University of Essex

Understanding Domestic Abuse Perpetrators

Using quantitative analysis to develop perpetrator profiles and exploring their implications for targeted intervention and risk assessment

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Abbreviation/term	**Meaning**
Agglomerative Hierarchical Clustering (AHC)	A method of clustering which starts by pairing individual observations based on similarity to each other and then grouping these individuals into larger clusters in a 'bottom up' approach. These clusters are then separated by additional (dis)similarity measures.
Cluster	A group of distinctive groups of suspects of domestic abuse incidents.
CPA	Child-to-parent abuse. This category includes abuse by minors and abuse by adult children. However, police only record abuse by over-16s as domestic abuse, in line with UK legal definitions.
CRN	Crime reference number- a unique distinguisher linked by police to each reported incident or crime
DA	Domestic abuse
Ethnic minoritized groups	People who identify as or are treated as non-white, non-British or of a minoritized cultural or ethnic origin or background.
Factor analysis	A method of enabling more useful quantitative analysis of datasets using multiple variables. Factor analysis looks for correlation and patterns between variables to see whether the observed variables can be reduced to a smaller number of unobserved variables, which leads to a more parsimonious model that provides more useful insight.
LSOA	Lower Layer Super Output Area: a geographical area comprising an average population of 1,500 people. LSOAs are commonly used in Neighbourhood Statistics Geography.
Non-crime	A non-crime is an incident that police deem does not meet the threshold for recording as a discreet crime.
ODI	Ordered Dissimilarity Image: an image exploring graphically the potential existence of clusters in a

	database. Clusters are less likely to be present when an ODI produces an image that resembles the static noise in TVs. However, clusters may be present if the ODI produces large blocks of pixels.

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Note on terminology

- We use the term ‘victim’ in line with ONS and police recording practices
- We use the term ‘suspect’ rather than ‘perpetrator’ when referring to police data, as some of the crimes recorded by police are never prosecuted and a significant proportion of incidents are logged as ‘non-crimes’.
- We use the term ‘perpetrator’ when talking about large trends in the data and research.

- We define domestic abuse according to the 2021 Domestic Abuse Act, as abuse between people who are personally connected, encompassing:

(a) physical or sexual abuse;

(b) violent or threatening behaviour;

(c) controlling or coercive behaviour;

(d) economic abuse;

(e) psychological, emotional or other abuse;

Executive Summary

This project set out to address the following question:

Are there any common profiles of domestic abuse perpetrators in Essex, and do they present different risks and opportunities for targeted interventions?

To answer this question we conducted a mixed-methods study, analysing a large, longitudinal database of domestic abuse incidents and suspect data -relating to 16,491 suspects and 40,488 observations between 2016-2020- provided by Essex Police. Our findings, presented in this executive summary, reveal at least 4 distinct clusters of domestic abuse suspects in Essex. We explore the implications of these for interventions, training, and commissioning, and make recommendations for further research.

Our methods of analysis

Our analysis is based on 4 stages and research methods, which we developed collaboratively with Essex Police, who are one of our main stakeholders for this research and who provided the quantitative data:

First, we applied unsupervised **machine learning methods** to a database of domestic abuse incidents from Essex Police, in order to 'cluster' perpetrators and distinguish common profiles with shared characteristics. Domestic abuse is a high-volume crime involving thousands of perpetrators and victims in any given region. It does not correspond to specific acts or relationships but rather is an umbrella crime including a wide variety of criminal behaviours, drivers, motivations, risk factors, and harms. For this reason, the extent to which we can derive useful insights from analysing data on 'domestic abuse' as a discreet organising category is limited.

Unsupervised machine learning can discover structures and patterns in large, otherwise undifferentiated datasets of domestic abuse incidents, organising them into discreet 'clusters' or groups of profiles with common characteristics. This can help practitioners and policymakers understand the type and distribution of different kinds of abuse, to make decisions about where to invest resources and what kinds of intervention to explore.

We used unsupervised machine learning techniques to analyse a database of domestic abuse incidents from Essex Police representing 16,491 suspects over 40,488 observations. We used 3 different algorithmic techniques to 'cluster' all perpetrators into groups that are as different from each other as possible and as homogenous internally as possible. We then looked across the results produced by the 3 algorithms to identify common or similar perpetrator groups or profiles.

The algorithms clustered perpetrators according to 12 variables: *suspect gender, suspect nationality, whether the suspect has also been a victim, victim gender, number of crimes, number of victims, ages of suspect and victim, nature of abuse, crime-type, risk-level.* Each algorithm sorted perpetrators into between 4-7 groups, represented in 3 'cluster tables' – shown in the body of the report. These tables include a variety of comparative data and are therefore complicated to read. We provide some guidance on how to interpret the cluster tables in the body of the report.

It is important to stress that the suspects within each group identified by the clustering process are not homogenous but display significant differences. Having said that, we believe that the groups are distinctive enough to provide an organized view of criminal behaviour in the context of domestic abuse.

Our analysis yielded 4 distinct cluster groups or profiles, discussed in more detail below:

- **Repeat and serial male-to-female intimate partner violence (average 45% of suspect data)**
- **Repeat and serial familial abuse (average 11.5% of suspect data)**
- **Ethnic minoritized intimate partner violence (average 9% of suspect data)**
- **Female-to-male intimate partner violence (average 12% of suspect data)**

Second, we used **supervised learning** to analyse the location of the domestic abuse incidents featured in the data. We know that crime clusters geographically, so our aim was to explore the geographical variation between the number of domestic abuse incidents, the average number of incidents per perpetrator, and the number of perpetrators. Our ability to conduct a granular geographical analysis was limited by the lack of useable postcodes or grid references in the dataset.

Third, we added data from the 27 questions logged in a DASH risk assessment to the original database (using the crime reference number) and then performed **factor analysis** to produce a model of repeat victimization. Repeat victimisation is a key feature of domestic abuse, and our aim here was to understand better the factors associated with it. We focused on the relationship between repeat victimisation and 3 factors: ‘physical violence and terrorising behaviour,’ ‘coercive control,’ and ‘criminality/lifestyle’ (which includes the ‘toxic trio’ of domestic abuse, mental health and substance abuse). This analysis yielded some insights into domestic abuse in Essex as a whole. But it also allowed us to explore in more depth some aspects of the clusters that were discovered through machine learning. In particular, it enabled a more granular examination of features of our female-to-male and familial abuse cluster group, as detailed below.

Finally we **undertook in-depth qualitative interviews** with 18 domestic abuse practitioners to contextualise the findings from the quantitative analysis and to explore implications for commissioning, training, and interventions.

Our study presents a **baseline analysis of perpetrators of domestic abuse** and a point of departure for further research. The findings should be taken as a starting point, an initial scoping that can form the basis for more in-depth investigation. However, they do also yield clear and immediate implications for training, commissioning and practice as highlighted below.

Key findings

Our clustering analysis revealed 4 distinct clusters or profiles of perpetrators, which we then explored in more depth through the supervised techniques and qualitative interviews.

Cluster Group 1: Repeat and Serial Male-to-Female Intimate Partner Violence

This is the largest group of suspects containing an average of 45% all perpetrator data. Its features correspond with what most people would associate with the term 'domestic abuse' and what is known to be the bulk of domestic abuse criminality. We can therefore consider it the paradigm profile of DA. It consists of white, UK national, male perpetrators with multiple offenses, multiple female victims, and violent crimes under IPV. These perpetrators have committed more DA crimes than the median number of crimes for the sample in the specific time period (>5) and have more victims of DA than the median number (>2). Their risk level varies between clusters.

Our factor analysis of the DASH data supports these findings and confirms existing research in this field, which has found that repeat perpetration is more likely to take place if the victim is female, the perpetrator is male and they are in an intimate personal relationship (ONS, 2018; Walby and Allen, 2004; Walby and Towers, 2017). The factor analysis also supports the hypothesis that this group of suspects are more likely to use coercive behaviour and to experience substance misuse or mental health issues, as these factors are more likely to be present as the number of incidents increases.

A notable subgroup of this cluster group consists of younger-than-average males using IPV against younger-than-average females, with most incidents being rated medium or high risk. The apparent link between risk and age confirms previous national findings by SafeLives (2017) and merits further investigation, as does the possibility of specific provision for this especially vulnerable demographic.

Cluster Group 2. Repeat and Serial Familial Abuse

This cluster group (including about 11.5% of suspect data) appears to relate to familial abuse of various kinds, including child-to-parent abuse. Abuse is gendered, but less so than for other cluster groups, and less than 10% of incidents involve IPV. Suspects in this group appear to be prolific and serial offenders, with about 60% committing more than 5 DA-related crimes each and over 80% abusing more than 2 victims. However, there is a significant suspect/victim crossover - indeed, higher than for any other cluster group- with about 60% of suspects also having been victims of DA. Suspects are younger than average and tend to offend against people who are older than average.

Using DASH data to perform a factor analysis of repeat perpetration in the context of familial abuse, we found that repeat abuse increases with the ‘criminality/lifestyle score’ (which includes the ‘toxic trio’ of domestic abuse, mental health and substance abuse) and with the presence of coercive behaviour. In contrast to IPV, physical violence is not a significant factor in repeat familial abuse. This suggests diverging typologies of familial versus intimate partner violence and abuse.

Cluster Group 3. Ethnic Minoritized IPV

Group 3 (representing about 9% of perpetrator data) consists of male, non-white, mostly non-UK nationals, who commit IPV with female victims. Suspects in Group 3 commit fewer crimes than those in groups 1 and 2 and have fewer victims but are more likely to engage in violence. Both suspects and victims in this cluster are older than the mean (>32).

Qualitative findings reveal a gap around culturally and ethnically-sensitive perpetrator provision in Essex (especially for non-native English speakers and for members of the traveller community). Gaps in provision were mentioned by many participants in the qualitative interviews, especially in Probation services.

Cluster Group 4. Female-to-male IPV

This cluster group (representing about 12-13% of suspect data) consists of white, UK national, female suspects abusing male victims in a context of IPV. Half of the incidents are violent, but the other half are recorded as non-crimes or public order offences. Risk is lower than for other cluster groups with predominantly male suspects, with roughly 75% of incidents scored as standard risk across the clusters. Suspects in the female cluster commit fewer crimes than average and their victim is often the same individual, in contrast with male-to-female IPV suspects. They are highly likely to appear in the database as victims as well, with over 80% of suspects in 3 of the 4 clusters in this group also being victims. The suspect/victim crossover is therefore far more pronounced than in clusters with male suspects.

This confirms aspects of a 2021 study by the Essex Centre for Data Analytics which found that female suspects of domestic abuse are 3.7 times more likely to also be a victim than their male counterparts, and that female suspects are less likely to be repeat offenders than males.

In order to gain further insights into female perpetration, we ran our factor analysis of repeat perpetration using DASH data for female suspects. This revealed significant differences between the typology of abuse in this cluster and male-to-female IPV, including:

- Violent/terrorising behaviour is a factor when looking at all suspects, but violence is absent for female suspects, who exhibit only the terrorising behaviour that makes victims frightened.

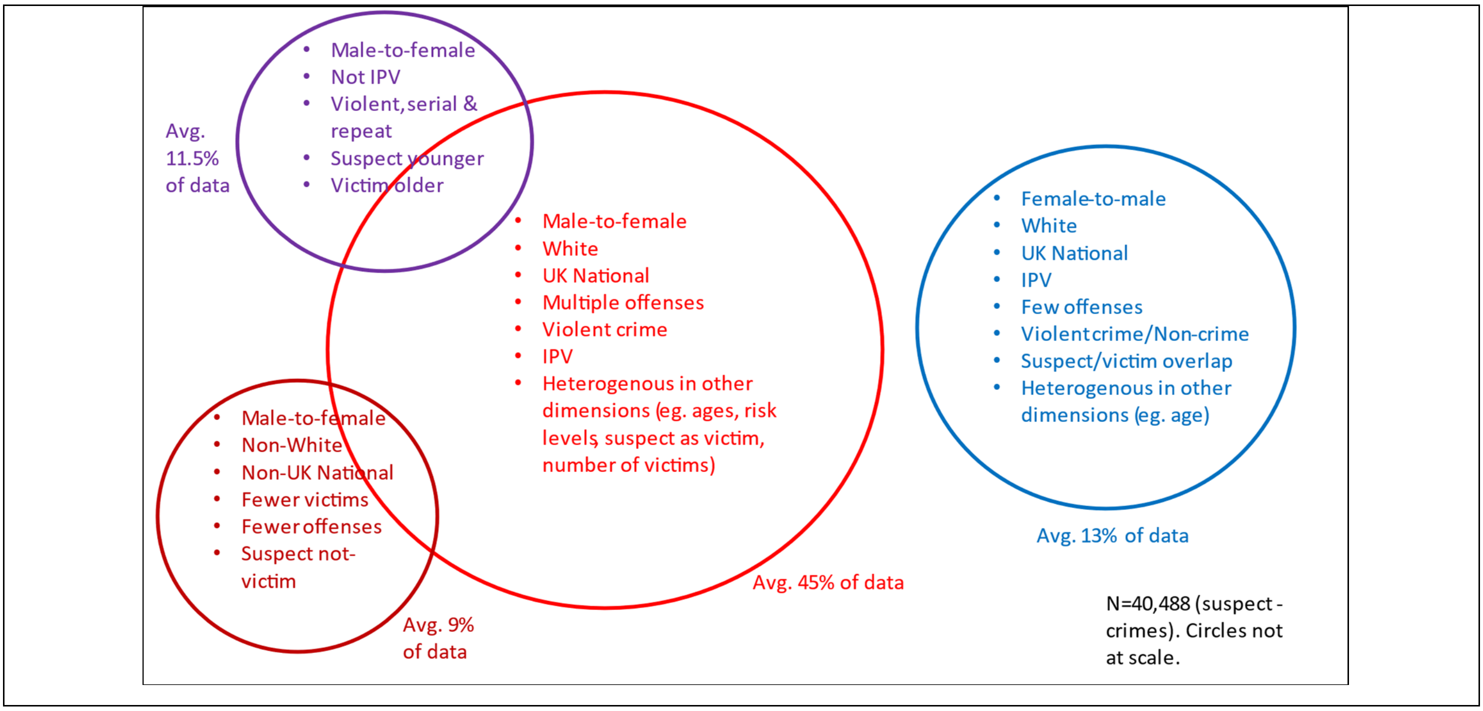
- Coercive control manifests in a similar way between female and male suspects, but the presence of sexual abuse and depression are factors only for abuse involving female suspects.

- Within the 'criminality and lifestyle' factor, threats of suicide and hurting children are factors in repeat abuse with female suspects but not all suspects, indicating female-specific typologies of abuse.

- For incidents of DA in which females are suspects, statistically significant factors for repeat perpetration include a suspect's broader criminality, their use of IPV, the number of victims and the age of the victim.

Figure 1 presents a visualization of the four main cluster groups of domestic abuse perpetrators and their crimes.

Figure 1. Four heterogenous clusters of domestic abuse perpetrators



Gaps and priorities for further research

Female perpetration of domestic abuse

There is a lack of research and understanding nationally about the nature of female perpetration of domestic abuse including risk factors, escalation pathways, typologies, suspect/perpetrator crossover and what works for female perpetrators. A key research priority emerging from this project is the development of a rigorous mixed-methods study of female perpetration in nationally, to inform efforts to devise interventions for prevention, response and rehabilitation.

Non-crimes, crimes, and gender

42.2% of all police-recorded DA incidents in Essex are categorised as 'non-crimes' and for incidents where the suspect is female, it is closer to 50%. Unlike the category 'crime' which contains 10 discreet subcategories, the category of 'non-crimes' is undifferentiated in our data so we have little understanding of what behaviours this includes. Our factor analysis showed that an incident being a non-crime was a significant factor for repeat perpetration for abuse categorised as IPV but not significant for familial violence. However, we do not understand the reasons for this. There is at the time of writing no academic literature on non-crimes in the context of domestic abuse. There is a need for new research examining the nature of non-crimes, and their link to violence, coercive control (both tactics of and the impact of legislation on recording) and other kinds of abuse to develop a better understanding of different typologies of abuse and the profiles of the perpetrators who use them.

Suspect/victim crossover in both IP and non-IPV contexts

Our research identified a significant crossover between suspect and victim both in the female-on-male IPV cluster and, even more significantly, in the context of non-IPV DA. This indicates distinct typologies and risk factors for these kinds of abuse, which merit deeper examination. For familial abuse, an exploration of systems theory as a basis for analysing and responding to reciprocal violence may be explored (though controversial). The crossover also implies a need for trauma-informed approaches to both victim and perpetrator response and intervention.

Male-to-female IPV amongst young people

Even though our clusters flagged IPV amongst young people as significant both in terms of prevalence and in terms of risk, there is little research on typologies of abuse and what works in terms of interventions with this demographic. A more in-depth analysis of quantitative and DASH data for 16-25 year-olds (and potentially younger children also), combined with qualitative interviews or surveys with victims, perpetrators and practitioners would provide the insight needed to develop reliable typologies of young person abuse and inform specialist provision. Mixed-methods and longitudinal research should also focus on how practitioners and indeed young people themselves can recognise abusive relationships in young people and what works both in terms of prevention and intervention with this age group, which has distinct vulnerabilities and challenges.

Future research methods and improved data

For all of the research areas identified above, natural language processing of DASH assessments would provide much more granular analysis of typologies and risk factors. Similarly, the inclusion of non-police data, and of more granular data on non-crimes and on ethnic background of suspects would yield a much more inclusive and richer dataset. A project that re-ran the clustering techniques on a much larger dataset, and which then triangulated this with natural language processing of DASH data and regression analysis of ethnic and other factors cluster-by-cluster would yield much more detailed insights into perpetrator profiles in Essex and by extension nationally. It would also enable deeper intersectional analysis using interaction terms (e.g. between age, gender and ethnicity).

