ACCURACY OF STATISTICAL MODELS FOR CRIME LINKAGE AND THE EXPLORATION OF SEXUAL OFFENCE CLASSES

by

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Thesis Overview

Chapter one of this thesis is a meta-analysis of the accuracy of statistical models used to link crimes, as measured by the Area Under the Curve statistic. This chapter includes the process used to gather, and extract relevant papers and data, the model selection, and findings of a three factor random effects model. In the empirical research paper (chapter two), subgroups of offence behaviours, offender traits, and demographic characteristics are identified in sexual offences. This research is based on the Swiss ViCLAS database and uses latent class analyses to identify subgroups of different variable sets. Associations between the three sets of subgroups are also evaluated using log-linear analysis. Finally, chapter three and four present press release documents of chapter one and two respectively. These chapters are written for the purpose of public dissemination. They both include brief overviews of the aims, findings, and conclusions from the meta-analysis and empirical research chapters.

Declaration

I confirm that this thesis has not been submitted for the completion or as part of any other degree or qualification. This thesis is the result of my own work, and appropriate acknowledgment is explicitly stated where the expertise of any other person or organisation have been used.

Dedication

For baba, thank you for dreaming with me, and gracing me with a model of patience and persistence. You will always be my secure base. To the mothership, the strongest and most resilient woman I know. And my brother, nothing without you is complete. My dear friends, thank you for guiding me gently through every phase of life. And to my partner, for sustaining me, at the best and worst of times. Your silent and unwavering presence is the loudest cheer.

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CHAPTER ONE

META-ANALYSIS

Accuracy of statistical models to link serial crimes:

a meta-analysis.

Abstract

Purpose: Crime linkage can be expensive, time-consuming, and the well-being of law enforcement staff conducting it, can be impacted. Part-automation of this process has been explored recently; whereby statistical models could be used to prioritise potential crime links for human attention. This meta-analysis evaluates the overall effectiveness of statistical models at predicting crime links, as measured by the AUC.

Methods: Following a systematic literature search, 29 papers were included in the meta-analysis, and quality assessed. A three factor random effects model was used to analyse the data for each crime category. Behavioural domains and statistical models which yielded the greatest accuracy for linkage predictions were evaluated.

Results: Crime types of sexual assault and burglary present with more robust data at present. Results indicate greater accuracy when using specific behavioural domains such as geographical information and aggregates of all MO behaviours. Further, the most effective statistical model to link crimes is dependent on the crime type.

Conclusions: Some findings support the use of classification models over data reduction tools for the purpose of developing crime linkage decision-support tools. Practice implications, and areas for future research are considered in line with the data available, and use of the AUC as a measure of accuracy.

Introduction

In 2021, the proven reoffending rate was ~25% in England and Wales (Ministry of Justice, 2023), and between 26% and 60% across 23 countries during a two-year follow-up[1] (Yukhnenko et al., 2019). These statistics indicate that many crimes are committed by repeat offenders (e.g., Falk et al., 2014). Further, the economic and societal cost of reoffending in England and Wales was estimated at ~£18 billion in 2016 (Newton et al., 2019). Societal cost includes physical and psychological injury, however, the emotional impact on survivors can be difficult to quantify. These statistics call for an investment in the identification and prevention of serial crimes. Crime linkage is one method used in different countries by law enforcement to identify serial offending and the offenders responsible (Woodhams et al., 2007a).

Crime linkage

Crime linkage is the practice of linking multiple crimes committed by the same individual or group of offenders (Woodhams et al., 2007b). Forensic evidence, such as DNA or other physical evidence, can be used to link crimes, however, it is also expensive and time-consuming to process, and often absent at crime scenes (Daves, 1991; Grubin et al., 2001). Alternatively, behavioural information may be used to link crimes (Hazelwood & Warren, 2003). This approach involves a detailed analysis of offender behaviour in an index crime (or series of crimes) to identify which behaviours are likely to be repeated by the offender in other

[1] Note that reoffending rates may not be comparable between countries given the variability in recording. The statistics provided may also be an underestimation as they only include *proven* reoffences or *rearrests*.

crimes they have committed. Searches of police databases for these behaviours may or may not uncover other crimes with similar *modus operandi* (MO), that is also distinctive from other crimes of the same type committed by different offenders. For example, in sexual offences, an analyst may consider how the victim was approached, controlled, or sexual behaviours of the offence itself. Crime linkage can be advantageous as it allows efficient use of police resources to investigate multiple crimes committed by the same offender(s), build evidence for prosecution, and facilitate the use of information sharing across police jurisdictions and prevent duplication of work (Woodhams et al., 2007a). If the offender's identity is known, crime linkage may support the linkage of other crimes committed by the offender where their identity was hidden. Alternatively, if the offender's identity is unknown, crime linkage may be helpful to link a series of crimes to each other.

Linking crimes based on behavioural information follows two assumptions, i.e., that an offender will behave consistently across crimes within their own series, and in a manner distinctive from other offenders (Bennell & Canter, 2002). For crime linkage to be accurate in practice, empirical evidence is needed that these two assumptions are valid. The validity of the underlying principles of crime linkage have been a topic of debate in court cases where crime linkage analysis was being presented as expert evidence (Labuschagne, 2014; Pakkanen et al., 2014). Therefore, the accuracy of predictions regarding series membership is of interest to researchers and practitioners alike (Slater et al., 2015).

A considerable body of research has now amassed testing the validity of these two assumptions for different crime categories including burglary (Bennell & Jones, 2005; Goodwill & Alison, 2006; Markson et al., 2010), robbery (Burrell et al., 2012), homicide

(Bateman & Salfati, 2007; Santtila et al., 2008), arson (Santtila et al., 2004), car theft (Tonkin et al., 2008), and sexual offences (Grubin et al., 2001; Woodhams & Labuschagne, 2012). Testing for *difference* in levels of similarity between linked and unlinked pairs, does not equate with linkage prediction. The current paper focuses on statistical models which have been used to make *predictions* of crime linkage. Often, the validity of the assumptions is tested using statistical methods which predict which crimes are linked to one another based on behavioural similarity and these predictions are compared to what is known to be the case in reality (are two crimes linked or not). Confidence in attribution of crimes to the correct series is often assured by including crime series in the test dataset which have been solved or for which a conviction has been secured.

Statistical models to link crimes

In the past decade, the processes and barriers for analysts linking crimes have been explored. Human decision making can be fallible, as memory and processing are limited (Tonkin & Weeks, 2021). For example, an analyst may be tasked with comparing an offence to hundreds of other offences to determine whether they are linked (or not). This process can be time consuming and there is inherent subjectivity and variability in how analysts may choose which behavioural variables are prioritised for linking crimes (Burrell & Bull, 2011; Davies, 2018). Finally, the exposure to potentially distressing material over multiple hours can have a negative impact on an analyst's mental well-being (Duran & Woodhams, 2022).

Given the obstacles for human analysts, partial automation of the crime linking process, and development of decision support tools for analysts is underway. The aim is to use statistical methods previously used in empirical research studies to support prioritisation of offences, which analysts can then focus on. This would save time, improve accuracy, provide standardisation in practice, and evidence decision making (Tonkin & Weeks, 2021), provided that crime linkage predictions can be made accurately using these methods. For example, logistic regression models can provide a predicted probability of a pair of crimes being linked (or not) based on selected behavioural variables. This can be computed for all possible pairs in a dataset, and they can then be arranged in descending order of predicted probability. Those higher up on the list can be prioritised by analysts as potential links to analyse further (Tonkin et al., 2019).

The recent focus of crime linkage research has been to test the performance of different statistical models in predicting if crimes are linked or not with a variety of different crime types. When making decisions about the application of such models in practice, it is important to ascertain their accuracy, and factors which influence accuracy (for example, crime type, statistical model used, behavioural variables used, sample composition etc.) when making predictions about crimes being linked or not (Bennell et al., 2014).

Measuring predictive accuracy of crime linkage models

The predominant approach for evaluating accuracy of statistical models to link crimes has been to calculate the Area Under the Curve (AUC) statistic produced by Receiver Operating Characteristic (ROC) analyses. This was introduced to crime linkage research by Bennell and Canter (2002) to measure accuracy of crime linkage predictions. They described crime linkage as a diagnostic task in which two possible predictions can be made (linked or unlinked) with there being two outcomes in reality (linked or unlinked). This leads to four outcomes (hits, misses, correct rejections, and false alarms) (Table 1). The ROC analysis plots hit rates vs false alarm rates to produce a curve of all possible decision thresholds. The AUC ranges from 0 to 1, whereby 0.5 suggests that the prediction accuracy of the model is no better than chance, 0.5-0.7 is low, 0.7-0.9 reflects moderate predictive accuracy, and 0.9-1 high accuracy (Swets, 1988). Anything below 0.5 suggests that the model's ability to predict whether crimes are linked or not is less than chance performance.

Table 1

The four potential outcomes for prediction of crime linkage (adapted from Bennell & Canter, 2002, p. 154)

PREDICTION	**REALITY**	
	Linked	**Unlinked**
Linked	Hits	False alarms
Unlinked	Misses	Correct rejections

The AUC value denotes a probability. For example, an AUC of 0.70 would mean that there is a 70% chance that a randomly selected linked pair is likely to have a higher similarity co-efficient or probability of being linked compared to a randomly selected unlinked pair (Bennell et al., 2009; Davidson & Petherick, 2021). "High" and "low" accuracy are dependent on the consequences of a false alarm or miss for different diagnostic tasks (Bennell et al., 2014). The AUC is considered a useful measure of diagnostic accuracy as it is independent of the threshold or criterion that is placed by the model, which can often be arbitrary, and would allow practitioners to select a threshold depending on the context and consequences for a range of false alarm rates and hit rates (Ewanation et al., 2023). It is also independent of the prevalence of the target condition (linked crimes) in the test sample (Swets, 1988; Douglas et al., 2013), and instead depends on the proportion of possible predictions and actual outcomes of linked and unlinked crimes (Ewanation et al., 2023). Another benefit of the AUC statistic is that it can be used to compare different statistical models used for crime linkage.

Other measures of accuracy have been used to evaluate statistical models for crime linkage. This has been considered in further detail by Burrell et al (2024). Other measures include hits and false alarms, precision, and position in a ranked list. These measures of effectiveness provide a percentage accuracy. The probabilities or percentages of correct predictions will vary as a function of the decision threshold applied for the model (Swets, 1992). For example, when calculating the hit rate of a model that provides a ranked list of offences, the decision of how many rankings should be considered for scanning potential links will impact the hit rate. This means that if stricter decision thresholds are applied for whether two crimes are linked or not this would reduce the false alarm rate and also the hit rate. Alternatively, more lenient decision thresholds would improve the hit rate but also increase the false alarm rate (Bennell & Canter, 2002).

Given the predominance of the AUC statistic in the crime linkage literature, and the potential implementation of statistical models in decision support tools, it was considered timely to summarise the levels of accuracy (as measured by AUC) that have been reported in the crime linkage research. Therefore, this meta-analysis focuses on this measure of how accurately statistical models can predict whether crimes are linked and the factors that can impact on this.

Rationale

In a literature review, Bennell and colleagues (2014) considered the effectiveness of statistical models used in crime linkage. They highlighted that an evaluation of effect sizes was not possible in 2014 due to considerable variation in statistical models and approaches in the literature. Further, Fox and Farrington (2018) completed a systematic review and meta-analyses of the offender profiling literature. This included a sub-analysis of the effectiveness of statistical models for crime linkage, as measured by the AUC statistic. The results suggested that statistical models performed in the moderate to high range when applied to crime linkage. However, Fox and Farrington (2018) did not evaluate different statistical models, and only included the most common behavioural domains used in the literature. They completed a quality evaluation for the studies included in the meta-analysis, however it did not consider certain nuances. For example, the sample size used in studies was evaluated, but not the quality of the sample. The number of variables used in a study was considered, and the complexity of statistics; however, the impact of these factors or the specific statistical models on effectiveness of crime linkage was not explored.

There are multiple factors which can influence how effectively crimes can be linked. This includes the behavioural domains used to link crimes, the crime type/category, the sample composition, and statistical model used. The latter has not been explored to date. The aim of the current meta-analysis is to assess the accuracy of different statistical models for linking crimes, for different crime categories, as measured by the AUC statistic. The variation and influence of behavioural domains used to conduct crime linkage are also considered in this analysis. Important variables of interest such as sample quality and composition are assessed within the quality evaluation for included studies. This meta-analysis aims to contribute to the field's overall understanding of the effectiveness of statistical models. It adds to the evidence base and provides a foundation to direct future research to prioritise the more beneficial models, which can be of assistance to crime analysts in the field. Finally, it updates the previous review (Bennell et al., 2014) and meta-analysis (Fox & Farrington, 2018) by at least six years, as the previous papers had included studies from 2002 to 2013 and 2016 respectively[2].

Methods

Identifying primary studies

Search of electronic databases

A systematic search of the literature was conducted in June 2022 (updated until 31st December 2022), using the OVID platform, and included the following databases: *APA PsycInfo*, *APA PsychArticles*, *Embase*, *Ovid Medline*, and *Social Policy and Practice*. *Web of Science* and *PubMed* were used as additional databases. The aim was to obtain a comprehensive overview of the literature pertaining to the accuracy of crime linkage. The search terms used are outlined in Table 2.

[2] Bennell et al (2014) included 17 papers between 2002 and January 2013, and Fox and Farrington (2018) included 18 papers from 2002 to 2016.

Table 2

Search terms used to identify studies pertaining to crime linkage.

Construct	Free text search terms			Method of search	Limits
	OVID	**PubMed**	**Web of Science**		
Offence	arson* burglar* car thef* child abuse material child porn child sex* abuse material child sex* exploitation contact offen* crim* groom* homicid* indecent image* murder* offen* p?edophil* rap* rapist* robber* serial offen* sex* abuse sex* assault* sex* exploitation sex* offen* theft*1 vehicle ADJ1 crime	arson* burglar* car thef* child abuse material child porn child sex* child sex* abuse material contact offen* crim* criminal* groom* homicid* indecent image* murder* non?contact offen* paedophil* rape* rapist* robber* serial offen* sex* abuse sex* assault* sex* exploitation sex* offen* theft* vehicle crime	arson* burglar* car thef* child abuse material child porn child sex* abuse material child sex* exploitation contact offen* crim* groom* homicid* indecent image* murder* non?contact offen* p?edophil* rape* rapist* robber* serial offen* sex* assault* sex* exploitation sex* offen* sex*abuse theft*1 vehicle NEAR/1 crime	Search terms within each construct were combined with *OR* Search terms of Offence and search terms of Crime linkage were combined with *AND*	Peer reviewed. English language. Title
Crime linkage	profiling crim* link*	profiling crim* link*	profiling crim* link*		

link* crim*	link* crim*	link* crim*
psychological link	psychological link	psychological link
behavio* link*	behavio* link*	behavio* link*
comparative case	comparative case	comparative case
analys?s	analys?s	analys?s
linkage analys?s	linkage analys?s	linkage analys?s
case link*	case link*	case link*
linking crim*	linking crim*	linking crim*
link* ADJ5 serial	link* serial	link* NEAR/5
link* ADJ5 series	link* series	serial
series membership	series membership	link* NEAR/5
crim*4 analysis	crim* analysis	series
behave?ral case	behave?ral case	series membership
link*	link*	crim*4 analysis
computer decision	computer decision	behavi?ral case
support tools	support tools	link*
behavi?r*	behavi?r*	computer decision
consistenc*	consistenc*	support tools
behave?r*	behave?r*	behavi?r*
distinct*	distinct*	consistenc*
signature analys?s	signature analys?s	behavi?r*
behavi?r* link*	link*	distinct*
link*		signature analys?s
		link*

Inclusion Criteria

The aim of the literature search was to identify primary studies which reported the accuracy of crime linkage predictions using the AUC measure. The AUC measure was considered necessary to compare predictive accuracy across studies. Eligible studies were those that included offences committed in the physical world (rather than online offences). The studies were required to have used offence (i.e., crime scene) behaviours to link crimes. Finally, it was important that the study evaluated *predictions* of crime linkage made by statistical models. Studies which measured the similarity between crime pairs *only*, even if they included tests of difference for different types of crime pairs (e.g., linked vs. unlinked), were not included because no *prediction* was made. A complete set of inclusion and exclusion criteria are described in Table 3.

Table 3

Inclusion and exclusion criteria applied to search results returned from databases.

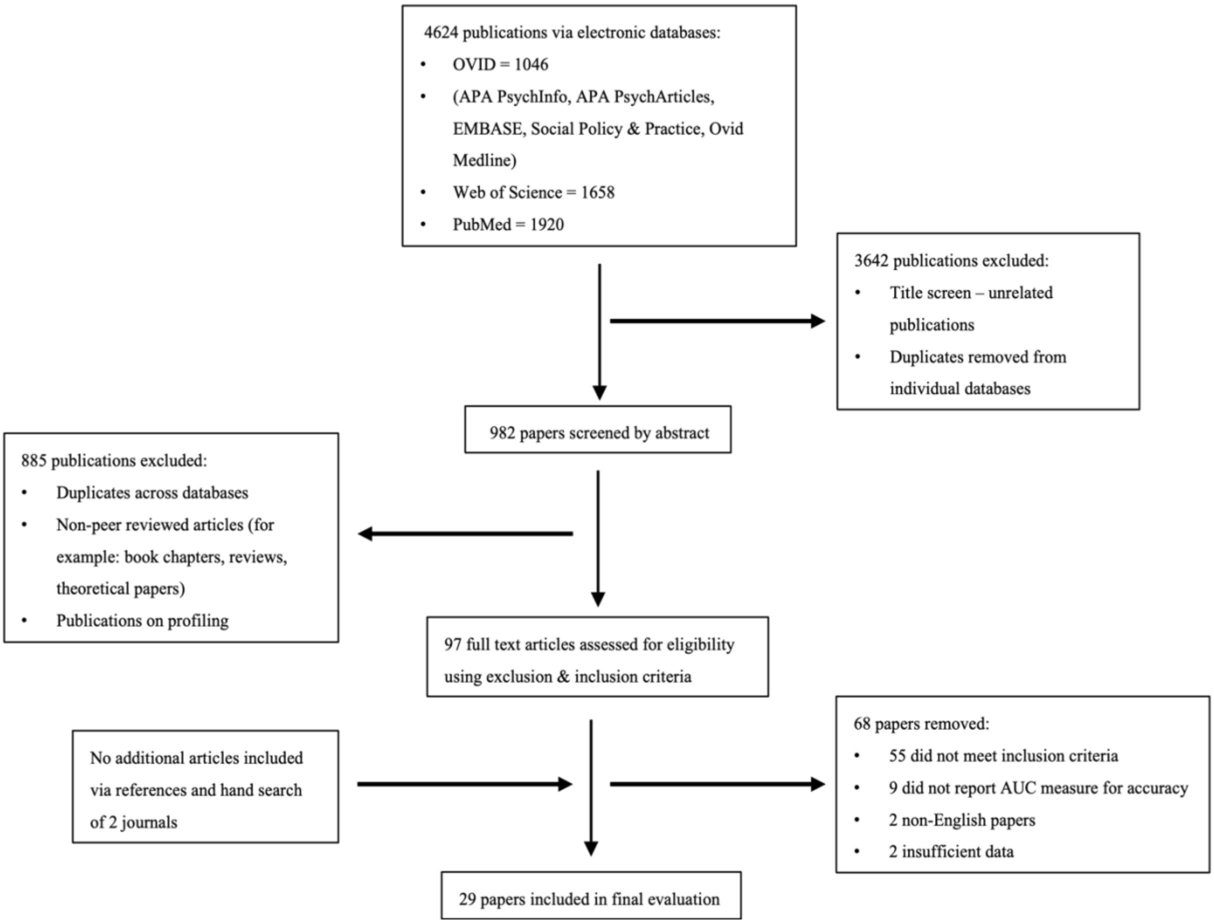
Inclusion criteria	Justification
Publication	
Included: peer reviewed journal articles. Excluded: Meta analyses, theoretical papers and commentaries, book chapters, reviews, theses, conference papers and proceedings, unpublished data, case studies.	Excluded papers did not provide necessary outcome data, i.e., AUC measure for accuracy of crime linkage, or robustness of peer review process. It is important to note that theses are subject to a type of peer review process, however the standard is not comparable to a peer review process for journal publication. Further, theses were not included in the previous review (Bennell et al., 2014) and meta-analysis (Fox & Farrington, 2018) relating to crime linkage. To ensure consistency in the type of publications evaluated this exclusion criteria was retained. Finally, for the development of policy and practice it is more likely that research produced in journals, commissioned project reports, or fellowships/placements/secondments are used (Government Office for Science, 2013). For example, rapid evidence reviews also include grey literature, however these are often commissioned projects reports as opposed to doctoral or master's level theses (e.g. Moniz et al., 2023).
Data characteristics	

<u>Included</u>: crime linkage of offences in the physical world using behavioural data (for example: sexual assault, car thefts) <u>Excluded</u>: crime linkage of online offences (for example: cyber offences), or crime linkage using forensic material (for example: DNA, soil analyses, fingerprints).	Online offences are considered a different type of offending. Currently, there is not sufficient research on linking online offences to make a sensible comparison to offences in the physical world. Crime linkage using forensic material does not address the aim of this meta-analysis.
Treatment	
<u>Included</u>: studies that provide a test of crime linkage using behavioural data, and accuracy of crime linkage. <u>Excluded</u>: studies that test principles of crime linkage – i.e., behavioural consistency and/or distinctiveness only (for example: tests of difference), and studies that link crimes using forensic material.	Excluded studies did not address this meta-analysis.
Outcomes	
<u>Included</u>: studies of crime linkage that reported an accuracy measure of the crime linkage method, using AUC. <u>Excluded</u>: studies that did not provide an accuracy measure of crime linkage, and studies that included an accuracy or precision measure of crime linkage that is not AUC (for example: percentage correct)	At this stage it was not possible to compare different accuracy measures of crime linkage. The AUC measure provides a statistic that is based on hits, false positives, misses, and correct rejections. Other measures of accuracy include percent accurate, for example based on a ranked list of linked pairs. This measure provides the hits and false alarms, however not the correct rejections or the misses which makes it a) difficult to calculate the AUC, and b) if the AUC is calculated, the percent accuracy is only relevant to a proportion of the dataset selected (where the researchers set the cut-off), instead of the entire dataset. Therefore, the meta-analysis focused on the most common method of measuring accuracy in crime linkage, i.e. the AUC.

