

Advancement of Criminal Profiling Methods in Faceted Multidimensional Analysis

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Abstract

The current study seeks to advance the faceted multidimensional scaling (termed FMDS) procedure used in much of the investigative psychology research. To this end, recent research on street robbery by Goodwill and colleagues will be utilised to illustrate the effectiveness of a facet scale method for offender profiling. Four FMDS themes of street robbery (Con, Blitz, Confrontation and Snatch) were revealed by the crossing of two underlying axial facets: the offenders' level of violence and interaction with the victim. The facet scale method, utilising offenders' axial facet scores, was compared to previous count, proportional and centroid classification methods in the prediction of offender criminal histories. Utilising logistic regression and receiver operating characteristic analyses, the axial facet scale method was found to significantly outperform the qualitatively based dominant theme classification methods that typically employ angular and radial facets for FMDS interpretation. Implications for the use of axial facet scales within FMDS analysis for offender profiling research are discussed. Copyright © 2012 John Wiley & Sons, Ltd.

Key words: offender profiling; robbery; multidimensional scaling; facet theory; axial facets; duplex; previous convictions

INTRODUCTION

A multitude of papers have been published in the area of investigative psychology (IP) using multidimensional scaling (MDS) techniques for purposes ranging from *conceptual* thematic investigation (e.g. Canter, Bennell, Alison, & Reddy, 2003), to dominant theme *classification* (see Trojan & Salfati, 2008, for review), to the *prediction* of offender

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characteristics from crime scene information (e.g. Häkkänen, Lindlöf, & Santtila, 2004). For conceptual thematic investigation of crime scene information, most studies have used a facet theory (FT)-based approach in which the content domain under study (typically represented by an MDS plot) is partitioned into qualitatively different regions or themes on the basis of an *a priori* review of the expounding literature (Canter & Heritage, 1990). For the purpose of this paper, MDS analysis based on an FT approach will be referred to as faceted MDS, or FMDS. FMDS is common to IP and is often used successfully to conceptually map out new content domains, define areas of study, and investigate the interrelatedness of crime-related variables, items, or behaviours (Canter, 2000). However, although useful advancements have been made in criminal profiling on the basis of FMDS analysis for conceptual thematic purposes (e.g. Canter *et al.*, 2003), the success and pragmatic utility of FMDS for classification and prediction in criminal profiling has been less auspicious (see Snook, Eastwood, Gendreau, Goggin, & Cullen, 2007, for a review of the criminal profiling literature).

In fact, with a few notable exceptions (Canter & Fritzon, 1998; Häkkänen, Lindlöf *et al.*, 2004; Häkkänen, Puolakka, Pia, & Santtila, 2004; Salfati, 2000; Salfati & Canter, 1999; Salfati & Park, 2007), there is a paucity of research within the criminal profiling literature that illustrates a clear link between crime scene information analysed using FMDS¹ methods and offender characteristics. This is particularly concerning for a field in which one of the main tenets and purpose is to discover and utilise reliable and theoretically sound relationships between crime scene information and offender characteristics to profile or prioritise suspects within investigations (Alison, Goodwill, Almond, Van den Heuvel, & Winter, 2010). It is posited that this lack of success linking FMDS approaches to offender characteristics lies partially in the choice of methodology used to: (a) interpret MDS plots; (b) classify offenders using FMDS; and (c) predict offender characteristics. The current paper seeks to take a step towards improving the utility and success of FMDS approaches for dominant theme classification and prediction of offender characteristics, by introducing an axial facet method that utilises the latent scales of the content domain. In essence, it is argued that researchers conducting FMDS analysis for criminal profiling purposes should be utilising quantitatively based axial facets over qualitatively based angular facets, whenever possible.

Facet theory and multidimensional scaling (faceted multidimensional scaling)

The use of FT in IP was pioneered by Professor David Canter, who applied it to the analysis of crime scene information for criminal profiling research and application (Canter, 1985; Canter, Heritage, Wilson, Davies, Kirby, Holden, McGinley, Hughes, Larkin, Martin, Tsang, Vaughan, & Donald, 1991). FT was developed by the late Louis Guttman in an effort to develop a conceptual basis for behavioural research that could deal with complex issues through statistical analysis (Guttman & Greenbaum, 1998). The overriding goal of an FT approach is to conceptualise and define, in substantive terms, seemingly complex issues into their principle components or facets (Guttman, 1941). In FT, researchers construct a 'mapping sentence', a verbal statement using ordinary language that utilises one or more 'facets' and verbal connectives to define the semantic

¹Nevertheless, some notable work on linking crime scene actions to offender characteristics has been achieved by Santtila, Häkkänen, Canter, and Elfgrén (2003), Santtila, Ritvanen, and Mokros (2004), and by Kocsis *et al.* (2002) using alternatives to FMDS.

and conceptual domain of their study (Shye, 1978). Facets come in three varieties: *population*, *content*, and *range* facets, and each is needed to construct a mapping sentence. Content facets are arguably the most conceptually important, as they represent the content domain under study; while population facets define the population under study, and the range facet relates to the level of measurement of the content.

A content facet then can be defined as 'a set of elements (variables) that together represent the underlying conceptual and semantic components of a content universe' (Guttman & Greenbaum, 1998, p. 17). Mapping sentences and their facet components are defined *a priori* to an experiment with MDS procedures used to evidence the mapping sentence. Evidence is provided by determining that the facet(s) 'play(s) a role in the component set of the Cartesian set' (Shye, Elizur, & Hoffman, 1994, p. 23), with facet *elements*, those things that make up each *facet*, forming regional boundaries within the MDS plot. For example, Canter and Heritage (1990) proposed that offenders' sexual behaviour could be conceptualised using the mode of offenders' interaction with their victims as a facet of rapists' behaviour (Figure 1). On the basis of their summation of the research literature at the time, Canter and Heritage hypothesised that the facet 'mode of interaction' would have at least five elements: (1) sexuality; (2) violence and aggression; (3) impersonal, sexual gratification; (4) criminality; and (5) interpersonal intimacy. Accordingly, Canter and Heritage conducted an analysis of crime scene information collected by police investigators in 66 sexual assaults using smallest space analysis (SSA) (SSA-1: Lingoes, 1973) to verify the existence of the five facet elements.

Smallest space analysis is a specific type of non-metric MDS procedure, in which the rank order of the intercorrelations (or similarity) among variables are represented as points in *n*-dimensional Euclidian space with the distance between points corresponding to the intercorrelations between them (see Borg & Shye, 1995, for detailed description of SSA). Much of the early research in IP used the *Guttman-Lingoes* SSA (SSA-1) approach developed by Lingoes (1973) to run FMDS analyses, whereas current approaches often utilise more generic MDS statistical packages (e.g. such as the proximity data scaling procedure, PROXSCAL, found in SPSS), albeit using non-metric transformations of measures of association (Goodwill, Alison, & Humann, 2009). FMDS² allows researchers to examine *n*-dimensional Cartesian space for the following: (1) *axial* patterns—where facet elements vary with location along an axis; (2) *radial* (or modular) patterns—where facet elements vary with location along a radius (e.g. as concentric circles in an MDS plot); and (3) *angular* (or *circumplex*; Guttman, 1954) patterns—where facet elements vary by angle around the MDS plot centre and are thus circular in nature (Shye *et al.*, 1994).