Limitations to the research

- Our findings relate only to those DA incidents that have been reported to police. The Crime Survey for England and Wales estimates that only 21 per cent of victims report their abuse to the police (Flatley, 2016). In addition, it is unlikely that those who report to the police are the same in profile as those who do not, as we know that certain groups --including groups relevant to clusters identified in this study-- under-report. For example, we know that male victims of domestic abuse are less likely to report to the police than females. This has implications for the representativeness of our data in general and in particular for our data relating to the female perpetrator cluster.
- We did not have access to non-police data on DA, due in part to a reluctance of other agencies to share data and in part to difficulties linking datasets reliably. Linking police data with social services data and mental health, substance abuse and alcohol data (often highlighted as risk factors in Domestic Homicide Reviews) would provide a much richer picture of the extent and nature of domestic abuse in Essex.
- We had to delete a significant amount of data during the cleaning process. There is a possibility that this may have introduced bias into the sample. It also meant that we could not include important but under-recorded variables such as victim self-harm and presence of children.
- As our data was limited to a specific time period, we will not have captured the full extent of repeat perpetration which began earlier and/or continued after our time period began and ended. Nevertheless, this does not affect the validity of the comparative findings revealed through clustering.
- It was not possible to model the neighbourhood level predictors as the police ward boundaries could not be linked with other datasets. We recommend police use GIS to add LSOAs in future.
- We were not able to analyse data on the ethnic background of victims and perpetrators beyond ‘non-white or non-British’. This limits the extent to which our research can identify specific cultural or language needs.
- As police do not record data on DA for children younger than 16 (due to legal definitions of DA) our analysis excludes this group. However, there is research indicating that IPV and abusive friendships are prevalent amongst younger age groups also.

Policy and practice actions and recommendations

Our findings and analysis support a number of recommendations for government both national and local, statutory agencies, funders and the third sector. We also highlight local recommendations where appropriate.

Female perpetration

- Our data suggests female perpetration typologies differ significantly from those for males. Therefore interventions and provisions for females should be designed specifically for them, informed by female-specific research, and not merely adapted from existing provision for males. This recommendation has implications for the National Probation Service, Drive and other organisations providing perpetrator programmes.
- The significant overlap between victim and suspect in female perpetration underscores the importance of implementing a trauma-informed approach to perpetrator response, interventions, and programmes for women.
- Training on female perpetration should be developed and offered to perpetrator-facing DA practitioners including police.
- Currently provision for female perpetrators is offered by some organisations locally[1], but it is one-to-one. Research has shown that group programmes have distinct benefits. Investment into the development of group programmes for female perpetrators should therefore be considered.
- There is currently very little local provision for male victims of domestic abuse. Male IDVAs or IDVAs specialising in support for male victims have been introduced in some local authorities[2] and should be evaluated to identify best practice in this area.

[1] See, for example, The Change Project in Essex (https://www.thechange-project.org/domestic-abuse/); Phoenix Domestic Abuse Services in Gwent (https://phoenixdas.co.uk/perpetratorprogrammes/).
[2] For example, Southend, Peterborough, Swansea Bay, Blackpool, Stockport.

Minoritized ethnic groups

A needs assessment and geographic analysis of minoritized ethnic victim and perpetrator services and interventions in Essex should be carried out to understand if there are specific groups with specific cultural or language needs (the traveller community was mentioned in qualitative interviews). Where targeted provision might be difficult due to e.g. prohibitive costs of interpretation, or insufficient numbers to run bespoke group sessions, more informal interventions, prevention and support could be explored by linking with community leaders and community groups; or culturally non-specific group sessions could be combined with 1-2-1 support addressing ethnic or cultural nuances (as also recommended in a report by Tonic, 2021). At the same time, national organisations could have a role to play where communities are dispersed.

Suspect/victim crossover

Training in trauma-informed responses to perpetration would help DA practitioners in police and probation in particular respond more effectively to the significant subset of perpetrators *across clusters* who have also been victims.

Young people and domestic abuse

Young people were not mentioned frequently in the qualitative interviews and were not flagged as a cluster in previous analysis for the ECDA project, suggesting this group is currently not a priority for DA services in Essex. There is some provision for young people offered in Essex: since 2019 there has been a female mentoring programme delivered by Goodman and Sisters in Strength in the Southend and Thurrock area, and Break The Cycle is a dedicated CYPVA service for those aged 13-19yrs who have witnessed abuse. But there is no specific IDVA provision for young people who are victims in Essex, and no services for children and young people who are perpetrators. Specialist young person's IDVA services are being introduced in other force areas (see, for example the use of specialist Children and Young Person's IDVA services in London Boroughs such as Islington, provided by Solace Women's Aid). The potential for further development of services and interventions, especially early prevention through schools and youth hubs, and through trusted relationships with e.g. youth workers and youth offending teams for this demographic group should be explored.

Recording practices

While we appreciate that for police attending incidents recording of data is time-consuming and sometimes difficult, the presence of children in a family or around a relationship involving abuse is significant both for child welfare and for perpetrator response and intervention. Studies have shown access to and relationships with children are a strong motivational factor for perpetrators to reform (Morgan et al. 2019) and that perpetrator participation in rehabilitation programmes has demonstrated benefits to child welfare (Alderson et al., 2013). Efforts should be made to collect this data more comprehensively.

Background

In August 2021 the Home Secretary reaffirmed the government's commitment to tackling DA offences, declaring that "we must deepen our understanding of who commits them, why they do so, and how it may escalate…to better understand key behaviours so we can put a stop to them for good'. This project meets that need by developing empirically-grounded insights into the profiles of DA perpetrators. Unlike most previous research in this field, which has tended to focus on one specific type of abuse or one specific kind of perpetrator, this research provides an overview of some of the salient forms of DA perpetration represented in a large police dataset. As Essex is itself a large county with a varied geographic and demographic profile and a relatively high prevalence of DA, the results presented here should be seen as potentially generalisable with national implications.

This study builds on a precursor analysis of domestic abuse perpetrators in Essex, undertaken in 2021 by the Essex Centre for Data Analytics (ECDA- a partnership venture between Essex County Council, Essex Police and The University of Essex). ECDA carried out an initial analysis clustering domestic abuse perpetrators in Essex but did not publish a report of their analysis of domestic abuse perpetrators, which makes it is difficult to know all the details of their analysis. However, an ECDA technical report provided some information about the techniques they used and the results they produced. Our analysis differs from and advances the ECDA analysis in the following important ways:

- In this project we used improved techniques and assumptions to clean and pre-process data.

- ECDA's clustering techniques seem to have used only 5 or 6 features of the data. Our analysis used 12 features. Our study therefore provides more information and detail about the characteristics of suspects and their crimes.
- ECDA seems to have used only one type of linkage method in their agglomerative hierarchical clustering, while our analysis used four different types of linkages, thus producing a richer and more robust set of results.
- ECDA did not validate its results with an alternative, comparable method. We checked the external validity of our results by implementing an analysis of association rules. This is another unsupervised learning method that allows us to find clear groups of perpetrators using probability theory. The results are therefore more reliable.

Altogether, the results of ECDA's analysis and our own results are not necessarily comparable.

The report is organized as follows. We first present our unsupervised learning approach to the analysis. We describe the data used in the project, as well as evidence about the potential for finding structure in the data. We then describe agglomerative hierarchical clustering and present its implementation to the domestic abuse dataset. The results from clustering are followed a description of the method of association rules, and present results from the analysis. In the second section of the report, we present our supervised learning methods. There we present relevant aspects of the data for the analysis including geographic distribution, as well as our approach to the use of DASH and regression analyses. Finally, we outline the qualitative research. The findings from the interviews are not presented separately but rather are drawn on throughout the report to provide context and interpretation to the quantitative methods.

We conclude with a discussion on the potential for interventions.

1. Using Unsupervised Machine Learning to Discover Clusters of Perpetrators

The goal of this project is to discover any existing clusters of perpetrators of domestic abuse. To do so, we use multiple unsupervised learning methods.

A computer learns from data if its performance in respect to some task improves with data (Mitchell 1997). This is a very useful logic in a context of supervised learning, which aims at predicting a particular outcome variable –such as the number of crimes committed by an individual– using a set of inputs, such as the age of such individual.[3] If a program learns from data, its predictions of the outcome variable should improve with data. From this perspective, we could study domestic abuse (DA) by predicting the number of DA incidents, the severity of the crimes, the gender of the victim, or any other aspect of a DA record, as determined by other aspects of an incident such as the relationship between perpetrator and victim.

Useful as supervised learning is, this project approaches domestic abuse from a different perspective. Specifically, it relies on unsupervised learning to find groups over all features of the data rather than predicting a particular outcome of a DA incident. In unsupervised learning (Wagonner 2020, 1): "the researcher feeds unlabelled data to a learning algorithm and allows patters to emerge, typically based on similarity among observations (within-group homogeneity) and dissimilarity between groupings of observations (between-group heterogeneity)." Indeed, we use unsupervised learning methods to find structures and patterns hidden in large amounts of data. Specifically, we aim at finding distinctive groups of suspects in domestic abuse incidents. We refer to these distinctive groups as 'clusters of perpetrators.'

This section uses two classes of unsupervised learning methods: Agglomerative Hierarchical Clustering (AHC) and Association Rules (AR). Before describing these methods, we first describe the data used for analysis.

1.1 Data

The data from Essex Police consists of two files in comma separated values. These two files were appended by the team in order to produce a single database with 410,528 observations. The unit of analysis in the data is the crime-person, where person is either a suspect or a victim. In other words, the database has a record for each crime, as given by the *Crime Reference Number* (CRN), and each crime has rows for suspects and victims.

The data has 56 variables or features organized in four categories: investigation features, victim features, suspect features, and features for the suspects' previous records.[4] These four categories

[3] Outcome variables are also known as outputs or even as dependent variables. Features are also known as inputs or independent variables.

[4] Essex Police and Essex County Council aimed at joining relevant datasets in order to explore a wider set of features in the context of domestic abuse. Unfortunately, the datasets from both organizations do not share a common identifier at the individual level. Instead, EP and ECC aimed at joining datasets using an identifier for households rather for individuals. However, this identifier was also not present in Essex Police data, so a manual procedure was implemented to join the datasets. While we commend the organizations for their efforts, this procedure is unreliable.

come from different databases joined by CRN by Essex Police. In addition to these four categories, Essex Police provided data from DASH, also joined by CRN. Data from DASH is used in the supervised learning section of this project.

This project focuses on perpetrators, and therefore we deleted crime records for victims. This produced a dataset where the unit of analysis is the crime-suspect. This process does not delete information about the victim, which is preserved in the four fields described above. Indeed, the four categories of information are present for each crime-person, so the key aspects of the DA incident are in fact duplicated across the rows for the suspect and the victim for the same crime.

The dataset has numerous problems, including unnecessarily repeated records, missing values, and conflicting information for the same individual, either suspect or victim. Altogether, we aimed at producing a dataset with reliable information and no missing values. This entailed deleting many features, which interesting as they were, reduced the sample to a size that could not be used effectively for machine learning. For instance, we deleted a feature related to self-harm behaviour in victims because it had more than 13,000 missing values. A feature related to links between the domestic abuse incident and children had more than 52,000 missing values. If these and other problematic features were kept in for analysis, the sample size would be too small to extract statistically valid insight. We understand that keeping detailed records of incidents is resource-intensive and very time consuming, but accurate data will facilitate future analysis.

At the end of the data cleaning and pre-processing, we produced a usable dataset with 40,488 observations, covering the years 2016 to 2020. The dataset has 59 features, which includes some of the original features as well as new variables we created in order to capture aspects of a crime more effectively.

There are many ways of organizing this data for analysis. However, the data does have a longitudinal structure with individuals committing multiple crimes over time. Therefore, we organized the data such that the unit of analysis is the suspect-crime. In other words, we have all DA incidents for the same individual. In some cases, an individual only has one row of data because there is only one crime. In other cases, an individual has multiple rows of data because they have committed multiple offenses. This is a very useful organization of the data because we can track the number of crimes per suspect –both the count of crimes over time as well as the total number of crimes over the period covered by the data– and the number of victims over those crimes, as well as characteristics of the suspect and the victims. We also know whether the

For this reason, we did not use information from ECC datasets. However, our supervised learning analysis does include relevant variables that consider social aspects of a DA incident.

suspect has appeared in the database as a victim. Altogether, this data organization is ideal for an analysis of perpetrators of domestic abuse. This version of the data has 16,491 suspects over 40,488 observations.[5]

Justification of the variables selected

As mentioned, the processed data has 59 features that capture key aspects of a DA incident. Machine learning algorithms often fail when they explore large numbers of features; this is popularly known as the 'curse of dimensionality.' For this reason, researchers often implement dimension reduction techniques, such as principal components, to overcome this problem. This is a useful technique, although often produces challenges for the interpretation of results.

This project takes a different approach and focuses on 12 features of the data, which are described below.[6] These are features that enable some insight into the different types of domestic abuse and domestic abuse perpetrator within Essex, allowing us to disaggregate domestic abuse into distinct crimes, e.g. by distinguishing IPV from other, less well-understood kinds of domestic abuse, while also highlighting the continuities between them. In this light, this report provides only a baseline analysis of perpetrators of domestic abuse and a point of departure for further, more in-depth research. The dataset has many more variables and constructions –such as polynomials for age differences between suspects and victims– but the scope of this project did not allow for sufficient time and space for a full analysis, which would have required additional work to perform dimension reduction on large numbers of features. We hope to carry out this analysis soon.

Having said this, out of these 12 features, 10 are measured as binary variables: *Suspect Gender* (female or male), *Suspect is UK National* (yes=1 or no=0), *Suspect is White British* (yes=1 or no=0), *Suspect is Also Victim* (yes=1 or no=0), *Victim Gender* (female or male), *Intimate Partner Violence* (yes=1 or no=0), *Many Crimes Above Median* (yes=1 or no=0), *Many Victims Above Median* (yes=1 or no=0), *Suspect Age Above Median* (yes=1 or no=0), and *Victim Age Above Median* (yes=1 or no=0).

A record is considered *Intimate Partner Violence* (IPV) if the suspect is either an ex-partner, partner, or spouse of the victim. 85.3 per cent of all incidents are recorded as IPV. The variable

[5] The longitudinal stricture suggests that there may be auto-correlation across observations for the same suspect. While this is a challenge for supervised learning methods due to information leakage between training and test samples, this is not usually a problem in unsupervised learning. In this light, while we assume that observations are i.i.d, we do include a measure of the total number of crimes for the suspects, which addresses part of the auto-correlation issue. Future work will address this issue more directly.
[6] Appendix 1 has summary statistics of relevant variables, including new variables created for our analysis of DASH risk.

Many Crimes Above Median is equal to 1 if the total number of crimes for a suspect is larger than the median of the total number of crimes, otherwise it is equal to 0. The median total number of crimes is 5. The variable *Many Victims Above Median* is equal to 1 if a suspect's number of different victims is larger than the median of the number of different victims, otherwise it is equal to 0.[7] The median of the number of different victims is 2 (suggesting that most people involved in DA in Essex have more than one victim). The same logic applies to the ages of the suspect and the perpetrator at the time of the incident. The median ages of the suspect and the perpetrator are both 32 years of age (younger than the median age in the UK, which is 40). The distribution of these variables is skewed and this will displace the sample mean away from the centre of the distribution. Therefore, we use the median as a more useful point of reference.

In the 12 features in the data, 2 have multiple categories. The variable *Risk* consists of three levels of risk for the incident: High (16.1 per cent), Medium (27.9 per cent), and Standard (55.9 per cent). The variable *Crime* is the higher level of the offense, consisting of 10 categories: damage and arson offenses (4.7 per cent), miscellaneous crimes against society (1 per cent), non-crime (42.4 per cent), non-notifiable (0.03 per cent), possess weapon offenses (0.04 per cent), public order offenses (2.2 per cent), robbery (0.07 per cent), sexual offenses (1.5 per cent), theft offenses (1.7 per cent), and violence against the person (46 per cent).

As mentioned, we rely on unsupervised learning to discover potential clusters of perpetrators. Learning from data is never perfect, and this is particularly the case in unsupervised learning because there is no outcome to predict, and therefore it is not possible to tell whether a prediction, according to some rule, was successful or not. Yet, we believe that this approach to studying DA is useful and may shed light on future studies of DA by creating labels that can then be used by supervised learning techniques (Waggoner 2020). For instance, domestic abuse incidents in this dataset may be categorized into clusters, and this categorization may be used to predict the type of future incidents of domestic abuse.

1.2 Structure in the data

Before presenting results from clustering methods, it is important to explore whether there is potential for clustering in the first place. Wagonner (2020) recommends the use of the Hopkins

[7] Many suspects have multiple crimes, but the victim may be the same person in these crimes. In other cases, the multiple crimes relate to different victims. This variable reflects the number of different victims for the same perpetrator.

statistic as well as Ordered Dissimilarity Images (ODI) to explore whether there are clusters –and therefore structure– in a dataset. In order to calculate the Hopkins statistic and produce the ODI, the team standardized the data so that all features are on the same scale.

The Hopkins statistic reflects the probability that the data in the sample is generated by a random variable from a uniform distribution. If the data is the result of random noise, clusters are not likely to be found. However, if there is structure and the data was generated by a systematic, non-uniform process, there may be clusters to discover. High values of the Hopkins statistic indicate that the data is not the result of random noise. The Hopkins statistic for the data is 0.853, which is close to one; this suggests that there may be clusters in the data.

The potential existence of clusters in a database can also be explored graphically with an Ordered Dissimilarity Image. ODIs present a measure of dissimilarity between observations, with higher values indicating higher dissimilarity. Measures of dissimilarity will be discussed in a moment. Meanwhile, it is valid to say that observations are highly dissimilar when an ODI produces an image that resembles the static noise in TVs. However, clusters may be present (eg. observations are less dissimilar) if the ODI produces large blocks of pixels (Wagonner 2020).