The results of the systematic search are presented in Figure 1. The search yielded 4,624 publications. After screening titles (for publications unrelated to the topic) and removing duplicates, 3,642 were excluded. Examples of unrelated publications include those relating to rapeseed oil or linking personality constructs to behaviours. The abstracts of the remaining 982 publications were screened, and a further 885 were excluded. The most common reasons for exclusion were that publications were not peer reviewed (for example, book chapters), related to profiling, not crime linkage. Subsequently, the full text of 97 articles were assessed for eligibility using the exclusion criteria for publication, data characteristics, treatment, and outcome measures outlined in Table 3. A total of 29 articles met the inclusion criteria and were evaluated in the meta-analysis. No additional articles were identified from reference lists of included articles, or previous reviews.

Figure 1

Results of the systematic search and the application of the inclusion criteria.



Data extraction

Data from the papers were extracted by the author. The expectation was to extract hit rates and false positive rates, or sensitivity and specificity, to calculate the AUC measure and produce a summary ROC plot. However, the full text screening revealed that majority of papers only produced AUC values, and other measures of accuracy stated above were not available. Therefore, the AUC outcomes and corresponding standard errors (SE) were extracted. The index tests (the statistical model used to link crimes), reference tests (how crimes are known to be linked, for example solved cases, or linked by DNA), crime category, and behavioural domain for each AUC outcome were also extracted. For two papers, authors were contacted, and SEs were provided by them as these were not included in the published paper. Two additional papers were excluded in the identification stage as authors were unable to provide SEs for the corresponding AUC values and were excluded as outlined in Figure 1. Table 4 provides a list of extracted variables, their definitions, and examples.

Table 4

Variables extracted for the meta-analysis, definitions, and examples.

Variable	**Example**
Crime category: the category of offences being linked	Sexual assault, burglary, robbery, car theft, homicide, arson, within crime types, across crime categories, across crime types
Index test: the statistical models used to link crimes	Logistic regression, Bayesian analyses, classification trees, similarity coefficient, multidimensional scaling, discriminant functional analysis, multiple correspondence analyses.
Reference test: how crimes are known to be linked	DNA linked, convictions, solved

Behavioural domain: behaviours used as input for the index test to link crimes.	MO, All MO, Geographical, Temporal proximity, Combined, Optimal.

Each paper produced multiple AUC values and SEs, based on variation at different levels. These levels included difference in *index test* (e.g., logistic regression vs Bayesian analyses vs classification trees); difference in *crime category* (e.g., crime linkage for car thefts vs. crime linkage for burglaries); different *behavioural domains* used by the index test (e.g., inter-crime distance (ICD), vs temporal proximity (TP), vs entry behaviours); and, less often, difference in *similarity coefficient* (e.g., Jaccard's coefficient vs simple matching index). On completing data extraction from the 29 papers (n_s), 206 outcomes (n_o) were retrieved. An inherent limitation in this dataset was a lack of absolute sample independence between effects. At times, different statistical models were used on the same sample to compare performance within a study. However, the effect of the statistical model's performance is being assessed in this meta-analysis, as opposed to an effect of the sample. Further, in choosing the meta-analytic model a three-level model was evaluated, which would control for within and between studies variation. Finally, when samples have been reused across studies, these are different subsets of a dataset, and often manipulated differently across studies. Therefore, they are not identical samples. The previous meta-analysis by Fox and Farrington (2018) also reported on multiple effects from each study and used a random effects model to evaluate the weighted mean effects.

Data reduction

Papers significantly varied in description, number, and type of behavioural domains used. Behavioural domains were therefore collapsed to represent broader behavioural domains, which were used in the analyses (see Table 5), and statistical models were collapsed to reflect broader analytic methods, described in Table 6.

Table 5

Definition and examples of data reduction for behavioural domains.

Reduced variable for behavioural domain
MO (Modus operandi): any individual behavioural domain that is used by the index test to link crimes. This excludes behaviours of geographical distance and temporal proximity. For example, included MO behaviours may be target selection, or control, or entry behaviour.
All MO (all MO behaviours in study): all individual MO behaviours are combined into one variable (one overall measure of behavioural similarity) and used by the statistical model to link crimes.
Combined: a variable which combines all MO behaviours, and/or geographical proximity, and/or TP. For example, combining TP, ICD, target selection, entry behaviours, internal behaviours, and property stolen. This would represent a 'combined' behavioural domain. In the primary papers, the combined domain was represented by statistical models which included all MO behaviours, and/or geographical proximity, and/or TP (e.g. forced entry method for logistic regression) to predict crime linkage.
Optimal: The optimal combination of MO behaviours, geographical proximity, and TP as suggested by the statistical model used to link crimes. For example, in a crime linkage study of burglaries, the logistic regression indicated the combination of ICD and TP was the optimal combination for predicting whether crimes were linked (Markson et al., 2010). Such variables were named Optimal behavioural domain for the meta-analysis. In the primary papers, the statistical model would select what it considers to be the optimal subset of variables from a larger set that were entered into the model (e.g. via stepwise logistic regression), for crime linkage prediction.
Geographical: ICD or inter-dump distance (IDD)
TP: time between two offences (for example, number of hours, days, months).

Table 6

Data reduction of index tests to represent broader index tests in the meta-analysis.

Specific index test types	**Reduced variable for index test**
Simple logit, stepwise logistic regression, direct logistic regression	Logistic regression
Naïve Bayes, naïve Bayesian classifier, bayesian analyses, bayesNet	Bayesian analyses

Iterative classification tree, boosted trees, decision trees, random forest decision tree, simple decision tree, logistic decision tree, standard classification tree	Classification trees
Similarity coefficient	Similarity coefficient
Discriminant functional analyses	Discriminant functional analyses
Multidimensional scaling	Multidimensional scaling
Multiple correspondence analyses	Multiple correspondence analyses

The guidelines for meta-analyses produced by Dr Christopher Jones at the Centre for Applied Psychology (University of Birmingham, UK), were followed to conduct this meta-analysis.

Defining variance

A study level effect is considered heterogeneous if it presents with variation from the meta-analysis synthesis that cannot be attributed to true variation in the distribution of the measured effects. Heterogeneity can result from methodological differences, measurement error or uncontrolled individual difference factors within the body of literature. Higgins I^2 is a commonly used measure of heterogeneity (between studies variation not attributable to the effect itself, and instead reflects differences in methodology, participant characteristics, and/or precision of measurements). Greater values of I^2 indicate variation in effect that cannot be attributed to true variation in the distribution of effect. As there is considerable variation in methodologies used to study the accuracy of crime linkage models[3], problematic heterogeneity was defined as a Higgins I^2 value greater than 75%. This threshold value was selected as it

[3] There were multiple sources of variation between studies that aimed to assess the effectiveness of statistical models to make linkage predictions, e.g., the sample composition (whether or not one-off offences were included in the sample), or the type and number of behavioural domains used.

represents “high” levels of heterogeneity in original description of the index (Higgins et al, 2003). Where unacceptable or problematic heterogeneity is observed then the focus of the subsequent analyses will be upon the identification of the sources of heterogeneity between the estimates of effect in the primary studies.

Risk of bias assessment

To assess potential risk of bias within the articles included in the meta-analysis, a set of criteria were developed. These criteria were adapted from the Quality Assessment of Diagnostic Accuracy Studies–2 checklist (QUADAS-2 Whiting et al., 2011). This checklist is a validated tool containing four areas to be assessed for risk of bias when completing a literature review. These areas include *patient selection*, *index test*[4], *reference standard*, and *flow and timing* (Whiting et al., 2011). The first three areas have two sub domains each: *risk of bias* and *applicability concerns*. For the outcomes synthesised in the current meta-analysis, *flow and timing* were not considered relevant. The *risk of bias* and *applicability concerns* in the three areas, and criteria for *Low*, *Unclear,* or *High* risk are described in Table 7. For each risk of bias domain, multiple prompt questions were used by which a study could be assessed for level of risk. In cases where multiple prompt questions were used, the highest risk indicator was used as the score for the specified area of risk. This provided a conservative and strict assessment of a study. The study design was also scored, whereby retrospective studies were considered less robust than prospective studies.

[4] Note that in the methods and results index tests refer to statistical models used to link crimes.

Summary of risk of bias assessment

An example of the risk of bias ratings for different risk domains for each primary study has been illustrated in Table 8. The complete list of risk of bias ratings can be requested from the author.

Table 7

Definitions and criteria for risk of bias areas, and derivation of overall quality index (OQI).

Domain	Description	Risk of bias
Patient selection Risk of bias	*Definition:* Studies should include a consecutive or random sample of eligible patients with the target disease. Excluding patients that are difficult to detect with the target condition may lead to overestimation of diagnostic accuracy. *Signalling question:* • Did the sample include unsolved cases, and/or one off offences?	**Low risk:** Yes, sample included unsolved cases and/or one off offences. **Unclear risk:** Unclear whether sample included unsolved and/or one off offences. **High risk:** No, sample did not include unsolved and/or one off offences.
Patient selection Applicability concerns	*Definition:* The sample and setting should be reflective of the review question. If the sample differs in severity, features, setting, or comorbidity with the target disease addressed by the review question it may increase sensitivity of detection in the study. *Signalling question:* • Does the sample consider base rates of the crime being evaluated either in the population or a relevant police database? • Does the study use a uniform number of offences per series or control for highly prolific offenders with longer series? This is to avoid undue weight being given to highly prolific offenders with high or low levels of behavioural similarity or distinctiveness.	**Low risk:** Yes, series are reflective/consider base rates. Uniform number of offences per series are used or weight of highly prolific offenders is considered in analysis. **Unclear risk:** Insufficient information about whether series and offences are reflective of base rates. **High risk:** No, series of linked offences and unlinked offences are not representative of base rates. Study does not use uniform number of offences per series or control for highly prolific offenders.

Index test Risk of bias	*Definition:* The index tests (i.e., the statistical procedure used to link crime) should be interpreted without the knowledge of the reference test (i.e., whether offences are linked or not). Prior knowledge about linkage status can influence the interpretation or operationalisation of the index test. *Signalling question:* • Was the index test used to link crimes tested on training and experimental samples, or was another form of cross validation used (for example: leave one out method)? • Is interrater reliability of coding behaviours reported? • Is the analyst/researcher blind to linkage status when coding behaviours and using index tests?	**Low risk:** Yes, training, and experimental sample was used, or another form of cross validation. The interrater reliability was reported. The analyst/researcher was blind to linkage status. **Unclear risk:** Not reported whether cross validation was used or experimental and training example. Unclear whether interrater reliability was conducted. Blinding to linkage status is not mentioned. **High risk:** No cross validation or training and experimental sample is used. Interrater reliability was not used. Analyst/researcher has knowledge of linkage status.
Index test Applicability concerns	*Definition:* The conduct and interpretation of the index text should match the review question. If non-standardised conduct or interpretation of index test is used it can influence the estimate of diagnostic accuracy. *Signalling question:* • Do the statistical procedure used to link crimes match real world application of crime linkage/are accessible to analysts or police who link crimes? • Are behavioural variables used for index test recognised, coherent, and logical for the purpose of linking crimes?	**Low risk:** Yes, the statistical procedure used to link crimes is accessible to analysts/police and match real world application. Behavioural variables used for index test are appropriate. **Unclear risk:** Insufficient information about whether the statistical procedure used to link crimes matches real world application or is accessible to analysts/police. Unclear whether behavioural variables have been established as recognised, logical, and coherent in previous literature. **High risk:** The statistical procedure used to link crimes is not recognised or match real world application. Selection of behavioural variables for index test are not established in literature.

Reference test Risk of bias	*Definition:* The references standard (i.e. how we know that offences are part of a series) should be 100% sensitive. This is to ensure that differences between the index test (the statistical procedure used to link crimes) and reference standard are due to incorrect classification by the index test. It is also important that the reference test is interpreted without prior knowledge of the index test to avoid influence of prior knowledge on its interpretation. *Signalling question:* • Is the reference standard (ground truth that offences are linked) 100% accurate? • Is the reference standard interpreted prior to the knowledge of the index test?	**Low risk:** Yes, highly objective criteria were used to consider offences as linked (i.e. DNA evidence). The statistical procedure used for linking offences did not influence the reference test and do not form part of it. For example: linkage status was confirmed prior to analyses, or blinding to index test results if reference standard is conducted prospectively. **Unclear risk:** The reference standard for confirming linked offences is convictions or considered solved. Both of which cannot be 100% sensitive and the potential for miscarriages of justice. Insufficient information about whether the behavioural variables used for the index test formed part of the reference standard. **High risk:** The reference standard for whether offences are linked is via arrests or charges, which are less likely to be 100% sensitive. Behavioural variables used for index test formed part of the reference standard. For example, in prospective studies where the index test influences arrests or charges of an offender.
Reference test Applicability concerns	*Definition:* Even when the reference standard is free of bias, the condition it defines may differ from that specified by the review question. For example, the threshold at which offences are considered as linked by the reference standard in a study may differ from the review question. *Signalling question:*	**Low risk:** Yes, the study's reference standard matches the review questions definition of linked offences. **Unclear risk:** Unclear whether linked offences as defined by the reference standard match linked offences as defined by the review question. **High risk:** No, linked offences as defined by the reference standard do not match linked offences as defined by the review question.

- Do linked offences defined by the reference standard match linked crimes as defined by the review question?

**OQI is the percentage representation of the Overall Quality Score (OQS). The OQS was derived from the sum of the study design score and the overall risk of bias score. According to the rating scale, higher OQI and OQS reflect better study quality.

Table 8

Ratings of risk of bias for primary studies included in the meta-analysis.

Study (Behaviour domain) – crime	Selection Bias	Selection Concerns	Test Bias	Test Concerns	Reference Bias	Reference Concerns	OQI
Tonkin, Woodhams, Bull, Bond & Santtila, 2012 (MO) - Car theft							21%
Bennell, Jones, Melnyk 2009 (Combined) - Sexual assault							19%
Woodhams, Toye 2007 (MO) - Robbery							19%
Porter 2016 (Combined) - Burglary							19%
Woodhams, Labuschagne 2012 (Combined) - Sexual assault							25%
Tonkin, Woodhams, Bull & Bond, 2012 (Geographical) - Across crime categories							25%
Bennell, Jones 2005 (Optimal) - Burglary							21%
Ellingwood et al 2013 (Optimal) - Arson							19%
Bennell, Bloomfield et al 2010 (Geographical) - Burglary							22%
Tonkin et al 2011 (Geographical) - Across crime categories							21%
Halford 2022 (Optimal) - Burglary							19%
Burrell, Bull, Bond 2012 (MO) - Robbery							19%
Markson, Woodhams, Bond 2010 (Geographical) - Burglary							19%
Woodhams et al 2019 (All MO) - Sexual assault							25%
Slater et al 2015 (All MO) - Sexual assault							22%
Davies et al 2012 (MO) - Car theft							19%
Tonkin, Santtila, & Bull, 2012 (Optimal) - Burglary							21%
Tonkin, Grant, Bond 2008 (MO) - Car theft							19%
Winter et al 2013 (All MO) - Sexual assault							21%
Tonkin et al 2017 (All MO) - Sexual assault							26%
Tonkin et al 2019 (Combined) - Burglary							19%

Melnyk et al 2011 (All MO) - Burglary							19%
Davidson, Pertherick 2021 (All MO) - Sexual assault							19%
Bennell, Gauthier et al 2010 (All MO) - Sexual assault							19%
Bennell et al 2021 (All MO) - Sexual assault							19%
Yokota et al 2017 (All MO) - Sexual assault							19%
Winter, Rossi 2021 (All MO) - Sexual assault							19%
Pakkanen et al 2021 (All MO) - Homicide							22%
Oziel, Goodwill, Beauregard 2015 (All MO) - Sexual assault							19%

Patient selection: risk of bias

Overall, the selection of offences in the sample (i.e., solved, unsolved, and one-off offences) were evaluated as 'High' risk (n_s = 23; n_o = 165). Such high-risk samples were due to inclusion of only solved and serial offences in the sample. Some studies were rated as 'Low' risk (n_s = 5; n_o = 40). Studies with a low-risk rating clearly included one-off offences, unsolved offences, or both, within their sample (Slater et al., 2015; Tonkin et al., 2012; Tonkin et al., 2017; Tonkin, Woodhams, Bull & Bond, 2012; Woodhams et al., 2019; Woodhams & Labuschagne, 2012). One study sample was evaluated as unclear risk, as it included unlinked offences, however it was not clear whether these were unsolved or one-off offences (Bennell et al., 2010).

Patient selection: applicability concerns

Applicability concerns for sample selection (i.e., the extent to which the offence composition is reflective of base rates) was generally rated as 'High' risk (n_s = 24; n_o = 143). This rating was often due to a lack of consideration of base rates in the composition of offences (solved, unsolved, serial, and one-off). However, most studies used a uniform number of offences per series (e.g., Tonkin, Woodhams, Bull & Bond, 2012; Yokota et al., 2017) or controlled for the weight of highly prolific offenders with longer series in the analyses (e.g., Porter, 2016). Including a fixed number of crimes per series or including all crimes per series (whilst controlling for the influence of highly prolific offenders) has pros and cons. A fixed number of crimes per series reduces the influence of undue weight of highly prolific offenders on the results, however it is ecologically less valid. Whereas, including all crimes per series is a more ecologically valid approach, however undue weight of prolific offenders is not accounted for. Therefore, it was considered appropriate to consider it low risk if a primary paper adopted either of these approaches. Some studies were considered to have an 'Unclear' risk (n_s = 5; n_o = 63), attributed to base rates being considered in the text, however there was ambiguity about whether the sample was reflective of these considerations. No studies were rated at a 'Low' risk as none clearly outlined base rates of offences and how this was incorporated in the sampling approach.

Index test: risk of bias

The risk of bias for the index test (i.e., the statistical model used to link crimes) was generally rated as 'High' risk (n_s = 22; n_o = 149). The three criteria for assessing risk of bias for this domain included reporting interrater reliability, cross validation procedures, and analyst/researcher blindness to linkage status. Studies rated as high risk were often unclear about whether the analyst/researcher was blind to linkage status at the time of analyses. Knowledge of linkage status (the reference standard) during analyses may influence the estimation of the index test's accuracy. Interestingly, Bennell and Jones (2005) have argued that even though low inter-rater reliability may decrease data quality, it is likely to add noise. Therefore, significant findings, if found, would be despite the noise rather than attributed to it. However, studies often conducted cross validation procedures (e.g., Bennell & Jones, 2005; Tonkin et al., 2011) (e.g., leave one out method cross validation), which was a strength. At other times, interrater reliability for coding behavioural variables was missing or vice versa. The remaining outcomes from studies were rated as 'Unclear' risk (n_s = 7; n_o = 57). In these studies, interrater reliability was always reported (e.g., Pakkanen et al., 2021; Tonkin, Santtila,

& Bull, 2012) or not applicable if using ICD or TP. Cross-validation procedures were also applied to samples using the index test. However, these studies were unclear on whether the researcher/analyst was blind to linkage status at the time of analyses. None of the studies were rated as 'Low' risk for this domain.

Index test: Applicability concerns

The applicability concerns of the index test for all studies were rated as 'Unclear' risk. Studies almost always used behavioural variables for the index test, which were recognised in the literature as pertinent to linking the specified offence categories. However, studies did not outline whether a specific index test is being used in practice by police departments or analysts. At present, there is a lack of clarity about whether specific index tests match the real-world application of crime linkage. Using statistical models to link offences is a relatively new field, and police/analyst practitioner work is not always available in the public domain. Therefore, the use of statistical tools in crime linkage practice is information that may not be accessible to researchers.

Reference test: Risk of bias

The reference test (i.e., ground truth about whether crimes are linked) was rated as 'Unclear' risk for most outcomes (n_o = 183). Most studies included samples of offences that were known to be linked or unlinked by convictions. Convictions require considerable evidence, but there is always potential for error or miscarriages of justice. In such instances, there cannot be absolute certainty that convictions are an accurate measure of reference. A strength of all studies was the interpretation of the reference test prior to predictions from the index test. This is due to the fact that all studies included in the meta-analysis were retrospective, i.e., offences were already known to be linked or unlinked. There were some studies which were evaluated at ‘Low’ risk for this domain. In these cases, the studies used DNA linked and solved offences as the reference standard (Tonkin et al., 2017; Tonkin, Woodhams, Bull & Bond, 2012; Woodhams et al., 2019; Woodhams & Labuschagne 2012). DNA evidence is currently the most accurate method to link or solve crimes, although it can be time-consuming and expensive to process during an investigation. DNA evidence is also only available in a minority of offences and so its use as a reference standard can be challenging.

Reference test: Applicability concerns

The applicability concerns around the reference test were considered ‘Low’ risk across all studies. This domain refers to whether the definition and threshold of whether crimes are linked by the reference standard in a study matches the definition and threshold of linked crimes addressed by the review question. The query about whether crimes are linked or not is a binary question and is widely agreed upon within the field. Therefore, this is a strength across studies and within the field.

Results

Overview of study composition

A total of 29 studies were included in the meta-analysis. Each study produced multiple effect sizes. These were due to studies investigating variations in index tests (i.e., statistical models used to link crimes, e.g., logistic regression), sample composition (e.g., inclusion/exclusion of one-off offences, and/or unsolved offences linked by DNA), and behavioural domain (i.e., behaviour used by index test to link crimes, e.g., ICD). Some studies also reported on more than one crime category or type (Melnyk et al., 2011; Tonkin, Woodhams, Bull, Bond & Santtila, 2012; Tonkin, Woodhams, Bull & Bond, 2012). Table 9 provides an overview of the crime categories, number of effect sizes and studies included, and outlines the countries represented in the studies.

Table 9

Distribution of studies by crime category and country.

