in a black Vauxhall Vectra

Control Behaviours:
Two offenders took part in the robbery
One offender used his forearm to pin a staff member behind the counter causing soreness to the throat but no visible injuries
The offenders said "Where's the money? Where's the till? Open the till. Where's the safe? Don't worry it's not your money, we don't care we're heroin addicts. Come on we've got to go they're on their way"

Property Stolen:
Cash
Cigarettes

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 10

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 11

Commercial Robbery 21	Commercial Robbery 22
Distance: Robbery 21 occurred 26.35 kilometres (16.37 miles) away from robbery 22	Distance: Robbery 22 occurred 26.35 kilometres (16.37 miles) away from robbery 21
Time: There were approximately 349 days separating robbery 21 and robbery 22	Time: There were approximately 349 days separating robbery 21 and robbery 22
Target Characteristics: The target of the robbery was a shop The robbery occurred at approximately 11:00 on a Friday	Target Characteristics: The target of the robbery was a shop The robbery occurred at approximately 17:00 on a Thursday
Planning: There is no evidence that the offenders covered their faces The offenders carried the stolen goods away in plastic tubs they had brought to the scene They left the scene in a vehicle	Planning: The offender had their face fully covered The offender left the scene on a mountain bike
Control Behaviours: Four offenders took part in the robbery Three offenders jumped behind the counter and one offender stated “I will not hurt you” The fourth offender stood at the exit/entry to the store	Control Behaviours: The robbery was committed by a lone offender who entered the store holding a knife in his right hand The offender shouted at the two shop assistants saying “Open the till”. The assistants refused. The offender then hit the till and it opened
Property Stolen: Cigarettes Gift vouchers/Gift cards	Property Stolen: Cash was stolen from the till

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 11

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 12

Commercial Robbery 23	**Commercial Robbery 24**
Distance: Robbery 23 occurred 1.67 kilometres (1.04 miles) away from robbery 24	Distance: Robbery 24 occurred 1.67 kilometres (1.04 miles) away from robbery 23
Time: There were approximately 10 days separating robbery 23 and robbery 24	Time: There were approximately 10 days separating robbery 23 and robbery 24
Target Characteristics: The target of the robbery was a shop The robbery occurred at approximately 18:00 on a Thursday	Target Characteristics: The target of the robbery was a shop The robbery occurred at approximately 00:00 (midnight) on a Monday
Planning: One offender wore a balaclava. There is no evidence that the other two offenders had covered their faces The offenders had brought a sports bag with them to carry the stolen goods The offenders ran off from the scene	Planning: There is no evidence that the offender covered their face The offender approached the scene on a bicycle
Control Behaviours: Three offenders took part in the robbery The offender wearing the balaclava walked up to the counter and waved a gun in the shopkeeper's face, demanding that she put money into a sports bag The offenders are then challenged by the a member of the public who stated that the gun was not real and dared them to fire it The offenders did not discharge the weapon	Control Behaviours: The robbery was committed by a lone offender The offender walked up to the counter with goods and when asked for payment produced a handgun that was pointed at the victim A struggle between the offender and the victim occurred where punches were exchanged. The offender hit the victim twice in the face with the gun
Property Stolen: No items were stolen	Property Stolen: No items were stolen

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 12

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 13

Commercial Robbery 25

Distance:
Robbery 25 occurred 16.14 kilometres (10.03 miles) away from robbery 26

Time:
There were approximately 6 days separating robbery 25 and robbery 26

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 23:00 on a Thursday

Planning:
There is no evidence that the offenders covered their faces
All of the offenders were dressed in black

Control Behaviours:
Five offenders took part in the robbery
The three staff members were ushered in to warehouse and office
The offenders forced one member of staff to open the safe
Throughout the offence staff were warned to “Shut your mouths” or else they would “Get hit”

Property Stolen:
Gift vouchers/Gift cards stolen from the Safe
Stamps stolen from the safe

Commercial Robbery 26

Distance:
Robbery 26 occurred 16.14 kilometres (10.03 miles) away from robbery 25

Time:
There were approximately 6 days separating robbery 25 and robbery 26

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 20:00 on a Wednesday

Planning:
There is no evidence that the offenders covered their faces
The offenders used a bag they had brought to the scene to carry the stolen goods