Unfortunately, we were unable to present the ODI for the original data base of 40,488 observations due to memory restrictions in our computers. For this reason, we chose to generate a random sample of 4048 observations (10 per cent of the data) to produce an ODI of Figure 1. The Hopkins statistic for this random sample is 0.7812

Figure 2. Ordered Dissimilarity Image for Sample of Data

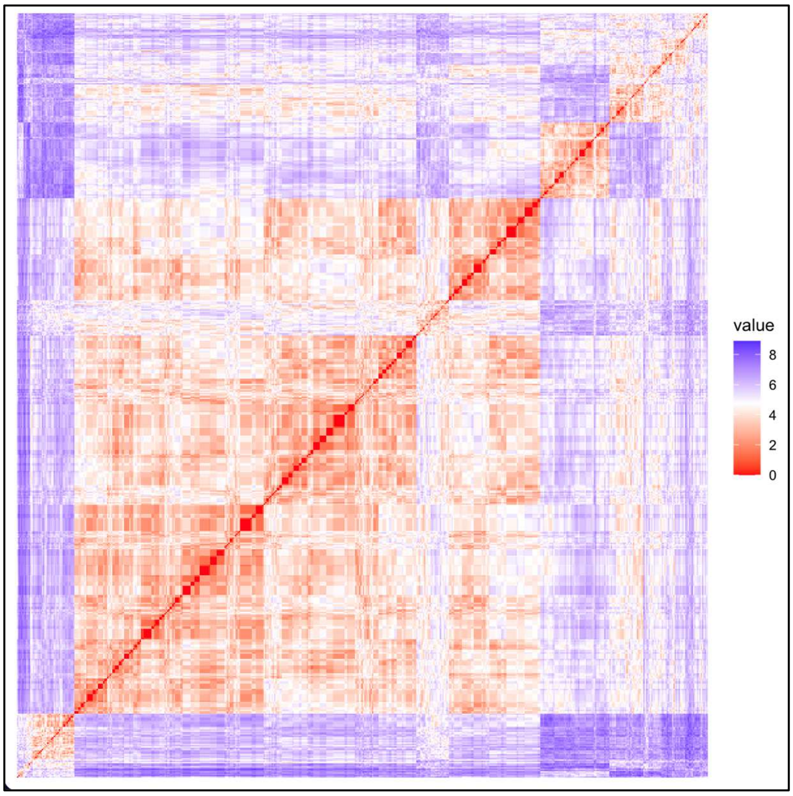


Figure 2 presents clear blocks of data, which indicates that clusters may be present in the dataset, thus confirming the conclusion produced by the Hopkins statistic.

1.3 Clustering

This section focuses on Agglomerative Hierarchical Clustering (AHC). Clustering methods such as AHC aim at grouping similar observations and creating groups that are distinct from each other. This latter aspect of clustering is important because it highlights the need to discover sufficiently different groups (Hastie, Tibshirani, and Friedman 2009). In other words, clustering should ideally produce heterogenous groupings with homogenous cases within them.

The (dis)similarity –and therefore the homogeneity or lack thereof– between units is particularly crucial in clustering exercises. (Dis)similarity in machine learning is often a function of a measure of distance between observations. While this distance between observations may be geographic, it may entail distance along other dimensions. For this reason, a more convenient term for 'distance' in this context may be 'separation.' Regardless, note that 'distance' or 'separation' is often multidimensional. Indeed, the 'distance' between identical twins is relatively small: they have very similar ages, similar family background, and probably live in the same household. However, the 'distance' between one of these twins and a next-door neighbour –even a neighbour born on the same day– is larger simply because they have different family backgrounds and addresses.

In machine learning, popular measures of distance between observations are Euclidian, Manhattan, or Pearson measures of distance. These measures are useful for continuous random variables, such as the weight in grams of individuals. However, the features of the domestic abuse database in this project consist of discrete random variables, such as gender, ethnicity, or the type of crime. For instance, variables such as gender take two values: female or male. Perpetrators are also classified as white British or not white British. The types of crimes are also discrete and include categories such as 'violence against the person' or 'public order offenses.'

When data features are discrete, or a mix of continuous and discrete random variables, it is necessary to use a measure of distance between features that are quantified very differently. This project uses Gower's distance, which is based on Gower's coefficient (1971). Specifically, we use the *R* package *cluster* and its *daisy* command to standardize the data and produce a (dis)similarity matrix (Maechler 2022): "Each variable (column) is first standardized by dividing each entry by the range of the corresponding variable, after subtracting the minimum value; consequently the rescaled variable has range [0,1], exactly." Dissimilarities close to zero reflecting minimal dissimilarity and numbers close to one reflecting maximum dissimilarity.

This process produces a very large (dis)similarity matrix for all 40,488 observations in the data. It is worth noting that the calculation of this (dis)similarity matrix takes a couple of days of computer run time.

Agglomerative Hierarchical Clustering

The characteristics of features also drive, to a large extent, the selection of the clustering algorithm. For instance, the k-means clustering method is quite useful for continuous random variables. K-medoids may also be used for cases in which (dis)similarity is not Euclidian distance. Regardless, both k-means and k-medoids require that researchers choose an optimal number of clusters to be found. While this aspect of the learning method does not present a problem (Hastie, Tibshirani, and Friedman 2009), we prefer to use an algorithm that does not require such restrictions on the parameters. Future work could use other algorithms.

Agglomerative Hierarchical Clustering, like other agglomerative algorithms, does not require that researchers set the optimal number of clusters to be found. Instead, AHC focuses on a measure of (dis)similarity between clusters, in addition to the more fundamental aspects of distance between observations within clusters. We focus on agglomerative clustering, as opposed to divisive clustering, in order to pair observations into clusters from the bottom up, which in the case of domestic abuse seems an intuitive starting point to build clusters. Indeed, this method starts by pairing individual observations and then grouping these individuals into larger clusters, as opposed to divisive clustering, which begins by subdividing a cluster that includes all observations.

AHC produces a dendrogram, which is easy to interpret and may present clearly visible clusters of observations. Even if the clusters are not immediately clear, dendrograms can be cut at a specific level of (dis)similarity in order to obtain clusters based on that particular cut.

It is worth noting that results from AHC are highly dependent on the selection of the parameters of the algorithm, particularly the linkage methods, which is discussed in a moment. As indicated by Hastie, Tibshirani, and Friedman (2009, 523): "Thus the dendrogram should be viewed mainly as a description of the clustering structure of the data as imposed by the particular algorithm employed." Yet, a systematic approach to implementing and interpreting the results of different linkage methods, might produce stable results.

This project implements AHC with different linkage options. Like other clustering methods, AHC requires a measure of (dis)similarity between observations. In addition, AHC requires methods to link groups of observations as it joins them to build clusters (Hastie, Tibshirani, and Friedman 2009; Wagonner 2020). Starting from the bottom up, AHC assumes that each observation is its own cluster; eventually the algorithm moves from joining single observations to joining groups of observations. Based on the chosen measure of distance, the 'complete linkage' method pairs groups of observations based on the maximum distance between them, while the 'average linkage' method pairs clusters according to their mean (dis)similarity.

The *cluster* package offers several linkage options. Each option may produce different clusters and different insights. At the same time, we are interested in clusters that are similar across linkage options, as this will improve the external validity of our results. For these reasons, we used four different linkage options as provided by the *cluster* package: single link, complete link, average link, and Ward's link. However, the single link method did not produce distinctive clusters and therefore we focus on the results produced by the complete link, average link, and Ward's link methods. It is worth noting that each clustering algorithm takes about two days of computer run time.

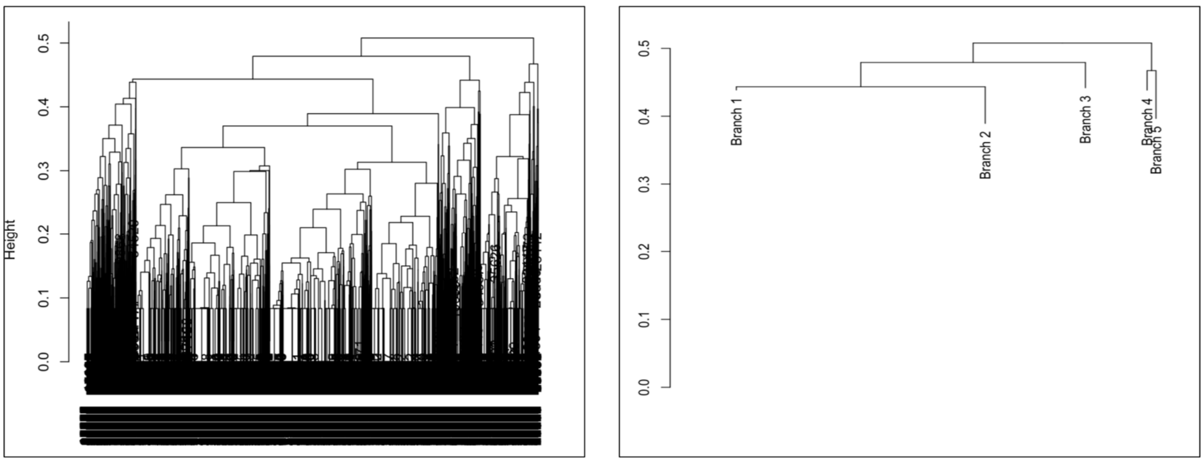
To place substantive results in context and explain how this project selected clusters in the data, we present the full dendrograms produced by the three linkage algorithms under AHC. These dendrograms are difficult to interpret due to the large number of observations at the bottom of the tree. However, we also present a stylized version of the dendrograms that indicates the clusters found in the analysis.

There are many ways of obtaining clusters from dendrograms (James, Witten, Hastie, and Tibshirani 2017). One option is to identify long branches in the tree, which indicate different levels of (dis)similarity for different clusters as determined by their height in the vertical axis. A second option is to cut the tree at a particular height –which is the level of (dis)similarity– and retrieve the clusters generated by the cut. In this case, the number of clusters is given by the number of intersections between the chosen hight and the tree branches. In some other cases, it is valid to choose branches based on relatively obvious groups, although it is important to consider that these groups should have different dissimilarities (ie. branches of different lengths). In this project, we make cuts to trees at heights that produced easily identifiable clusters.

It is important to note that clusters can be quite heterogenous. Only when clusters are very different is it possible to have clusters with homogenous observations, although this is almost impossible. This will be evident in the tables that present substantive results about clusters of perpetrators.

Figure 3 presents the full dendrogram and the stylized dendrogram for the average linkage method.

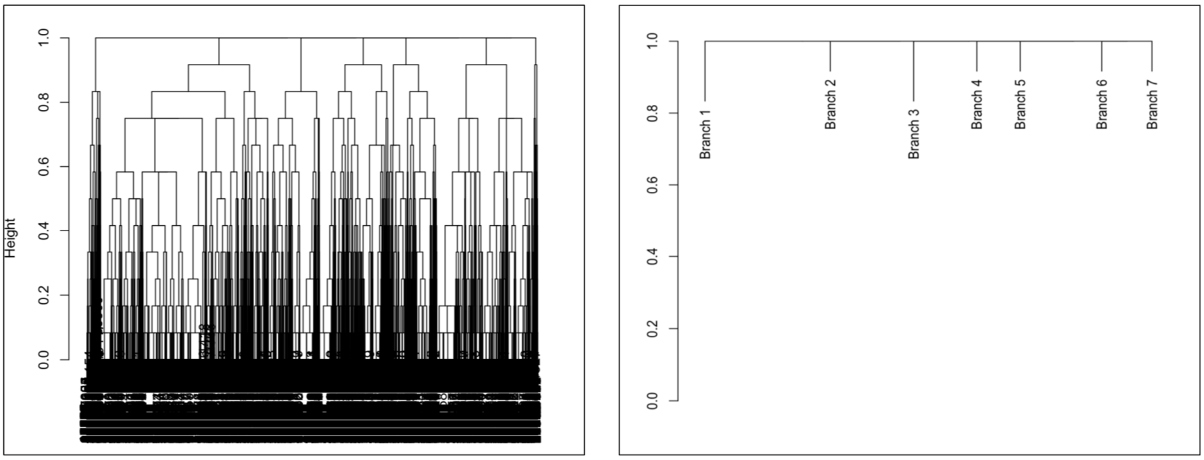
Figure 3. Dendrogram for AHC with Average Link and Clusters



This linkage method produced four clusters. The first cluster is given by all observations (ie. perpetrator-crimes) in Branch 1. The second cluster is given by all observations in Branch 2, while the third cluster is given by all observations in Branch 3. The fourth cluster is given by all observations in Branches 4 and 5. These clusters created by a cut at height 0.442, but Branches 4 and 5 (essentially two different clusters for that particular height) were aggregated into one.

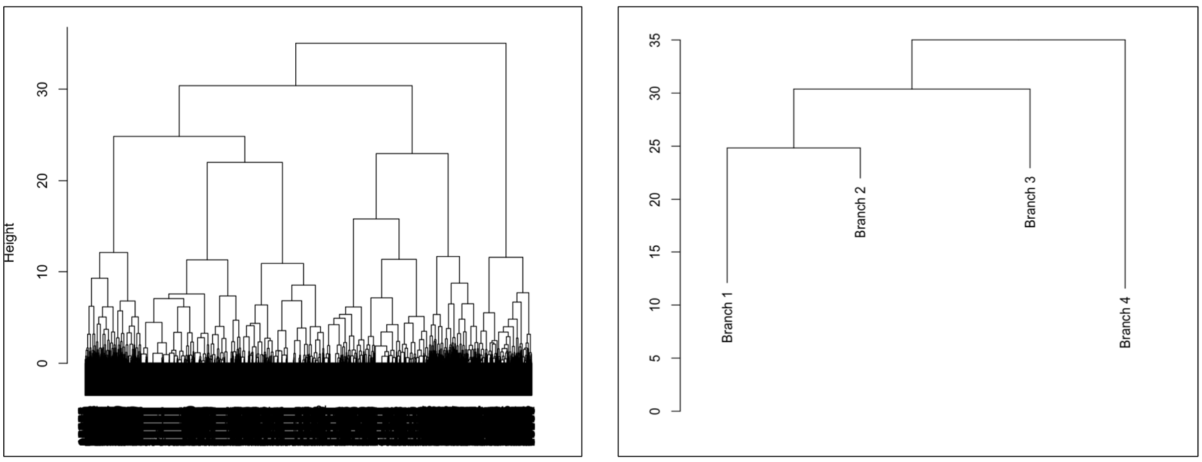
Figure 4 presents the full dendrogram and the stylized dendrogram for the complete linkage method. This method produced seven clusters, all indicated by the branch numbers in the stylized version of the dendrogram.

Figure 4. Dendrogram for AHC with Complete Link and Clusters



Lastly, Figure 5 presents the full dendrogram and the stylized dendrogram for Ward's linkage method. This method produced four clusters, all indicated by the branch numbers in the stylized version of the dendrogram.

Figure 5. Dendrogram for AHC with Ward's Link and Clusters



Feature	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Sus Gender	Male: 2777 Female: 1638	Male: 27099 Female: 56	Male: 3705 Female: 20	Male: 349 Female: 4844
Sus UK National	Yes: 4364 No: 51	Yes: 26951 No: 204	Yes: 1069 No: 2656	Yes: 4756 No: 437
Sus White British	Yes: 4170 No: 245	Yes: 26074 No: 1081	Yes: 139 No: 3586	Yes: 4600 No: 593
Sus Also Victim	Yes: 2842 No: 1573	Yes: 13888 No: 13267	Yes: 1106 No: 2619	Yes: 4370 No: 823
Victim Gender	Male: 925 Female: 3490	Male: 27 Female: 27028	Male: 81 Female: 3644	Male: 5077 Female: 116
Crime	Non-crime: 1545 Violence against the person: 2219	Non-crime: 12011 Violence against the person: 11889	Non-crime: 1432 Violence against the person: 1931	Non-crime: 2213 Violence against the person: 2586

IPV	Yes: 115 No: 4300	Yes: 26416 No: 739	Yes: 3329 No: 396	Yes: 4698 No: 495
Risk	High: 465 Medium: 952 Stand: 2998	High: 5058 Medium: 8100 Stand: 13997	High: 815 Medium: 1171 Stand: 1739	High: 198 Medium: 1083 Stand: 3912
Many Crimes	Above: 2595 Below: 1820	Above: 17346 Below: 9809	Above: 1541 Below: 2184	Above: 1789 Below: 3404
Many Victims	Above: 3692 Below: 723	Above: 13803 Below: 13352	Above: 1246 Below: 2479	Above: 1989 Below: 3204
Sus Age	Above: 1478 Below: 2937	Above: 14509 Below: 12646	Above: 2515 Below: 1210	Above: 2722 Below: 2471
Victim Age	Above: 2986 Below: 1429	Above: 12248 Below: 14907	Above: 2363 Below: 1362	Above: 3184 Below: 2009
Perpetrators	4415 (11%)	27155 (67%)	3725 (9%)	5193 (13%)

Having presented the dendrograms and the clusters, the following tables present substantive results. For each linkage method and for each cluster, the tables present the number of observations (ie. perpetrator-crimes) at the bottom of the table, and the number of observations by feature. For instance, in Table 1 for the average link method, Cluster 1 has 4415 perpetrator-crimes. Out of these 4,415 perpetrators, 2,777 are male and 1,638 are female. Likewise, 4,364 perpetrators are UK nationals and 51 are not UK nationals.