In IP research that utilises an FMDS approach, the vast majority of studies have used angular and radial facets, while the use of axial facets is extremely rare. Nevertheless, it is important to note that the regional boundaries created using axial, radial, or angular facets must correspond to the hypothesised facet elements determined *a priori* within the initial mapping sentence. As such, Guttman (1954) suggests that although FMDS approaches are similar to other correlational techniques, such as factor analysis (FA), they also differ appreciably. In FMDS, the major emphasis is on *a priori* conceptualization and definition followed by post hoc interpretation, whereas FA emphasises statistical analysis to determine content structure by factor loadings alone (Guttman & Greenbaum, 1998).

²The term FMDS will be used to refer to both non-metric MDS and SSA-1 because of their theoretical and computational similarity.

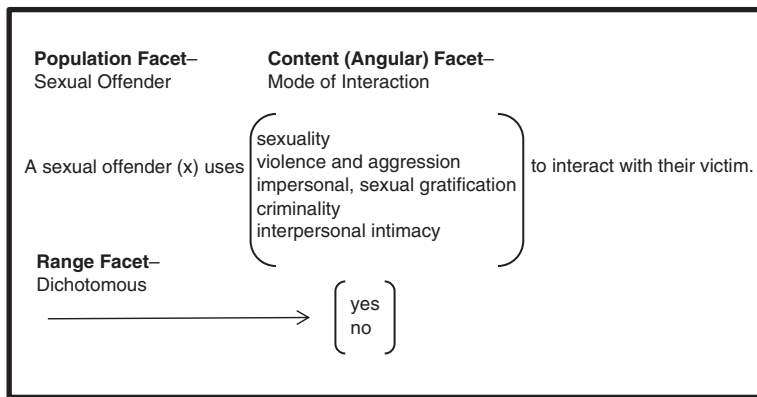


Figure 1. A mapping sentence corresponding to Canter and Heritage (1990) study of sexual offenders.

Conceptualisation and classification using faceted multidimensional scaling in investigative psychology

The use of FMDS in IP for *conceptualising* content domains has had widespread success in various areas, including offender behaviour in cases of arson (Canter & Heritage, 1990; Häkkänen, Puolakka *et al.*, 2004), homicide (Salfati, 2000; Salfati & Bateman, 2005; Salfati & Haratsis, 2001; Salfati & Park, 2007; Trojan & Salfati, 2010), sexual offences (Canter & Fritzon, 1998; Canter *et al.*, 2003; Canter & Wentink, 2004; Häkkänen, Lindlöf, & Santtila, 2004; Santtila, Junkkila, Sandnabba, 2005), robbery (Goodwill *et al.*, 2012), burglary (Kocsis, Cooksey, & Irwin, 2002), and youth crime (Almond, Canter, & Salfati, 2006; Youngs, 2004). MDS analyses have also been successfully used in non-forensic literature such as test construction and analysis (Sireci & Gesinger, 1992), molecular dynamics (Andrecut, 2009), and in perceptions of illness symptoms in pulmonary heart disease patients (Insel, Meek, & Leventhal, 2005).

However, after conceptualisation has been achieved using FMDS, IP researchers have typically sought to then classify offences into one theme over another in a typological fashion, albeit under the guise of doing so ‘thematically’ (e.g. Salfati & Canter, 1999). Typically, researchers do this by utilising the conceptual regional boundaries delineated using FMDS to *dominantly* allocate an offence to a specific region or theme, on the basis of the crime scene behaviours present in the offence. There have been several methods proposed for how to determine dominant allocation of offenders to themes, yet they are all based on using the regional divisions of the FMDS plot as distinct typological boundaries. However, as Shye and colleagues (1994) point out, FMDS regional boundaries should not be interpreted as distinct boundaries that beget types, but instead as nominal ‘fuzzy’ boundaries between areas of item relatedness. Nevertheless, in some cases, the allocation, or classification, of offenders into dominant themes, or types, may be useful as an *exploratory* measure to link themes of offending behaviour to offender characteristics. Thus, building on the recent work of Trojan and Salfati (2008), the current study attempts to compare the various methods used in FMDS interpretation and dominance classification in terms of their ability to predict offender characteristics.

Current classification methods using faceted multidimensional scaling in investigative psychology

As recently reviewed by Trojan and Salfati (2008), there are two main methods used by researchers to interpret an FMDS plot for dominant theme classification: the *count* method and the *proportional* method. Although not mentioned in Trojan and Salfati (2008), there is one additional FMDS interpretation method that will also be used in the current study comparisons that utilises an offender's behavioural average or 'centroid' (as discussed in Mokros & Alison, 2002). Research studies using FMDS methods for classification and the various rule sets employed are shown in Table 1 as follows.

The count method

Salfati and Canter (1999) were the first to use FMDS to classify offences as dominantly³ belonging to a particular regional theme on the basis of the crime scene behavioural profile of the offender. Salfati and Canter accomplished this by utilising what is herein referred to as the count method. For example, they classified an offender as being dominantly of one thematic style if the number of behaviours observed in an offence for one region was *greater than* the sum of behavioural variables in all other themes combined. As reported in Table 1, the count method has been used in several earlier studies with some minor modifications to the rule set used to define the count methodology. For example, although stating that they used the same approach as Salfati and Canter (1999), Canter and colleagues (2003) actually used a slightly different rule set to determine dominance. An offender was classified as dominantly one theme over another if the number of his or her behavioural variables in a theme was greater than or equal to the sum of their behavioural variables in all other themes combined. Additionally, Almond *et al.* (2006) used the greater than rule set, while Trojan and Salfati (2008) used both the greater than and the greater than or equal rule sets in their dominance classification comparison study.

As outlined by Trojan and Salfati (2008), one problem with the count method is that there is no adjustment for the number of behaviours within a theme in comparison with other themes. For example, an offender may have a count of six out of eight behaviours in theme A and 6 of 20 behaviours in theme B, suggesting that the offender is engaging in nearly all of the behaviours of theme A and only a few of the total number of behaviours from theme B, yet the thematic count of the regions would be identical. One way to address this limitation is to utilise the *proportions* of the behaviours in each theme rather than their absolute thematic count.

The proportional method

The first study using a proportional method in FMDS for dominantly classifying offenders into themes was Salfati's (2000) study of expressive and instrumental aggression in homicide. The proportional method addresses the limitation of the count method by dividing the number of behaviours observed within a particular theme by the total number of variables of that theme. This results in the offence receiving a score that reflects the proportionality of the

³Canter and Fritzon (1998) utilised an FMDS plot to count the number of behaviours committed by an offender for each MDS region (e.g. theme). However, they used the number of behaviours for each theme to create a scale score for each offender for each theme and thus did not try to classify or type an offender to a particular theme.