	Car theft	**Robbery**	**Sexual assault**	**Homicide**	**Arson**	**Burglary**	**Across and within crime types/categories**	**Total**
UK	4	2	5	0	1	5	2	19
Finland	0	1	0	0	0	3	0	4
USA	0	0	0	1	0	1	0	2
Canada	0	0	2	0	0	0	0	2
Japan	0	0	1	0	0	0	0	1
*Across five countries	0	0	2	0	0	0	0	2
Italy	0	0	0	1	0	0	0	1
Australia	0	0	1	0	0	0	0	1

South Africa	0	0	1	0	0	0	0	1
Total	4	3	12	2	1	9	2	0
Number of outcomes produced	29	19	40	5	16	82	15	0

**The five countries include the UK, Belgium, Finland, South Africa, and Netherlands*

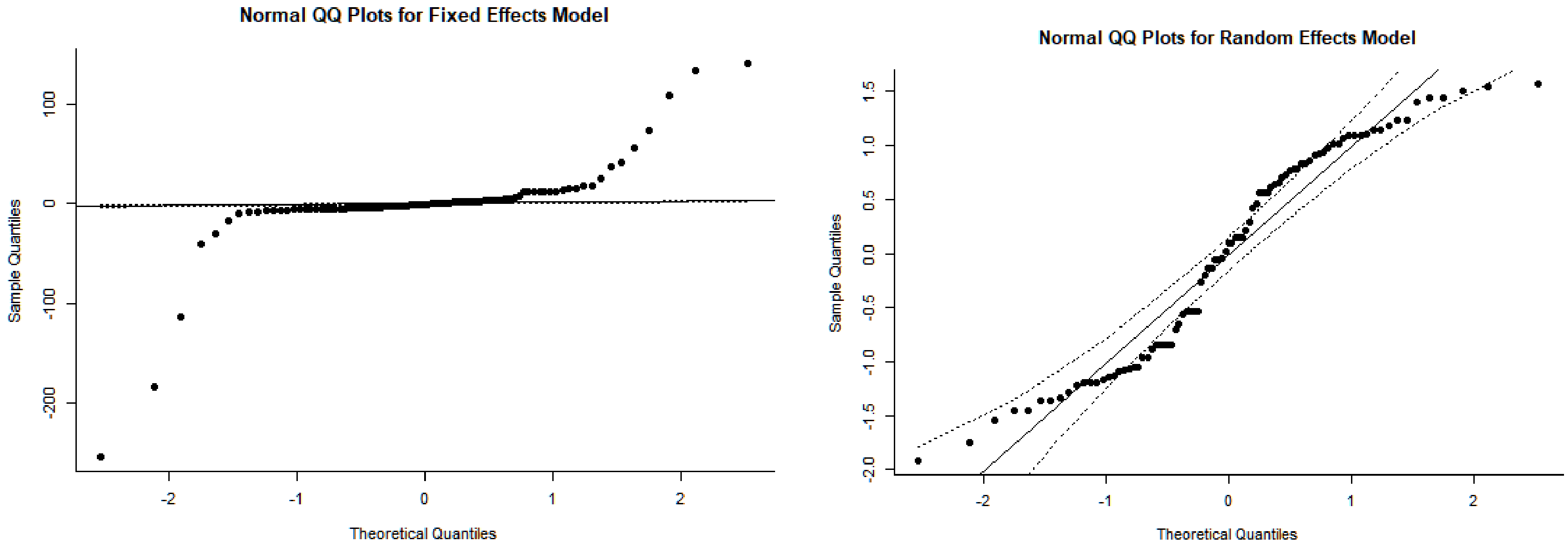
Selection of the meta-analytic model

The distribution of primary study effects using a fixed effects model and random effects model is shown in Figure 2 (a) and (b) respectively. The between studies variance (tau^2) in the random effects model was calculated using the Restricted Maximum-likelihood estimator.

Firstly, as can be seen from Figure 2a, there is clear evidence of non-linearity in the distribution of AUC outcomes in the fixed effects model, which is largely absent when the random effects model is used (Figure 2b). Accordingly, the random effects model using the restricted maximum likelihood estimator appears to be an appropriate analytical model for this dataset. Secondly, as multiple effects were reported for most studies, the three factor random effects model (which controls for between and within study variation) was compared to the two factor random effects model (which only controls for between study variation).

Figure 2

QQ plot of the distribution of AUC within the primary studies using a (as) fixed effects model and a (b) random effects model.



(a) (b)

As can be seen from Table 10, controlling for within studies variation (i.e., variation attributable to multiple sources of variation[5]) resulted in a statistically reliable improvement in accuracy of the random effects model.

Table 10

Likelihood Ratio Test of Within-Studies Variance

	df	AIC	BIC	AICc	logLik	LRT	*p*-value
Three factor model	3	-91.1	-83.7	-90.8	48.6		
Two factor model	2	160423.7	160428.7	160423.9	-80209.9	160516.8	<.0001

Table 11 outlines the decomposition of variance attributable to sampling variation, between studies variations and within studies variations. As approximately 74.6% of the total variation between studies could be attributed to within study variation (i.e., the reporting of multiple effect sizes from within a single study), the three-level model was selected as the appropriate random effects model for analysis.

Table 11

Decomposition of variance attributed to sampling variation, between studies variation, and within studies variation.

Source of variation	**Percent of total variation**
Sampling variation	0.8
Within-study variation	74.6
Between-study variation	24.6

[5] This is described in the methods section. Sources of variation at multiple levels include type of index test, crime category or type, behavioural domain, sample composition, and (less often) similarity coefficient, which could influence AUC outcomes.

The weighted average AUC was calculated by crime category, for each behavioural domain using the three level random effects model and the restricted maximum likelihood estimator of between and within groups variation. The typical ranges of AUC are as mentioned in the introduction. Therefore, a weighted average AUC greater than 0.7 would be required for the behavioural domain to be considered useful in the linking of crime. In addition, five or more separate effects are required for the weighted average AUC to be considered robust. Five was selected as a nominal minimal value, as there are no specific criteria which dictate the number of effect sizes required. It is possible that this cut off may not provide sufficient statistical power, and the results should be interpreted with caution.

AUC for crime linkage by crime category

Overall, the AUC values for different crime categories, across behavioural domains and index tests, ranged from moderate to high (see Table 12). An exception to this was car thefts, whereby the average AUC for crime linkage prediction was low. Despite homicide having the highest average AUC, the effect sizes are relatively few and therefore less robust. Crime categories of sexual assaults, burglary, car theft, and robbery have more robust results given the number of studies and effect sizes produced.

Table 12

Overall AUC value for each of the crime types across all behavioural domains and index texts

Crime Type	k	AUC	95%-CI	Q	I^2
Homicide	5	0.92	0.85; 0.98	15.23	73.70%
Sexual assault	40	0.84	0.81; 0.88	1170.29	96.70%
Arson	16	0.84	0.81; 0.87	212.37	92.90%
Across crime categories	6	0.81	0.73; 0.89	23.60	78.80%

Within crime types	5	0.81	0.75; 0.88	13.22	69.70%
Robbery	19	0.77	0.60; 0.938	240.34	95.40%
Across crime types	4	0.75	0.59; 0.90	23.06	87.00%
Burglary	82	0.74	0.71; 0.78	147505.79	99.90%
Car theft	29	0.68	0.63; 0.73	822996.98	100.00%

Note: Q represents the weighted sum of squares attributable to variation between studies or effects and conforms to a chi-squared distribution (Borenstein et al., 2009).

I^2 represents the heterogeneity between effects or studies attributed to differences between effects or studies, rather than by sampling error (chance) (Higgins et al., 2003).

Burglary

The three level random effects model for burglary, sub-grouped by behavioural domain demonstrated that the 'combined', 'geographical' and 'optimal' behavioural domains had an AUC > 0.7, derived from more than five effect sizes (see Table 13). The 'TP' domain reported a weighted AUC of 0.84 but this estimate was derived from only three effect sizes and is therefore unlikely to be robust. The 'All MO' and 'MO' domains reported weighted AUC values below the minimum value.

Table 13

Weighted AUC for crime linkage of burglaries across index tests, sub-grouped by behavioural domain.

Behavioural domain	k	AUC	95%-CI	tau^2	tau	Q	I^2
Optimal*	13	0.88	0.85; 0.91	0.002	0.0428	85.92	86.00%
Geographical*	12	0.88	0.86; 0.99	0.001	0.0327	50.26	78.10%
Temporal Proximity	3	0.84	0.80; 0.88	<0.0001	<0.0001	0.98	0.00%
Combined*	14	0.78	0.67; 0.90	0.06	0.2373	144898.91	100.00%
MO	36	0.64	0.58; 0.70	0.01	0.1039	155.18	77.40%
All MO	4	0.66	0.54; 0.78	0.006	0.0799	9.35	67.90%

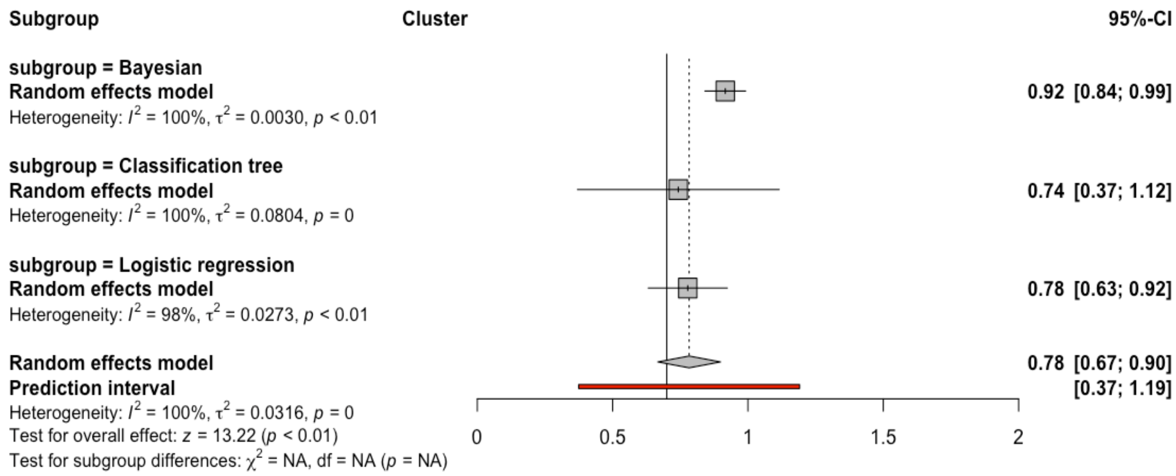
* *Behavioural domains that meet threshold for further subgroup analysis*

Note: tau^2 is a measure of heterogeneity between studies, and tau is the "estimated standard deviation of underlying effects across studies" (Deeks et al., 2019, pp. 264).

For the ‘combined’ behavioural domain, a subgroup analysis was conducted to examine difference in weighted AUC for the different index test types. The weighted AUC across index test types was 0.78 derived from 14 effect sizes combined from five studies. As can be seen from Figure 3, Bayesian approaches evidenced the greatest weighted AUC (0.92), followed by logistic regressions (AUC = 0.77), and classification trees (0.74).

Figure 3

Weighted AUC for crime linkage of burglaries using the Combined behavioural domain, sub-grouped by index test[6].



For the ‘geographical’ and ‘optimal’ behavioural domains, it was not possible to examine the difference in weighted AUC for different index test types (i.e. the statistical models used to link crimes). For the ‘geographical’ behavioural domain, only logistic regressions were used to link crimes across studies, with a weighted AUC = 0.88 derived from

[6] Note: The horizontal lines or ‘whiskers’ represent 95% confidence intervals, and the red horizontal line provides a spread of effects across all studies. It may be that the effect of the subgroup is unlikely to be significant when the whiskers cross the reference line (i.e. the dotted vertical line). The longer the whiskers, and bigger the box the more likely it is that the study or effects are smaller and less robust.

12 effect sizes, combined from six studies. For the 'optimal' behavioural domain, logistic regressions and classification trees were used to link crimes, however the latter was represented by only one effect size. The logistic regression for the 'optimal' behavioural domain had a weighted AUC = 0.88 derived from 12 effect sizes combined from four studies, and the classification tree for the 'optimal' behavioural domain had an AUC = 0.80 represented by one effect size from one study.

Sexual Assault

Table 14 shows that the 'All MO' behavioural domain evidenced a weighted AUC > 0.7 from 33 effect sizes. The 'MO' and 'combined' behavioural domains reported weighted AUC > 0.7 but this estimate was derived from only four and three effect sizes, respectively.

Table 14

Weighted AUC for crime linkage of sexual assault across index tests, sub-grouped by behavioural domain.

Behavioural domain	k	AUC	95%-CI	tau^2	tau	Q	I^2
MO	4	0.85	0.83; 0.88	0.0003	0.02	6.30	52.40%
All MO*	33	0.85	0.81; 0.89	0.009	0.09	1140.57	97.20%
Combined	3	0.81	0.72; 0.89	0.005	0.07	20.53	90.30%

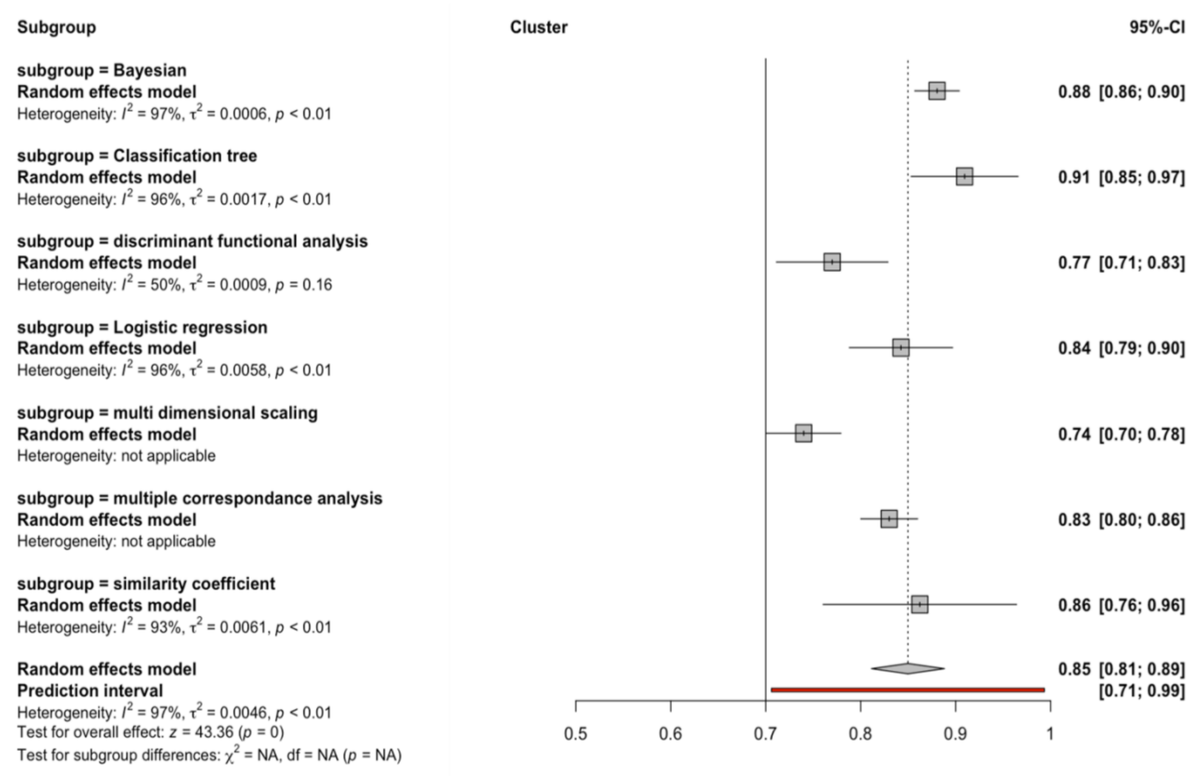
* *Behavioural domains that meet threshold for further subgroup analysis*

For the 'All MO' behavioural domain, a subgroup analysis was conducted to examine differences in weighted AUC for different index test types. The weighted AUC across index test types was 0.85 derived from 33 effect sizes combined from 10 studies. As can be seen from Figure 4, classification trees evidenced a greater weighted AUC (0.91) then Bayesian approaches (AUC = 0.88), Similarity coefficient approaches (AUC = 0.86), logistic regressions

(AUC = 0.84), multiple correspondence analyses (AUC = 0.83), discriminant functional analyses (AUC = 0.77), and multi-dimensional scaling (AUC = 0.74).

Figure 4

Weighted AUC for crime linkage of sexual assault using the All MO behavioural domain, sub-grouped by index test.



Car theft

Table 15 shows that the ‘geographical’ behavioural domain evidenced a weighted AUC > 0.7 derived from five effect sizes and combined from three studies. The ‘optimal’, and ‘TP’ behavioural domains reported a weighted AUC > 0.7 but these estimates were derived from only one effect size. Alternatively, the ‘combined, and ‘MO’ behavioural domains evidenced a weighted AUC < 0.7.

Table 15

Weighted AUC for crime linkage of car theft across index tests, sub-grouped by behavioural domain.

Behavioural domain	k	AUC	95%-CI	tau^2	tau	Q	I^2
Optimal	1	0.92	0.8612; 0.9788	--	--	0	--
Geographical*	5	0.839	0.7807; 0.8974	0.0022	0.047	11.61	65.50%
Temporal Proximity	1	0.78	0.7016; 0.8584	--	--	0	--
Combined	10	0.6819	0.5864; 0.7774	0.0235	0.1534	822027.52	100.00%
MO	12	0.5743	0.5143; 0.6343	0.0068	0.0824	34.59	68.20%

* *Behavioural domains that meet threshold for further subgroup analysis*

For the 'geographical' behavioural domain, it was not possible to examine the difference in weighted AUC for different index test types as only logistic regression had been used across studies to make linkage predictions for serial car thefts.

Robbery

Table 16 shows that the 'MO' behavioural domain and the 'combined' behavioural domain evidenced an AUC > 0.7 from more than five effect sizes. The 'geographical', 'optimal', and 'TP' behavioural domains reported a weighted AUC > 0.7 but this estimate was derived from less than five effect sizes.

Table 16

Weighted AUC for crime linkage of robbery across index tests, sub-grouped by behavioural domain.

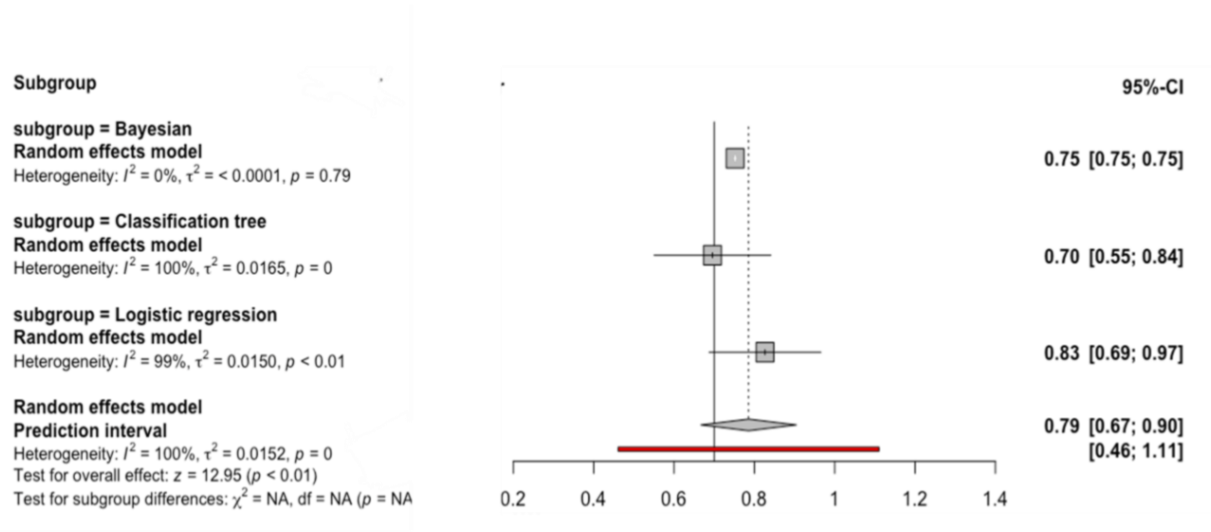
Behavioural domain	k	AUC	95%-CI	tau^2	tau	Q	I^2
Combined*	9	0.79	0.67; 0.90	0.03	0.17	16284.91	100.00%
MO*	6	0.71	0.51; 0.91	0.05	0.23	56.06	91.10%
Geographical	2	0.83	0.69; 0.96	0.01	0.09	4.95	79.80%
Optimal	1	0.78	0.68; 0.88	--	--	0.00	--
Temporal Proximity	1	0.72	0.60; 0.83	--	--	0.00	--

* *Behavioural domains that meet threshold for further subgroup analysis*

For the ‘combined’ behavioural domain, a subgroup analysis was conducted to examine the difference in weighted AUC for different index test types. The weighted AUC across index test types was 0.79 derived from nine effect sizes combined from three studies. As can be seen from Figure 5, the logistic regressions evidenced a greater weighted AUC (0.83) than classification trees (AUC = 0.70) or Bayesian approaches (AUC = 0.75).

Figure 5

Weighted AUC for crime linkage of robbery using the combined behavioural domain, sub-grouped by index test.



It was not possible to examine the difference in weighted AUC for different index test types for the ‘MO’ behavioural domain or any of the other behavioural domains as only logistic regressions were used to link robbery crimes.

Homicide

Table 17 shows that the ‘All MO’ behavioural domain evidenced a weighted AUC > 0.7 from five effect sizes. No other behavioural domains were used in the two studies to link homicide crimes; however, two types of index tests were used, namely Bayesian approaches and similarity coefficient.

Table 17

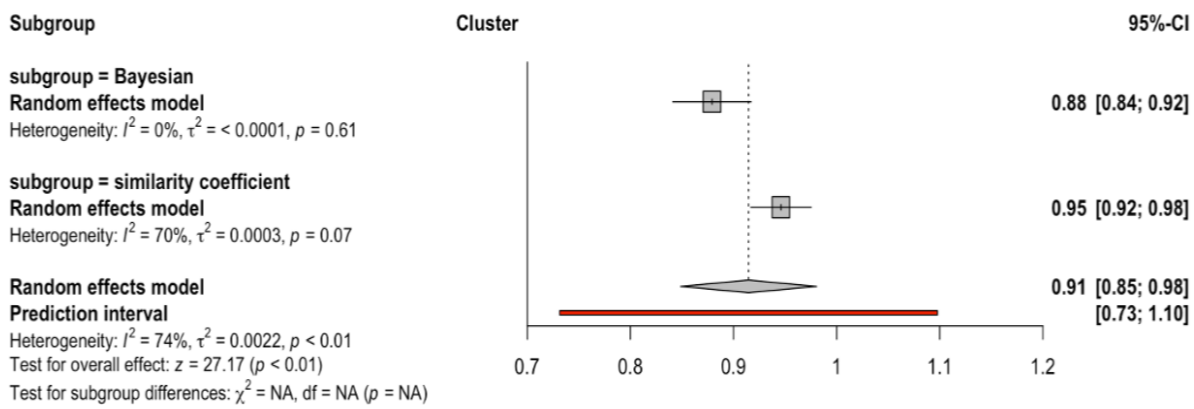
Weighted AUC for crime linkage of homicide across index tests by the behavioural domain All MO.