For transparency, we present the number of observations for each category in each feature, except for type of crime– we only present the two categories with the largest number of observations rather than all 10 categories. As mentioned before, no cluster is perfectly homogenous, and therefore it is important to capture heterogeneity by tabulating the number of observations by category for each data feature. However, in order to facilitate interpretation, we highlight in red the category with the largest number of observations. Often, the category with the largest number of observations has order of magnitude more observations than the complementary category. When feature categories have similar numbers of observations, we highlight all categories. We also highlight in orange any categories that seem particularly relevant due to their impact and their number of observations.

Table 1 presents the substantive clusters for the average linkage method. Table 2 presents the substantive clusters for the complete linkage method, while Table 3 presents results from Ward's linkage method.

Table 1. Clusters for AHC with Average Link

As an example, Cluster 1 consists mainly of white, male perpetrators who are UK nationals. These perpetrators' age is below the median age of perpetrators in the sample, but their victims' age is above the median age of victims. The victims are mostly female, and the crimes do not entail IPV. The majority of crimes committed by these perpetrators is violence against the person. These perpetrators have committed more DA crimes than the median number of crimes for the sample, and have more victims of DA than the median number. It is worth noting that these perpetrators also appear in the database as victims. The risk for these DA incidents is mostly standard.

Table 2. Clusters for AHC with Complete Link

Feature	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
Sus Gender	Male: 1082 Female: 167	Male: 15035 Female: 15	Male: 3351 Female: 1248	Male: 6082 Female: 109	Male: 1680 Female: 2653	Male: 6687 Female: 1946	Male: 13 Female: 420
Sus UK National	Yes: 1106 No: 143	Yes: 12890 No: 2160	Yes: 4536 No: 63	Yes: 5714 No: 477	Yes: 4313 No: 20	Yes: 8477 No: 156	Yes: 104 No: 329
Sus White British	Yes: 983 No: 266	Yes: 11847 No: 3203	Yes: 4555 No: 44	Yes: 4794 No: 1397	Yes: 4227 No: 106	Yes: 8490 No: 143	Yes: 87 No: 346
Sus Also Victim	Yes: 759 No: 490	Yes: 3377 No: 11673	Yes: 1953 No: 2646	Yes: 4435 No: 1756	Yes: 3846 No: 487	Yes: 7576 No: 1057	Yes: 260 No: 173
Victim Gender	Male: 596 Female: 653	Male: 26 Female: 15024	Male: 1309 Female: 3290	Male: 55 Female: 6136	Male: 2005 Female: 2328	Male: 1720 Female: 6913	Male: 399 Female: 34
Crime	Non-crime: 429 Violence against the person: 611	Non-crime: 6862 Violence against the person: 6437	Non-crime: 1973 Violence against the person: 2223	Non-crime: 2206 Violence against the person: 3042	Non-crime: 1807 Violence against the person: 2119	Non-crime: 3741 Violence against the person: 3957	Non-crime: 183 Violence against the person: 236

IPV	Yes: 7 No: 1242	Yes: 14656 No: 394	3974 625	Yes: 4645 No: 1546	Yes: 2873 No: 1460	Yes: 8043 No: 590	Yes: 360 No: 73
Risk	High: 68 Medium: 329 Stand: 852	High: 3557 Medium: 4390 Stand: 7103	High: 274 Medium: 1199 Stand: 3126	High: 752 Medium: 2898 Stand: 2541	High: 381 Medium: 947 Stand: 3005	High: 1482 Medium: 1451 Stand: 5700	High: 22 Medium: 92 Stand: 319
Many Crimes	Above: 923 Below: 326	Above: 9077 Below: 5973	Above: 138 Below: 4461	Above: 4219 Below: 1972	Above: 2502 Below: 1831	Above: 6400 Below: 2233	Above: 12 Below: 421
Many Victims	Above: 1115 Below: 134	Above: 7103 Below: 7947	Above: 419 Below: 4180	Above: 4536 Below: 1655	Above: 3028 Below: 1305	Above: 4484 Below: 4149	Above: 45 Below: 388
Sus Age	Above: 164 Below: 1085	Above: 6588 Below: 8462	Above: 3932 Below: 667	Above: 1574 Below: 4617	Above: 1796 Below: 2537	Above: 6900 Below: 1733	Above: 270 Below: 163
Victim Age	Above: 1113 Below: 136	Above: 4663 Below: 10387	Above: 2859 Below: 1740	Above: 2900 Below: 3291	Above: 983 Below: 3350	Above: 7908 Below: 725	Above: 355 Below: 78
Perpetrators	1249 (3%)	15050 (37%)	4599 (12%)	6191 (15%)	4333 (11%)	8633 (21%)	433 (1%)

Feature	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Sus Gender	Male: 3546 Female: 1536	Male: 16499 Female: 114	Male: 13852 Female: 121	Male: 33 Female: 4787
Sus UK National	Yes: 4999 No: 83	Yes: 16479 No: 134	Yes: 11225 No: 2748	Yes: 4437 No: 383
Sus White British	Yes: 4810 No: 272	Yes: 16533 No: 80	Yes: 9331 No: 4642	Yes: 4309 No: 511
Sus Also Victim	Yes: 2939 No: 2143	Yes: 9290 No: 7323	Yes: 5677 No: 8296	Yes: 4300 No: 520
Victim Gender	Male: 1216 Female: 3866	Male: 20 Female: 16593	Male: 93 Female: 13880	Male: 4781 Female: 39
Crime	Public order offenses: 1884 Violence against the person: 2441	Public order offenses: 7097 Violence against the person: 7288	Public order offenses: 6142 Violence against the person: 6508	Public order offenses: 2078 Violence against the person: 2388
IPV	Yes: 478 No: 4604	Yes: 16118 No: 495	Yes: 13332 No: 641	Yes: 4630 No: 190
Risk	High: 333 Medium: 1370 Stand: 3379	High: 3935 Medium: 5087 Stand: 7591	High: 2112 Medium: 3876 Stand: 7985	High: 156 Medium: 973 Stand: 3691
Many Crimes	Above: 2535 Below: 2547	Above: 15451 Below: 1162	Above: 3474 Below: 10499	Above: 1811 Below: 3009
Many Victims	Above: 3553	Above: 12244	Above: 3009	Above: 1924

	Below: 1529	Below: 4369	Below: 10964	Below: 2896
Sus Age	Above: 1442 Below: 3640	Above: 7654 Below: 8959	Above: 9617 Below: 4356	Above: 2511 Below: 2309
Victim Age	Above: 3677 Below: 1405	Above: 6330 Below: 10283	Above: 7768 Below: 6205	Above: 3006 Below: 1814
Perpetrators	5082 (12%)	16613 (41%)	13973 (35%)	4820 (12%)

Table 3.

Clusters for AHC with Ward's Link

Discussion

Tables 1-3 present results from Agglomerative Hierarchical Clustering using different types of linkage methods. In some cases, Agglomerative Hierarchical Clustering produces very distinctive clusters, identifiable by long branches in a tree. However, algorithms may not always produce obviously distinctive clusters. In these cases, researchers and practitioners may cut the tree at a particular level of (dis)similarity and retrieve the clusters generated by this cut.

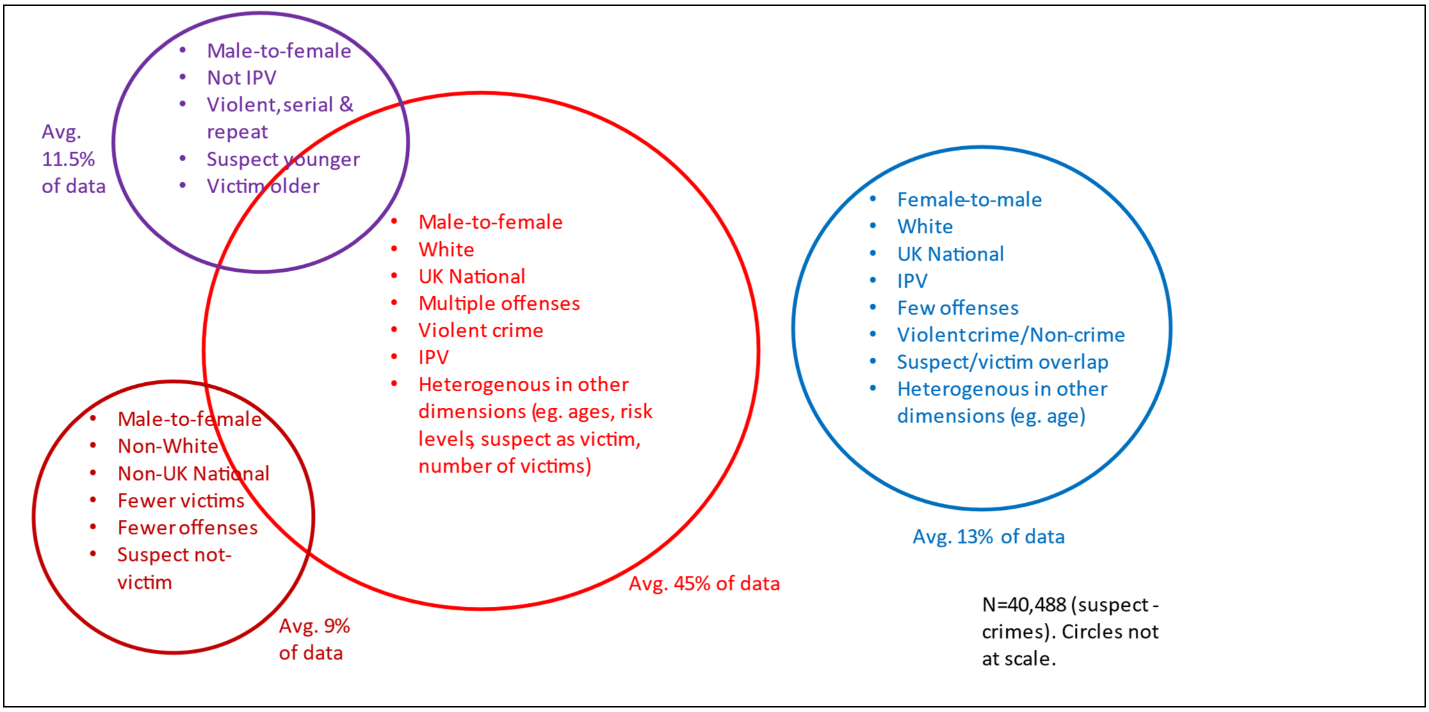
Regardless of the method to discover clusters, no cluster will consist of identical cases. Every cluster will exhibit heterogeneity, and every set of clusters will exhibit some homogeneity. For these reasons, we chose to present the actual number of observations for each feature of each cluster for each algorithm. These numbers reflect key nuances in criminal behaviour that should not be ignored. For instance, consider the number of observations in the feature *Risk* in Cluster 2 in Table 3. For this cluster, 7,591 observations (46% of the data for that cluster) are considered high risk, but 5,087 (30% of the data for that cluster) are considered medium risk, and 3,935 (24% of the data for that cluster) are considered high risk. While the majority of incidents are considered standard risk, the prevalence of the other levels of risk should not be dismissed. Altogether, we recommend that tables are read in detail in order to capture the nuances of clusters.

At the same time, some features for some clusters present less heterogeneity. Consider the feature *Sus Gender* in Cluster 2 in Table 1. For this cluster, 27,099 observations (99.8% of the data for that cluster) consist of male suspects, but only 56 (0.2% of the data for that cluster) consist of female suspects. Across the tables of results, we have highlighted in red the category in the feature with the majority of observations.

In order to visualize a summary of our results, we have used majority categories across features, clusters, and algorithms to produce four distinct groups of domestic abuse perpetrators. Each of these clusters will exhibit heterogeneity, and heterogeneity will be higher in groups with larger numbers of observations. To give an approximation of the number of perpetrator-crimes in each group, we present the average proportion of observations that similar clusters have across algorithms. For instance, Group 1 is based on Cluster 2/Table 1, Cluster 2/Table 2, and Clusters 2 and 3/Table 3, which represent 67%, 37%, 41%, and 35% of the data in each clustering algorithm. Therefore, we calculate that Group 1 has an average proportion of 45% of the data.

This is an imperfect method to capture and summarize all the results produced by the three different linkage methods discussed above. However, the groups are present across algorithms in one form or another, so the figure provides a useful baseline to explore in more detail the nuances of each table of clusters.

Figure 6. Four heterogenous clusters of domestic abuse perpetrators



Groups can be summarized as follows.

Group 1. Repeat and Serial Male-to-Female Intimate Partner Violence

This is the largest group of suspect clusters, containing an average of 45% all perpetrator data. Its features correspond with what most people would associate with the term ‘domestic abuse’ and what is known to be the bulk of domestic abuse criminality. We can therefore consider it the paradigm profile of DA. It consists of white, UK national, male perpetrators with multiple offenses, multiple female victims, and violent crimes under IPV. Over half of these perpetrators have committed more DA crimes than the median number of crimes for the sample in the specific time period (>5) and have more victims of DA than the median number (>2). Most existing perpetrator programmes, whether statutory (i.e. compulsory for people on probation) or otherwise, are already geared towards people who would fall within this group.

Perhaps unexpectedly, for the largest of these clusters (Table 1, Cluster 2, accounting for 67% of the perpetrator data in that cluster group) around half of the suspects have also been victims. A complementary analysis of association rules, another machine learning method, confirms the main characteristics of this group of perpetrators. These characteristics are confirmed by other clustering methods, which present key nuances (Table 2, Cluster 2; Table 3, Clusters 2 and 3).

IPV amongst young people

The most notable of these nuances is seen in Table 2, Cluster 2, which accounts for 37% of the data for that group. This cluster is demographically distinct in that the majority of abuse is perpetrated and experienced by people who are younger than average (>32). Confirming existing research into domestic abuse amongst young people (Safelives, 2017:7), the risk for this cluster is higher than for most other clusters, with almost 50% of incidents graded high or medium risk. Cluster 3.2, which also includes a majority of younger-than-average victims, confirms the link between victim age and risk, with 54% of incidents rated high or medium risk. Further research looking at precise ages and risk assessments and analysing DASH data and offending/victimisation pathways for these would provide more insight into prevalence and typologies of abuse by young people, which in turn could inform the development of specialist provision.

Nationally, there is evidence showing that young people are overrepresented in the cohort of victims of domestic abuse and are less likely than other age groups to report abuse. For example, the Crime Survey for England and Wales (CSEW) year found that for the year ending March 2020 women aged 16 to 19 years were more likely to be victims of any domestic abuse than women aged 25 years and over. Evidence presented in a 2017 report on abuse and young people by SafeLives also shows that there is a higher risk of severe abuse in children and young people.

These findings have implications for the design and delivery of young-person-facing perpetrator and victims services in Essex and beyond. Young people experiencing domestic abuse have distinctive vulnerabilities, experiences, challenges and needs. These cannot be met fully by existing adult-facing services, which often specify a fixed length of time and format for engagement and support. Young people experience a complex transition from childhood to adulthood, which impacts on behaviour, decision making, the way that they understand and respond to abuse as well as the way that they engage with services. They may be less able to recognise relationships as unhealthy or behaviours as abusive. Victims may also need additional support with practical problems such as moving home, dealing with police and other agencies, and accessing and managing finances.

Young people were not mentioned frequently in the qualitative interviews and were not flagged as a cluster in previous analysis for the ECDA project, suggesting this potential group is currently below the radar of DA services. There is some provision for young people offered in Essex: since 2019 there has been a female mentoring programme delivered by Goodman and Sisters in Strength in the Southend and Thurrock area, and Break The Cycle is a dedicated CYPVA service for those aged 13-19yrs who have witnessed abuse. But there is no specific IDVA provision for young people who are victims in Essex, and no services for children and young people who are

Feature	Table 1, Cluster 2	Table 2, Cluster 2	Table 3, Cluster 2	Table 3, Cluster 3
Sus Gender	Male: 27099 Female: 56	Male: 15035 Female: 15	Male: 16499 Female: 114	Male: 13852 Female: 121
Sus UK National	Yes: 26951 No: 204	Yes: 12890 No: 2160	Yes: 16479 No: 134	Yes: 11225 No: 2748
Sus White British	Yes: 26074 No: 1081	Yes: 11847 No: 3203	Yes: 16533 No: 80	Yes: 9331 No: 4642
Sus Also Victim	Yes: 13888 No: 13267	Yes: 3377 No: 11673	Yes: 9290 No: 7323	Yes: 5677 No: 8296
Victim Gender	Male: 27 Female: 27028	Male: 26 Female: 15024	Male: 20 Female: 16593	Male: 93 Female: 13880
Crime	Non-crime: 12011 Violence against the person: 11889	Non-crime: 6862 Violence against the person: 6437	Public order offenses: 7097 Violence against the person: 7288	Public order offenses: 6142 Violence against the person: 6508
IPV	Yes: 26416 No: 739	Yes: 14656 No: 394	Yes: 16118 No: 495	Yes: 13332 No: 641
Risk	High: 5058 Medium: 8100 Stand: 13997	High: 3557 Medium: 4390 Stand: 7103	High: 3935 Medium: 5087 Stand: 7591	High: 2112 Medium: 3876 Stand: 7985
Many Crimes	Above: 17346 Below: 9809	Above: 9077 Below: 5973	Above: 15451 Below: 1162	Above: 3474 Below: 10499

Many Victims	Above: 13803 Below: 13352	Above: 7103 Below: 7947	Above: 12244 Below: 4369	Above: 3009 Below: 10964
Sus Age	Above: 14509 Below: 12646	Above: 6588 Below: 8462	Above: 7654 Below: 8959	Above: 9617 Below: 4356
Victim Age	Above: 12248 Below: 14907	Above: 4663 Below: 10387	Above: 6330 Below: 10283	Above: 7768 Below: 6205
Perpetrators	27155 (67%)	15050 (37%)	16613 (41%)	13973 (35%)

perpetrators. Specialist young person's IDVA services are being introduced in other force areas (see, for example the use of specialist Children and Young Person's IDVA services in London Boroughs such as Islington, provided by Solace Women's Aid) and the potential for further development of services for this demographic group should be explored.