Table 1. Use of count, proportional, centroid, and scale methods in previous studies

Classification method (bold) and rule set (italicised) employed	FMDS study number (key below) in which rule was used
Count: <i>greater than or equal</i>	5
Count: <i>greater than</i>	1, 9, 11
Proportional: <i>greater than or 2×</i>	6, 7
Proportional: <i>1.5× next highest</i>	8, 11, 12
Proportional: <i>greater than</i>	3, 8, 10, 11, 12
Proportional: <i>2× greater than other theme[†]</i>	2, 8, 11, 12, 13
Centroid	4, 14
Key to FMDS study number and authors	Number of themes in FMDS
1 Salfati and Canter (1999)	3
2 Salfati (2000)	2
3 Salfati and Haratsis (2001)	2
4 Mokros and Alison (2002)	N/A
5 Canter <i>et al.</i> (2003)	4
6 Häkkinen, Lindlöf <i>et al.</i> (2004)	4
7 Häkkinen, Puolakka <i>et al.</i> (2004)	4
8 Salfati and Bateman (2005)	2
9 Almond <i>et al.</i> (2006)	3
10 Salfati and Park (2007)	4
11 Trojan and Salfati (2008; Comparison Paper)	N/A
12 Trojan and Salfati (2010)	2
13 Trojan and Salfati (2011)	2
14 Goodwill <i>et al.</i> (2012)	4

FMDS, faceted multidimensional scaling.

[†]The proportional rule 2× *greater than the other theme* was not used in study comparisons, as it applies when only two themes are present.

behaviours observed in a theme (e.g. the percentage of the overall number of variables in a theme), instead of simply the number of behaviours observed. For example, if an offender has six of eight variables from theme A, 6 of 20 variables for theme B, and 3 of 12 variables for theme C, then their proportions for each theme would be 75%, 30%, and 25%, respectively. Thus, this method takes into account that the offender engaged in a large proportion of theme A behaviours and only a small proportion of possible theme B behaviours, even though their absolute count score is equal. As in the count method, various rule sets have then been applied to determine dominant theme classification on the basis of the thematic proportions found.

As shown in Table 1, several researchers using the proportional method (Salfati & Bateman, 2005; Salfati & Park, 2007; Trojan & Salfati, 2008; Trojan & Salfati, 2010) have used the greater than rule set similar to the count method research of Salfati and Canter (1999) and Almond *et al.* (2006). Other proportional method rule sets have attributed dominant theme classification if that theme's proportion was greater than the sum of all other proportions combined and/or double the next largest theme's proportion if only two themes were present (Häkkinen, Lindlöf *et al.*, 2004; Häkkinen, Puolakka *et al.*, 2004). Additionally, a rule in which an offence is dominantly classified to a theme if that theme's proportion is 1.5 times larger than the next highest theme has also been used (Salfati & Bateman, 2005; Trojan & Salfati, 2008; Trojan & Salfati, 2010). Finally, several studies used proportional methods to classify a theme as dominant if it had twice the

proportion of the other theme (e.g. Salfati, 2000), yet these were not considered in the present study, as the rule set only applies when only two themes in total are present in the FMDS.

As can be gleaned from Table 1, classification and prediction using FMDS has predominantly utilised count or proportional methods, albeit with varying rule sets. However, both of these methods share a similar pragmatic limitation for criminal profiling research, using either method will inevitably result in the creation of a group of 'mixed' theme offenders. This mixed group will consist of offenders that could not be dominantly classified into a particular theme on the basis of the rule set and, as such, has been argued to reveal serious methodological problems (Santtila, Häkkänen, Canter, & Elfgrén, 2003). This limitation is perhaps even more serious when one considers that the mixed theme group typically consists of one third to over a half of the sample of offenders, varying somewhat by which method and rule set were used (e.g. Canter *et al.*, 2003; Salfati, 2000; Salfati & Bateman, 2005; Salfati & Canter, 1999; Salfati & Haratsis, 2001; Santtila, Canter, Elfgrén, & Häkkänen, 2001; Thijssen & De Ruiter, 2011; Trojan & Salfati, 2008).

Nevertheless, as Salfati (2000) quite rightly argues, there is perhaps *theoretical* support for the classification of offenders as mixed in their behavioural themes, as they may enact behaviours across a variety of themes during a single offence. In fact, this is precisely the reason for utilising FMDS approaches in the first place—to conceptualise a domain of study by thematic facets, not as distinct clusters of behaviours for classification (Canter, 2000). What is problematic about a mixed group, and this is more a pragmatic concern than a theoretical one, is that we are unaware of the ways in which mixed theme offenders are similar to and different from each other and how this may relate to the prediction of offender characteristics (Santtila *et al.*, 2003). Perhaps recognising this concern, Trojan and Salfati (2008) compared several count and proportional methods of classification using a variety of rule sets (termed 'stringency' in their study) to determine the method and rule that maximally reduced the number of offences classified as mixed. However, although Trojan and Salfati's (2008) study is an important one for those wishing to optimise count or proportional methods, there are alternative methods that eliminate the necessity of a mixed group altogether, namely the centroid and scale methods.

The centroid method

Utilising a method, colloquially known as the centroid method (Mokros & Alison, 2002), enables every offence to be classified without the need for designating offences as mixed. The centroid method delineates the average (e.g. centre) (x , y) coordinate of all behavioural variables' (x , y) coordinates that are present in a particular offence. The location of this single point within the FMDS plot is thus an aggregation of an offender's offence behaviours, and as such, it can be used to assign an offence to a specific theme eliminating the necessity of a mixed group. Although the removal of a mixed group is an obvious strength of this approach, researchers have not utilised this procedure to classify⁴ offenders apart from a recent study by Goodwill *et al.* (2012).

However, although eliminating mixed group classification is an important benefit of the centroid method, classification based on using the centroid is still ultimately constrained by the fact that it is a qualitative or typological method. Further, much of the quantitative

⁴In a study by Mokros and Alison (2002), the centroid was used as a means to judge the correspondence between an FMDS of crime scene behaviours and an FMDS of offender characteristics not as a classifier.

variation in centroid scores is lost by representing the centroid as one specific theme regardless of its position in that region. For example, one centroid may be on a regional border suggesting that the offence behaviours are a mix of bordering regions, and another may be located centrally within a region suggesting that it may be more congruent with the region it is located in.

The current study and the scale method

The current study is intended to be primarily a comparison of methodologies utilising robbery offences as an example and context for the offender profiling *paradigm* of predicting offender characteristics from crime scene actions. A novel scale-based method using an axial facet interpretation of the FMDS plot will be compared with traditional count, proportional, and centroid methods of FMDS classification in the prediction of the previous conviction record of offenders. Smith (2003) proposed four robbery offence types that described the approach taken by the offender during the commission of an offence: *blitz*, *confrontation*, *snatch*, and *con*. During a *blitz* offence, the offender uses violence to control the victim and subsequently removes their property. The *confrontation* offence is typified by an initial demand for property, which may be followed up by threats and/or violence. The *snatch* offence is characterised by the offender making a grab for easily accessible property carried by the victim, without prior demands or threats. Lastly, the *con* offence is characterised by the offender engaging the victim in a distracting or manipulative interaction—such as asking for the time or pointing out something interesting in the distance—before stealing the victim's property.