Behavioural domain	k	AUC	95%-CI	tau^2	tau	Q	I^2
All MO	5	0.9146	0.8486; 0.9806	0.0035	0.059	15.23	73.70%

For the 'All MO' behavioural domain, a subgroup analysis was conducted to examine the difference in weighted AUC for different index test types. As can be seen from Figure 6, similarity coefficient approaches evidenced a greater weighted AUC (0.95, derived from two estimates from one study) compared to Bayesian approaches (AUC = 0.88, derived from three estimates from the second study).

Figure 6

Weighted AUC for crime linkage of homicide using the All MO behavioural domain, sub-grouped by index test.



Arson

Table 18 shows that the 'MO' behavioural domain evidenced a weighted AUC > 0.7 from more than five effect sizes. The 'All MO' and 'optimal' behavioural domains reported a weighted AUC > 0.7 but this estimate was derived from less than five effect sizes.

Table 18

Weighted AUC for crime linkage of arson across index tests, sub-grouped by behavioural domain.

Behavioural domain	k	AUC	95%-CI	tau^2	tau	Q	I^2
All MO	2	0.91	0.87; 0.95	0.0004	0.02	2.00	50.00%
Optimal	2	0.88	0.81; 0.96	0.0025	0.05	4.92	79.70%
MO*	12	0.82	0.79; 0.85	0.0027	0.052	129.95	91.50%

It was not possible to examine the difference in weighted AUC for different index test types for 'MO' behavioural domain or any of the other behavioural domains as only logistic regressions were used to link arson crimes.

Across crime categories[7]

Table 19 shows that the 'combined' and 'geographical' behavioural domains evidenced a greater weighted AUC than the 'TP' domain. However, AUCs of all behavioural domains were derived from only two effect sizes from two studies. Both studies only used one index test type which was logistic regression.

[7] Crime categories refer to different crimes such as burglary, sexual offences, robbery, or car theft.

Table 19

Weighted AUC for crime linkage of Across Crime Categories across index tests, sub-grouped by behavioural domain.

Behavioural domain	k	AUC	95%-CI	tau^2	tau	Q	I^2
Combined	2	0.88	0.82; 0.94	0.00	0.00	0.00	0.00%
Geographical	2	0.87	0.83; 0.92	0.00	0.00	0.16	0.00%
Temporal Proximity	2	0.67	0.59; 0.75	0.00	0.00	0.00	0.00%

Across crime types[8]

Table 20 shows that the 'geographical' behavioural domain evidenced a greater AUC (0.86) compared to the 'TP' (AUC = 0.64) domain. Although the 'geographical' behavioural domain presented a weighted AUC > 0.7, it was derived from only two effect sizes. Both studies and all effect sizes were based on logistic regressions. Hence, it was not possible to examine the difference in weighted AUC for different index test types.

Table 20

Weighted AUC for crime linkage of across crime types across index tests, sub-grouped by behavioural domain.

Behavioural domain	k	AUC	95%-CI	tau^2	tau	Q	I^2
Geographical	2	0.86	0.75; 0.96	0.003	0.06	2.69	62.80%
Temporal Proximity	2	0.64	0.44; 0.85	0.020	0.13	4.96	79.80%

[8] Crime types refer to different types of crimes that belong to the same crime category. For example: commercial vs residential burglaries

Within crime types

Table 21 shows that the 'geographical' behavioural domain evidenced a greater AUC (0.85) compared to the 'combined' (AUC = 0.83) and 'TP' (AUC = 0.76) behavioural domains. However, these were derived from less than five effect sizes. Both studies and all effect sizes were based on logistic regressions. Hence, it was not possible to examine the difference in weighted AUC for different index test types.

Table 21

Weighted AUC for crime linkage of within crime types across index tests, sub-grouped by behavioural domain.

Behavioural domain	k	AUC	95%-CI	tau^2	tau	Q	I^2
Geographical	2	0.85	0.71; 0.98	0.01	0.09	5.76	82.70%
Combined	1	0.83	0.75; 0.91	--	--	0.00	--
Temporal Proximity	2	0.76	0.69; 0.82	0.00	0.00	0.18	0.00%

Risk of methodological bias

A high overall quality score indicates a low risk of methodological bias. To assess the impact of study level risk of methodological bias, the overall quality score was regressed to the study level AUC value using meta-regression (presented in Table 22). The effect of variation in methodological quality on AUCs at the study level could not be estimated for arson and robbery as they were represented by one and three studies respectively, and there was no variation in the quality score for methodological variation.

Table 22

Association between overall methodological quality of studies and reported AUC by crime category.

Crime category	β	SE	z val	*p*	Lower bound	Upper bound
Car Theft	-0.04	0.06	-0.64	0.52	-0.17	0.08
Burglary	0.01	0.01	1.07	0.28	-0.01	0.020
Sexual Assault	-0.0004	0.01	-0.05	0.96	-0.01	0.014
Across crime categories	-0.002	0.04	-0.04	0.97	-0.08	0.07
Across crime types	-0.05	0.06	-0.92	0.36	-0.16	0.06
Homicide	-0.02	0.01	-2.46	0.01	-0.03	-0.004
Within Crime types	-0.01	0.03	-0.53	0.59	-0.07	0.04

For homicide, effect sizes were negatively associated with overall risk of bias which means studies with low bias tended to report higher AUCs. However, there are only two studies for serial homicide crimes, and therefore this finding is unlikely to be robust, and the conclusion of influence of risk of bias may well change with the publication of more studies on serial homicide in the future. Otherwise, no systematic association between the overall methodological quality of the study and the reported size of the AUC was found.

Discussion

This meta-analysis aimed to evaluate the overall effectiveness of statistical models[9] used to make crime linkage predictions, as measured by the AUC. The analyses were completed for different crime categories and behavioural domains advancing Fox and Farrington's (2018) meta-analysis and including an additional six years of studies.

[9] Statistical models are referred to as index tests in the methods and results sections.

Effectiveness of crime linkage by crime category

Similar to Fox and Farrington's (2018) meta-analysis, greater crime linkage accuracy was found for interpersonal crimes (homicides, followed by sexual assaults) compared to acquisitive crimes (robbery, burglary, and car thefts). Arson, within and between crime types, and across crime categories were not included in Fox and Farrington's analyses and were interspersed in their predictive accuracy between other crime categories. The AUCs for all crime categories indicated moderate levels of linking accuracy, except for homicide which showed high linking accuracy. Another exception was for car thefts whereby the AUC reflected low linking accuracy.

It should be noted that crime categories such as homicide, arson, robbery, across and within crime types, and across crime categories have been researched by fewer than four studies. Therefore, the weighted AUC values may not be robust at this stage. The results from the review and analyses of the literature suggests that there is sufficient data for burglary and sexual assault crimes to assess the overall predictive accuracy of crime linkage. There were nine and 12 studies which applied statistical models to link serial burglaries and sexual assaults, respectively, and produced a large number of effect sizes on which to base a meta-analysis.

The majority of crime linkage research has been conducted on UK samples, representing research across all crime categories, with the exception of homicide. This can impact on the distinctiveness principle of crime linkage, whereby certain behaviours may be more or less common for a crime in different countries (Tonkin et al., 2012; Woodhams & Labuschagne, 2012). At this stage, findings of this meta-analysis are likely more applicable to crime linkage databases in the UK. The influence of cultural differences on how crimes are committed and, therefore, linked has not been researched in this study and may be a useful consideration in the future. This would require further research on crime linkage across different crime categories and types in different countries. Research on linking serial sexual offences has taken a step forward in this area (*UK*: Bennell et al., 2009; Bennell et al., 2010; Oziel et al., 2015; Winter & Rossi, 2021; *South Africa*: Woodhams & Labuschagne, 2012; *Across countries*: Tonkin et al., 2019; Woodhams et al., 2017; *Canada*: Bennell et al., 2021; *Japan*: Yokota et al., 2017; *Australia*: Davidson & Petherick, 2021).

Behavioural domains and crime linkage

The use of behavioural domains or themes versus individual behaviours for making crime linkage predictions have gained variable support in the literature. This difference highlights whether certain crimes are better linked using a 'domain' or rather as much information as possible, through an aggregate of 'individual MO behaviours'. Tonkin et al. (2019) argued that domains may be more helpful when linking car theft, burglary, or robbery whereby an offender may be unable to repeat a specific behaviour across crimes in a series, but they may exhibit a behaviour which represents a similar underlying theme. In such a circumstance, behavioural domains would capture this similarity. However, crime linkage studies of sexual offences are unequivocal on this argument. Based on an exploratory analysis Bennell et al (2009) found greater linking accuracy when using individual MO behaviours cumulatively, rather than domains. However, the results of the exploratory analysis were not presented in the paper. The majority of studies conducted since have found the same (e.g., Winter et al., 2013; Tonkin et al., 2017; Woodhams et al., 2019). This section predominantly focuses on crime types of sexual assault and burglary, as they were represented by more robust data in the analysis.

Interestingly, crime linkage studies of burglary, car theft, and robbery, all used behavioural domains. It was found that the ‘geographical’ (usually ICD) behavioural domain either on its own, or in combination with other behavioural domains (‘optimal’) was consistently a good predictor of crime linkage (*burglary*: Bennell et al., 2010; Bennell & Jones, 2005; Halford, 2022; Markson et al., 2010; Porter, 2016; Tonkin et al., 2019; Tonkin, Santtila, & Bull, 2012; Tonkin, Woodhams, Bull, Bond & Santtila, 2012; *car theft*: Davies et al., 2012; Tonkin et al., 2008; Tonkin et al., 2019; Tonkin, Woodhams, Bull, Bond & Santtila, 2012; *robbery*: Burrell et al., 2012; Tonkin et al., 2019; Woodhams & Toye, 2007). The results of the meta-analysis support this review for burglary and car thefts and are based on effect sizes from multiple studies. The evidence for robbery and across crime categories and types, and within crime types regarding the ‘geographical’ behavioural domain also support this, however, may be more robust as further effect sizes are produced from new studies. However, it is acknowledged that crime linkage across crime categories and types, and within crime types only used ICD and TP (Tonkin et al., 2011; Tonkin, Woodhams, Bull & Bond, 2012), due to challenges of identifying MO behaviours that occur in multiple crime types.

Crime linkage studies of sexual offences, arson, and homicide have not utilised ICD or TP. In some cases (e.g., Woodhams, 2008) this decision was taken to avoid inflating the performance of ICD in scenarios of small samples of series which were dispersed across an entire country. Further, researchers may not be given the geographical locations of such crimes due to concerns of identifying a particular crime in a sample given their relative rarity. However, future studies of these crime types should consider the use of at least ICD where large enough samples can be obtained. At present, the literature appears to have established sufficient support for the use of this behavioural domain and the ability to accurately link crimes may increase further if used for sexual offences, homicide, and arson.

Alternatively, crime linkage of property related crimes (burglary, car theft) and robbery have rarely utilised the ‘All MO’ domain (i.e., the behavioural domains except ICD and TP) while sexual offence research has. There are a few exceptions to this for burglary (including Markson et al., 2010; Melnyk et al., 2011; Tonkin et al., 2012). The meta-analysis suggests that this domain may not be as useful a predictor for crime linkage of burglary (AUC<0.7), in comparison to the ‘geographical’ domain but this would benefit from further study.

Finally, specific ‘MO’ domains have variable utility across studies when used in combination with ICD. This variability may be attributed to differences in crime type (commercial versus residential burglary), jurisdiction, or country (e.g., entry behaviour may be varied in countries such as Finland compared to the UK). Therefore, it is more likely that combining all ‘MO’ behaviours with ICD would be more conducive in practice when linking crimes than their individual use. At present, there is insufficient research linking crimes across categories and types, within crime types, and crimes of arson and homicide. In comparison there are a few more studies on car theft and robbery. More research across these crimes, and replication with different samples, is needed before drawing conclusions about which behavioural domains can be used to accurately link crimes.

Effectiveness of statistical models in linking crimes

The meta-analysis highlighted that the most common statistical model used to link crimes is logistic regression, followed by classification trees, Bayesian analyses, and the similarity coefficient alone. Other statistical models such as DFA, MDS, and MCA, were used less often to link crimes (of sexual assaults). The main difference between the two sets of statistical models is that the latter are data reduction tools. The results also suggested that classification models tended to perform better than data reduction approaches. This general pattern was supported by one study (Winter et al., 2013) that directly compared two statistical DFA and Bayesian analyses. This study suggested that data reduction tools require a smaller number of variables for analyses, whereas classification models such as Bayesian analyses are better able to manage a higher volume of variables. Linking crimes accurately may be dependent on having a larger number and variation of behaviours to calculate similarity. Alternatively, the presence of a larger number of variables in classification tools may just include more relevant behaviours for linking crimes correctly.

The most effective statistical model for crime linkage varied across different crime categories. The burglary and sexual offence research were represented by a more robust evidence base (with regard to number of studies, different samples, and replication), and are explored in more detail. For linking burglary crimes, Bayesian approaches outperformed logistic regression models and classification trees when using the ‘combined’ domain. Alternatively, for sexual offences, classification trees performed better at identifying linked (vs. unlinked) crimes than other statistical models when using ‘All MO’ variables.

One of the limitations of logistic regression when applied to crime linkage has been its “one size fits all approach” (Tonkin, Woodhams, Bull, Bond & Santtila, 2012, p. 238). Once a behavioural domain is considered to be a good predictor for crime linkage, this will be applied in the same manner to every case in the dataset (Steadman et al., 2000). There is sufficient evidence to suggest that whilst offenders can be consistent (to an extent) across crimes within their series, they can be consistent in different ways (i.e., in different behaviours or domains) (Grubin et al., 2001, Woodhams, 2008). Serial sexual offenders and serial burglary offenders may follow this pattern whereby they are consistent in different behavioural domains from other offenders. Logistic regression models may not be able to capture this distinction as well as other models.

Alternatively, classification trees allow consideration of which behavioural domains are distinctively similar for different crimes pairs and provide this flexibility when linking crimes. Therefore, serial sexual offences are better linked with such a model. However, there is a limitation of overfitting with classification trees (Thomas et al., 2005). The complexity of the model, which is able to capture the consistent distinctiveness between different offenders, is unable to fit to new samples or tests samples as well as to the sample on which it was developed (Tonkin, Woodhams, Bull, Bond & Santtila, 2012). These limitations of classification trees and logistic regression models may be more applicable to burglary offences, and Bayesian analyses may provide a better balance of nuance and generalisation to link serial crimes. It is also important to note that ICD has not been used with sexual offences, and this may well influence how the statistical models perform for this crime category.

Finally, for robbery crimes, logistic regression performed better compared to Bayesian analyses and classification trees when using the ‘combined’ domain. These results should be interpreted with caution as they are based on three studies only one of which used Bayesian analyses and classification trees. Different results may be observed if these two statistical models are applied to more samples of serial robberies. Crime linkage of homicide offences was based on multiple effect sizes, however produced by only two studies (Melnyk et al., 2011; Pakkanen, 2021). Therefore, the reliability of this difference is yet to be tested on different samples. Serial crimes of car theft, arson, across categories and types, and within types did not have sufficient effect sizes for any behavioural domain, or when they did the variation in statistical models was too little to warrant further analyses. This finding invites research to invest in comparing statistical models for these crime categories further to understand which models are more effective.

It is important to note that the number of effect sizes and studies are disproportionate for different crime categories. For example, Bayesian analyses and classification trees are used in one study on a Finnish sample, producing less than five effects, and are compared with logistic regression based on three studies from UK and non-UK samples, producing 14 effect sizes. The majority of studies for all crimes categories used logistic regression and were based in the UK. Different behaviour variables may be collected, or coded, in distinct ways in different countries. This may influence how statistical models predict linked crimes. This observation, again, highlights the need for replication of crime linkage studies across different crime categories, using different populations, and with a variety of statistical models. The paper also invites researchers to attempt standardising the use of behavioural domains and statistical models across studies to gain more comparative results measuring the effectiveness of crime linkage.

Limitations of the ROC

The AUC statistic, as produced by the ROC curve, provides a standardised measure to compare different models. However, it is not without limitation. Tonkin et al., (2019) demonstrated that despite a moderate AUC value (0.82) for linking car thefts using a logistic regression model, when looking for linked pairs within the top-500 pairs predicted to be linked using the model, only 5.8% of actually linked pairs were placed in this ranked list (Tonkin et al., 2019). This highlights the class imbalance problem in crime linkage studies that use AUC as a measure of accuracy. As research is usually conducted on databases with a comparatively larger number of unlinked crime pairs than linked crime pairs, the AUC may give a false impression of accuracy achieved in practice. This issue can occur as the correct rejection rate is much higher than the hit rate (Tonkin et al., 2017; Tonkin et al., 2019) and so the statistical model has achieved its success on the merit of correctly identifying unlinked pairs, rather than correctly identifying linked pairs. Further, the AUC metric is often left without interpretation in studies, thereby reducing its practical value. Even when selecting a threshold to control false alarm rates and hit rates, the frequency of the former in absolute numbers is likely much higher than the number of hits. It is therefore recommended that researchers publish the actual numbers of false alarms and hits for an accurate presentation of how a statistical model performs. Ewanation et al (2023) have discussed these limitations in further detail, alongside potential solutions.

Impact of quality evaluation

Except for studies of serial homicide, there was no considerable variation in methodological quality. This finding fits with the typical composition of crime linkage samples and methods. The majority of studies are characterised by small samples, of serial offences only. Studies often could not confirm researcher blindness at the time of coding behavioural variables or did not use highly objective reference standards (such as DNA). While the challenges in retrieving such data should be acknowledged, a small number of studies have presented the potential to use more ecologically valid samples (Woodhams & Labuschagne, 2012; Tonkin et al., 2017; Woodhams et al., 2019). Alternatively, there was no doubt that all studies used a reference standard, which matched the review question's definition of crime linkage, and were therefore marked as low risk in this area. Therefore, without much variation in methodological quality, the analyses were unlikely to uncover significant differences in reported AUC statistics based on this measure. However, the methodological limitations should be considered in future research, to provide a more ecologically valid evidence base for generalising the ability of statistical models to link crimes in practice.

Limitations

The current meta-analysis focused on one measure of effectiveness i.e., the AUC statistic, which has its limitations, as outlined. However, the evidence in this paper, allows comparison of the statistical models and behavioural domains, and can guide research in this regard. A second limitation is that behavioural domains, statistical models, and crime types were collapsed into higher level categories for the purpose of comparison. For example, commercial and residential burglary were collapsed into one burglary category. The performance of behavioural domains such as ICD may be different between such categories, and not evident due to the data reduction performed. Alternatively, Bayesian approaches may be more effective in linking one type of burglary over another. However, if behavioural domains, crime types, and statistical models were not collapsed, the variation in the studies would be too high to make any meaningful deductions from the crime linkage literature as it currently stands. This level of variation is likely to continue, as the evidence base is still being built. Therefore, this paper was timely, to take stock of what the research has found more broadly for different crime categories, behaviours, and statistical models, to guide future research.

Implications and conclusions

The accuracy of crime linkage using the AUC has been evaluated since 2002. There has been considerable research across countries and crime categories to understand which behaviours and statistical models are the most effective in identifying linked crimes. The current meta-analysis was timely in its attempt to collate and evaluate what the research has found so far. The analyses developed Fox and Farrington's (2018) review and considered the nuances of statistical models used to link crimes and included all behavioural domains and crime categories in the literature written in English.

Crime linkage in research is very different from practice. The potential ways to operationalise these statistical models in practice needs to be considered. Tonkin et al. (2019) have provided an example of this whereby pairs were ranked in descending order of predicted probability of linkage. The number of actually linked cases in a certain percentage of ranks was evaluated. Studies should provide sufficient information on the practical value of statistical models alongside AUC statistics. This can include frequency or rates of hits, false alarms, misses, and correct rejections.

It appears that crime linkage predictions can be made with classification models at moderate to high levels of accuracy, as determined from the AUC. Research on sexual assaults and burglaries have progressed further compared to other crime categories, and geographical and aggregated MO behaviours can be useful across different crimes categories. However, it is important that empirical evidence be built for the use of ICD in linking sexual offences, and alternatively exploring the use of aggregated 'All MO' behaviours in acquisitive offences. There is initial evidence to suggest that classification methods, such as Bayesian analyses, classification trees and logistic regression models, perform better than data reduction methods for the purpose of crime linkage. Focus on these models and investment in research for serial crimes of car theft, robbery, homicide, and arson, may be helpful. Research across crime categories should also be continued, whereby the types of crimes included are identified as well.

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CHAPTER TWO

EMPIRICAL PAPER

Exploration of Sexual Offence Subtypes in Switzerland using a LCA approach.

Abstract

Purpose: Sexual offence typologies can be useful to aid investigative efforts and clinical practice when working with offenders. However, development of past typologies has focused on either offence behaviours, or offender characteristics, or demographic variables. Subgroups for all three variable sets have not yet been evaluated in the sexual offending literature. The current study uses offence behaviours, offender traits, and demographic characteristics, to identify subgroups in each set, in a Swiss population, and explores the associations between these subgroups.

Methods: 17,566 cases of sexual offences were analysed from the Swiss ViCLAS database. Following Fox and Farrington's (2012) method, the study used 87 variables relating to offence behaviours, offender traits, and demographic characteristics. Latent class analyses were used to identify classes within each variable set. Subsequently, a log-linear analysis was conducted to evaluate the associations between the three LCA models.

Results: Three latent classes were identified for each variable set. Demographic characteristics were distinguished by victim gender and offender ethnicity. Offender trait groups were differentiated by victim-offender relationship. Three types of sexual offences were identified, which related to serious, moderate, and exhibitionism offences. Log-linear results indicated that subtypes of offence behaviours, offender traits, and demographic characteristics were significantly associated with each other.