Fig.7 Repeat and Serial Male-to-Female IPV Cluster Group: Table Data

Group 2. Repeat and Serial Familial Abuse

The clusters in this group (Table 1, Cluster 1; Table 3, Cluster 1) relate to a small cohort containing an average of 11.5% of perpetrator data. About 65% of the suspects are male (a significantly higher prevalence of female perpetration than in Group 1) and 80% of the victims are female. Crimes are equally likely to involve violence against the person or to be public order offenses or non-crimes. But, strikingly, less than 10% of the abuse is IPV. Suspects in this group appear to be prolific and serial offenders, with about 60% committing more than 5 DA-related crimes each and over 80% abusing more than 2 victims. However, there is a significant suspect/victim crossover -indeed, higher than for any other cluster group- with about 60% of suspects also having been victims of DA. Suspects are younger than average and tend to offend against people who are often older than average, suggesting that this group may be capturing child-to-parent and familial abuse.

Below, we represent the data for this cluster group- which only relates to 2 clusters- in table and graphic form.

Fig. 8. Repeat and Serial Familial Abuse Cluster Group: Table Data

Feature	Table 1, Cluster 1	Table 3, Cluster 1
Sus Gender	Male: 2777 Female: 1638	Male: 3546 Female: 1536
Sus UK National	Yes: 4364 No: 51	Yes: 4999 No: 83
Sus White British	Yes: 4170 No: 245	Yes: 4810 No: 272
Sus Also Victim	Yes: 2842 No: 1573	Yes: 2939 No: 2143
Victim Gender	Male: 925 Female: 3490	Male: 1216 Female: 3866
Crime	Non-crime: 1545 Violence against the person: 2219	Public order offenses: 1884 Violence against the person: 2441
IPV	Yes: 115 No: 4300	Yes: 478 No: 4604
Risk	High: 465 Medium: 952 Stand: 2998	High: 333 Medium: 1370 Stand: 3379
Many Crimes	Above: 2595 Below: 1820	Above: 2535 Below: 2547

Many Victims	Above: 3692 Below: 723	Above: 3553 Below: 1529
Sus Age	Above: 1478 Below: 2937	Above: 1442 Below: 3640
Victim Age	Above: 2986 Below: 1429	Above: 3677 Below: 1405
Perpetrators	4415 (11%)	5082 (12%)

We have also represented the data from the clusters in graphic form, to illustrate in a more visual way the characteristics of this cluster group.

Fig.9. Repeat and Serial Familial Abuse: graphic representation

Table 3/Cluster 1 | Table 1/Cluster 1 | Table 3/Cluster 1 | Table 1/Cluster 1

Existing research into perpetration typologies of family abuse has focused mainly on male perpetrators (Holtzworth-Munroe and Stuart, 1994). This means it is of limited relevance to our findings in this cluster group, because 30% of those included as suspects here are female. Nevertheless, there is some research into child-to-parent abuse, which is likely to be captured in this cluster group. We now consider some aspects of that research which could explain in part some of the key features and nuances of this group.

Types of abuse and link to general aggression

Child-to-parent abuse has been found to involve frequent incidents of verbal and emotional abuse, and notably financial abuse (Ibabe, Arnoso, & Elgorriaga, 2014), which may explain the relatively high prevalence of non-crimes and public order offences amongst this cluster group. CPA has also been shown to be prevalent amongst young people who are involved with the criminal justice system or who present aggressive behaviour in other contexts such as schools (Simmons et al, 2018:35). Therefore it would be useful to examine the overlap whether and which suspects in this cluster group have been implicated in other crimes. In terms of implications for practice, it may also be worth examining the potential for DA risk-assessments to be carried out by youth offending and other professionals, with all children and young people entering the criminal justice system.[8]

Gender effects

Research into CPA with community samples has typically found no significant differences in rates of perpetration between females and males (Simmons et al, 2018: 33). However, studies of police-recorded data (of which there are many) found that males accounted for 59–87% of suspected perpetrators. This accords with the gender distribution in our cluster group, in which only 30% of suspects are female. The higher representation of males in police-recorded data such as ours compared to community samples might be explained in part by gender biases in crime detection and reporting. Research has found consistently that female criminality is less likely to be recognised as such and less likely to be reported to police by victims. It is also possible that this cluster group may include honour-based abuse which is typically perpetrated towards females.

Mental health and substance abuse

A systematic review of current research into CPA found evidence across studies of a greater frequency of mental health concerns among young people who commit CPA compared to those who do not, including in particular depression (Simmons et al, 2018: 37). Research in community samples suggests that substance use predicts psychological and verbal CPA against both mothers and fathers (Calvete, Orue, et al.,2015; Pagani et al., 2009). However, research in offender populations suggests that substance use 'is related to an overall pattern of antisocial behaviour rather than CPA specifically' as there are no differences in rates of substance use between

[8] While the criminal law does not recognise abuse in under-16s as DA, professionals in youth offending and social services are not constrained in this way.

Feature	Table 1 Cluster 3
Sus Gender	Male: 3705 Female: 20
Sus UK National	Yes: 1069 No: 2656
Sus White British	Yes: 139 No: 3586
Sus Also Victim	Yes: 1106 No: 2619
Victim Gender	Male: 81 Female: 3644
Crime	Non-crime: 1432 Violence against the person: 1931
IPV	Yes: 3329 No: 396
Risk	High: 815 Medium: 1171 Stand: 1739
Many Crimes	Above: 1541 Below: 2184
Many Victims	Above: 1246 Below: 2479
Sus Age	Above: 2515

	Below: 1210
Victim Age	Above: 2363 Below: 1362
Perpetrators	3725 (9%)

CPA and non-CPA young offenders (Simmons et al, 2018, citing Contreras & Cano, 2015; Ibabe et al., 2014). Examining DASH data for suspects in this cluster group in more depth, to scan for mental health and substance abuse, may provide one avenue to exploring in more depth the significance of these risk factors for this cluster group.

Suspect/victim crossover

60% of the suspects in this cluster have also been recorded as victims in DA incidents. This very high rate of suspect/victim crossover is consistent with existing research into CPA which estimates that between 50–80% of CPA perpetrators have been exposed to, or have been targets of, family violence. This is similar both for studies using community samples (Browne & Hamilton, 1998) and those which, like our own, use suspect data (Ibabe et al., 2009; Routt & Anderson, 2011). Indeed, Simmons et al's 2018 systematic review found a significant reciprocal relationship between parent-to-child abuse and CPA, with CPA often being a response to parental aggression.

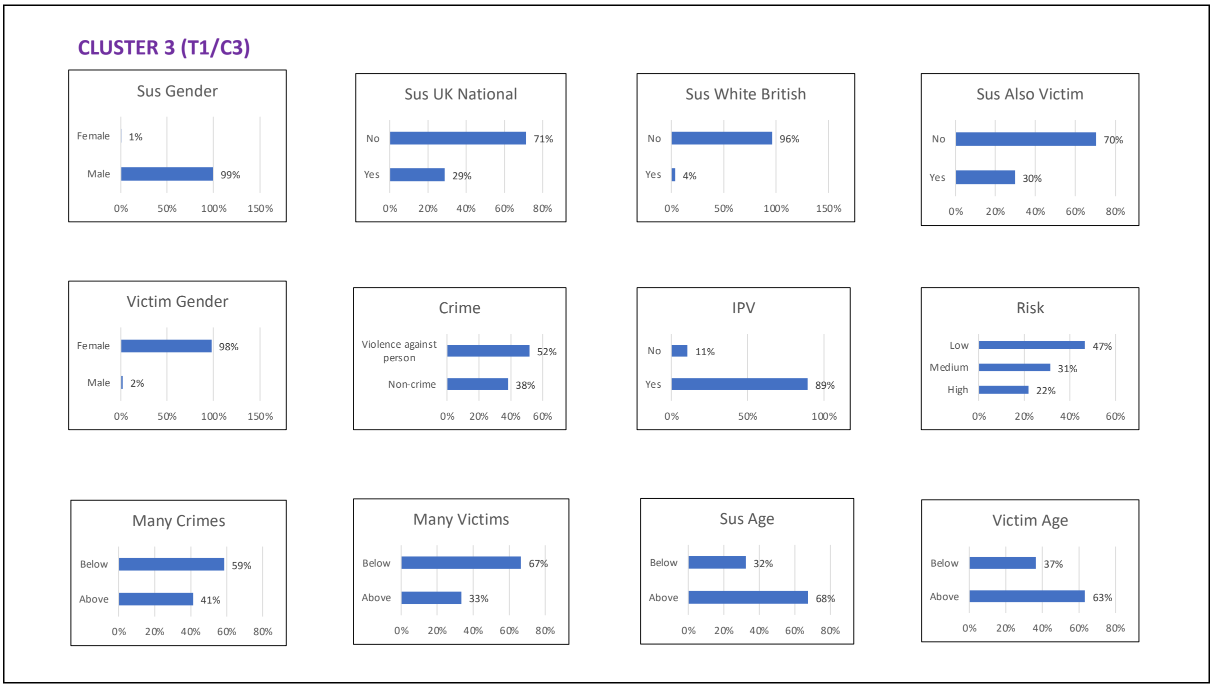
Group 3. Ethnic minoritized IPV

Group 3 (also representing an average of 9% of perpetrator data) consists of male, non-white, mostly non-UK nationals who commit IPV (Table 1, Cluster 3). This distribution is proportionate to the demographics of Essex, as the 2011 census reported 9.2% of the population as belonging to an ethnic minority. Suspects in Group 3 commit fewer crimes than average (and fewer than those in groups 1 and 2) and have fewer victims, but they are more likely to engage in violence. 53% of incidents perpetrated by suspects in this group are high or medium risk. Unlike other clusters, both suspects and victims in this cluster are older than the mean (>32). More than 1/3 of suspects have also been victims of domestic abuse themselves, but this figure is significantly lower than for most of the other cluster groups, indicating that perpetration is typically one-directional. It is difficult to speculate on the reasons for these distinctive features without doing qualitative research with victims and perpetrators in this group.

Fig.10 Ethnic Minoritized IPV Cluster Group: Table data

We have also represented the features of this cluster group graphically.

Fig.11. Ethnic Minoritized IPV Cluster Group: Graphic Representation



Our qualitative findings reveal a gap around culturally and ethnically-sensitive perpetrator provision in Essex (especially for non-native English speakers and for members of the traveller community). This was mentioned by many interview participants, especially those working in Probation services. It reflects a gap nationally in provision for these specific groups, as acknowledged by the Home Office in 2016 in their 'Violence Against Women and Girls, National Statement of Expectations' (p.6).

There has been a significant amount of research in recent years on DA amongst ethnic minoritized communities, including research funded by the Home Office (Adisa et al, 2021). But gaps remain, especially around knowledge about 'what works' with perpetrators belonging to different ethnic groups. The current cluster is insufficiently granular in its insights about ethnicity and race to support any concrete conclusions. More local research in this field is necessary, and geographical analysis would also assist to identify specific communities in need of targeted support.

Group 4. Female-to-Male IPV

This cluster group represents about 12.5% of suspects of DA. It consists of white, UK national, female suspects abusing male victims in a context of IPV. Around half of the incidents are violent, but the other half are recorded as non-crimes or public order offences- a more equal distribution than for other cluster groups. Risk is more likely to be assessed as standard than medium or high, and more likely to be standard than in other clusters with male perpetrators. Suspects in the female cluster commit fewer crimes than average and their victim is often the same individual. They are highly likely to appear in the database as victims as well, far more often than males. They are drawn from no specific age group, but their victims tend to be older than the mean.

This confirms a 2021 study by the Essex Centre for Data Analytics which found that 39% of female suspects have also been victims, that female suspects of domestic abuse are 3.7 times more likely to also be a victim than their male counterparts, and that female suspects are less likely to be repeat offenders than males.

Below we present the data relevant to this cluster group in table form. The clusters from Table 1 (column 1.4) and Table 3 (column 3.4) are remarkably similar, while those from table 2 present distinct nuances. For this reason, we have only presented the first two clusters graphically below.

Fig.12. Female-to-male IPV cluster group table data

Feature	Table 1, Cluster 4	Table 3, Cluster 4	Table 2, Cluster 5	Table 2, Cluster 7
Sus Gender	Male: 349 Female: 4844	Male: 33 Female: 4787	Male: 1680 Female: 2653	Male: 13 Female: 420

Sus UK National	Yes: 4756 No: 437	Yes: 4437 No: 383	Yes: 4313 No: 20	Yes: 104 No: 329
Sus White British	Yes: 4600 No: 593	Yes: 4309 No: 511	Yes: 4227 No: 106	Yes: 87 No: 346
Sus Also Victim	Yes: 4370 No: 823	Yes: 4300 No: 520	Yes: 3846 No: 487	Yes: 260 No: 173
Victim Gender	Male: 5077 Female: 116	Male: 4781 Female: 39	Male: 2005 Female: 2328	Male: 399 Female: 34
Crime	Non-crime: 2213 Violence against the person: 2586	Public order offenses: 2078 Violence against the person: 2388	Non-crime: 1807 Violence against the person: 2119	Non-crime: 183 Violence against the person: 236
IPV	Yes: 4698 No: 495	Yes: 4630 No: 190	Yes: 2873 No: 1460	Yes: 360 No: 73
Risk	High: 198 Medium: 1083 Stand: 3912	High: 156 Medium: 973 Stand: 3691	High: 381 Medium: 947 Stand: 3005	High: 22 Medium: 92 Stand: 319
Many Crimes	Above: 1789 Below: 3404	Above: 1811 Below: 3009	Above: 2502 Below: 1831	Above: 12 Below: 421
Many Victims	Above: 1989 Below: 3204	Above: 1924 Below: 2896	Above: 3028 Below: 1305	Above: 45 Below: 388
Sus Age	Above: 2722 Below: 2471	Above: 2511 Below: 2309	Above: 1796 Below: 2537	Above: 270 Below: 163

Victim Age	Above: 3184 Below: 2009	Above: 3006 Below: 1814	Above: 983 Below: 3350	Above: 355 Below: 78
Perpetrators	5193 (13%)	4820 (12%)	4333 (11%)	433 (1%)

Fig. 13

Female-to-male IPV Graphic Representation

Existing research into female perpetration and gaps

The features of this cluster group could be explained in part, and indeed confirm, existing criminological research which identifies two main typologies of female perpetration when there is also victimisation. The first is perpetration as violent resistance or ‘self-defence’ (Babcock et al, 2003). Here, the research reveals a tendency for female victims of abuse to be recorded as primary suspects when they use violence as resistance against an abusive partner (Boxall et al, 2019; Johnson, 2006; Hester, 2013). Both violent resistance, and the tendency to misinterpret it as primary perpetration, have been found to be more prevalent when the female is from a minoritised ethnic background (Boxall, 2019; Gleeson, 2022). The second typology, which Johnson (2006) called ‘situational’ or ‘common couple’ abuse, involves relatively low-level mutual violence and abuse used in the context of chaotic and toxic heterosexual relationships, often involving alcohol abuse (Hester, 2013). Either or both of these typologies could be characteristic of the suspects in this cluster group, but it is difficult to tell without carrying out more granular analysis of the data.

Natural language processing and regression analysis of the DASH data for the suspects in this cluster group, not only as suspects but also as victims, could help to disentangle violent resistance from situational couple violence, and indeed could provide much needed insight into the latter typology, which is the least well understood of Johnson's analysis. Such analysis could also enable a better understanding of the severity, gravity, and nature of the victimisation female suspects have experienced, which would be useful in informing the design of targeted female-focused interventions. On the face of it, the suspect/victim crossover by itself suggests a need for trauma-informed female-facing interventions. But better risk assessment would also be a desirable outcome, especially as violent resistance can kill.

A further research gap revealed by the clusters relates to the relatively low risk (as assessed by officers attending incidents) and the high prevalence of non-crimes in the offending profile of female suspects. In all the clusters in this group, an incident was roughly as likely to be a non-crime or public order offence as a crime of violence against the person. Recent research around female perpetration in the UK has found that females are most likely to use verbal abuse, and that violence with a weapon is more prevalent amongst female perpetrators who were *not* also recorded as victims (Hester, 2013). But there appears to be no existing research into the nature of non-crimes in domestic abuse. This indicates a significant gap in understanding of female perpetration. A more granular insight into and understanding of the nature both of non-crimes and of violent crimes in the context of female perpetration would be an important step towards devising tailored interventions of both a preventive and reactive nature.

Finally, it would be useful to examine the presence of risk factors such as mental health, self-harm, and substance abuse. Hester's study found that mental health issues were prevalent amongst female perpetrators, which has implications for interventions.

Existing interventions and gaps

The identification of the female cluster group is particularly significant for this study because our qualitative interviews highlighted female perpetration as a priority for intervention development in the region. There is currently no provision for female perpetrators from Probation services in Essex.[9] This was a source of frustration for some Probation officers, who pointed out that a structured programme that was adaptable for females had been developed in-house but was not being delivered due to organisational change. At the same time, one Probation officer complained

[9] According to all of our probation participants. One commissioning practitioner who reviewed this report pointed out that probation do offer 1:1 Healthy Relationship work to female perpetrators that can be delivered as part of Rehabilitation Activity Requirement Days (RAR). However, it seems probation practitioners are unaware of this.

that in their four years of service, they had not received ‘a single bit of training on female perpetrators’ (P7). This is clearly a gap in Probation knowledge, training and provision. This is unlikely to be unique to Essex. The Change Project does provide a trauma-informed female perpetrator intervention service, which was recently developed in response to findings from the ECDA analysis. This is a 1-2-1 service, but it is voluntary and so only captures a certain subset of female perpetrators.