A detailed discussion of the current FMDS solution and its correspondence to Smith's (2003) typology is given in Goodwill *et al.* (2012). In that study, Goodwill and colleagues proposed the existence of two orthogonal latent dimensions underlying Smith's typology on the basis of the distribution of variables in a two-dimensional FMDS plot: (a) the level of *violence* inflicted on the victim; and (b) the level of *interaction* exhibited between the offender and victim. As such, they argued that Smith's typology could be defined as the crossing of the two latent dimensions in a simple orthogonal (x, y) Cartesian axis framework. For example, *snatch* offences could be characterised as having low levels of interaction and violence, while *confrontation* offences were the opposite, characterised by high levels of interaction and violence.

Importantly, this not only meant that there was a strong quantitative basis for Smith's typology as an *angular* facet (e.g. offences could be qualitatively separated by a circular pattern) within the FMDS but also that each of Smith's types could be linearly ordered along axial facets as more or less interactive and more or less violent. In their study, Goodwill and colleagues (2012) used the centroid method—the cumulative average of all offence behaviours in each offender's offence—to determine an (x, y) coordinate for that offence, allowing each offence to be reduced to a continuous score of level of violence (x -axis score) and level of interaction (y -axis score). Although using the centroid in this way could potentially indicate the type (or theme) of offence,⁵ Goodwill and colleagues suggested that this is not a particularly sophisticated approach for predicting offender characteristics, particularly because of the arbitrary reduction of the quantitative data into qualitative data. Alternatively, Goodwill and colleagues argued that the underlying axial scale scores of

⁵For example, a positive score on the x -axis coordinate (e.g. high interaction) and a negative score on the y -axis (e.g. low violence) would result in a *con* offence type.

violence and interaction could be directly⁶ used to predict a robbery offender's previous conviction record, nullifying the need to classify offences at all in order to make offender characteristic predictions.

Because the motivation to commit robbery varies from drug acquisition, materialistic gain, getting a 'buzz' or high, and/or gaining the respect of fellow street offenders, the patterns of prior convictions may also vary (Bond & Sheridan, 2007; Deakin, Smithson, Spencer, & Medina-Ariza, 2007; Matthews, 2002; Wright, Brookman, & Bennett, 2006). However, there is research to suggest that some previous convictions are more common in the histories of robbery offenders. Some robbery offenders have been shown to be motivated by their drug use to commit robbery offences (Brookman, Mullins, Bennett, & Wright, 2007; Deakin *et al.*, 2007). Others have shown to be motivated by the interpersonal context of the crime (Brookman *et al.*, 2007; Youngs, 2004). Further, relationships have been found between prior property and/or theft convictions (Blumstein, Cohen, Das, & Moitra, 1988; Bond & Sheridan, 2007) in robbery offenders suggesting that crime scene actions, on the basis of an offender's underlying motivation for offending, may help predict their criminal background.

Overall, the study has several aims: (1) to introduce the lay reader to an FT methodology for MDS research (FMDS); (2) to compare the various methods historically and currently used in dominant theme classification in FMDS; and (3) to introduce a novel scale method on the basis of the interpretation of FMDS plots using axial facets that foregoes the need to use qualitatively based dominant theme classification altogether.

METHOD

Data

The Offender Assessment System (OASys), of the UK-based National Offender Management Service (NOMS), was utilised to compile offence information, including crime scene information, offender characteristics, and prior convictions of 72 male offenders convicted of a street robbery offence. OASys is used in the UK as a risk assessment and management tool for violent offenders. From this database, 28 crime scene variables were selected. For further details of the sample, criteria for selection and crime scene variables see Goodwill *et al.* (2012).

Step 1: classification of offences using count, proportional, and centroid methods

A similarity matrix consisting of 28 crime scene variables (see Goodwill *et al.*, 2012), on the basis of the Jaccard's measure of association (Jaccard, 1908), was inputted into an MDS analysis. As illustrated in Goodwill *et al.* (2012), the two-dimensional MDS plot of robbery crime scene variables could be partitioned using an axial interpretation of the robbery style facet by *x* and *y* axes into four regions representative of Smith's (2003) four types. Using this basic four-region MDS representation, offenders were classified into dominant themes of robbery using traditional MDS-based classification methodologies: (a) count method; (b) proportional method; and (c) a centroid method.

⁶Although the example given in this paper uses an axial facet that directly maps onto the FMDS axes, theoretically, the behavioural scales could have been non-orthogonal and/or rotated.

Count method

Two count methods of classification, varying in the rule sets used, were utilised in the current study classification methods comparison. The first classification rule was based on the approach outlined by Salfati and Canter (1999) and later by Almond *et al.* (2006) in which offences were classified into dominant theme (e.g. con, confrontation, snatch, or blitz) if the number of variables in a region was greater than the number of variables in all other regions combined. The second classification rule set utilised the approach outlined by Canter and colleagues (2003) in which offences were classified into dominant types if the number of variables in a region was greater than or equal to the number of variables in all other regions combined. Under both count method rule sets, offences that could not be dominantly classified were classified as a 'mixed' theme (see Table 2 for frequencies).

Proportional method

Three proportional methods of classification were also used in study comparisons, varying in the rule sets employed. Offences were classified into one of the four themes (con, confrontation, snatch, or blitz) on the basis of varying rule sets applied to the relative proportion of behaviours in each theme (e.g. the number of behaviours in a theme relative to the number of behaviours in other themes). First, offences were classified into a dominant theme if the proportion was greater than the summed proportions of all other regions combined (e.g. Salfati & Park, 2007). Second, offences were classified as dominantly one theme if the proportion of behaviours present in that theme was one and a half times greater than the proportion of behaviours in the next highest theme (as advocated for by Salfati & Bateman, 2005). Finally, offences were classified as dominantly one theme if the proportion of behaviours present in that theme were greater than the summed proportions of all other regions combined or if only two themes were present if one was 2× larger than the other (e.g. Häkkinen, Lindlöf *et al.*, 2004; Häkkinen, Puolakka *et al.*, 2004). The rule set 2x greater than other theme outlined in Table 1 as used for example by Salfati (2000) was not used in study comparisons, as it was a rule set utilised only for FMDS analyses with two themes. Offences that could not be dominantly classified under the three proportional rule sets were classified as mixed (see Table 2 for frequencies).