Conclusions: Serious sexual offences were usually committed by known/acquaintances, whereas most exhibitionism and moderate-level offences were committed by offenders who were strangers to the victim. The prevalence of different offence types and victim-offender dyads have important implications for our understanding of sexual offending in a Swiss population.

Introduction

Sexual offences are a public health issue (National Organisation for the Treatment of Abuse, 2018), which impact upon victims/survivors, and the public. Global trends suggest that the prevalence of sexual offences is declining, however, this trend is not observed in every country (Borumandnia et al., 2020). Within Switzerland, there has been an increase in sexual offences (Federal Statistical Office [FSO], 2023), yet this is likely to be an underestimate. For example, there were 5,859 victim consultations in Swiss hospitals after an indecent assault or rape in 2022 (FSO, 2022), compared to the Swiss FSO record of 1,619 in the same year (FSO, 2023). A Swiss epidemiological survey also found that only 44%-58% of girls and 6%-38% of boys reported child sexual abuse, depending on the incident (Mohler-Kuo et al., 2014). These crime estimates, and issues of public health, urge researchers to contribute to our understanding of those who sexually offend, the characteristics of their offences, and potential barriers to reporting crimes. Such research is underway with the aim to improve identification and management of offenders (for reviews see Beauregard, 2010, and Schmucker & Lösel, 2017), and work towards better outcomes for victims.

Typology Development and Implications

Typologies and offender profiling

Historically, research has attempted to support identification and treatment/management of sexual offence perpetrators by observing patterns of offender characteristics, and offence behaviours. These have been based on theoretical, clinical, and statistical approaches (Vettor et al., 2013). Initially typologies were developed from theoretical frameworks to infer motivation and function of sexual offending, including Knight and Prentky's (1990)

Massachusetts Treatment Center: Rapist Typology – Version 3, Groth and Birnbaum's (1979) typology of rapists driven by a sadistic, anger, or power motivation, and a criminality motivation of sexual offending (Scully and Marolla, 1983, as cited in Canter & Heritage, 1990). These typologies developed our understanding of why offenders may commit specific crimes. However, Canter and Heritage (1990) highlighted, that these typologies did not distinguish the offence behaviour from the offender as a person. This complicated the ability to predict and infer the potential types of characteristics of offenders from crime scene behaviours alone – or profile those offenders. In contrast, clinical approaches adopted a more idiosyncratic approach to profiling, based on clinicians' experience (Alison et al., 2010). Over time, typologies of offender behaviour and characteristics were progressed to support in police investigations. Canter (1995, as cited in Canter & Youngs, 2003) suggested a statistical approach to offender profiling. He suggested that this task could be considered as an *if A then C* link between (A)ctions at the crime scene and (C)haracteristics or traits of the offender. The aim is to infer offender's characteristics from crime scene actions, to aid investigative efforts. This was followed by research, which aimed to 1) create themes of offence behaviour, to identify potential offender motivations, and 2) use offence behaviour to predict, or evaluate the association with offender characteristics. The latter may be used to narrow down suspects with specific traits. Some studies have attempted to use crime scene characteristics to predict (ter Beek et al., 2010), or evaluate correlations with (Mokros & Alison, 2002), single offender characteristics. Other studies have evaluated the difference between offence behaviour themes, based on individual offender characteristics (e.g., Pedneault et al., 2012).

Offender profiling follows two assumptions; a) the consistency principle (Canter, 2004), and b) the homology principle (Alison et al., 2002). There is sufficient evidence supporting the consistency principle, i.e., offenders will behave in a consistent manner across their own crimes. However, the homology principle has not found strong empirical support, i.e., similar behaviours across offences will reflect similar personality traits in offenders (e.g., Mokros & Alison, 2002; for a review see Vettor et al., 2013). Alison et al. (2002) critiques the A to C relationship as too simplistic. This is because personality theory suggests that the offender's personality interacts with specific situational characteristics, to produce specific offence behaviours (Alison et al., 2002). However, studies referenced above, do not take this into consideration, which may explain why the empirical support for the homology principle is weak. Alison et al. (2002) also discouraged researchers/practitioners from making inferences about certain *demographic* features from crime scene actions and presenting it as a "profile", as personality theory does not suggest homology of demographic traits. Rather the homology principle should assess measurable personality constructs and their interactions with situation specific characteristics, to develop offender/offence profiles.

Typologies and clinical-practice implications

The preceding sections suggest that typology research has focused on offender profiling to aid investigative efforts. However, researcher-practitioners have recognised the value of typologies in clinical practice. Index offence analyses have implications for clinical and forensic assessment, formulation, and treatment planning (Ward et al., 1997; West and Greenall, 2011). West (2000) argues that understanding crime scene actions provides clarity on an offender's interpersonal, intrapersonal, and situational influences, when formulating offending behaviour. Information from diverse sources, such as victim and witness statements, police transcripts, crime scene analyses and photographs, in addition to the offender's narrative, can provide a more accurate evaluation of the offender's risk, triggers, and motivation (West & Greenall, 2011). Without focused attention to details of the offence behaviour, practitioners risk colluding with 'consolidated narratives' (Spence, 1982) of the offence constructed by the offender (West & Greenall, 2011). West and Greenall (2011) used an illustrative case example to suggest that a parricide offender's narrative may have led clinical and HM Prison and Probation Service professionals to view the offence and risk as one of rejection and impulse. However, consideration of typologies of similar offences, and a detailed analysis of the index offence actions, elucidated a greater level of planning, potential forensic awareness, and triggers around relationship instability associated with rejection. Thereby in this case, treatment planning was recommended to focus on relationship instability (in comparison to anger management or impulsivity) (Greenall & West, 2011). The implication stands that, beyond investigative efforts, offender typologies could add value to clinical work.

Similarly, Jones (2004) introduced the idea of offence paralleling behaviour (OPB) to clinical work. OPB is a set of behaviour patterns, that are similar in an important manner to the sequence of behaviours that lead up to the offence (Jones, 2010). Jones (2004) highlights, that OPB does not have to reflect the same actions as the offence, but the actions, thoughts, and emotions, leading up to the events, have a similar *function*, as those occurring at the time of the offence. Therefore, understanding the situation and function of offence behaviours is important. Subsequently, an offender's risk can be evaluated when in different situations, they present with functionally similar behaviours to the ones they exhibited at the time of their offence (Daffern et al., 2007). A thorough assessment and formulation can guide treatment and management of risk. An offender's crime scene actions before, during, and after the offence must be accurately understood by professionals and considered in conjunction with individual factors and research on typologies of similar offences. This would generate hypotheses about potential triggering situations and identification of OPB. These situations and behaviours can be used as opportunities for supporting offenders in adopting positive alternative behaviours (i.e., behaviours that have the same function as their OPB, but which are pro-social) (Daffern et al., 2007).

In summary, there are several ways in which a thorough understanding of offence behaviour can benefit clinical work with perpetrators of sexual offences. Understanding the typologies of offence behaviour would also provide the police with an empirically grounded understanding of the crimes they encounter. Theoretically and empirically derived typologies may enable police personnel to differentiate typical and atypical crime scene actions, and what these situations may present as. This section provides support for the use of typology development of offence behaviours and offender characteristics in clinical and police contexts beyond its application in profiling for investigative efforts.

Statistical models and typology development

Initially, the most popular group of statistical methods adopted to develop themes of offender behaviours and motivation was multidimensional scaling (MDS). This statistical model uses the distance – or associations – between all variables in a sample and represents these relationships as a visual plot where behaviours close together tend to co-occur in offences (Canter & Heritage, 1990). These models were used to assess the existence of previously proposed themes and generate new themes of sexual offending. For example, intimacy-, sexuality-, violence-, impersonal-, and criminality-oriented themes of sexual offences (Canter & Heritage, 1990). However, most studies that adopted this approach focused on offence behaviours in stranger sexual offences (Alison & Stein, 2001; Canter et al., 2003; Canter & Heritage, 1990; Canter et al., 1998; Greenall & West, 2007; Häkkänen et al., 2004; House, 1997; Kocsis et al., 2002).

With growing evidence of consistent themes, other statistical models came into use, including cluster analyses (CA) (e.g., Ramírez et al., 2018; Seat et al., 2016), and latent class analyses (LCA) (e.g., Pedneault et al., 2012; Vaughn et al., 2008). These studies identified clusters or classes of *offence behaviours* followed by an evaluation of whether these clusters/classes were associated with specific offender characteristics. Alternatively, some studies used LCA to identify themes of *offender characteristics* (e.g., criminal history) for specific crime types (e.g., multiple homicides; Vaughn et al., 2009), followed by an examination of whether these offender classes were associated with individual offender characteristics (e.g., age of criminal onset). The use of different statistical models, and the way they are operationalised, forms broadly two steps; 1) developing typologies, and 2) using typologies to examine associations with offender characteristics. An overview of statistical models, themes, and variables in sexual offences are outlined in Table 1.

Table 1.

Examples of statistical models, variable groups, and themes found in sexual offending.

Study	Classification Model	Variable Groups	Themes/Types of Sexual Offences/Offenders	Population notes
Canter & Heritage, 1990	MDS	Offence behaviours	Violence, criminal, impersonal, intimacy, sexuality	Adult
House (1997)	MDS	Offence behaviours	Aggression, criminality, intimacy, sadism	Adult
Canter et al., (1998)	MDS	Offence behaviours	Intimate, aggressive, criminal-opportunistic	Child
Alison & Stein (2001)	MDS	Offence behaviours	Compliance-gaining, dominance, hostility	Adult
Kocsis et al. (2002)	MDS	Offence behaviours	Undifferentiated, brutality, intercourse, ritual, chaotic	Adult
Canter et al. (2003)	MDS	Offence behaviours	Hostility, theft, control, involvement	Adult
Häkkänen et al. (2004)	MDS	Offence behaviours	Hostility, theft, involvement	Adult
Greenall & West (2007)	MDS	Offence behaviours	Sexual, violent	Adult
Sea et al., 2016	CA	Offence behaviours	<u>Six clusters</u> Serial housebreaking robbery-rape, planned housebreaking robbery-rape, serial outdoors rape, sex aroused housebreaking rape, serial impulsive outdoor robbery-rape, outdoor minority rape.	Adult and child victims of rape
Ramírez et al., 2018	CA	Offence behaviours + victim demographics	<u>Three clusters</u> Cluster 1: Involving a sex worker victims, rural setting, abuse of power, and involvement of a vehicle Cluster 2: Victims under the influence of substances, occurring in a closed space, involving vaginal penetration. Cluster 3: Involving physical and psychological violence, occurring in intermediate spaces, absence of sexual behaviour.	Stranger adult sexual offences
Lovell et al., 2020	LCA	Criminal history	Sexual specialists, high volume generalists, and low volume offenders	Suspected sexual offenders

Khoshnood et al., 2021	LCA	Criminal, substance use disorder, and psychiatric disorder	High offenders and low offenders	Rape, attempted rape, or aggravated rape against adult women
Khoshnood et al., 2022	LCA	Criminal, substance use disorder, and psychiatric disorder	Indoor rape classes: Low offending class, intermediate offending classes A and B, high offending class Outdoor rape classes: Low offending class, intermediate offending class, high offending class	Indoor and Outdoor rapes in adult victim populations

Latent Class Analyses and Typologies

As previously discussed, different statistical tools have been used to identify typologies of offence behaviours and offender characteristics. However, LCA has come into more frequent use over the past 15 years. The objective of this model is to derive the minimum number of underlying or 'latent' groups in a dataset, which can be best described by the associations between observed categorical variables (Muthén & Muthén, 2000). LCA uses case-based probabilities to estimate maximum likelihood and derive classes, in addition to objective measures of goodness-of-fit, instead of relying on "*ad-hoc* distance measures" (Vaugh et al., 2008, p. 1388). In a recent study, Fox and Escue (2022) compared the validity and strengths of MDS, CA, and LCA models to identify subtypes of burglaries. The authors concluded that LCA provided better predictive accuracy on the same outcome measure (i.e., recidivism). LCA also reduced the need for subjective interpretability and was found to manage missing data better. Therefore, the study demonstrated that LCA was a more reliable and valid tool to develop typologies compared to the other two models (Fox & Escue, 2022).

LCA has been used to identify subgroups of offence/offender characteristics for different crimes, including burglary (Vaughn et al., 2008), sexual burglary (Pedneault et al., 2012), sexual assault/rape (Khoshnood et al., 2021; Khoshnood et al., 2022; Lovell et al., 2020), homicide (Khoshnood et al., 2020; Vaughn et al., 2009), sexual homicide (Healey et al., 2016), and across serious crimes (Sea et al., 2020). However, these studies only focused on criminal histories (Khoshnood et al., 2020; Khoshnood et al., 2021; Khoshnood et al., 2022; Sea et al., 2020; Vaughn et al., 2008; Vaughn et al., 2009), offence behaviours (Fox & Escue, 2022; Healey et al., 2016; Pedneault et al., 2012), or other offender characteristics (e.g., psychiatric history) (Khoshnood et al., 2020) to identify latent classes. Subsequently, these studies investigated the associations between the latent classes and single offender characteristics. Fox and Escue (2022) summarised that classification and grouping analyses facilitate an assessment of how individual cases/offenders are similar within a group, and different from other groups. However, the LCA studies mentioned above identified latent classes based on only one set of indicator variables (e.g., criminal history variables). In a novel study of burglaries, Fox and Farrington (2012) used multiple variable sets, including criminal history, offence behaviours, and offender traits. They used LCA to examine subtypes within these three variable sets. Following this, associations between subtypes of offender traits, offence behaviours, and criminal history were evaluated using chi-square tests. This was a new approach to observe relationships between subtypes of offence behaviours and offender characteristics, instead of using single variables to investigate these associations.

Rationale and Current Study

LCA studies continue to identify subtypes using one set of indicator variables, and evaluate associations with individual demographic/trait variables, or vice versa. Fox and Farrington (2012) produced the only study to the author's knowledge that attempted to identify subtypes for different variable sets and evaluated associations between them. This means, that the analyses do not investigate simple 1:1 associations between offence and offender variables, but instead evaluate how different subtypes associate with each other. This approach may provide new information about the structure and nuance of how individual variables interact to form a similar group, and whether in specific combination they associate with other groups of variables.

Three studies have used LCA to evaluate sexual offences, and focused solely on criminal history (Khoshnood et al., 2021; Khoshnood et al., 2022; Lovell et al., 2020) and drug/alcohol and psychiatric disorders (Khoshnood et al., 2021; Khoshnood et al., 2022) to identify latent classes. These studies imposed tight parameters on the types of sexual offences investigated (e.g., offences occurring outdoors, Khoshnood et al., 2022), and only included female adult victims. Whilst these studies provided helpful insights to the types of offenders and their histories, subtypes and associations between types of behaviours, traits and characteristics were not evaluated. Therefore, an approach similar to Fox and Farrington's (2012) whereby all three are considered together is missing from the sexual offending literature.

No study, to date, has applied LCA to sexual offences in Switzerland. There is a lack of information on how subtypes of sexual offending behaviours associate with subtypes of offender traits, and demographic characteristics. Previous LCA studies have imposed multiple restrictions leading to narrowly defined samples. Therefore, this study uses a broader, exploratory approach to fill these gaps in the sexual offending literature using LCA. The study aimed to provide an empirical grounding and understand the types of sexual offences that occur, who commits them, and offender traits, in Switzerland, without tightly constraining the sexual offence types under study. With the use of the Swiss Violent Crime Linkage Analysis System (ViCLAS) database (Collins et al., 1998), this study provides a unique opportunity to use a large sample of sexual offences, and rich data about offender/offence characteristics, to understand associations between them. It also provides scope to direct future research. For example, identifying subtypes of offence behaviours, demographic characteristics, or offender traits which would benefit from further studies of prediction, or application of a similar approach. This study would also add to the comparative literature for sexual offences across countries, including the type and manner in which sexual offences occur, who are the most likely victim-offender dyads, and associations with subtypes of offender traits. This study therefore aimed to investigate:

1. Whether there are subtypes of offence behaviours, offender traits, and demographic characteristics across sexual offences recorded in Switzerland, and
2. The associations between different subtypes of offence behaviours, offender traits, and demographic characteristics.

Methods

Ethical approval was provided by the University of Birmingham's Ethical Review Committee (Appendix I). Approval for the research study was also given by the Bern Cantonal Police, Switzerland.

Sample

Data for this study were obtained from the Swiss ViCLAS database, and included 22,333 offences, recorded between 2003 and 2021. The ViCLAS is a computerised system used in different countries, including the UK, Belgium, the Netherlands, France, and Germany. These systems record detailed information on serious crimes within the country, and are used for various investigative purposes, including the linking of potential crime series (Davies et al., 2021). The Swiss ViCLAS database records crimes relating to murder, sexual assaults, missing people, non-parental abductions, suspicious approaches of children and adolescents (with a violent or sexual motive), and animal abuse (with a violent or sexual motive) (Davies et al., 2021)[10]. Part of the Swiss ViCLAS dataset was made available for this study. There were 495 variables provided, relating to the offence, and offender[11] and victim characteristics. There was no information available on whether cases were linked, apparent one-off offences, or if solved or unsolved.

For this study, the dataset was trimmed, and relevant variables were collapsed and included to improve theoretical parsimony. Only sexual offences with single victim-offender dyads were included. Male and female victims and offenders, and adult and child victims were retained. The cases included completed and attempted contact and non-contact sexual offences[12]. The resulting sample size for analyses was 17,566. Variables were selected and collapsed based on previous typology literature on sexual offending (see Appendix II[13]). In total, 87 variables were selected, relating to three variable sets for the LCA, i.e. demographic characteristics, offender traits, and offence behaviours. Variables were coded in binary format and are described below. Each variable was coded as absent or present, instead of dichotomous

[10] The ViCLAS database only includes cases reported in the German speaking part of Switzerland, and cases which present behaviours that have the potential to link these crimes to other cases.

[11] Offender is used instead of suspect, as it is more commonly referred to within the literature, and although the offender may not be known or is suspected, it is assumed that if recorded the offence has occurred, and therefore the variables refer to an offender.

[12] All homicide, animal cruelty, child abduction, suspicious approaches of children, missing people, multiple offender and/or multiple victim cases were removed from the dataset, as behaviourally these crimes may be very different.

[13] As we are not allowed to share all original variables which were collapsed, these have not been listed.

or polytomous categories. For example, victim gender was coded as present or absent for male and female. Therefore, victim gender was reflected by two variables, not one.

Variables for LCA

Demographic characteristics

For the demographic variable set, 16 variables relating to *victim* and *offender gender* (male or female), *victim ethnicity* (White European and four minority ethnic variables), *offender ethnicity* (White European and four minority ethnic variables), and *victim age* (adult or child) were included. For victim and offender ethnicity, separate variables were collapsed to represent overarching groups. For example, variables of ethnicity relating to different parts of Eastern Asia were collapsed to represent one variable, i.e., Asian. Collapsing specific ethnicities into one may dilute nuances of different ethnic groups, however, this was considered necessary to use a large enough sample of each ethnic group in the analyses. This approach provided a balance between keeping ethnic groups separate to an extent (as depicted in Table 1) and avoiding a Eurocentric/White reference point (i.e., collapsing all ethnic minorities into one).

Offender traits

In the offender traits' variable set, 34 variables relating to offender *motivation* (e.g., sexual motive), potential offender *influencing* factors (e.g., substance use), *relationship* between the victim and offender (e.g., stranger relationship), and the offender's *living status* if known (e.g., living alone) were included.

Offence characteristics

The offence behaviours variable set included variables relating to the offender's behaviour during the offence. Initially 74 variables were identified, however only variables occurring in more than 10% of the sample were retained. When analysing data to build a typology, or observation of distinct groups, very low frequency variables are more likely to be relevant to specific offences and linking such offences (Canter & Heritage, 1990). However, infrequent variables are less likely to be helpful in developing a classification of behaviours with such a large sample.

There were 37 variables included in the analyses, which related to the offender's *approach* (e.g., con), offence *completion*, *location* (e.g., outdoors), *vehicle involvement*, *sexual acts* (e.g., masturbation), *blunt force*, *speech* characteristics (e.g., threatening), *undressing* of the victim and offender, *victim escape*, and *victim injuries*.

These variables were selected to align with previous literature on sexual offending (Appendix II). A number of variables were collapsed together to represent a more cohesive variable. For example, different sexual acts relating to fellatio (such as fellatio performed on victim or offender) were collapsed into an overarching variable of fellatio. However, variables were kept as individual indicators, in comparison to developing themes of behaviour. This was based on Goodwill et al.'s (2009) observation that individual crime scene indicators provide greater predictive ability compared to themes of indicators (e.g., using an offence theme of 'dominance', instead of individual variables of 'control' or 'violence', which indicate levels of dominance).

Analytic Strategy

Three sets of LCA were conducted using the R poLCA package plug-in for IBM's SPSS Version 29. The aim was to analyse homogenous groups of two to five class solutions for demographic characteristics, offender traits, and offence behaviours. More class solutions could have been analysed, however following previous LCA research, five classes are usually used as the maximum when testing for subgroups in offence data. Increasing the number of classes may improve model fit, however the number of classes should also have theoretical standing and be interpretable in a meaningful manner. The optimal class solutions were selected based on four commonly used goodness-of-fit indicators, i.e., the Bayesian Information Criterion (*BIC*), the Akaike Information Criterion (*AIC*), the log-likelihood (*LL*), and the log-likelihood ratio chi-square (G^2). Therefore, theoretical interpretability and empirical aspects of the number of classes were considered (Khoshnood et al., 2021). As the poLCA package does not include a bootstrap function to assess significant differences between class solutions, this was not included in the model selection criteria. However, future research should consider this when selecting the software used for LCA in this field. Finally, entropy and average latent class posterior probabilities are two generally reported classification diagnostic statistics, which provide an estimate of how well the model defines or predicts class membership (Weller et al., 2020). As the SPSS plugin for LCA did not provide entropy statistics, the average latent class posterior probability was reported for each of the latent class solutions selected in the results. The main strengths of using the poLCA package were that it is accessible to the public, and the plug-in for SPSS provides a more user friendly interface. This means analysts, researchers, and police departments would be able to use and interpret similar datasets more easily as well. This would also support replicability of analyses for future research.