Gaps also exist around provision for male victims of DA. Apart from a male IDVA pilot in the Southend area, currently seconding a practitioner to be based in the council offices, there is no specific provision for male victims. The 3 main victim services are all Women’s Aid accredited which means that men cannot attend their buildings. As a result, male victims are currently signposted to Mankind, which is a national rather than a local organisation. Investing resources in provision for male victims- or indeed female perpetrators- would be controversial, given the heavily gendered nature of most domestic abuse and the clear need for more resources to prevent and respond to violence against women and girls. However, it is something that should be explored further.

1.4 Association Rules (ARA)

Association rule analysis (ARA) is another type of unsupervised learning method that has been widely used for commercial purposes.

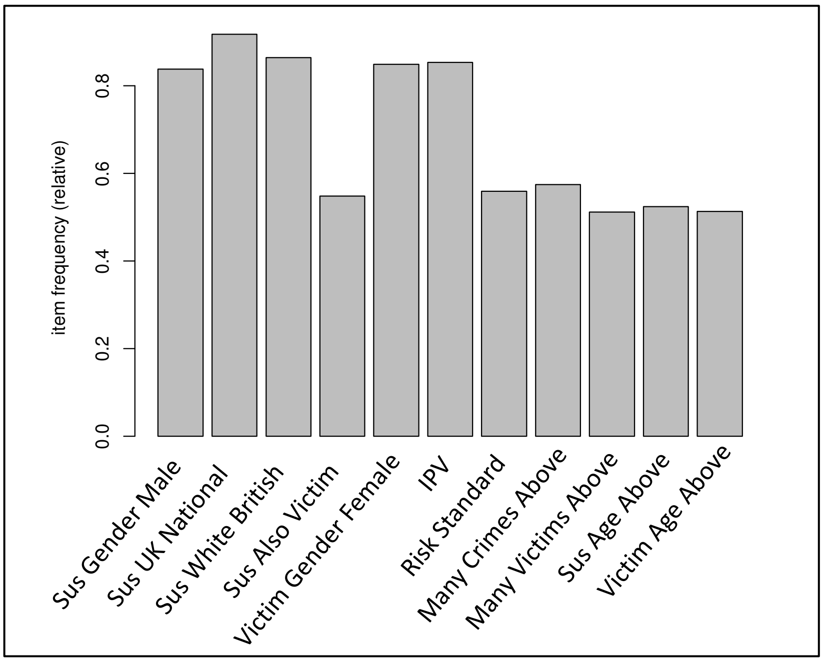
In unsupervised learning, researchers want to infer the probability density function of a vector of p-features **X** (Hastie, Tibshirani, and Friedman 2009). For instance, in this project, our working sample has 12 variables, which form the vector **X**. The goal of unsupervised learning methods would be to estimate the joint probability p(**X**).

ARA takes a particular route to estimating the density p(**X**)–in our case, it finds the joint values of these 12 variables that occur most frequently in the data. If these 12 variables were items bought in a supermarket, the goal of ARA would be to find the groups of items that are bought most frequently. This is a good example of the logic of ARA, which has been used extensively to mine databases of purchases.

In our case of domestic abuse, ARA would find the characteristics of observations for suspect-crimes that appear most frequently in the data. This would resemble a joint probability density for a group of characteristics. Perhaps more importantly, ARA facilitates the calculation of conditional probabilities, such as the probability that violence against the person was committed given than the perpetrator is male, non-white, and that the victim is female.

Figure 14 presents the most frequent features in the data.

Figure 14. Most Frequent Features



A detailed description of ARA and the *Apriori* algorithm used to overcome the computational obstacles of ARA (Hastie, Tibshirani, and Friedman 2009) is beyond the scope of this project. However, it is relevant to present key concepts. First, there is an *item set* of size *k*. This is often a subset of relevant features in the data, but it could include all features in the data. It is worth noting that ARA is implemented with features measured as dummy variables, that is, discrete variable with only two values (often 1 and 0). In this case, a variable with multiple categories is broken down into multiple dummy variables. For example, our data has 12 features, but once they are transformed into multiple dummy variables (for instance, the types of crimes), the data for ARA consists of 33 dummy variable inputs. Consequently, the maximum size of an item set is 33.

For simplicity, assume that an item set has 12 features. ARA breaks down this set in two parts, labelled A and B. For instance, the set A could include all demographic characteristics of a perpetrator (eg. race, age) and the set B could be the gender of a victim. These two sets are written $A \Longrightarrow B$ (Hastie, Tibshirani, and Friedman 2009). The set A is the antecedent and B is the consequent. It may be more useful to label the set A as “the prior” and B as “the posterior,” which are key concepts in probability and Bayesian statistics.

A key concept in ARA is the *support* of the rule T(A ⟹ B). From a probability perspective, this can be interpreted as p(A and B), that is, the joint probability of observing sets A and B. In our project, this could be the probability that an item set consists of a white perpetrator with age below the median (ie. set A) and a female victim (ie. set B). Another key concept is the *confidence* of the rule C(A ⟹ B). From a probability perspective, this can be interpreted as p(B|A), that is, the probability of B given A. In our project, this could be the probability that the victim is female (ie. set B) given that the perpetrator is white and with age below the median (ie. set A).

Part of the effectiveness of the *Apriori* algorithm resides on the specification of support thresholds. ARA produces a set of association rules such that T(A ⟹ B) > *t* and C(A ⟹ B) > *c*, where *t* and *c* are thresholds for the support and confidence of item sets. In practice, researchers set the thresholds *t* and *c*, which then yield association rules T and C. In this project, we set *t*=0.5 and *c*=0.9. We implement this with the packages *arules* (Hahsler et al. 2022) and *arulesViz* (Hahsler, Giallanza, and Chelluboina 2021) in *R*.

Table 5 presents 18 different association rules. Many of these rules are very similar and, in fact, their support can be identical because their item sets are the same. However, their levels of confidence are different simply because the conditional probabilities are distinct.[10] As an illustration, the support for Rules 1 and 2 is the same because *Sus Gender Male* and *Victim Gender Female* are in the item set for both rules. In this light, the probability that *Sus Gender Male* and *Victim Gender Female* occur jointly is 0.81. However, the probability that the victim is female given that the perpetrator is male is 0.96 but the probability that the perpetrator is male given that the victim is female is 0.95. Indeed, these two conditional probabilities are different theoretically and empirically.

Table 5. Association Rules

Rule	Prior	Posterior	Support	Confidence
1	Sus Gender Male	Victim Gender Female	0.81	0.96

[10] Technically, they are different because the marginal probabilities in the denominator are different.

2	Victim Gender Female	Sus Gender Male	0.81	0.95
3	Sus Gender Male Sus UK National	Victim Gender Female	0.74	0.96
4	Sus UK National Victim Gender Female	Sus Gender Male	0.74	0.95
5	Sus Gender Male IPV	Victim Gender Female	0.73	0.99
6	Victim Gender Female IPV	Sus Gender Male	0.73	0.99
7	Sus Gender Male Sus White British	Victim Gender Female	0.69	0.96
8	Sus White British Victim Gender Female	Sus Gender Male	0.69	0.95
9	Sus Gender Male Sus UK National Sus White British	Victim Gender Female	0.68	0.96
10	Sus UK National Sus White British Victim Gender Female	Sus Gender Male	0.68	0.95

11	Sus Gender Male Sus UK National IPV	Victim Gender Female	0.67	0.99
12	Sus UK National Victim Gender Female IPV	Sus Gender Male	0.67	0.99
13	Sus Gender Male Sus White British IPV	Victim Gender Female	0.62	0.99
14	Sus White British Victim Gender Female IPV	Sus Gender Male	0.62	0.99
15	Sus Gender Male Sus UK National Sus White British IPV	Victim Gender Female	0.62	0.99
16	Sus UK National Sus White British Victim Gender Female IPV	Sus Gender Male	0.62	0.99

17	Sus Gender Male Many Crimes Above	Victim Gender Female	0.50	0.97
18	Victim Gender Female Many Crimes Above	Sus Gender Male	0.50	0.97

In general, the association rules reflect not only the most frequent features in the data, as demonstrated by Figure 5, but also frequent clusters from the AHC analysis where the typical perpetrator is a white, British male with a female victim in a context of IPV–Rule 15 with support of 0.62 and confidence of 0.99. In other words, the probability that a suspect is white, British male with a female victim in a context of IPV is 62 per cent, but the probability that the victim is female given that the perpetrator is a white, British male in a context of IPV is 99 per cent.

2. Supervised Learning

This section of the report presents supervised learning analysis of the profiles of perpetrator-crimes. It uses the same work data from the previous section, which has 40,488 observations and the perpetrator-crimes as unit of analysis. This is a longitudinal dataset that tracks the crimes committed by individual suspects over time.

In this section of the report, we focus on particular aspects of domestic abuse incidents from a supervised learning perspective. Specifically, we focus on the number of domestic abuse incidents, the average number of incidents per perpetrator, and the number of perpetrators, as outcome variables and explore geographical variation.

We then proceed to explore the DASH risk assessment. There we perform factor analysis to reduce the dimensions of the DASH data and focus our analysis on a model of repeat victimization.

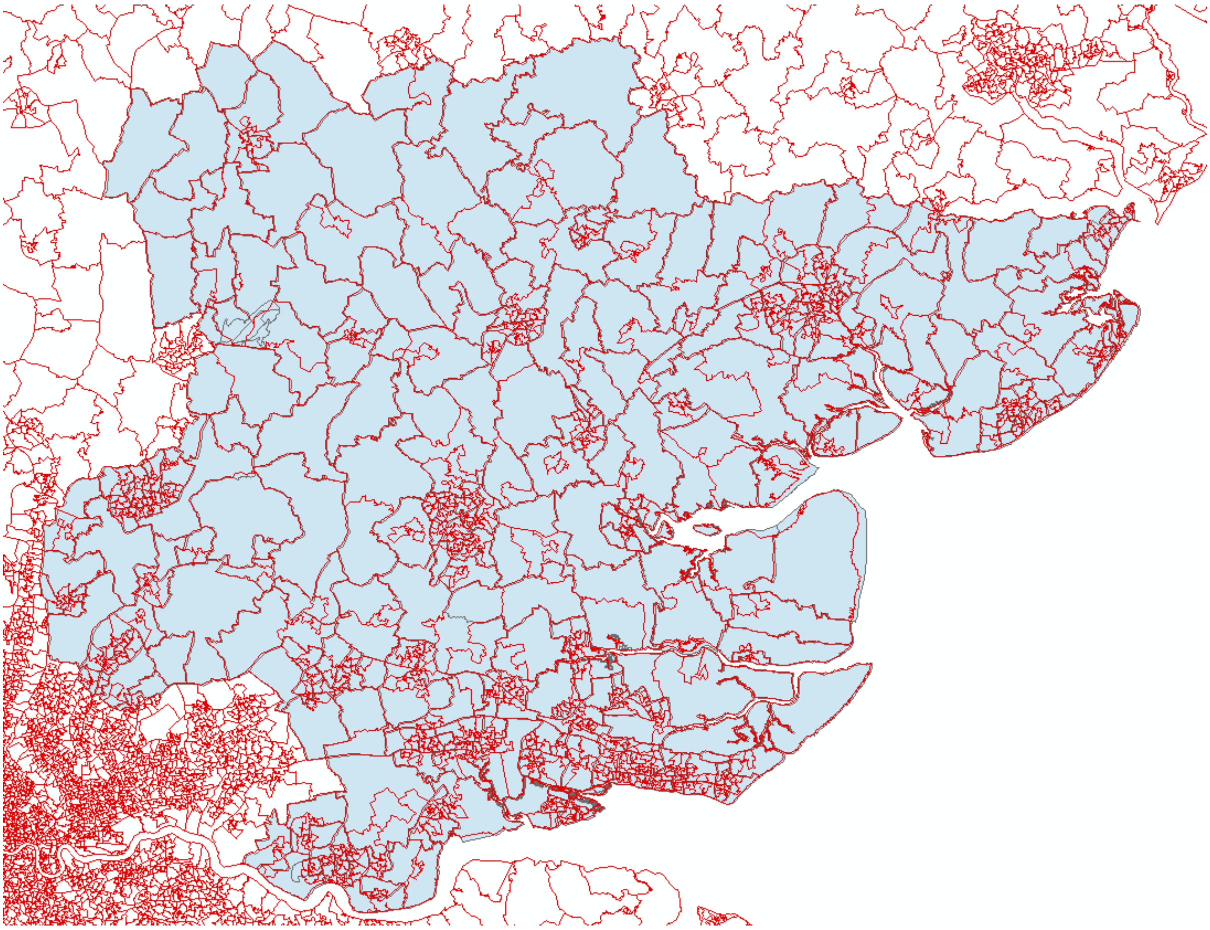
It is important to note that while we implement supervised learning models, the scope of the project does not allow us to elaborate on the performance of our model. In other words, we do not focus on predicting outcome variables and rather invest in estimating models. Future work will take these and other models and engage in prediction and performance.

2.1 Geography

In this section we explore the spatial distribution of domestic abuse. We know that crime also clusters geographically, so here we look at where the highest concentrations of domestic abuse are in Essex. Understand the geographical distribution of reported incidents allows finite resources to be allocated to those areas where the need and risk is greatest.

We analysed the location of the domestic abuse incidents featured in the modelled data (40,488 observations). Geographic analysis was limited by pseudonymisation, which meant that there were no useable postcodes or grid references in the dataset. The only geographic data was the police ward. Unfortunately, police ward is not coterminous with the boundary datasets used by the Office for National Statistics (ONS), so data such as deprivation and population statistics could not be joined to the dataset. This limited the amount of analysis and geographic modelling that could be done with the dataset, as illustrated in the below figure, which shows the more detailed LSOAs (Lower Layer Super Output Area) in red and police wards in blue.

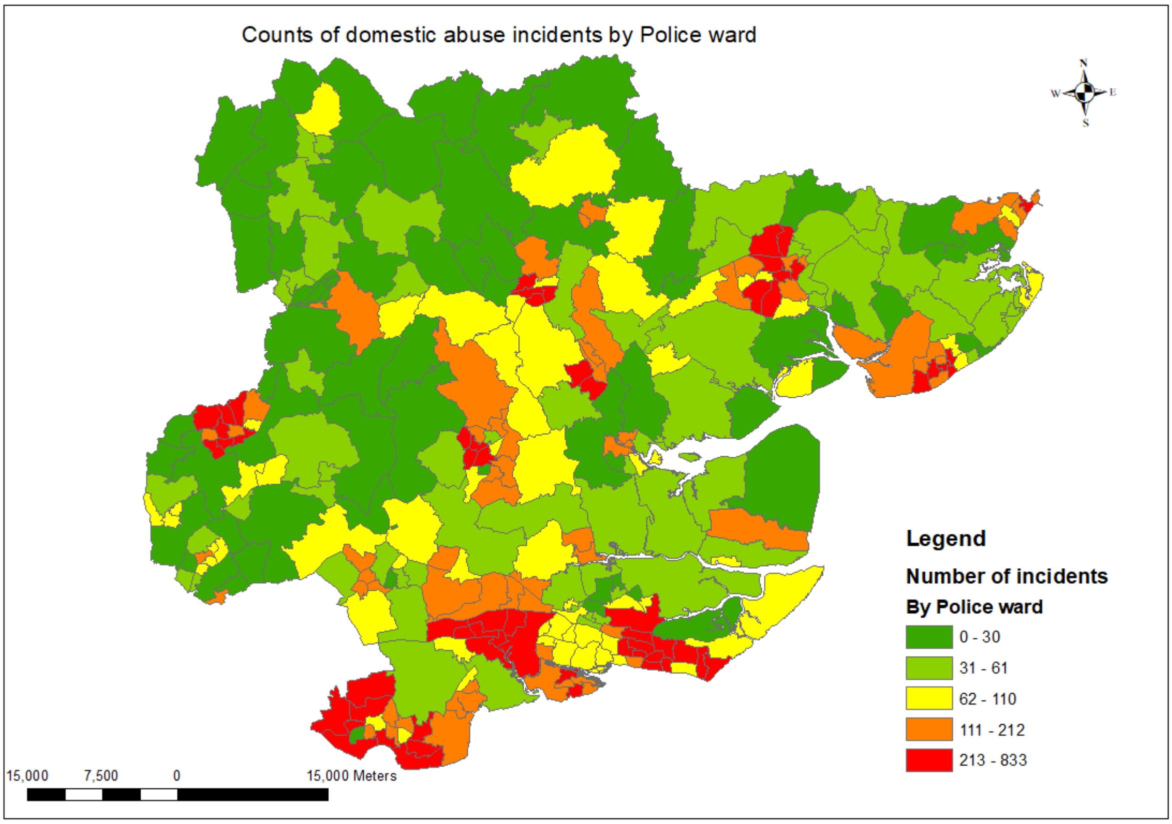
Fig.15 LSOA and police wards comparison



It was not possible to model the neighbourhood level predictors as the police ward boundaries could not be linked with other datasets. To be able to use a much wider range of neighbourhood level data the police should add the LSOA to data before pseudonymisation. This can be done using a GIS and the boundaries are available here https://data.gov.uk/dataset/fa883558-22fb-4a1a-8529-cffdee47d500/lower-layer-super-output-area-lsoa-boundaries. Examples of what can be done using Essex data are here in Weir, R. (2019).

Figure 15 shows the number of incidents reported in each police ward. The areas in red represent the wards with highest number of incidents and those in dark green the lowest. The highest number of incidents were found in Kursaal ward in Southend, followed by Lee Chapel North in Basildon, Fryerns in Basildon, Southend Central and St Andrews in Colchester. The three wards with the lowest numbers of incidents were all in the rural district of Uttlesford (Clavering, Littlebury and Stort Valley).

Figure 16. Counts of domestic abuse incidents by police ward



A similar pattern is observed when looking at the number of perpetrators by ward (Figure 17), with the wards in Southend and Basildon having the top 5 highest number of perpetrators.