Centroid method

Two centroid methods of classification were utilised for comparisons; a *weighted* and *non-weighted* (normal) method. For the non-weighted (normal) method, the centroid, or average (x, y) coordinate of all crime scene variables whose values were present in an

Table 2. Frequency (percentage) of classification of offences into themes based on count, proportional, and centroid methods

Robbery theme	Count		Proportional			Centroid	
	Greater than or equal	Greater than	Greater than or 2×	1.5× next highest	Greater than	Weighted	Non-weighted
Blitz	1 (1.4)	0	3 (4.2)	3 (4.2)	7 (9.7)	24 (33.3)	22 (30.6)
Snatch	13 (18.1)	12 (16.7)	8 (11.1)	13 (18.1)	11 (15.3)	20 (27.8)	19 (26.4)
Con	0	0	0	0	2 (2.8)	6 (8.3)	4 (5.6)
Confrontation	28 (38.9)	26 (36.1)	15 (20.8)	19 (26.4)	17 (23.6)	22 (30.6)	27 (37.5)
Mixed	30 (41.7)	34 (47.2)	46 (63.9)	37 (51.4)	35 (48.6)	0	0

offence, was computed for each offence (as outlined in Mokros & Alison, 2002). The exact (x, y) coordinate of the centroid (e.g. where it was located on the MDS plot) was used to demarcate the offence to a specific theme. For example, if the centroid was located in the lower right quadrant of the FMDS robbery plot (e.g. centroid had a positive x-axis value and negative y-axis value), the offence would be classified as a 'Con' offence.

For the weighted centroid method, the variables within each region were weighted on the basis of the number of variables in that region, similar to the proportional method. Specifically, the actual number of variables in a region was divided by the mean number of variables per region, and the resultant multiplier was used as a correction factor for each variable within that region. To obtain the weighted centroid, the following steps are involved: (1) Total number of variables are divided by number of FMDS regions (or themes) to give the *mean number of variables per theme* (Equation 1a); (2) The *correction factor for each region* is computed by taking the *mean number of variables per theme* and dividing it by the number of variables in the region (Equation 1b); (3) The x, y coordinates of all variables are then multiplied by their respective regions correction factor (Equation 1c); and (4) Centroids for each offender are then computed as aforementioned utilising the weighted variable coordinates, resulting in a weighted centroid (Equation 1d).

$$\text{mean number of variables (v) per theme (k)} = \frac{\sum v}{\sum k} \quad (1a)$$

$$\text{mean number of variables (v) per theme (k)} = \frac{28}{4} = 7 \quad (\text{Example 1a})$$

$$\text{correction factor (CF) for each theme } k = \frac{\sum v}{\sum_{i=1}^k v} \quad (1b)$$

$$CF(\text{Blitz}) = \frac{7}{6} = 1.17; CF(\text{Snatch}) = \frac{7}{7} = 1.0; CF(\text{Con}) = \frac{7}{6} = 1.17; CF(\text{Conf.}) = \frac{7}{9} = 0.78 \quad (\text{Example 1b})$$

$$\text{weighted variable [x, y] coordinates} = [x, y] \text{ coordinates for variables } v_{i=1} \times CF_{i=1}^k \quad (1c)$$

$$\begin{aligned} &\text{if amicable (blitz)} [x, y] = [1.03, 0.22] \text{ then,} \\ &\text{weighted amicable } [x, y] = [1.03, 0.22] \times 1.17 = [1.21, 0.26] \end{aligned} \quad (\text{Example 1c})$$

$$\text{weighted centroid } [x, y]_{i=1}^n = \frac{\sum \text{weighted variable } [x, y] \text{ present in offence}}{\text{number of variables present in offence}} \quad (1d)$$

$$\text{offence 7 } [x, y] = \frac{\text{weighted } v_1 + \text{weighted } v_2 + \text{weighted } v_3 + \dots \text{weighted } v_6}{6} \quad (\text{Example 1d})$$

The weighting procedure essentially moves variables in the FMDS plot on the basis of the proportionality of variables within a region before the centroid is computed. Variables

within regions that have fewer variables than average (e.g. correction factor greater than 1.0) are 'pushed' towards the diagonal periphery of that region, while variables that had more variables than the average (e.g. correction factor less than 1.0) are pulled towards the centre of the FMDS plot. The final weighted centroid for each offender will be based on the proportionality of the number of variables in each region, given the offender's individual variable profile. As in the non-weighted centroid procedure, the x , y coordinate of the final weighted centroid will demarcate (e.g. pinpoint) the type of offender the offence is most representative of.

Step 2: utilising latent scales to make predictions—the scale method

Given the correspondence of the x and y axes to the axial facet of robbery style, offences were given scale scores on the basis of the offence centroid to predict offender characteristics (e.g. previous convictions). The centroid for each offence, on the basis of the crime scene variables whose values were present in that offence, derived the scale score for level of interaction (x -axis value) and level of violence (y -axis value). A weighted scale method was also used on the basis of the weighted centroid procedure as described earlier (Equation 1a–1d).

Step 3: comparison of the traditional and novel approaches to predict previous conviction records

Logistic regression models

Four types of previous convictions (e.g. property offences, offences against a person, theft and kindred offences, and drug offences) were separately regressed by the offence classifications derived using the following: the two count methods (1) greater or equal and (2) – greater than; the three proportional methods (3) greater than or $2\times$, (4) $1.5\times$ next highest, and (5) greater than; the centroid method (6) weighted and (7) non-weighted; and the scale method (8) weighted and (9) non-weighted. Table 2 indicates the predictors used in each individual model including a category for mixed group offenders where applicable. The results were then examined on the basis of the model significance, variance accounted for, and the extent of model residuals (error).

Receiver operating characteristic analysis

A receiver operating characteristic (ROC) analysis (Swets, 1988) was conducted using MedCalc (ver. 9.2.1.0) on each prior conviction using the resultant probabilities from the logistic regression models. ROC analysis has been used within IP to compare the ability of statistical models to discriminate between dichotomous outcomes, such as whether a crime is linked or not (Winter, Lemeire, Meganck, Geboers, Rossi, & Mokros, 2013). ROC analysis plots the true positive rate (e.g. sensitivity) versus the false positive rate (1-specificity) for a binary outcome, as its discrimination threshold is varied (see Bennell & Jones, 2005, for a comprehensive review of ROC analysis in investigative contexts). In the current context, ROC is utilised to investigate the ability of each method and rule set to predict an offender's previous conviction record across all discrimination thresholds. The ROC results are reported as area under the curve (AUC), a measure of predictive accuracy ranging from zero (e.g. no accuracy) to one, representing perfect accuracy. A score of 0.5 represents only chance predictive accuracy.

RESULTS

Classification of offences

Count classification rules

The use of either count rule resulted in no offences being classified as con offences. Both the count rules resulted in the majority of offences being classified into the 'mixed' theme; the greater or equal rule resulted in 30 (41.7%) mixed offences, and the greater than rule resulted in 34 (47.2%) mixed offences. Using the greater or equal rule resulted in 42 (58.3%) offences classified as blitz, snatch, and confrontation offences, while using the greater than rule resulted in 38 (52.8%) of the offences being classified as snatch and confrontation offences (see Table 1 for exact proportions).