Control Behaviours:
Three offenders took part in the robbery
The offenders entered the store, a rear grabbing three members of staff and pushing them in to the rear warehouse of the shop
One of the offenders had a hammer and used threatening actions and behaviour, saying “Where’s the money? Where’s the keys?”
One offender entered the safe while the other offenders tied the staff’s hands behind their backs using cable ties

Property Stolen:
MP3 player/iPod
Cash
Driving licence
Non-payment card/loyalty card
Payment card (credit/debit card)
Purse

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 13

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 14

Commercial Robbery 27

Distance:
Robbery 27 occurred 11.24 kilometres (6.99 miles) away from robbery 28

Time:
There were approximately 109 days separating robbery 27 and robbery 28

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 16:00 on a Saturday

Planning:
There is no evidence that the offender covered their face
The offender wore gloves
The offender ran off on foot

Control Behaviours:
The robbery was committed by a lone offender
The offender took goods to the checkout and when the assistant opened the till the offender leant across, grabbing the assistant’s arm and pushing her back.

Property Stolen:
Cash was stolen from the till

Commercial Robbery 28

Distance:
Robbery 28 occurred 11.24 kilometres (6.99 miles) away from robbery 27

Time:
There were approximately 109 days separating robbery 27 and robbery 28

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 21:00 on a Tuesday

Planning:
There is no evidence that the offender covered their face

Control Behaviours:
The robbery was committed by a lone offender
The offender entered the store threatening staff with a hammer

Property Stolen:
Alcohol
Jacket/Coat
Trousers/Jeans

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 14

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 15

Commercial Robbery 29

Distance:
Robbery 29 occurred 4.59 kilometres (2.85 miles) away from robbery 30

Time:
There were approximately 280 days separating robbery 29 and robbery 30

Target Characteristics:
The target of the robbery was a bank
The robbery occurred at approximately 17:00 on a Wednesday

Planning:
There is no evidence that the offender covered their face

Control Behaviours:
The robbery was committed by a lone offender
The offender walked up to a customer who was being served at the cashier's counter and grabbed the customer in a cuddle-type fashion
Using his right hand he produced a black pistol and said to the cashier "Gimme all that money now"
The offender then walked off and as he left said "Stand still, don't move". While doing this he held the gun and moved it around in a sweeping fashion towards staff
then raised the gun above his head and fired

Property Stolen:
Cash
Photographs/Prints/Posters

Commercial Robbery 30

Distance:
Robbery 30 occurred 4.59 kilometres (2.85 miles) away from robbery 29

Time:
There were approximately 280 days separating robbery 29 and robbery 30

Target Characteristics:
The target of the robbery was a shop
The robbery occurred at approximately 18:00 on a Wednesday

Planning:
There is no evidence that the offender covered their face

Control Behaviours:
The robbery was committed by a lone offender
The offender picked up goods and tried to leave the store without paying
The shopkeeper confronted the offender, which resulted in an altercation where the offender punched the shopkeeper several times
The shopkeeper returned to the store and the offender followed him and threatened him with a large piece of wood
The offender then attempted to steal He goods again. Another struggle occurred before a customer intervened

Property Stolen:
No items were stolen

COMMERCIAL ROBBERY OFFENCE PAIR NUMBER 15

1) Do you think these two crimes were...

[ ]	[ ]
Committed by the same person	Committed by different people

[PLEASE PLACE AN X IN THE APPROPRIATE BOX]

2) How likely is it that these two crimes were committed by the same person?

0	1	2	3	4	5	6	7	8	9	10
Not at all likely										Very likely

[PLEASE CIRCLE THE APPROPRIATE RESPONSE]

3) To what extent did you base your decision on the map information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

4) To what extent did you base your decision on the distance information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

5) To what extent did you base your decision on the time information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

6) To what extent did you base your decision on the target information?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

7) To what extent did you base your decision on planning behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

8) To what extent did you base your decision on the control behaviour?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

9) To what extent did you base your decision on the property stolen?

0	1	2	3	4	5	6	7	8	9	10
Not at all										Very much

If you have any comments about this study, please provide them in the space below.

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If you would be interested in taking part in another similar study, please provide your contact details here (e.g. an e-mail address):

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We understand that becoming a victim of crime and reading about crimes can be distressing. So, if you feel distressed by any of the issues raised in this questionnaire, please contact the:

Victim Supportline on 0845 3030 900 or via e-mail at **supportline@victimsupport.org.uk**

Or visit their website at http://www.victimsupport.org.uk/

Many thanks for taking part

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