Figure 17. Number of perpetrators by police ward

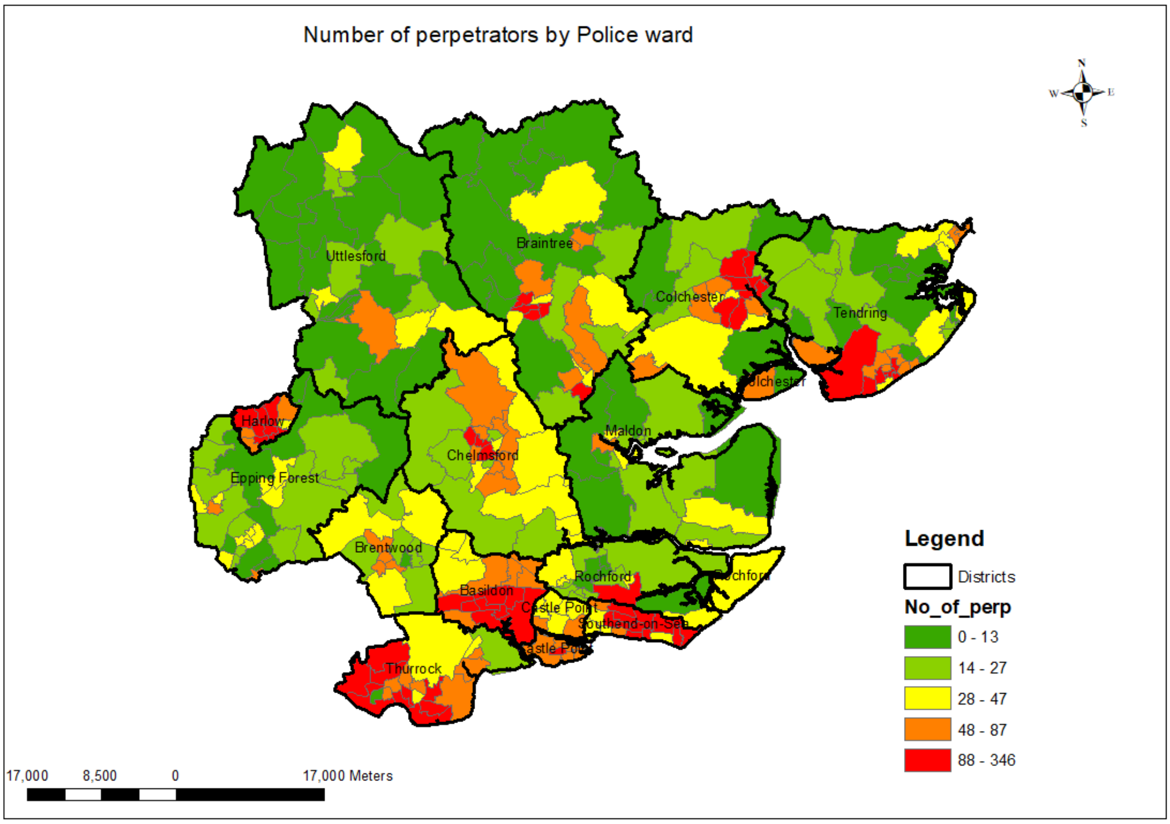
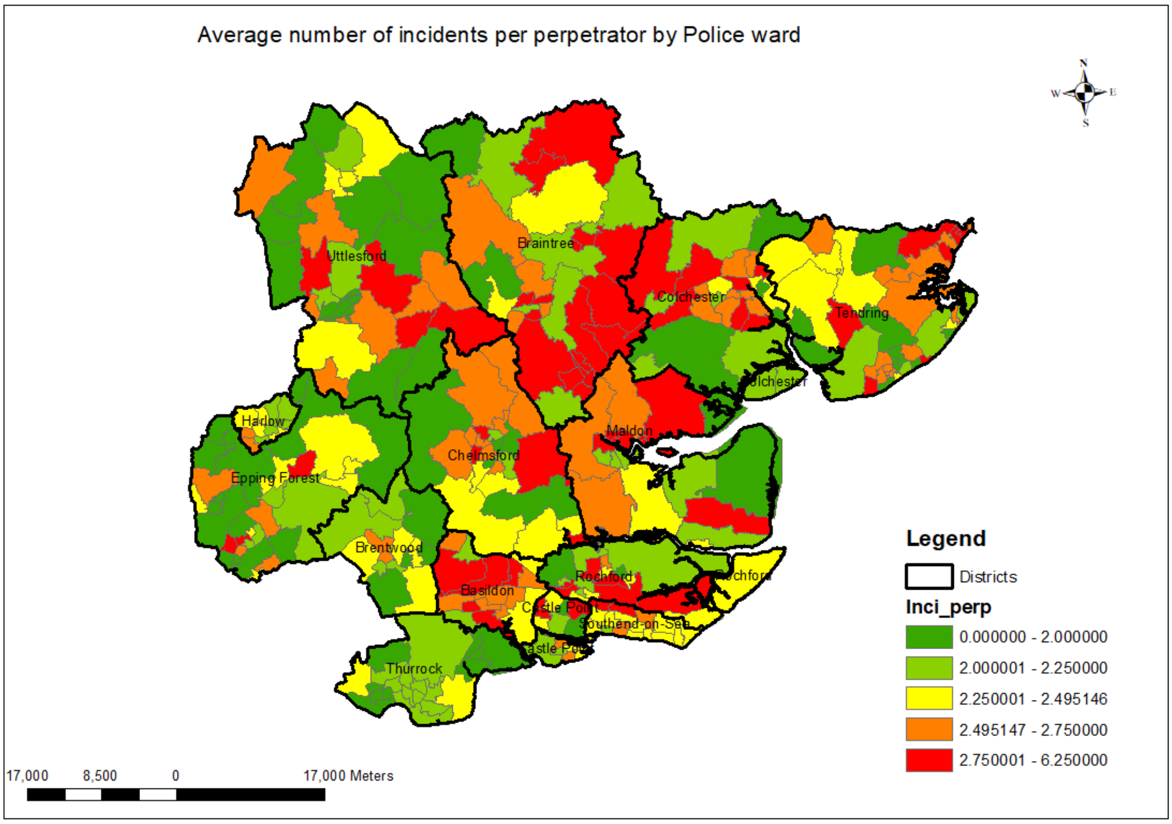


Figure 18, however, factors in repeat perpetration by identifying the average number of incidents per perpetrator. The pattern observed is quite different to the counts of incidents and perpetrators, with some geographic clustering of higher than average numbers of incidents per perpetrator in the south and east of the Braintree district area. At the ward level the highest average number of incidents per perpetrator observed in Black Notley and Terling ward in Braintree district, followed by The Easterns in Uttlesford, Halstead Trinity in Braintree district, Heybridge West in Maldon and St George's in Castle Point.

Figure 18. Average number of incidents per perpetrator by police ward



2.2 Analysis of DASH

In this section we analyse responses in the DASH assessment. As mentioned before, DASH data was added to the original database using the crime reference number. However, out of the 40,488 suspect-crimes, only 51 per cent have DASH data.

Factor Analysis

DASH assessments are retrieved from a questionnaire with 27 questions. This large number of questions presents challenges for the analysis and therefore this section reduced the number of features using factor analysis. Factor analysis looks for correlation and patterns between variables to see whether the observed variables can be reduced to a smaller number of unobserved variables, which leads to a more parsimonious model that provides more useful insight.

Analysis of the DASH variables found strong and moderate correlations between several variables. The exploratory factor analysis reduced the number of variables but also allowed the variables to be aggregated to represent latent concepts.[11] These concepts included 'physical violence and terrorising behaviour', 'coercive control' and 'criminality/lifestyle'. Table 6 shows the variables in each concept and the degree of correlation (factor loading) between the variables.

Table 6. Oblique Rotated Factor Pattern (Loadings ³ 0.4)

Variable	Factor Loading
Physical Violence/terrorising	
Afraid	0.72
Injury	0.65
Strangle	0.61
Frightened	0.59
Weapon	0.58
Threat to kill	0.50
Kuder-Richardson = 0.71	
Coercive Control	
Control	0.77
Stalk	0.75
Isolated	0.61

[11] Appendix 1 has summary statistics of relevant variables.

Separated	0.56
More often	0.50
Kuder-Richardson = 0.68	
Criminality/lifestyle	
Police	0.82
Breach bail	0.70
Hurt others	0.53
Drugs/alcohol/mental health	0.45
Kuder-Richardson = 0.59	

N= 18,503

These variables were selected because they all showed a moderate or strong correlation (0.4 and over) with the other variables in each factor. It is beneficial to separate 'physical violence and terrorising behaviour' from 'coercive control' as research suggests that coercive control often accompanies physically violent behaviour, but coercive control may be experienced without physical violence, particularly in the earlier stages of abusive behaviour (Johnson, 2006; Stark, 2006). The 'criminality/lifestyle' factor will also enable further analysis of the impact of criminality and the toxic trio (domestic abuse, substance misuse and mental ill health). These are known nationally as risk factors of serious harm (Coordinated Action Against Domestic Abuse, 2014), and were also highlighted as key risk factors for domestic abuse in Essex by all participants in the qualitative study that formed part of this research.

On the basis of the explanatory factor analysis, we created a scale where the mean score for the 'physical violence and terrorising behaviour,' 'coercive control,' and 'criminality/lifestyle' factors were calculated for each incident. Using the mean to standardise the factors means that the coefficient values can be compared and their influence on each other and other variables modelled.

The analysis was also run for just female perpetrators (Table 7). Whilst there are still three clear factors, the first factor does not have the violent behaviour that is seen when looking at all perpetrators, but just the terrorising behaviour that makes victims frightened. The coercive control variables are similar, but rather than the abuse occurring more often sexual abuse and depression are part of the cluster. Within the criminality and lifestyle cluster the perpetrator threatening or attempting suicide and hurting children are present with female perpetrators, but not when looking at all perpetrators.

Table 7. Oblique Rotated Factor Pattern (Loadings ^{3} 0.4) for female perpetrators

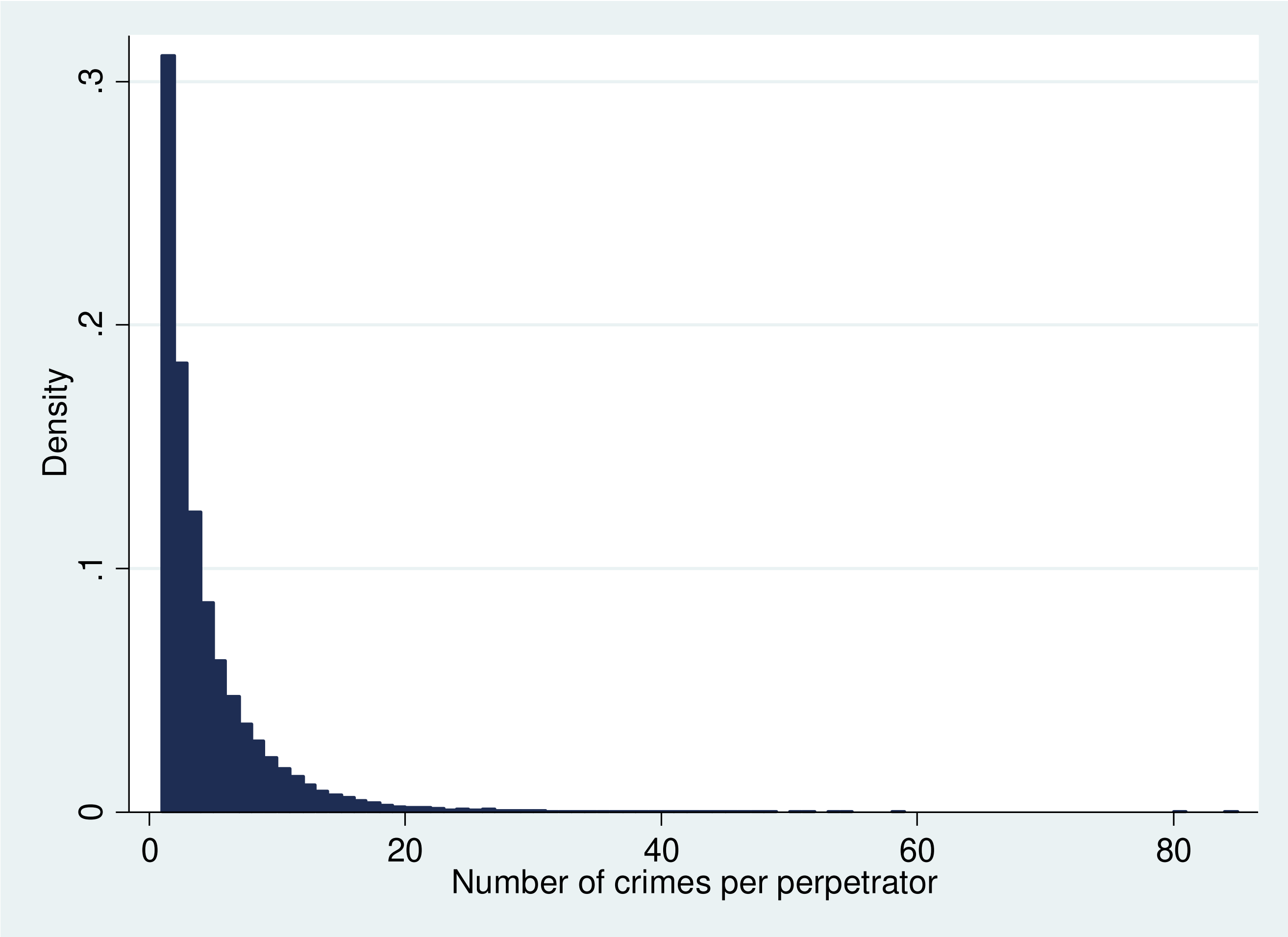
Variable	Factor Loading
Terrorising	
Frightened	0.92
Afraid	0.77
Kuder-Richardson = 0.72	
Coercive Control	
Control	0.77
Separated	0.63
Isolated	0.62
Stalk	0.59
Sexual	0.46
Depressed	0.44
Kuder-Richardson = 0.60	
Criminality/lifestyle	
Hurt others	0.67
Police	0.67

Drugs/alcohol/mental health	0.63
Suicide	0.54
Hurt children	0.53
Breach bail	0.49

Kuder-Richardson = 0.60

N= 2275

Figure 19. Histogram of the number of crimes per perpetrator



Negative Binomial Regression Model

Having done this, we then proceeded to estimate a negative binomial model of repeat perpetration. As illustrated by figure 19, repeat perpetration represents a significant proportion of crimes with 69% of suspects in two or more incidents, and therefore identifying risk factors associated with repeat offending will help identify one of the cohorts which needs interventions to break a cycle or course of abuse. A negative binomial regression is used to model count data, so in this case it is looking at predictors of the number of incidents a suspect will be involved in. This was also broken down to distinguish between whether the relationship between the victim and suspect was intimate personal violence (partner or ex-partner) or family violence (which includes relationships like siblings, parents, children and grandparents). This breakdown was included as previous research by Weir (2020) found that risk of repeat victimisation varied according to the relationship between the victim and the suspect. The independent variables are similar to those used in the unsupervised model, but in additional we also included the summated scores from ‘physical violence and terrorising behaviour’, ‘coercive control’ and ‘criminality/lifestyle’ DASH factors, the IMD decile[12] and the year of the incident.

Table 8. Negative binomial regression model of repeat victimisation

Variable	All incidents model IRR coefficient (std error)	IPV model IRR coefficient (std error)	Family violence model IRR coefficient (std error)
Physical scale	0.829 (0.028)***	0.827 (0.030)***	0.894 (0.089)
Coercive scale	1.045 (0.029)*	1.064 (0.030)	1.313 (0.030)**
Criminality scale	1.545 (0.044)***	1.553 (0.048)***	1.441 (0.121)***
IPV	1.120 (0.029)***		
Perpetrator White British	1.167 (0.028) ***	1.170 (0.032) ***	1.081 (0.065)
Perpetrator previous victim	1.351 (0.029)***	1.363 (0.031)***	1.189 (0.071)**
Victim age	1.003 (0.001) ***	1.002 (0.002)	1.000 (0.002)
Perpetrator age	0.999 (0.001)	0.999 (0.002)	0.999 (0.002)
Perpetrator male	1.253 (0.053)*	1.253 (0.053)*	1.173 (0.088)*

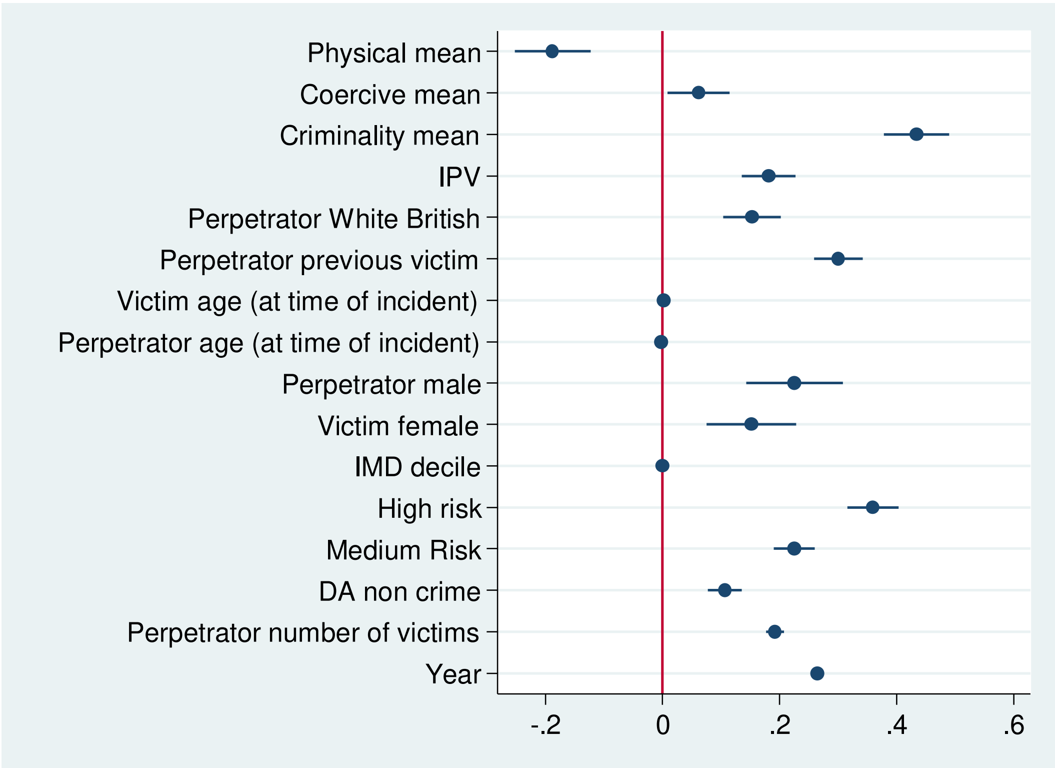
[12] Data was from the IMD 2019, with decile 1 being the most deprived and decile 9 the least deprived. The geography was based on the Lower Super Output Area (LSOA) in which the centroid of the police ward was found. As the two boundaries are not coterminous there may be some error in this approach.