Proportional classification rules

Of the three proportional rules, only the greater than rule was able to classify offences into each of the four robbery themes. Neither the greater than or $2\times$ nor the $1.5\times$ next highest rules resulted in offences being classified as con offences. The mixed theme classification was also prominent under proportional methodology; the greater than or $2\times$ rule resulted in 46 (63.9%) mixed offences, the $1.5\times$ next highest rule resulted in 37 (51.4%) mixed offences, and the greater than rule resulted in 35 (48.6%) mixed offences. Similar to the count approach, very few offences were classified as blitz offences (see Table 1 for exact proportions).

Centroid rules

Both the weighted and non-weighted centroid rules classified all offences into one of the four robbery themes, eliminating the necessity of a mixed theme. Offences were less frequently classified into the con category than blitz, snatch, or confrontation; the weighted rule generated 6 (8.3%) con offences, while the non-weighted rule generated 4 (5.6%) con offences (see Table 1 for exact proportions).

Comparison of the count, proportional, centroid, and scale classification rules

Property offences

A total of 48 offenders (66.7%) had a previous conviction for a property offence. When offences were classified using the count rules, there was no significant predictive ability for property offence convictions (Table 3). Of the proportional rules, predictive ability for prior convictions of property offences was only significant when using the greater than rule ($\chi^2(4) = 12.33, p < 0.05$) and accounted for 22% of the variance in the model. Of the centroid rules, predictive ability for prior property offences was significant using both the weighted ($\chi^2(3) = 12.06, p < 0.01$) and non-weighted rules ($\chi^2(3) = 12.68, p < 0.01$) and accounted for 21% and 22% of the variance, respectively. Of the scale rules, predictive ability for prior property offences was significant using both the weighted ($\chi^2(2) = 11.23, p < 0.01$) and non-weighted rules ($\chi^2(2) = 10.89, p < 0.01$), and both accounted for 20% of the variance. Of the count, proportional, centroid, and scale rules, classification accuracy based on the scale rules was the highest and exceeded base rate prediction, each with accuracy of 75%. The greatest amount of residual error was found in the count methods,

Table 3. Comparison of the predictive ability of methods and rule sets for an offender's previous conviction record for property offences

	Count		Proportional		Centroid		Scale	
	Greater than or equal	Greater than	Greater than or 2×	1.5× next highest	Greater than	Weighted	Non-weighted	Non-weighted
Logistic regression comparisons								
R^2	0.078	0.029	0.103	0.071	0.219	0.214	0.224	0.201
Classification accuracy	Base rate	Base rate	68.10%	Base rate	73.60%	72.20%	70.80%	75.00%
Residuals	30.28	31.31	29.87	30.74	26.66	26.64	26.48	27.24
ROC analysis								
Area under the curve	0.625	0.581	0.629	0.598	0.705*	0.722**	0.733**	0.741***
Standard error ^a	0.070	0.072	0.070	0.069	0.069	0.066	0.063	0.062

ROC, receiver operating characteristic.
^aunder nonparametric assumption;
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

followed by proportional and scale methods, with the least error found under the centroid methods. ROC analyses results corresponded showing that the predictive accuracy using centroid (weighted: $AUC = 0.72$, $p < 0.01$; non-weighted: $AUC = 0.73$, $p < 0.01$) and scale (weighted: $AUC = 0.74$, $p < 0.001$; non-weighted: $AUC = 0.73$, $p < 0.01$) methods were superior to count and proportional methods overall, although the greater than proportional method achieved significant predictive accuracy as well ($AUC = 0.71$, $p < 0.05$).

Person-related offences

In total, 56 of the offenders or 77.8% of the sample had a prior conviction categorised as a person-related offence (e.g. violent offence). When offences were classified using the count or proportional rules, there was no significant predictive ability for person-related offence convictions (Table 4). Of the centroid rules, predictive ability for prior person-related offences was significant using the weighted rule ($\chi^2 (3) = 8.03$, $p < 0.05$) and accounted for 16% of the variance. Of the scale rules, predictive ability for prior person-related offences was significant using both the weighted ($\chi^2 (2) = 7.88$, $p < 0.05$) and non-weighted rules ($\chi^2 (2) = 7.93$, $p < 0.05$), and both also accounted for 16% of the variance. Of the count, proportional, centroid, and scale rules, only classification based on the weighted and non-weighted scale rules allowed for prediction of person-related offences better than base rates, both at 79.2% accuracy. The greatest amount of residual error was found in the proportional methods, followed by count and centroid methods, with the least error found under the scale methods. ROC analyses also revealed significant predictive accuracy using the weighted scale and centroid methods ($AUC = 0.73$, $p < 0.01$; $AUC = 0.71$, $p < 0.05$) and non-weighted scale and centroid methods ($AUC = 0.71$, $p < 0.01$; $AUC = 0.68$, $p < 0.05$) for prior person-related offences.

Theft offences

A total of 55 or 76.4% of the offenders had committed a theft offence prior to their robbery conviction. When offences were classified using the count or proportional rules, there was no significant predictive ability for theft offence convictions (Table 5). As with person-related offences, predictive ability for prior theft offences was significant using the centroid rules (weighted: $\chi^2 (3) = 11.18$, $p < 0.01$; non-weighted: $\chi^2 (3) = 11.30$, $p < 0.01$) and scale rules (weighted: $\chi^2 (2) = 6.82$, $p < 0.05$; non-weighted: $\chi^2 (2) = 11.30$, $p < 0.05$), and the variance accounted for ranged from 22% to 14%, respectively. Again, as with person-related offences, only classification based on the weighted and non-weighted scale rules allowed for prediction of person-related offences better than base rates, both at 75.0% accuracy. The greatest amount of residual error was found in the proportional methods, followed by count and scale methods, with the least error found under the centroid methods. ROC analyses also revealed significant predictive accuracy using the centroid (weighted: $AUC = 0.75$, $p < 0.01$, non-weighted: $AUC = 0.74$, $p < 0.01$) and scale (weighted: $AUC = 0.71$, $p < 0.01$; non-weighted: $AUC = 0.71$, $p < 0.05$) methods. However, the proportional method greater than ($AUC = 0.67$, $p < 0.05$) and the greater than or equal count method ($AUC = 0.66$, $p < 0.05$) rules were also found to have significant predictive accuracy.

Drug offences

In the sample, 30 offenders or 41.7% had a previous drug offence. When offences were classified using the count and centroid rules, there was no significant predictive ability for

Table 4. Comparison of the predictive ability of methods and rule sets for an offender's previous conviction record for person-related offences

	Count		Proportional		Centroid		Scale		
	Greater than or equal	Greater than	Greater than or 2×	1.5× next highest	Greater than	Weighted	Non-weighted	Weighted	Non-weighted
Logistic regression comparisons									
R^2	0.061	0.057	0.047	0.014	0.085	0.162	0.123	0.159	0.160
Classification accuracy	Baserate	Baserate	Baserate	Baserate	Baserate	Baserate	Baserate	79.2%	79.2%
Residuals	23.93	24.03	24.36	24.66	23.64	22.03	22.76	22.10	22.00
ROC Analysis									
Area under the curve	0.618	0.617	0.570	0.558	0.644	0.709*	0.682*	0.727**	0.714**
Standard error ^a	0.080	0.077	0.078	0.081	0.075	0.075	0.076	0.073	0.075

ROC, receiver operating characteristic.