Class solutions were examined to consider variables that differentiated classes. The LCA output provides class solutions as probabilities or the percentage of cases in the sample which occur in each class for each variable. In order to validate class solutions and distinguishing variables, a series of chi-square tests were conducted. For example, if offender gender was seen as differentiating between two classes in the class solution, a chi-square test would be used to test the association between gender, and the latent classes. This was in line with Fox and Farrington's (2012) method of validating class solutions and indicator variables.

Finally, a log-linear analysis was conducted to assess the relationship between classes of offence behaviours, demographic characteristics, and offender traits. Log-linear analysis provides a test of association between more than two categorical variables. Therefore, this was considered a more appropriate statistical approach than chi-square tests. This provided a test of whether the three sets of classes significantly associated with each other, and which interactions and/or main effects were significant. In order to breakdown the associations found in the log-linear analyses, the associations between subtypes of offence behaviours and offender traits were assessed, for each demographic subtype using 3x3 contingency tables and chi-square tests. All analyses were conducted using IBM's SPSS Version 29.

Results

Sample composition

17,566 cases were included in the analyses. Almost half the sample included offences against adults, and one-quarter against a child (less than 16 years old). For one-quarter of the sample, victim age was missing. This may have resulted from how the data was recoded.

Victims of child molestation/harassment were clearly indicated in the database; however other offences did not always indicate victim age. To avoid interpretation bias or errors by the researcher, these were left as absent. The majority of victims were women or girls, and offenders were usually male. Offender age was not available, and therefore not included in the analyses. Table 2 provides descriptive statistics of demographic variables for this sample.

Table 2.

Descriptive statistics for demographic variables within this dataset.

Demographic domain	Variable	Proportion of sample (%)
Victim age group	Adult	46.79
	Child (Under 16)	24.53
Victim gender	Male	12.50
	Female	87.50
Offender gender	Male	99.51
	Female	0.49
Victim ethnicity	White European	71.35
	Asian	2.12
	African	1.70
	Latin American	4.17
	Indian	0.92
Offender ethnicity	White European	72.77
	Latin American	1.06
	Asian	7.26
	African	9.59
	Indian	0.03

Latent class solutions

Two to five class solutions were analysed for each variable set (i.e., demographic characteristics, offender traits, and offence behaviours). For all three models, the three-class solution was favoured by BIC, AIC, LL, and G^2 indicators, and for interpretability. Although goodness-of-fit values continued to reduce, the largest drop and the largest change in model fit was found when moving from a two- to a three-class solution. Table 3 presents the goodness-of-fit values for different class solutions, and Figures 1a-c illustrate the difference in the BIC statistic[14].

Table 3.

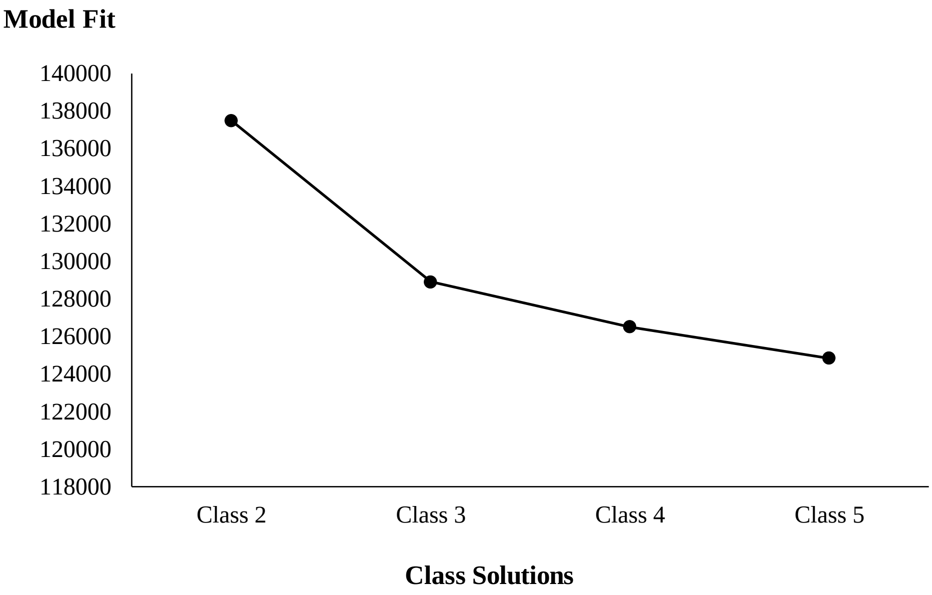
Fit indices for class solutions using LCA.

Class solution	AIC	BIC	LL	*npar*	G^2/LR
Demographic characteristics					
2	137494.7	137494.72	-68586.09	33	18464.44
3	128522.63	128911.31	-64211.31	50	9714.89
4	125988.16	126509.	-62927.08	67	7146.42
5	124182.55	124835.5	-62007.28	84	5306.81
Offender trait characteristics					
2	160802.29	161338.86	-80332.15	69	26732.25
3	155916.14	156724.87	-77854.07	104	21776.10
4	154178.08	155258.98	-76950.04	139	19968.04
5	151847.55	153200.61	-75749.77	174	17567.72
Offence characteristics					
2	579084.11	579667.14	-289467.06	75	273005.29
3	540058.40	540936.83	-269916.20	113	233903.58
4	523922.20	525096.08	-261810.12	151	217691.42
5	514312.40	515781.67	-256967.22	189	208005.61

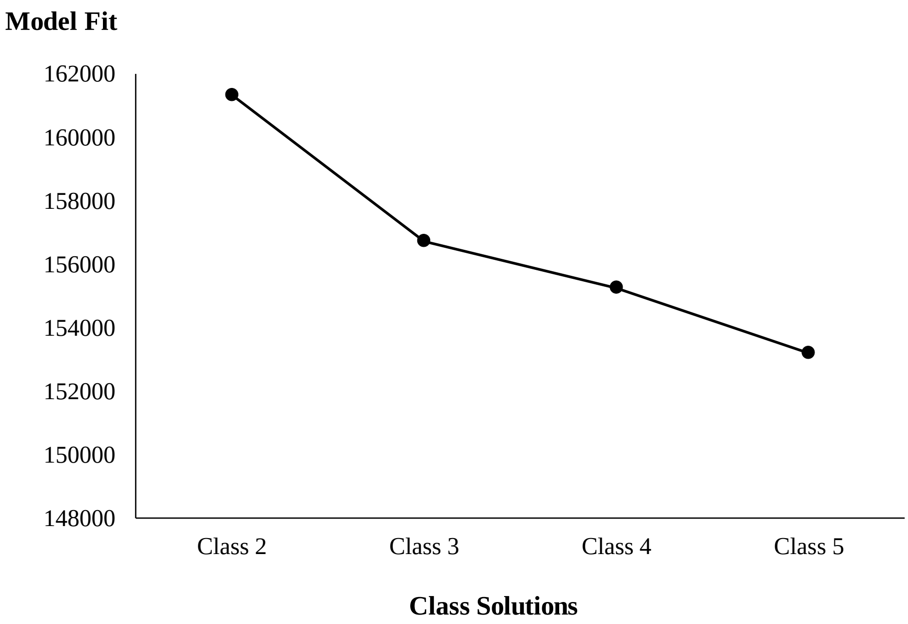
[14] The BIC statistics were selected for visual representation, as this is the most commonly used statistic for goodness-of-fit indicators in LCA studies of offence/offender typologies (e.g., Fox & Farrington, 2012; Healey et al., 2016; Khoshnood et al., 2021; Vaughn et al., 2008), and it illustrated the difference from a two- to three- class model most clearly.

Figure 1.

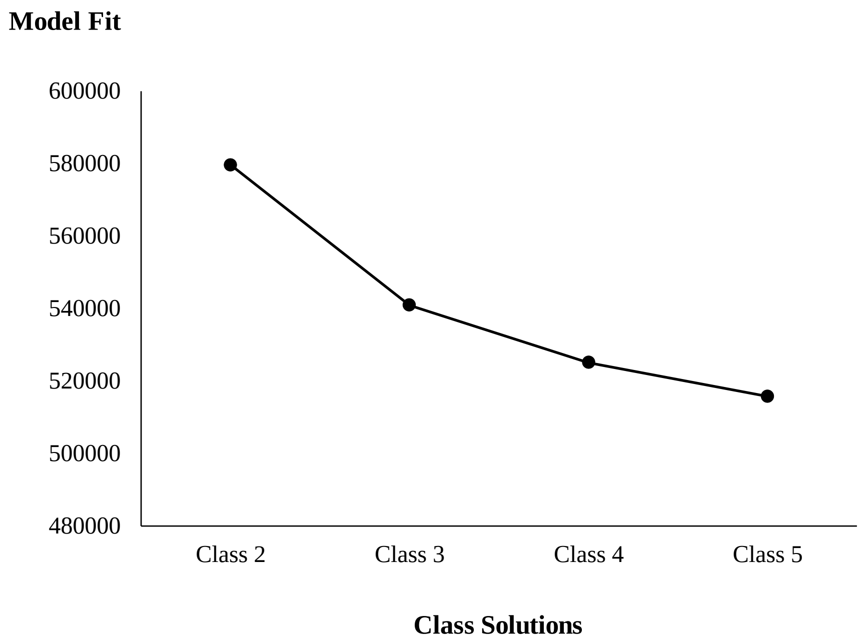
The BIC indicator for two, three, four, and five class solutions for the (a) demographic characteristics model, (b) offender traits model, and (c) offence behaviours model.



(a)



(b)



(c)

LCA class compositions

Demographic characteristics model

The first demographic characteristics class was labelled *Female Victim-White European Offender* and included the largest proportion of the sample (63%). This class was characterised by female victims, who were White-European (75%). Close to half the victims were adults, and approximately one-quarter were children. The offenders were usually male and White-European. The proportion of female offenders was considerably low (0.3% of cases in this class).

The second class was labelled *Male Victim*, included the smallest proportion of the sample (13%), and was characterised by a similar percentage of adult (36%) and child victims (40%). However, the percentage of child victims was higher in this class compared to other classes. Only male victims were present in this class, and the majority were White-European (72%). The offender was usually male (98%), and White-European (77%). A smaller percentage (~5%) were from two other ethnic minority groups. Although the proportion of female offenders in this class was low (1.7% of cases in this class), it was higher compared to the other classes.

The third class was labelled *Female Victim-Non European Offender* and included 24% of the sample. This class was characterised by victims who were usually adults (58%), and less often children (15.5%). Victims in this class were women or girls, the majority of whom were White-European (63%). The offender was usually male (99.5%) and from an ethnic minority group, including Asian (27.1%), and African (37.5%) ethnicities. These proportions were higher than ethnic minority groups in the other classes, and White-European offenders in this class. Similar to the other classes, the proportion of female offenders was low (0.5% of cases in this class).

The average latent posterior probability represents the average probability that a case is assigned to a class for a given latent class model, given the response on respective indicator variables (Weller et al., 2020). The average latent posterior probability ranges from 0 to 1, with probabilities closer to 1 representing a greater probability (Muthén & Muthén, 2000). For the three class model for the demographic dataset the average posterior probability was 1. All cases in the dataset had a posterior probability of over 0.8. Victim gender and offender ethnicity seem to influence the differentiation between classes. The distribution of adult and child victims showed some variability in female victim groups, however, were similar in the male victim group. Table 4 presents the class composition for this model. Following Fox and Farrington's (2012) methodology, a series of chi-square tests supported significant associations between variables of victim gender, offender ethnicity, and victim age, and the demographic classes. As bootstrapping could not be used to measure significant differences between classes, this was an alternative approach to validate whether individual variables were significantly associated with the classes.

Table 4.

Comparison of demographic characteristics across classes.

Variable	Class 1 (%)	Class 2 (%)	Class 3 (%)
	Female Victim-White European Offender	Male victim	Female Victim-Non European Offender
% of sample (n)	63.0 (11,067)	13.0 (2,283)	24.0 (4,216)
Victim Age			
Adult victims	44.7	35.6	58.0
Child Victims	25.1	39.5	15.5
Victim Gender			
Male Victims	0.0	100.0	0.0
Female Victims	100.0	0.0	100.0
Victim Ethnicity			
African	1.2	2.3	2.6
White European	74.5	71.8	63.1
Latin American	4.1	3.6	4.7
Asian	1.9	1.5	3.1
Indian	0.8	0.7	1.4
Offender Gender			
Male	99.7	98.3	99.5
Female	0.3	1.7	0.5

Offender Ethnicity			
White European	100.0	77.4	0.0
Asian	0.0	5.1	27.1
African	0.0	3.6	37.5
Indian	0.0	0.0	0.1
American	0.0	1.3	3.7

Offender traits model

The first latent class for the offender traits model was referred to as the *Stranger* group and included the largest proportion of the sample (70%). This class consisted of victim-offender pairs who were strangers. Most cases had a sexual motive (98%), and the only influences present in small proportions in this class were alcohol/drug use (12%) and criminality (10%). The offender was married/cohabiting or living with a parent in 10% of cases.

Class 2 in this model was labelled as the *Known/Acquaintance* group and included 20% of the sample. This class consisted of victim-offender pairs who were known to each other or acquaintances. The majority of cases had a sexual motive (99.5%). In 27% of cases the offender was living with a parent, married/cohabiting in 24% of cases, divorced/widowed in 12% of cases, or single/separate in 20% of cases. The only offender influences present in this class were alcohol/drug use (23%) and criminality (16%), similar to the *Stranger* group.

The third latent class was labelled the *Intimate Relationship* group and included the smallest proportion of the sample (10%). This group was characterised by a mixture of victim-offender relationships including romantic relationships (34%), familial relationships (16%), caring role relationships (21%), and relationships related to sex work (13%). Strangers and known/acquaintance relationships were present in less than 2% of cases. The relationships in this class represent physical and/or emotional intimacy and have been labelled thus. Living status included offenders living with a partner (30%), widowed/divorced (17%), living with a parent (24%), or single/separated (19%). Offender influences were similar to the Known/Acquaintance group (23% influenced by drugs/alcohol and 18% influenced by criminality). Most cases within this class had a sexual motive (96.3%). However, a smaller proportion also indicated an anger (17%) or conflict/dispute (11.4%) motive.

For the three class model for the offender traits dataset the average posterior probability was 0.99. The majority of cases (99.7%) in the dataset had a posterior probability of over 0.8. Victim-offender relationship appeared to differentiate classes more than other variables in this model. Chi-square tests supported a significant association between relationship variables and offender traits classes. A sexual motive was considered to be present in all classes. However, the Intimate relationship group also included smaller proportions of conflict/dispute and anger motives. The class solution for the offender traits model is provided in Table 5.

Table 5.

Comparison of offender traits across classes.

Variables	Class 1 (%)	Class 2 (%)	Class 3 (%)
	Strangers	Known/Acquaintance	Intimate
% of sample (n)	70 (12,296)	20 (3,513)	10 (1,757)
Living Status			
Single/Separate	8.4	20.9	18.6
Married/Cohabiting	9.8	24.3	29.9
Divorced/Widowed	3.2	11.5	17
Same sex relationship	0.3	0.9	0.9

Living with a parent/s	10.3	26.6	23.7
Victim-Offender Relationship			
Stranger	100	0	1.5
Known/Acquaintance	0	100	1.7
Caring Role	0	0	21.1
Related to sex work	0	0	12.7
Relatives	0	0	6
Family	0	0	15.5
Romantic	0	0	33.6
Offender Influencing Factors			
Drugs/Alcohol	12.4	23.1	23
Sociability	0.1	1.1	0.7
Loner	0.6	1	1
Homeless	0.4	0.3	0.2
Traveller/Tourist	0.3	0.1	0.1
Drug dealer/Criminality	10.6	16.1	17.8
Related to sex work	0.1	0.3	0.4
Homosexual	1.6	6.5	4.2
Physically impaired	1	2	1.9
Mentally impaired	3.3	4.8	3.3
Motivation			
Sexual	97.5	99.5	96.3
Revenge	0.1	0.5	3.7
Anger	1.1	1.9	17
Jealousy	0	0.4	9.8
Thrill	0.8	0.6	0.9
Financial	2.5	1	5.4
Religious/cultural/social	0.1	0.2	1
Concealment	0	0	0.1
Mental illness	3.1	4.4	4.4
Dispute/Conflict	0.1	0.7	11.4
Organised crime	0	0.1	0.3
Kidnapping	1	0.3	0.8

Offence behaviours model

In the offence behaviour model, the first latent class, was labelled *Serious Sexual Offences*[15], and included 29% of the sample. This class was characterised by completed sexual offences (91% of cases in this class). The offence usually occurred at the victim or offender's residence (29% and 39%) of cases respectively. In 70% of cases, the offender used a con approach, and less often used a surprise/blitz approach (15%). The offence was characterised by multiple contact sexual acts, including penetration (53%), masturbation (53%), touching (44%), kissing (36%), and fellatio (34%). Non-contact acts such as exhibitionism only occurred in 1.6% of cases. The offender was usually partially undressed (74%) and the victim was partially (51%) or completely (27%) undressed. Blunt force was used in 20% of cases in this class. The offender's speech was generally concealing/containing in nature (95%), in one-quarter of cases the speech was threatening/degrading, and in one-quarter of cases the speech was pseudo-intimate. In 30% of cases the speech was commanding/guiding. Therefore, a variety of speech was used by offenders in this class in addition to concealing/containing speech. The percentage of victims who were released by offenders was the highest in this class (67.3%) compared to other classes, and in comparison, to victims that escaped within this class (14%).

The second latent class was referred to as the *Moderate-Level Sexual Offence* group and included the majority of the sample (47%). This class had the lowest proportion of completed

[15] Qualitative indicators of severity such as serious or moderate have been used to describe classes, as this is reflective of distinctions that may be used by police forces and the criminal justice system globally. However, this does not intend to imply a personal opinion about the impact of different sexual offences on victims.

offences (50%), and the highest proportion of attempted offences (26%), compared to the other classes. Most offences in this group occurred outdoors (75%). Offenders often used a con approach (58%), and less often a blitz/surprise approach (32%). The offence included contact sexual acts such as touching (42%), similar to the first class, and kissing (12%). However more severe contact sexual acts occurred in less than 1%. Non-contact sexual acts were present in <10% of cases, and the offender and victim were usually dressed (92% and 81% respectively). Compared to the first class, blunt force was rarely present in this group. The offender's speech was usually concealing/containing in nature (97%), and less often pseudo-intimate (37%), self-oriented (26%), threatening/degrading (10%), or unknown (10%). Approximately one-third of victims in this class were released by the offender, which is lower than the first class but higher than the third class. Finally, 30% of victims escaped from the offender, which was higher compared to the other two classes.

The final latent class was termed as the *Exhibitionism* group and included 24% of the sample. This class was characterised by the highest percentage of completed offences (96%), and the lowest proportion of attempted offences (2%). Most offences in this class occurred outdoors (82%), and offenders used a surprise/blitz approach (40%) slightly more often than a con approach (33%). The surprise/blitz approach was also more common in this class compared to the other classes. This group was characterised by the highest proportion of exhibitionism behaviours (83%), and masturbation (77%). Less than 5% of cases in this group involved contact sexual acts. Offenders were usually partially undressed in this class (98%), whereas the victim was almost always dressed (96%), and blunt force was rarely present (0.8% of cases). The offender's speech was usually containing/concealing (97%), and in 64% of cases there was no speech at all. Only in 13% and 16% of cases was the victim released or escaped, respectively.

If this class represents exhibitionism offences, it is likely that this type of offence does not involve the victim needing to be released or to escape because they are not being contained physically by the offender. Instead, they can just move away voluntarily.

For the three class model for the offence behaviours dataset the average posterior probability was 0.98. The majority of cases (96%) in the dataset had a posterior probability of over 0.8. The offence behaviour classes appear to be differentiated by the degree of sexual acts, offence location, offence completion, undressing, speech, and escape. A series of chi-square tests supported significant associations between these variables and the offence behaviour classes. Table 6 provides the class solution for the offence behaviours model.

Table 6.

Comparison of offence behaviours across classes.

Variables	Class 1 (%)	Class 2 (%)	Class 3 (%)
	Serious Sexual Offences	**Moderate-Level Sexual Offences**	**Exhibitionism**
% of sample (n)	29 (5,094)	47 (8,256)	24 (4,216)
Offence completion			
Completed	91.5	50.2	95.9
Attempted	7.3	25.9	2.3
Offender Travel			
Foot	22.9	12	11.8
Car/Motor/Cycle	23	11.5	15.5
Vehicle Involvement	9.9	14.6	22.1
Offence Location			
Victim's Residence	29.4	3.8	1.3
Offender's Residence	38.6	3.9	3.9
Business Location	14.6	10.3	6.8
Vehicle Location	9.2	13.1	21.9

Public Events/Buildings Facilities	12.8	12.4	10.9
Outdoor Location	35.7	75.2	82.1
Approach			
Con	69.9	58.1	32.6
Surprise/Blitz	14.8	32.4	39.5
Sexual Acts			
Exhibitionism	1.6	1.2	82.8
Touching	44.1	42.2	4.1
Masturbation	53.1	9.2	77.4
Kissing	36.5	12.9	0.6
Penetration	52.8	3.1	0.6
Fellatio	34.1	2.2	1.6
Blunt Force Use	20.9	9.1	0.8
No Injuries	78.6	91	97.2
Offender Speech			
Pseudo-intimate	25.2	36.6	13.4
Self-Oriented	15.8	12.2	4.7
Threatening/Degrading	24.5	9.8	4.1
Containing/Concealing	94.9	95.3	97.4
Commanding/Guiding	28.4	17	7.7
No Speech	5.2	26.5	64
Speech Unknown	37.5	10.4	5.9
Disrobing			
Offender did not disrobe	19.3	91.7	0.9
Victim not disrobed	6.2	80.5	96.4
Victim disrobed	27	9.8	0.1
Victim partially disrobed	50.8	0.8	0
Offender partially disrobed	74	1.3	98
No damage to clothing	77.1	8.3	0.3
Victim not redressed	88.9	73.7	72.7
Victim Exit			
Released	67.3	31.7	12.5
Escaped	14.3	30	16.3

Crosstabulation

A cross-tabulation for the three models (Table 7) indicated that the majority of women and girls victimised by White-European men in serious sexual offences, were acquainted with the offender. However, in exhibitionism and moderate-level sexual offences, the offender was usually a stranger. This pattern was also true for male victims. Women or girls, victimised by non-European male offenders, in exhibition and moderate-level sexual offences, usually involved stranger perpetrators. However, the distribution of strangers and known/acquaintance offenders were similar for serious sexual offences. The smallest percentage was Intimate Relationships across all demographic and offence classes.