^aunder nonparametric assumption; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

drug offence convictions (Table 6). However, prediction of prior drug offences was significant using the $1.5\times$ next highest proportional rule ($\chi^2(3)=8.5$, $p<0.05$) and scale rules (weighted: $\chi^2(2)=6.11$, $p<0.05$; non-weighted: $\chi^2(2)=6.32$, $p<0.05$) with variance accounted for ranging from 15% to 11%, respectively. Comparatively, classification accuracy based on the $1.5\times$ next highest proportional rule and weighted and non-weighted scale rules was 63.9%, 62.5%, and 62.5%, respectively. The greatest amount of residual error was found in count methods, followed by centroid and proportional methods, with the least error found under scale methods. ROC analyses also revealed significant predictive accuracy using the $1.5\times$ next highest proportional rule ($AUC=0.65$, $p<0.05$) and the scale rules (both weighted and non-weighted: $AUC=0.66$, $p<0.05$).

DISCUSSION

The current study sought to introduce the reader to a faceted method of MDS research (FMDS), while contrasting the traditional methods of FMDS interpretation and classification (e.g. count, proportional, and centroid) against a novel quantitative scale-based method on the basis of an axial facet. The methods were compared using various convergent statistical analyses (e.g. regression model fit, variance, error, and AUC predictive significance) for their ability to predict specific aspects of an offender's previous conviction record on the basis of their offence variables. The novel scale method, under both weighted and non-weighted rule sets, was found to significantly predict the prior conviction record(s) of an offender and generally outperformed the more traditional count, proportional, and centroid methods. Thus, the introduction of an axial scale method for FMDS analysis in the current study provides some support for the canonical correlation equation as set out by Canter (1995). The canonical correlation equation (see Canter, 2011, for review) relates directly to the theory that the way in which an offender carries out their offence (e.g. its level of interaction and violence) will be related to the type of person they are and/or background characteristics they possess (e.g. type of previous conviction record).

Predictive accuracy

Overall, the novel scale method demonstrated the greatest predictive accuracy for prior convictions when compared against the current qualitative methods of classification and prediction. Regardless of rule sets, the count, proportional, and centroid methods seldom showed better predictive accuracy for previous conviction records across a number of statistical analyses. These findings suggest that the prediction of offender characteristics should involve scale-based approaches where possible and new techniques to develop scale-based multivariate analyses need further development.

In terms of the predictive accuracy of the axial facet under study, the interaction scale was a significant predictor of previous convictions, whereas the violence scale was not.⁷ One possible explanation for this finding may be that robbery, by definition, involves a substantial level of physical or threatened violence, which may result in a more limited range of violent behaviours relative to the variables suggestive of interaction. Further, the predictive effectiveness of each underlying scale may be reliant on both the offender's

⁷The beta values of the individual regression models are not given in this paper because of space limitations. However, all model results are obtainable from the first author.

Table 5. Comparison of the predictive ability of methods and rule sets for an offender's previous conviction record for theft offences

	Count		Proportional		Centroid		Scale	
	Greater than or equal	Greater than	Greater than or 2 ×	1.5 × next highest	Weighted	Non-weighted	Weighted	Non-weighted
Logistic regression comparisons								
R^2	0.103	0.075	0.061	0.096	0.216	0.218	0.136	0.136
Classification accuracy	Baserate	Baserate	Baserate	Baserate	Baserate	Baserate	75.0%	75.0%
Residuals	24.30	24.72	25.16	24.65	22.14	22.11	23.70	23.66
ROC Analysis								
Area under the curve	0.660*	0.637	0.598	0.626	0.746**	0.743**	0.710**	0.705*
Standard error ^a	0.072	0.075	0.076	0.072	0.065	0.065	0.065	0.067

ROC, receiver operating characteristic.

^aunder nonparametric assumption; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 6. Comparison of the predictive ability of methods and rule sets for an offender's previous conviction record for drug offences

	Count		Proportional		Centroid		Scale	
	Greater than or equal	Greater than	Greater than or 2 ×	1.5 × next highest	Weighted	Non-weighted	Weighted	Non-weighted
Logistic regression comparisons								
R^2	0.040	0.009	0.059	0.151	0.050	0.021	0.109	0.113
Classification accuracy	59.7%	Base rate	62.5%	63.9%	Base rate	Base rate	62.5%	62.5%
Residuals	34.11	34.75	33.42	31.40	33.77	34.48	32.24	32.16
ROC Analysis								
Area under the curve	0.557	0.543	0.602	0.652*	0.594	0.563	0.658*	0.656*
Standard error ^a	0.069	0.069	0.069	0.067	0.067	0.068	0.065	0.065

ROC, receiver operating characteristic.

^aunder nonparametric assumption; * $p < 0.05$; *** $p < 0.001$.

characteristics and situational influences. Thus, the presence of violence may rely more heavily on situational aspects of the offences, such as the offender's response to victim resistance (Beauregard, Lussier, & Proulx, 2008; Davies, Wittebrood, & Jackson, 1991). Therefore, the level of interaction in robbery appears to be an important component and one that researchers have only recently begun to study in depth (Barker, Geraghty, Webb, & Key, 1993; Canter & Youngs, 2009; Deakin *et al.*, 2007; Indermaur, 1996; Porter & Alison, 2006). Although this study may not have provided substantive proof of homology, it is interesting to note that high levels of interaction were correlated strongly with previous convictions for person-related offences. One explanation for this may be that higher levels of interaction in some offences may indicate a higher level of offender comfort in the commission of the crime, perhaps reflecting a greater level of offender experience with person-related crimes, such as robbery.

Comparison of methods

Although some improvements were found in the centroid method, compared with the proportional and count methods (e.g. eliminated the necessity of a mixed group), and in proportional methods compared with count methods (e.g. eliminates bias of unequal number of variables per theme), all three qualitative methods suffered from the following: (a) the 'regional pinning' of variables and centroids; and (b) the loss of statistical power by reducing quantitative, multivariate data into qualitative categories. Table 7 gives a brief tabled breakdown of the various integral aspects and limitations of each approach as will be discussed.