The SPSS *z*-tests also indicates which column values significantly differ from each other at the 0.05 level, for each row in the crosstabulation, in addition to Pearson's chi square associations (Field, 2018). Table 7 indicates that for each demographic and offender trait group, the proportion of offence subtypes were significantly different from each other. The only exception was for male victims, whereby the proportions of strangers who committed moderate-level and exhibitionism offences did not significantly differ from each other. Neither did the proportions of known/acquaintances who committed moderate-level and exhibitionism offences.

Table 7.

Observed and expected frequency of cases occurring within each class of the three indicator sets.

Demographic Class	Offender Traits class	Frequency	Offence Behaviours Class		
			Serious sexual offences	Moderate-level sexual offences	Exhibitionism offences
Female Victim-White European Offender Group	*Stranger Offences Group*	Count	**884_a**	**3848_b**	**2935_c**
		Expected Count	2141.1	3282.5	2243.4
		% within Trait characteristics class	11.50%	50.20%	38.30%
		% within Behaviour characteristics class	28.60%	81.10%	90.50%
		% of Total	8.00%	34.70%	26.50%
	Known/Acquaintance Group	Count	**1296_a**	**690_b**	**256_c**
		Expected Count	626.1	959.9	656
		% within Trait characteristics class	57.80%	30.80%	11.40%
		% within Behaviour characteristics class	41.90%	14.50%	7.90%
		% of Total	11.70%	6.20%	2.30%
	Intimate Relationships Group	Count	**915_a**	**207_b**	**52_c**
		Expected Count	327.8	502.6	343.5
		% within Trait characteristics class	77.90%	17.60%	4.40%
		% within Behaviour characteristics class	29.60%	4.40%	1.60%
		% of Total	8.30%	1.90%	0.50%
		% of Total	27.90%	42.80%	29.30%
Male Victim Group	*Stranger Offences Group*	Count	**180_a**	**1062_b**	**237_b**
		Expected Count	477.1	826.1	175.9
		% within Trait characteristics class	12.20%	71.80%	16.00%
		% within Behaviour characteristics class	25.40%	86.60%	90.80%

		% of Total	8.20%	48.40%	10.80%
	Known/Acquaintance Group	Count	**388$_a$**	**112$_b$**	**22$_b$**
		Expected Count	168.4	291.6	62.1
		% within Trait characteristics class	74.30%	21.50%	4.20%
		% within Behaviour characteristics class	54.80%	9.10%	8.40%
		% of Total	17.70%	5.10%	1.00%
	Intimate Relationships Group	Count	**140$_a$**	**52$_b$**	**2$_c$**
		Expected Count	62.6	108.4	23.1
		% within Trait characteristics class	72.20%	26.80%	1.00%
		% within Behaviour characteristics class	19.80%	4.20%	0.80%
		% of Total	6.40%	2.40%	0.10%
		% of Total	32.30%	55.90%	11.90%
Female Victim-Non White European Offender Group	*Stranger Offences Group*	Count	**483$_a$**	**1926$_b$**	**651$_c$**
		Expected Count	918.4	1639.2	502.4
		% within Trait characteristics class	15.80%	62.90%	21.30%
		% within Behaviour characteristics class	37.50%	83.80%	92.50%
		% of Total	11.30%	44.90%	15.20%
	Known/Acquaintance Group	Count	**468$_a$**	**269$_b$**	**42$_c$**
		Expected Count	233.8	417.3	127.9
		% within Trait characteristics class	60.10%	34.50%	5.40%
		% within Behaviour characteristics class	36.40%	11.70%	6.00%
		% of Total	10.90%	6.30%	1.00%
	Intimate Relationships Group	Count	**336$_a$**	**102$_b$**	**11$_c$**
		Expected Count	134.8	240.5	73.7
		% within Trait characteristics class	74.80%	22.70%	2.40%
		% within Behaviour characteristics class	26.10%	4.40%	1.60%

	% of Total	7.80%	2.40%	0.30%
	% of Total	30.00%	53.60%	16.40%

Note: different subscript letters denote a subset of offence behaviour classes whose column proportions significantly differ from each other within each row.

Model associations

A loglinear analysis was used to evaluate the associations between demographic characteristics, offender traits, and offence behaviours classes. This analysis uses backward elimination to assess model fit, and the test assumptions require that no expected frequencies be less than one, and no more than 20% of counts should be less than five (Field, 2018). A contingency table (Table 7) confirmed that the lowest expected count was 23. Three variables were included (i.e., demographic characteristics class, offender traits class, and offence behaviour class), and each variable had three levels – the classes described in the LCA section.

The three-way loglinear analysis suggested that the final model should retain all effects. The likelihood ratio of this model was $X^2(0) = 0$, $p = 0$, as loglinear analysis begins with a saturated model, including all higher-order effects. This indicates that the highest order interaction (demographic characteristics X offender traits X offence behaviours) was significant, $X^2(8) = 62.12$, $p < 0.01$. The Pearson and likelihood ratio statistics reflect that removing the highest order effect would significantly impact model fit. Higher order effects indicate variable effects at different levels. For example, the *K-way and higher order effects* in Table 8 reports the effect of the three way interaction, three two-way interactions, and main effects of variables, at the first level. In comparison the *K-way effects* at the first level refers to the main effects, without considering any higher order effects. When the higher order effects are significant, K-way effects are not usually considered. This is because the higher order effects supersede the K-way effects, and their removal would significantly affect the model (Field, 2018).

Table 8.

K-Way and Higher-Order Effects for the three-way loglinear analysis of demographic characteristic classes, offender trait classes, and offence behaviour classes

	K	df	Likelihood Ratio		Pearson	
			Chi-Square	Sig.	Chi-Square	Sig.
K-way and Higher Order	1	26	24749.41	<.001	33913.60	<.001
Effects[a]	2	20	5965.78	<.001	6174.21	<.001
	3	8	62.12	<.001	59.73	<.001
K-way Effects[b]	1	6	18783.64	<.001	27739.39	<.001
	2	12	5903.66	<.001	6114.48	<.001
	3	8	62.12	<.001	59.73	<.001

The partial associations of the loglinear analysis indicated that all two way interactions and main effects were significant, in addition to the three way interaction (Table 9)[16].

Table 9.

Partial associations indicating two way interactions effects, and main effects for individual variables.

Effect	**df**	**Partial Chi-Square**	**Sig.**
Behaviour class * Demographic class	4	558.24	<.001
Behaviour class * Offender traits class	4	5343.42	<.001
Demographic class * Offender traits class	4	61.54	<.001
Behaviour class	2	1499.26	<.001
Demographic class	2	7164.18	<.001
Offender traits class	2	10120.20	<.001

To break down the higher order effects, chi-square tests were performed for offence behaviour and offender trait subtypes for each demographic class. For Female Victim-White European Offenders, there was a significant association between the offence behaviour and

[16] Standardised measures of effects are provided in Appendix III for the interested reader.

offender traits, $X^2(4) = 3558.07$, $p < 0.001$; this was also true for Female Victim-Non European Offenders, $X^2(4) = 1079.18$, $p < 0.001$. For Male Victims there was a significant association between offence behaviour and offender traits classes, $X^2(4) = 850.89$, $p < 0.001$. However, whilst the Stranger group significantly differed from the Known/Acquaintance and Intimate Relationship groups, the latter two were not significantly different from each other, for any offence subtype.

Generally, stranger perpetrators were more likely to commit Exhibitionism and Moderate-Level Sexual offences, across demographic subtypes. For male victims and female victim-white European offender dyads, offenders known or acquainted with the victim were more likely to commit Serious Sexual offences. For women victimised by ethnic minority offenders, strangers were as likely as known/acquaintance offenders to commit Serious Sexual offences. Appendix IV includes the likelihood ratios of the above associations.

Discussion

This study identified subtypes of offence behaviours, offender traits, and demographic characteristics in sexual offences in Switzerland. It also evaluated associations between these subtypes. The implications for who commits which types of sexual offences, and against whom, are discussed in the subsequent sections.

Latent class solutions

The LCA class solutions indicated three groups of offence behaviours: Serious Sexual offences, Moderate-Level Sexual offences, and Exhibitionism. These groups reflect differences in severity of physical, sexual, and possibly interpersonal violation. Canter et al., (2001) highlight that speech and interaction characteristics, physical and sexual violence, and sexual acts can represent interpersonal, physical/sexual, and sexual levels of violation. The current results provide a high level distinction between types of sexual offences. The subtypes of offence behaviours in the current study indicate a focus on penetrative, non-penetrative, and non-contact offences. Most typologies of sexual offences have focused on sexual assault or rape (for a review see Wojcik & Fisher, 2019), whereas typologies of exhibitionism are few, and outdated (Forgac & Michaels, 1982; Kopp, 1962; McCreary, 1975). Non-penetrative and exhibitionism offences have had limited attention in sexual offence typologies, as specific types of sexual offences.

Three offender traits subtypes were identified based on victim-offender relationships. These groups included Strangers, Known/Acquaintances, and Intimate relationships. *Differences* between stranger and acquaintance offenders (e.g., Woods & Porter, 2008), and between domestic/intimate partners, strangers, and known perpetrators of sexual assaults (Jung et al., 2021) have been previously evaluated. However, these studies neglect to consider other forms of emotionally intimate relationships beyond romantic relationships, such as caring or mentoring roles. The subtypes of relationships identified in the current study, need to be considered simultaneously, to understand potential differences between them. These subtypes are important when considered with *betrayal trauma theory* (Freyd, 1996) which posits, that in childhood sexual abuse, the level of trust between the perpetrator and victim, can impact how the victim processes, remembers (Freyd et al., 2007), and responds (Edwards et al., 2012; Ullman & Siegal, 1993) to the offence. 'High' betrayal (where the victim has a close or dependent relationship with the offender) has been found to predict multiple negative psychological and physical health symptoms compared to 'Low' betrayal traumas (Goldsmith et al., 2012). Similar research could be extended to adult victims of sexual abuse. For example, DePrince and Freyd (2002) suggest that in more intimate or dependant relationships, the victim's response to abuse may include distortions or changes in memory of the betrayal. This response may be a coping strategy to adapt and survive in a dependent relationship. In the current study, the subtypes of offender-victim relationships represent varying degrees of intimacy or closeness. Future research could consider whether sexual offences in adulthood also impacts on processing, memory, and response in victims, and whether this is influenced by the relationship with the offender. In line with betrayal trauma theory, studies could assess whether closer or more dependent relationships influence areas of memory and processing more negatively or not.

The demographic characteristics were distinguished into three subtypes based on victim gender and offender ethnicity. These groups included Female Victims-White European offenders, Female Victims-Non European offenders, and Male Victims. Previous typology research has constrained its sampling based on victim or offender gender, or victim age (Wojcik & Fisher, 2019). However, there may be three distinct groups of victim-offender combinations, which are different from each other and require consideration simultaneously. The approach taken by previous studies to constrain the nature of the sample prior to analysis has therefore missed such classes. Victim age did not seem to direct as much of the differentiation between classes. In the Male Victim group the distribution of adult and child victims was similar. Whereas there were higher proportions of adults compared to child victims in the female groups. It is possible that boys and potentially vulnerable adult men are equally targeted. Alternatively, young victims of sexual offences are known to be underreported (Mohler-Kuo et al., 2014), and therefore may be underrepresented in this database. The third explanation for these distributions may be cross-over offending in offence series (i.e. offending across age groups, gender, and/or relationships) (Heil et al., 2003; Wortley & Smallbone, 2014). However, the number of serial offences was not available, and it is unclear whether there would be sufficient serial offences to account for child and adult victim distributions.

Male offenders were more common across all classes, and likely across offence subtypes. This is in line with a general pattern of men offending at higher rates than women (Smith, 2014). Despite small proportions of female offenders, the percentage who victimised men and boys were relatively higher than those who victimised women and girls. However, a meta-analysis of the prevalence of female sexual offenders indicated a considerable underreporting of female perpetrators by victims, and more so female victims (Cortoni et al., 2017). Alternatively, a previous study has suggested that female solo offenders are more likely to offend against male victims (Vandiver, 2006).

A high proportion of all victim groups were found in moderate-level sexual offences, usually committed by strangers. This finding implies that a considerable proportion of young people are also targeted by stranger perpetrators in public spaces. However, in a Swiss epidemiological survey of adolescents, it was found that *non-contact* offences were more common, and perpetrated by strangers or acquaintances, usually through virtual platforms, in their home (Mohler-Kuo et al., 2014). The current study did not include offences occurring in virtual space, so this could not be compared. The cases included in this dataset are an underestimate of sexual offences, and only include cases that may have potential links to other offences. Despite this underestimation, there is a necessity to safeguard children, through closer police monitoring and access to victim support, in areas that young people may frequent (e.g. schools, public transport, parks). Offenders with histories of sexual violence, should also be closely supervised. Education for the general public and offender populations, on the harm caused by non-contact and less severe offences may be used as a deterrent. Further, education in schools, and via parents, around suspicious approaches by strangers, appropriate and inappropriate physical contact among peers, and awareness of support or reporting agencies could be beneficial.

Association between offence behaviour, offender traits, and demographic subtypes

The results highlighted general patterns of association. Serious sexual offences, which were characterised by completed, penetrative sexual acts, were more often committed indoors, by offenders known/acquainted with the victim. This was true for male victims and female victims with White-European offenders. This finding counters myths that "real" sexual assaults are more likely committed by strangers (Cowan, 2000; Spohn & Holleran, 2001). However, in female victim-ethnic minority offender dyads, the likelihood that the perpetrator was a stranger or known/acquainted with the victim was similar. Finally, serious sexual offences were less likely in intimate victim-offender dyads, across demographic groups. The only exception was a slightly higher likelihood of female victim-White European offender dyads being in an intimate relationship compared to strangers, in serious sexual offences.

If serious sexual offences are usually committed by perpetrators acquainted/known to victims, prosecution and police resources should focus more on the corroboration of such crimes given the lack of external witnesses and claims of consent from suspects. Such evidence would be useful, given the current focus on victim characteristics in such crimes, when the perpetrator is known/acquainted with the victim (Spohn & Holleran, 2001). Indoor locations may facilitate greater control over the environment and victim, which can enable known/acquaintance perpetrators to complete serious sexual offences. Fantasy and motivation may also influence why known/acquaintances commit more serious offences in comparison to strangers. Perpetrators who know the victim but lack an emotional or physical intimacy with them may have distorted fantasies about their relationship. Previous research has illustrated different scripts, which may influence perpetrators beliefs towards their victims (Gemberling, 2012; Ryan, 2004). Early typology research also attempted to understand perpetrator motivation in stranger sexual offences (e.g., intimacy, aggression, criminal-opportunistic, Canter et al., 1998). Motivation and fantasy could be investigated in future research to differentiate between offender beliefs about the victim, in acquaintance, stranger, and intimate relationships. Potential beliefs which influence or justify an offender's behaviour are important in the treatment of sexual offenders.

Within moderate-level offences, offenders were more likely to be strangers, across all demographic subtypes. These offences usually involved non-penetrative sexual contact. Most of these offences occurred outdoors, or in public events/buildings/facilities. Compared to indoor offences, outdoor settings may hinder the perpetrator's ability to control the environment/victim, and hence complete or commit penetrative offences. This aligns with research in other European countries, which suggests that sexual assaults that occur outdoors, are more likely to be committed by strangers (e.g. Ceccato et al., 2019; Friis-Rødel et al., 2021), although there is a difference of how sexual assaults are defined in the current study and in Ceccato et al.'s (2019) study.

Contrary to our understanding that fewer sexual offences are committed by strangers, there may be a greater number of stranger sexual offences, which are not classed as "rapes". Although the majority of victim impact research focuses on "rape" offences, Mason and Lodrik (2013) suggest that the impact on victims of other sexual offences can be similar. This finding could be compared with future research in other countries, or cantons of Switzerland. The comparison may provide insight to the prevalence of levels of non-penetrative stranger sexual offences. The high proportion of stranger sexual assaults occurring outdoors has serious implications for women, and more generally victim safety (Khoshnood et al., 2022). These findings suggest a need for greater support and surveillance, in areas where these offences occur. Potential offenders or those assessed at higher risks for sexual offending, may benefit from education and awareness about the impact and consequences of such crimes.

Research has found factors that are more relevant to stranger perpetrated sexual offences, for example, possession of weapons, threats, violence, and outdoor locations (Bownes et al., 1991; Friis-Rødel et al., 2021). Variables of force and injuries in the current study did not greatly differentiate between offences. These may be useful to consider in the next stage of research. For example, specific offence types can be examined separately, to assess influence of location and violence used in different victim-offender dyads.

Exhibitionism offences were also more likely to be committed by strangers, across all demographic groups. These usually occurred outdoors or in vehicles. Exhibitionism can be considered a minor crime compared to contact sexual offences, however such offences cause considerable distress, and behavioural changes for victims (e.g., avoiding public transport) (Choi et al., 2020). The current findings that link this offending with public spaces highlight a need for effective ways to increase support and surveillance in these areas.

Offence behaviours and offender traits

Previous studies on stranger sexual offences (Canter et al., 2003; Canter & Heritage, 1990; Häkkänen et al., 2004) and lone offenders (da Silva et al., 2013) suggested that surprise/blitz approaches were more common. However, the current results indicate that in the Swiss database, most moderate-level offences, involved a con approach. Within this population the use of a con approach may be more efficient to access victims. A con approach may lower the chance of victims raising an alarm prior to the offence occurring, especially when outdoors. Con approaches may also imply a degree of confidence or need to seek intimacy with the victim (Canter et al., 2003; Canter & Heritage, 1990), which is supported with the higher proportions of pseudo-intimate speech presented in moderate-level offences. However, the surprise/blitz approach was used in a smaller proportion of these offences. Therefore, there may be some cases where the perpetrator felt a need to control the situation or victim more (Canter et al., 2003).

There was also a higher proportion of con approaches in serious sexual offences (often committed by perpetrators acquainted/known to the victim). This may align with perpetrators using the victim's trust to commit the offence. Alternatively, for exhibitionism there was a comparable proportion of surprise and con approaches. This makes it more difficult to predict how exhibitionists may present to their victims. The use of confidence approaches with a stranger may indicate a degree of social competence (Fesmire et al., 2019) or a need for control in the case of a surprise/blitz approach. However, con approaches by acquaintances could be associated with the perpetrator's capacity to manipulate/violate the victim's trust, or a function of their relationship. Understanding the perpetrator's approach, offence behaviours, and relationship to the victim, can inform aspects of formulations with offenders and guide treatment foci (e.g., attitudes towards victims, impulsivity, distorted beliefs/perceptions of victim desires).

The above discussion also provides an example of some differences in approach style (con versus surprise/blitz) in the current dataset compared to studies from other countries. The con approach was found to be more prevalent outdoors and in serious and moderate level offences. It may be that the social expectations in the German speaking canton are different (e.g. reserved or polite conversation may be more common and is less likely to raise alarm by a victim). The second explanation for the difference in approach could be a function of the dataset. The current data only represents a proportion of sexual offences, those containing sufficient behavioural information to make them suitable for crime linkage analysis. Some approach styles may be associated with crimes that contain less behavioural information (e.g., due to a high level of violence being inflicted on a victim as in the case of a blitz rape [Oziel et al., 2015]) meaning they are under-represented in this analysis.

Demographic characteristics

The majority of victim-offender dyads were White-European in the male victim group and one female victim group. There may be an underestimation of ethnic minority *victims*. While not from Switzerland, previous research in the UK has highlighted a lack of effective victim interviewing, language barriers, and insufficient outreach support to facilitate sexual offence reporting by victims of ethnic minorities (Heimer et al., 2024; Widanaralalage et al., 2024). In the second female victim group there was a high proportion of *offenders* from an ethnic minority (usually Asian or African). There is a complex relationship whereby perpetrators of African and Asian ethnic groups are more likely to be convicted of sexual offences when the victim is a stranger and White, in comparison to an acquaintance (Spohn & Cederblom, 1991). In a literature review, Shaw and Lee (2019) clarify that racial dynamics in the prosecution of ethnic minority and White perpetrators is multifaceted, and dependent on factors such as time, country, and relationship. The current results do not settle this complexity, and there was no information on conviction, or analyses of associations between victim and offender ethnicity. Further research may consider the complexity of these associations, and whether these are simply reliant on frequencies, or if there are systemic factors that influence the frequencies of certain victim-offender dyads.

Implications

The preceding discussion highlights a need to increase awareness of moderate-level and exhibitionism offences, often committed by strangers, and occurring outdoors. This may inform surveillance, and access to victim support agencies, to facilitate apprehension and reduction of such crimes. Most serious sexual offences, occur indoors, by perpetrators known to the victim. Supporting such victims in reporting, and securing convictions is important. There are small but significant numbers of minority victim groups, such as men/boys and ethnic minorities who are also victimised in serious sexual offences. Further clarity is needed on the context and complexity of these offences. This may be an avenue for future research, to understand issues of underreporting, factors that undermine prevalence, and complexity of victim-offender dyads.

The associations between different sexual offences and victim-offender relationships are of clinical importance. Forensic and clinical practitioners involved in the management and treatment of offenders should understand offence and trait subtypes. These can be compared with offender's narratives of their offences. Such triangulation facilitates a more accurate and thorough formulation of the offender's insight into their behaviours, their attitudes, or motivations. Subsequently, these can inform hypotheses of OPB, and treatment opportunities.

As this study was exploratory, the high level distinctions in offence behaviour and demographic subtypes were not anticipated. Nonetheless, this study provides empirical support for significant associations between high level compositions of sexual offences, offender traits, and demographic characteristics in Switzerland. It is advised that researchers next focus on specific types of sexual offences, and evaluate subgroups of behaviours, offender traits, and demographic characteristics within these. Typology profiles for different sexual offences can then be compared. This study provides a precedence for association between latent classes, for future investigations using the ViCLAS database. Different offence types can be analysed separately within this database (e.g., sexual homicide). The levels of violence, approach, motivations, and victim-offender relationships may form distinct subgroups, which could inform our understanding of specific combinations or situations within these offences.