The centroid and proportional methods of classification treat each variable as a discrete point in geometric space 'belonging' to a specific region and that region alone. Thus, individual variables can be thought of as 'pinned' to a region. For example, no weighting or adjustments are made for behavioural variables that are very close to regional boundaries; they are interpreted to fully represent the thematic concept, as strongly as any other variable within the regional boundary, regardless of location. In FMDS, the regional boundaries drawn onto the MDS plot are not fixed formal boundaries delineating clusters of variables, but instead delineate 'a subset of points [variables] separated from other points [variables] by a boundary' (Guttman & Greenbaum, 1998, p. 19). In fact, an item at the edge of one regional boundary may correlate stronger with items of the other region than it does

Table 7. Tabular comparison of faceted multidimensional scaling (FMDS) interpretation methods and parameters

Method	Methodological parameters					
	Regional bias for unequal variable numbers	Regional 'pinning' of variables	Regional boundaries used for classification	Offences can be dominantly of a mixed theme	Typical facet structure used in FMDS interpretation	Prediction basis for offender characteristics
Count	Yes	Yes	Yes	Yes	Angular/radial	Qualitative
Proportional	No	Yes	Yes	Yes	Angular/radial	Qualitative
Centroid	No	No	Yes	No	Angular/radial	Qualitative
Scale	No	No	No	No	Axial	Quantitative

with the items of the region it belongs to. Therefore, methods that count behaviours to create thematic scores (e.g. count and proportional methods) are particularly susceptible to this limitation. Although the centroid method somewhat addresses the issue of regional pinning of behavioural variables—as it is instead computed on the basis of the average (x , y) coordinate of all behaviours irrespective of regional placement—it still is limited by regional biases. Similar to regional pinning of items, the centroid may also lie on or close to regional boundaries, making interpretation of which theme an offence is most representative of less clear.

Each of the three traditional methods of FMDS classification currently lead to a qualitative classification of offences and hence lead to categorically based predictions of offender characteristics. The rich relational data between variables are reduced in dimensionality to a single, qualitative predictor, typically with only a few different themes available into which to classify an offence (Table 1). Even more problematic from a pragmatic standpoint is that many studies attempt to classify an offence into one of only two themes (e.g. Salfati, 2000). Although thematic models with just two or more themes may be important because they are able to conceptualise a vast range of behavioural responses, interactions, and situational variations into just two or more themes, they may nonetheless be less pragmatic for predicting offender characteristics because of the limited number of themes.

Accordingly, research papers that have used count, proportional, or centroid methodology to predict offender characteristics have had mixed success (Snook *et al.*, 2007). Clearly, the inability to show relationships between crime scene behaviours and offender characteristics, the basic tenet of offender profiling research (Goodwill, Alison, & Beech, 2009), is a significant problem for a field of research borne from this apparent goal (Canter, 2011), and to this end, criminal profiling has been heavily criticised (Kocsis, 2006; Snook, Cullen, Bennell, Taylor, & Gendreau, 2008). Therefore, one goal of the current study is to illustrate that, in the past, the lack of correspondence between crime scene behaviours and offender characteristics using FMDS methods may have been due to the methodology used, rather than theoretical or ideological failures, such as those suggested by Kocsis, Middledorp, and Karpin (2008).

Axial facets in faceted multidimensional scaling

The present study provided a practical example of the lesser-known axial type content facet that is used to characterise the linear ordering of facet elements using generalised simplex patterns. The interpretation of an FMDS into two or more regions by ordered parallel lines is known as a *generalised simplex*. The combination of two axial generalised simplexes, orthogonal or juxtaposed against one another, creates a facet pattern known as a *duplex* (Shye *et al.*, 1994). The results of this study suggest that the linear-ordered facet elements (e.g. robbery styles) do indeed form a duplex, formed by the crossing of two axial facets, the *level of violence* juxtaposed by the *level of interaction*. The mapping sentence in Figure 2 captures this relationship in schematic form.

The importance of analysing the FMDS plot for axial facets in the current study is two-fold. First, the majority of FMDS interpretations in IP and criminal profiling research are made using angular and radial (e.g. modular) facets, and thus, the present study is perhaps enlightening for social and investigative psychologists new to facet methodology and FMDS. Second, the partitioning of an FMDS plot into axial regions, which correspond to the FMDS axes, enables the direct use of centroid coordinates as scale scores for descriptive and predictive purposes. Further, the discovery of a duplex pattern in the FMDS afforded

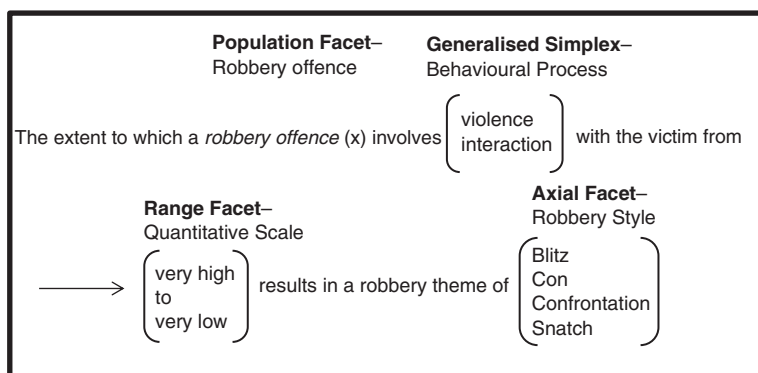


Figure 2. The robbery mapping sentence operationalizing the hypothesised content domain by an axial facet of robbery style defined as duplex of the two generalised simplexes of violence and interaction.

further construct validity to the theoretical model proposed by Smith (2003). Accordingly, each robbery type proposed by Smith can be shown to be a structuple (e.g. an individual profile) of the crossing of the two generalised simplexes of violence and interaction, ranging from high to low, evidenced in Goodwill *et al.* (2012). For example, an offence centroid that is high on the violence scale and low on the interaction scale would be located in the blitz region of the FMDS and correspond to the definition of a blitz offence according to Smith (2003). However, of particular importance to the use of an axial facet in the present study is that it enables a quantitative interpretation of the FMDS plot that affords greater statistical power for drawing links between crime scene behaviour and offender characteristics than traditional angular facet approaches.

Implications and future research

Future research using MDS-based dominance classifications should consider weighting variables on the basis of their frequency of occurrence, such that each variable is adjusted as more or less representative of a crime theme. Although, as Canter (2011) describes, while the modular facet, which is most commonly a radial projection of concentric circles, has typically been interpreted on the basis of variable frequencies, researchers have thus far not provided a quantified way of incorporating specific variable weights into FMDS analysis. Therefore, a detailed study exploring variable frequency and geometric location on the substantive importance of the variable to a theme is timely.

One suggestion is that 'core' elements (e.g. those with frequencies over 50%), typically located in the middle of the MDS plot, can be excluded from centroid calculations because of their commonality to the crime under investigation. The exclusion of common variables from the centre of the FMDS plot would then preferentially give greater weight or substantive importance to variables on the periphery of the plot. Alternatively, a conceivable method might be to weight variables (e.g. by the reciprocal of the variable frequency) on a sliding scale such that the closer to the periphery of the plot they are, the more they would contribute to the offence centroid. The idea being that these variables are the ones that may provide the most differentiation between themes, as argued by Canter (2011), and are thus the most important for differentiating offenders. It follows that the greater discriminability a model

has between themes, the more homogenous offence themes will become, making links between crime scene actions and offender characteristics more evident and predictable.

CONCLUSION

This study provided a comparison of methods typically used in the classification of FMDS plots on the basis of angular and radial facets and contrasted this with an approach using an axial facet to incorporate the underlying latent dimensions of the FMDS into the prediction of offender characteristics. The results suggest that scale-based methods of crime scene analysis based on FMDS are superior to those using qualitative classification, regardless of whether count, proportional, or centroid rules are used.

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