The current results may guide education policies around sexual activity, and clinical practice. For example, the proportion of women and girls victimised by known/acquaintance offenders could inform education for residents from a young age, around healthy and consensual relationships (Schwartz, 1991). Access to victim support, and awareness of the prevalence of sexual offences committed by acquaintances should be a focus for policy makers, education and health professionals, and police personnel (Krug et al., 2002). Such information should also be disseminated in areas where adults may be more likely to engage in risky behaviours (e.g., University campuses). This could improve public awareness, reduce bias, and increase support for the number of victims targeted by perpetrators known to them.

Limitations

The introduction highlighted the underestimate of sexual offences, as reported to the police. Therefore, conclusions drawn from the current study's analysis should be considered with caution and may not be generalisable to the population. Information on offender age, criminal history, whether cases were solved or unsolved, part of a series or apparent one-off offences was not available to the researcher. This limited the study's ability to identify other offender traits that may be linked to certain offence subtypes. Most studies using LCA have included criminal history and offender age to identify subtypes of offenders, and their associations with specific offence or demographic variables (e.g., Khoshnood et al., 2021). This produced suggestions for investigative efforts, to narrow down suspects based on criminality, psychiatric history, or age group.

To enter crimes onto the ViCLAS database, an offence must have sufficient behavioural information recorded about it to enable the linking of it to other crimes were it part of a series in reality. Further, entry onto ViCLAS also requires a victim to have reported their crime to the police. The ViCLAS dataset used in the current research also only included offences from the German speaking canton of Switzerland. Given this, it is likely that many sexual offences that have occurred in the respective cantons, were not included in the sample analysed here and this underestimate of sexual offending could have influenced the resultant classes. Whether crimes were linked, solved, or one-offs was also not known. It is unclear how this may have influenced the results. If there is an overrepresentation of serial offences over one-offs, the latent classes may be more representative of serial offenders and their offences, or vice versa. This prevents an ecologically valid representation of latent classes of demographic features, behaviours, and characteristics in sexual offences. It may be helpful for future partnerships to look at subsets of data where analysts can indicate whether offences have been solved, and whether they are one-offs or serial offences. These offences can be looked at separately to observe any differences in latent class formations. Other sources of data (e.g. emergency departments, hospital records) could be considered in future studies which include more information (such as offender age) and provide a more ecologically valid estimate of sexual offences.

Contrary to previous research, motivation did not vary between offence behaviour classes. Sexual motivation may underpin all sexual offences, regardless of the offence type, similar to Canter et al.'s (2001) levels of violation, which suggested that some sexual violation acts are too frequent to distinguish between rapes. Alternatively, motivation is usually inferred by analysts, based on crime scene actions. In a previous LCA study on burglary Fox and Farrington (2012) found that motivation did differentiate between classes. The way motivation is coded by Swiss analysts may be more conservative, whereby almost all cases were coded as having a sexual motivation in the current database as they related to sexual offences. Only a small proportion of offences were deemed as displaying an anger or dispute/conflict motive. It is possible that there are other motivations driving these offences, which have not been captured (e.g., criminality, House, 1997).

Despite these limitations, the current analyses have highlighted important associations between relationship, demographic, and offence characteristics in the Swiss population. The restrictions placed upon the analyses can be overcome in future studies, via partnerships with police organisations. This would be to evaluate other associations between offence actions, offender characteristics, and situation specific variables (e.g., victim resistance) in sexual offences.

Conclusion

Various statistical models have been used to develop typologies and evaluate links between offence behaviours and offender characteristics. This study is the first attempt at using the most current approach, i.e., LCA, to develop typologies of demographic characteristics, offender traits, and offence behaviours of sexual offences, in a Swiss population. The results highlighted associations between strangers and moderate-level sexual offences, which usually occur outdoors, against female victims by White-European perpetrators. There is also evidence that the majority of serious sexual offences are completed, committed indoors, and often perpetrated by someone known to the victim. There are important implications for improving policing and victim safety in public areas, and dissemination of evidence to prosecutors and jurors. Professionals involved in the treatment and management of offenders should engage with typology research and index offence analyses to inform formulation and treatment.

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CHAPTER THREE

META ANALYSIS PRESS RELEASE

Statistical models to help link serial crimes – how accurate are they?

The current research focused on how accurate statistical models are at linking serial offences. It was found that different models are better for linking different categories of offences. Over the past two decades researchers have tried to aid investigative efforts, in linking serial offences. This is also known as 'crime linkage'. Crime linkage is the practice of linking two or more crimes that been committed by the same offender (Woodhams et al., 2007). To do this police and researchers rely on two assumptions. The first, is that the offender will behave in a similar manner in the different crimes they commit. The second assumption is that the offender will behave differently compared to other offenders in the crimes they commit (Bennell & Canter, 2002).

Trying to link serial offences is a time consuming and expensive task for the police force. This is because there are a large number of crimes recorded by the police, and they have to assess many behaviours in different crimes to check if they may be linked. At other times DNA or forensic evidence may not be available to connect serial offences (Daves, 1991; Grubin et al., 2001). Therefore, researchers have tried to use statistical models to automate part of this process, and help the police prioritise a smaller number of offences, that they can analyse to identify potential serial offences. There are many different statistical models that have been used, and it is important to understand how accurate they are at predicting potentially linked crimes before the police can use them in practice. Currently, the most commonly used statistical models are logistic regressions, Bayesian analyses, and classification trees. All these models use different algorithms to assess how similar or different pairs or groups of crimes are to each other in terms of their behaviours and provide predictions of how likely it is that they may be linked. The accuracy of the model is then assessed using the Area Under the Curve (AUC) statistic. This statistic ranges from 0 to 1, whereby >0.7 reflects moderate to good accuracy (Bennell et al., 2009).

The current research gathered all relevant studies that have used statistical models to predict linkage of serial offences, and measured accuracy using the AUC statistic. The overall or average AUC for different models was evaluated, for different types of crimes (e.g., serial burglaries and serial homicides). In total 29 studies were evaluated. The results of the study showed that statistical models perform moderately when making linkage predictions of serial offences. The most accurate statistical model was different for each crime category. It was also found that the most useful behaviours to link crimes was different for different crime categories. Bayesian analyses were the most accurate when linking serial burglaries and using a combination of behaviours. Classification trees were the most accurate for linking serial sexual assaults and using all behaviours. Finally, logistic regressions were the most accurate for linking serial robberies and serial homicides.

There are specific behaviours which are more useful in linking crimes than others. This includes the 'distance between crimes', when linking serial burglaries, and a combination of all behaviours, when linking serial sexual assaults. At present, statistical model accuracy for predicting serial sexual assaults and burglaries have been studied more than other crime categories. Also, the studies for these two crime categories are more robust. Research needs to invest in assessing statistical models for crime linkage for other crime categories now. It is also important to assess whether behaviours like distance between crimes will be as useful to predict serial sexual assaults, as they have been for linking serial burglaries. It seems that more studies need to be completed that look at the accuracy of statistical models for different crime types before they are used by the police. The current study has given an overview of where the research currently stands in terms of how accurate statistical models are at narrowing down potentially linked offences. It is worth investing in continuing this work, as statistical models have shown some potential to automate the crime linkage process.

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CHAPTER FOUR

EMPIRICAL RESEARCH PRESS RELEASE

Different types of offences and offenders in sexual assaults committed in Switzerland

As part of a doctoral programme, research was conducted to identify the types of behaviours and offender and victim characteristics, present in sexual offences, from the Bern Contonal Police database, Switzerland. Three types of offence behaviours, offender traits, and demographic characteristics were found. In the past, researchers have used statistical models to develop typologies of sexual offences. This involves using behaviours that occur in an offence, or characteristics of the offender or victim to understand the motivation or function behind the crime (Canter & Heritage, 1990). Typologies allow us to understand how a group of cases or offenders are similar to each other, and different from cases or offenders in another group. Typologies of sexual offences have been applied to offender profiling, to aid investigative efforts. However, these typologies can also be useful for professionals working with offenders (West & Greenall, 2011). For example, understanding the typology of a sexual offence or offender, and the behaviours they presented in a crime, may enhance a clinician's knowledge about the offender's motivations, the offender's insight, and develop treatment foci.

Latent class analyses (LCA) are a more recently used statistical tool to identify classes or types within different offences (e.g., burglaries). However, no study to date had used this statistical model to identify groups of offence behaviours, offender traits, and demographic characteristics simultaneously, for different sexual offences. This has also not been considered in a Swiss population. Therefore, the empirical research paper attempted to identify subgroups within these three sets of variables. The study also evaluated how these subgroups associated with each other.

Three groups of offence behaviours were identified, including serious sexual offences, moderate-level sexual offences, and exhibitionism offences. There were also three groups of demographic characteristics (male victims, female victim with European offenders, and female victims with non-European offenders) identified. Finally, three types of offender traits were also found, including offenders who were strangers, or known/acquainted, or in an intimate relationship with the victim. In general, serious sexual offences were more often perpetrated by offenders who were known/acquainted with the victim. Whereas exhibitionism and moderate-level sexual offences were more often committed by a stranger. There are important implications around education, surveillance, and evidence corroboration for these crimes.

The majority of sexual offences were of a moderate-level and occurred outdoors. This finding highlights a need to increase surveillance and access to victim support in public areas, transport, and outdoor settings. Serious sexual offences were most often completed and occurred indoors in the victim or offender’s residence. The majority of these crimes were perpetrated by offenders known or acquainted with the victim. Prosecutors, jurors, and the police may benefit from increasing resources to corroborate such offences. This is important as victims often do not have witnesses to these crimes, and offenders may claim consent in these instances. There were also a considerable proportion of exhibitionism offences which occurred outdoors and in vehicles. These offences can also impact on victims in a significant way. Therefore, supporting such victims and improving surveillance is important to reduce these crimes and apprehend the responsible offender.

Given the current findings, it is important to increase awareness about such crimes. Education for the general public, and specifically for perpetrators with a known history or risk of sexual offending around the impact of such crimes may act as a deterrent. It was also clear that most victim offender dyads of all crimes tend to be white European. However, this is likely to be an underestimate of the number of victims from ethnic minority groups, and male victims. Improving access to ethnic minority communities in Switzerland, may facilitate reporting of such crimes, and access to support for victims.

Finally, there was a similar proportion of men and boys who were victimised in sexual offences, however, the proportion of victims who were women compared to girls was higher. We know that there is an issue of underreporting by young people who are victims of sexual offences (Mohler-Kuo et al., 2014). It is therefore crucial to safeguard children and young people, through monitoring in areas where young people may frequent. Education for Swiss residents from a young age and via parents, may also increase awareness around who perpetrates such crimes, where, and the impact of these offences.

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West, A. G., & Greenall, P. V. (2011). Incorporating index offence analysis into forensic clinical assessment. *Legal and criminological psychology*, *16*(1), 144-159. https://doi.org/10.1348/135532510X495124

Appendix I: Ethical approval received from the University of Birmingham

Application for amendment ERN_19-0761A

Susan Cottam (Research Support Services) [redacted]
Wed 26/01/2022 11:23

[redacted]

Dear Professor Woodhams

Re: "Exploration of stranger sexual offence themes in adult and child victims: analysis of offence behaviours"
Application for amendment ERN_19-0761A

Thank you for the above application for amendment, which was reviewed by the Science, Technology, Engineering and Mathematics Ethical Review Committee.

On behalf of the Committee, I can confirm that this amendment now has full ethical approval.

I would like to remind you that any substantive changes to the nature of the study as now amended, and/or any adverse events occurring during the study should be promptly brought to the Committee's attention by the Principal Investigator and may necessitate further ethical review. A revised amendment application form is now available at https://intranet.birmingham.ac.uk/finance/accounting/Research-Support-Group/Research-Ethics/Ethical-Review-Forms.aspx . Please ensure this form is submitted for any further amendments.

Please also ensure that the relevant requirements within the University's Code of Practice for Research and the information and guidance provided on the University's ethics webpages (available at https://intranet.birmingham.ac.uk/finance/accounting/Research-Support-Group/Research-Ethics/Links-and-Resources.aspx) are adhered to and referred to in any future applications for ethical review. It is now a requirement on the revised application form (https://intranet.birmingham.ac.uk/finance/accounting/Research-Support-Group/Research-Ethics/Ethical-Review-Forms.aspx) to confirm that this guidance has been consulted and is understood, and that it has been taken into account when completing your application for ethical review.

Please be aware that whilst Health and Safety (H&S) issues may be considered during the ethical review process, you are still required to follow the University's guidance on H&S and to ensure that H&S risk assessments have been carried out as appropriate. For further information about this, please contact your School H&S representative or the University's H&S Unit at healthandsafety@contacts.bham.ac.uk.

If you require a hard copy of this correspondence, please let me know.

Kind regards

Mrs Susan Cottam
Research Ethics Manager
Research Support Group
University of Birmingham
Email: [redacted]
Video/phone: If you would like to arrange a Teams/Zoom/telephone call, please email me and I will get in touch with you as soon as possible.
Web: https://intranet.birmingham.ac.uk/finance/RSS/Research-Support-Group/Research-Ethics/index.aspx
Postal address: Mrs Sue Cottam, Finance Office, University of Birmingham, c\o Room 106 Aston Webb, B Block, Edgbaston, Birmingham, B15 2TT.

Click Research Governance for further details regarding the University's Research Governance and Clinical Trials Insurance processes, or email researchgovernance@contacts.bham.ac.uk with any queries relating to research governance.

Appendix II: Variables Included in LCA

List of variables considered relevant to developing subtypes of offence behaviours, demographic characteristics, and offender traits. This list has been compiled using previous literature of sexual offending (Alison and Stein, 2001; Canter et al, 2003; Canter and Heritage, 1990; Canter et al., 1998; Greenall & West, 2007; Häkkänen et al., 2004; Khoshnood et al., 2021; Khoshnood et al., 2022; Wojcik & Fisher, 2019).

Variable Set	**Variable Set**	**Variable Set**
Offender Traits	Offence behaviours	Demographic Characteristics
Living Status	*Offence completion*	*Victim Age*
Single/Separate	Completed	Adult victims
Married/Cohabiting	Attempted	Child Victims
Divorced/Widowed	*Offender Travel*	*Victim Gender*
Same sex relationship	Foot	Male Victims
Living with a parent/s	Car/Motor/Cycle	Female Victims
Victim-Offender Relationship	*Vehicle Involvement*	*Victim Ethnicity*
Stranger	*Offence Location*	African
Known/Acquaintance	Victim's Residence	White European
Caring Role	Offender's Residence	Latin American
Related to sex work	Business Location	Asian
Relatives	Vehicle Location	Indian
Family	Public Events/Buildings Facilities	*Offender Gender*
Romantic	Outdoor Location	Male
Offender Influencing Factors	*Approach*	Female
Drugs/Alcohol	Con	*Offender Ethnicity*
Sociability	Surprise/Blitz	White European
Loner	*Sexual Acts*	Asian
Homeless	Exhibitionism	African
Traveller/Tourist	Touching	Indian
Drug dealer/Criminality	Masturbation	American
Related to sex work	Kissing	
Homosexual	Penetration	
Physically impaired	Fellatio	
Mentally impaired	*Blunt Force Use*	
Motivation	*No Injuries*	

Sexual
Revenge
Anger
Jealousy
Thrill
Financial
Religious/cultural/social
Concealment
Mental illness
Dispute/Conflict
Organised crime
Kidnapping
Sociability
Loner
Homeless
Traveller/Tourist
Drug dealer/Criminality
Related to sex work
Homosexual
Physically impaired
Mentally impaired

Motivation

Sexual
Revenge
Anger
Jealousy
Thrill
Financial
Religious/cultural/social
Concealment
Mental illness
Dispute/Conflict
Organised crime
Kidnapping

Offender Speech

Pseudo-intimate
Self-Oriented
Threatening/Degrading
Containing/Concealing
Commanding/Guiding
No Speech
Speech Unknown

Disrobing

Offender did not disrobe
Victim not disrobed
Victim disrobed
Victim partially disrobed
Offender partially disrobed
No damage to clothing
Victim not redressed

Victim Exit

Released
Escaped

Appendix III: Standardised measure of effects for variables included in the loglinear analysis.

Standardised measure of effects for variables included in the loglinear analysis.

Table 10.

Standardised measure of effects for main effects and interaction.

Effect	Parameter	Estimate	Std. Error	Z	Sig	95% Confidence Interval	
						Lower Bound	Upper Bound
Offence behaviour X Demographic characteristics X Offender Traits	1	0.01	0.04	0.21	0.838	-0.066	0.082
	2	-0.10	0.04	-2.30	0.022	-0.18	-0.01
	3	-0.13	0.06	-2.17	0.03	-0.25	-0.01
	4	0.17	0.07	2.54	0.011	0.04	0.30
	5	-0.01	0.04	-0.28	0.779	-0.09	0.06
	6	0.14	0.05	3.02	0.003	0.05	0.22
	7	0.09	0.06	1.42	0.155	-0.03	0.21
	8	-0.27	0.07	-3.85	<.001	-0.41	-0.13
Offence behaviour X Demographic characteristics	1	-0.19	0.03	-5.44	<.001	-0.25	-0.12
	2	0.16	0.06	2.84	0.005	0.05	0.27
	3	-0.24	0.04	-6.60	<.001	-0.31	-0.17
	4	0.17	0.06	2.92	0.004	0.06	0.29
Offence behaviour X Offender Traits	1	-1.33	0.03	-38.76	<.001	-1.40	-1.27
	2	0.41	0.04	10.75	<.001	0.34	0.48
	3	0.37	0.04	10.69	<.001	0.30	0.44
	4	-0.24	0.04	-5.81	<.001	-0.32	-0.16
Demographic characteristics X Offender Traits	1	-0.09	0.03	-2.58	0.01	-0.15	-0.02
	2	0.03	0.04	0.68	0.496	-0.05	0.10
	3	0.02	0.06	0.37	0.715	-0.09	0.13
	4	0.11	0.06	1.78	0.075	-0.01	0.24
Offence behaviour	1	0.62	0.03	19.61	<.001	0.56	0.685
	2	0.46	0.03	13.86	<.001	0.40	0.53
Demographic characteristics	1	1.00	0.03	30.94	<.001	0.93	1.06
	2	-0.91	0.05	-16.75	<.001	-1.01	-0.80
Offender Traits	1	1.27	0.03	40.862	<.001	1.21	1.34
	2	-0.10	0.04	-2.71	0.007	-0.17	-0.03

Appendix IV: Likelihood Ratios

Tables 11 to 19 present the likelihood ratios for offender trait subtypes for each offence behaviour and demographic characteristics group.

Table 11.

Likelihood of offender traits group for Serious Sexual Offences across in the Female Victim-White European Offender group.

	Known/Acquaintance Group	Intimate Relationship Group	Stranger Group
Stranger Group Likelihood	-	-	N/A
Known/Acquaintance Group Likelihood	N/A	1.42	1.47
Intimate Relationships Group Likelihood	-	N/A	1.04

Table 12.

Likelihood of offender traits group for Serious Sexual Offences across in the Male Victim group.

	Known/Acquaintance Group	Intimate Relationship Group	Stranger Group
Stranger Group Likelihood	-	1.29	N/A
Known/Acquaintance Group Likelihood	N/A	2.77 (n.s.)	2.16
Intimate Relationships Group Likelihood	-	N/A	-

Note: n.s. = variables were not significantly different in the chi-square analyses and contingency tables.

Table 13.

Likelihood of offender traits group for Serious Sexual Offences across in the Female Victim-Non European Offender group.

	Known/Acquaintance Group	Intimate Relationship Group	Strange r Group
Stranger Group Likelihood	1.03	1.44	N/A
Known/Acquaintance Group Likelihood	N/A	1.39	-
Intimate Relationships Group Likelihood	-	N/A	-

Table 14.

Likelihood of offender traits group for Moderate-Level Sexual Offences in the Female Victim-White European Offender group.

	Known/Acquaintance Group	Intimate Relationship Group	Strange r Group
Stranger Group Likelihood	5.58	18.59	N/A
Known/Acquaintance Group Likelihood	N/A	3.33	-
Intimate Relationships Group Likelihood	-	N/A	-

Table 15.

Likelihood of offender traits group for Moderate-Level Sexual Offences in the Male Victim group.

	Known/Acquaintance Group	Intimate Relationship Group	Strange r Group
Stranger Group Likelihood	9.48	20.42	N/A
Known/Acquaintance Group Likelihood	N/A	2.15 (n.s.)	-

Intimate Relationships Group Likelihood	-	N/A	-

Note: n.s. = variables were not significantly different in the chi-square analyses and contingency tables.

Table 16.

Likelihood of offender traits group for Moderate-Level Sexual Offences in the Female Victim-Non European Offender group.

	Known/Acquaintance Group	**Intimate Relationship Group**	**Stranger Group**
Stranger Group Likelihood	7.16	18.88	N/A
Known/Acquaintance Group Likelihood	N/A	2.64	-
Intimate Relationships Group Likelihood	-	N/A	-

Table 17.

Likelihood of offender traits group for Exhibitionism Offences in the Female Victim- White European Offender group.

	Known/Acquaintance Group	**Intimate Relationship Group**	**Stranger Group**
Stranger Group Likelihood	11.46	56.44	N/A
Known/Acquaintance Group Likelihood	N/A	3.33	-
Intimate Relationships Group Likelihood	-	N/A	-

Table 18.

Likelihood of offender traits group for Exhibitionism Offences in the Male Victim group.

	Known/Acquaintance Group	**Intimate Relationship Group**	**Stranger Group**

Stranger Group Likelihood	10.77	118.50	-
Known/Acquaintance Group Likelihood	-	11 (n.s)	-
Intimate Relationships Group Likelihood	-	-	-

Note: n.s. = variables were not significantly different in the chi-square analyses and contingency tables.

Table 19.

Likelihood of offender traits group for Exhibitionism Offences in the Female Victim-non European Offender group.

	Known/Acquaintance Group	**Intimate Relationship Group**	**Stranger Group**
Stranger Group Likelihood	15.50	59.18	-
Known/Acquaintance Group Likelihood	-	3.81	-
Intimate Relationships Group Likelihood	-	-	-