Victim female	1.165 (0.045)***	1.157 (0.096)**	1.134 (0.056)*
IMD decile	1.000 (0.004)	0.999 (0.004)	1.004 (0.012)
High risk	1.433 (0.032)***	1.446 (0.033)***	1.267 (0.135)*
Medium risk	1.253 (0.023)***	1.257 (0.024)***	1.189 (0.079)**
DA non crime	1.113 (0.017)***	1.122 (0.018)***	1.028 (0.050)
Perpetrator number of victims	1.212 (0.009)***	1.207 (0.010)***	1.232 (0.019)***
Year	1.303 (0.007)***	1.306 (0.007)***	1.278 (0.022)***
Constant	1.1e-232 (1.2e-231)***	9.4e-235 (1.1e-233)***	9.4e-235 (1.1e-233)***
Log-likelihood	-41704.6	--3207.6	-4347.9
AIC	83445.3	72449.2	8729.7
BIC	83586.7	72580.2	8825.8

Significance levels: * p≤ 0.05;** $\text{p} \leq 0.01$; *** $p \leq 0.001$. N: All incidents= 19,032 IPV = 16,366, family violence = 2,100

Table 8 and figure 20 shows the results of the negative binomial regression models. The only variable that decreases with the number of incidents recorded is the physical score (from the DASH), all the other variables increase or are not statistically significant. The results for the all counts model finds that if there is an increase of one in the score on the physical scale the number of incidents committed by the perpetrator decreases by a factor of 0.829, while holding all other variables in the model constant. However, when the coercive and criminality scale increase by one the number of incidents committed by the perpetrator increases by a factor of 1.045 and 1.545 respectively. When the incident is intimate partner violence (IPV) (compared to familial violence) an increase of one increases the number of incidents committed by a factor of 1.120. If the perpetrator is White British the number of incidents increases by 1.167 and by 1.351 if the perpetrator has previously been a victim. For every year a victim's age increases the number of incidents committed increases by a factor of 1.003, however for perpetrators there is no significant relationship between age and the number of incidents committed. The perpetrator being male increases the number of incidents by a factor of 1.253 and the victim being female by 1.165. There is no statistically significant relationship between the IMD decile and the number of incidents, but a victim being high risk (compared to standard) increases the number of incidents by a factor of 1.433 and medium risk by 1.253. The incident being categorised as a non-crime increases the number of incidents by a factor of 1.113 and every additional victim a perpetrator is linked to increases the number of incidents by a factor of 1.212. The year variable was included to control for the fact that the number of incidents would increase over time.

Figure 20. Negative binomial regression coefficient plot for all incidents model, N= 19,032



Relationship type

Table 7 and Figure 21 and 22 also break down the model results into intimate partner violence and familial violence. Overall, the results are similar to the model of all incidents. The main differences were that the physical scale was not statistically significant for family violence and the coercive scale for IPV. The perpetrator being White British was also not significant for family violence and the victim's age was not significant for IPV or familial violence. An incident being a non-crime was also only significant for IPV and not familial violence.

Figure 21. Negative binomial regression coefficient plot for IPV incidents model, N=16,366

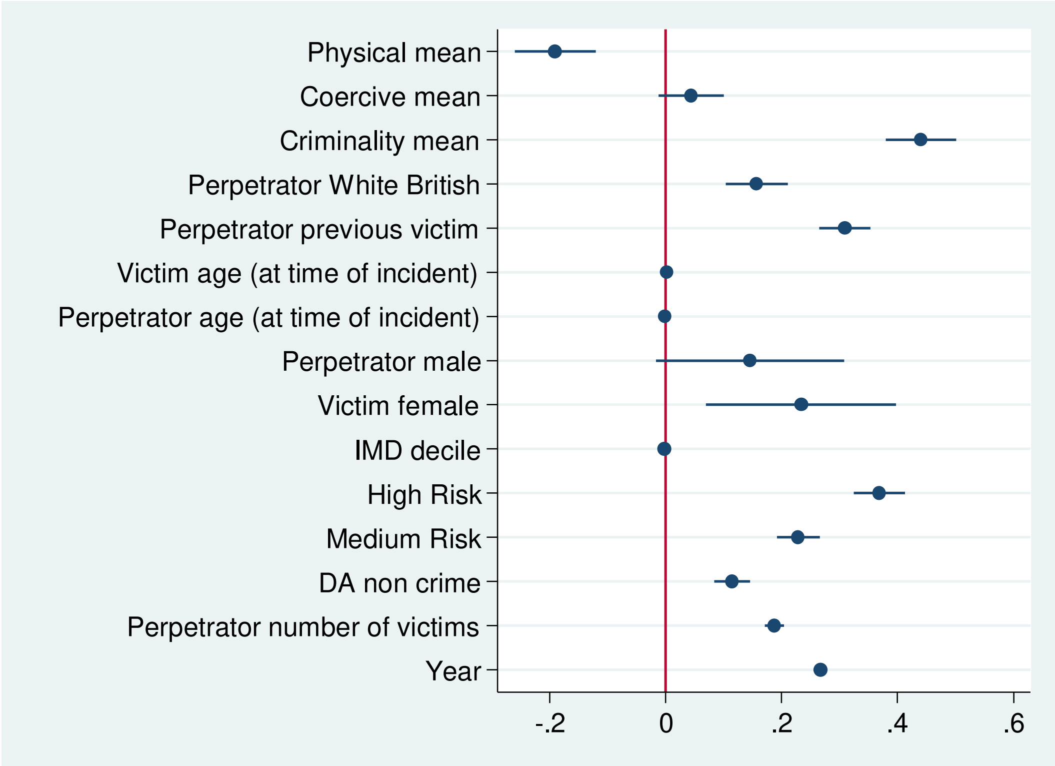
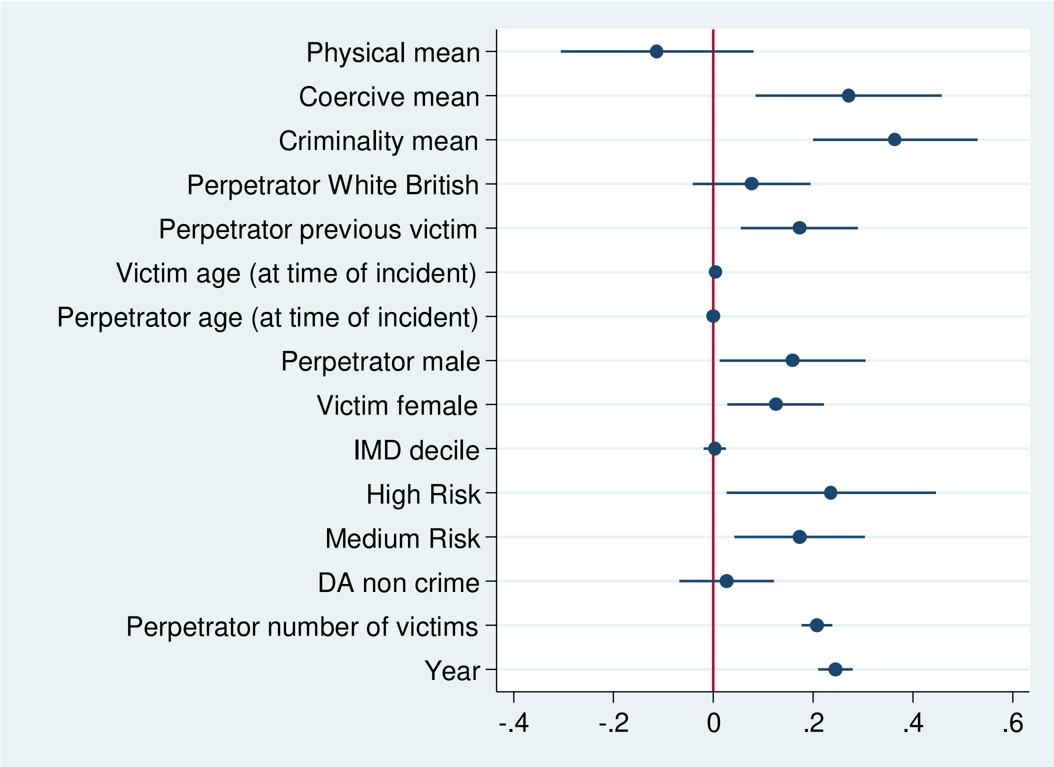


Figure 22. Negative binomial regression coefficient plot for familial incidents model, N= 2,100



Perpetrator gender

Figure 23 and 24 show the coefficient plot by gender of the perpetrator. The male perpetrators is very similar to the plot of all perpetrators, however for female perpetrators only a few variables are statistically significant (which in part could be down to the sample size being a lot lower), with only the criminality scale, IPV, victim age, number of victims and year being statistically significant.

Figure 23. Negative binomial regression coefficient plot for female perpetrator incidents model, N=2,405

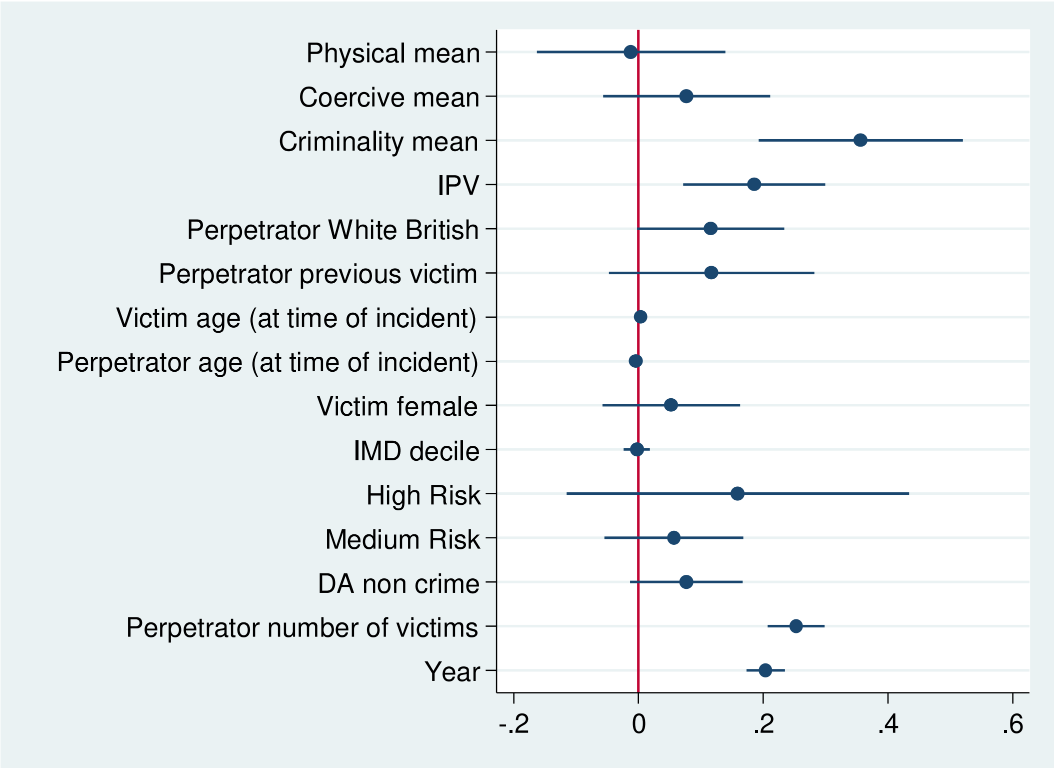
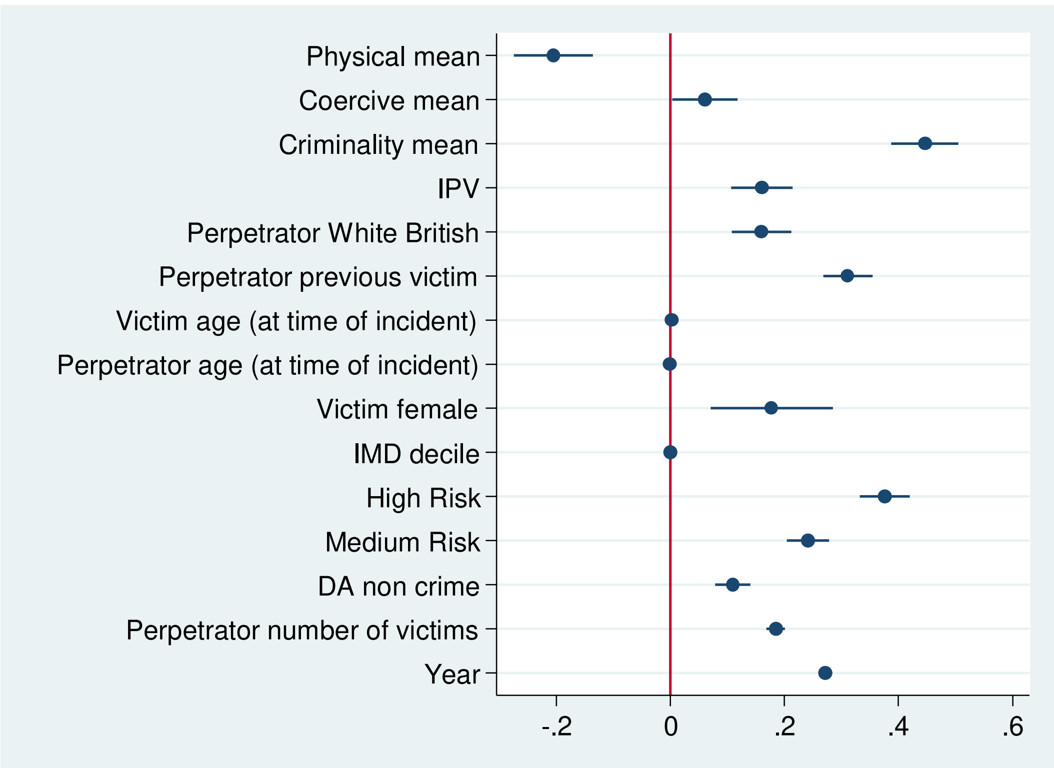


Figure 24. Negative binomial regression coefficient plot for male perpetrator incidents model, N= 16,641



Conclusion

Overall, the analysis finds that coercive behaviour and previous criminality, substance misuse or mental health issues experienced by the perpetrator are more likely to be present as the number of incidents increases. This confirms what practitioners told us in the qualitative interviews for this study, with mental health issues highlighted as a prominent risk factor and a challenge for interventions.

Interestingly when physical violence is present it is likely there are fewer incidents reported to the police. This is a different pattern to that observed in previous research (Weir, 2020), which found that physical violence increased the odds of repeat victimisation by 4.45 for every one-unit increase in physical violence, compared with 1.45 for coercive behaviour. One possible explanation for the apparent discrepancy is that Weir (2020) used data from before coercive control became an offence in 2015, which could have led to a change in the nature of the incidents that are reported. Another possibility is that perpetrators do not use physical violence during every incident. For example, research has found that a violent act only has to take place once for perpetrators to then use the threat of a repeat incident to coercively control their victim Palmer and Wiener (2021).

Whilst the criminality and lifestyle score increase the number of incidents for both IPV and familial violence, physical violence is only significant in IPV relationships and coercive behaviour in familial relationships, which suggests that the nature of the violence and abuse could be different.

The analysis supports existing research that finds that repeat perpetration is more likely to take place if the victim is female, the perpetrator is male and they are in an intimate personal relationship (ONS, 2018; Walby and Allen, 2004; Walby and Towers, 2017).

It is notable that 42% of reports captured in this analysis are non-crime incidents, but it is not clear whether this marks a shift from previous trends. Nationally the incident to crime conversion rate has been increasing with 59% of all domestic abuse incidents becoming crimes (ONS, 2020). Essex data is in line with this current figure, with roughly 58% of incidents recorded as crimes. We can speculate based on what research tells us about domestic abuse that non-crimes may include verbal abuse and minor kinds of stalking and harassment or threats, but we have no evidence to support this. Although risk being classified as high or medium is more likely as the number of incidents increases, it is also more likely that the incidents are not recorded as a crime. It is possible that this is because the threshold has not been met with the one-off incident, which if the behaviour is coercive, rather than physically violent, may be more difficult to evidence. Insight into the links between violence and non-crimes could provide a more detail understanding of different typologies of abuse and the profiles of the perpetrators who use them. For example, it may enable better understanding of the differences between violence that is reactive or situational in nature, and that which is linked to a broader campaign of coercive control.

The geographic analysis found concentration of incidents and perpetrators in the large urban areas of Essex. However, unlike previous research that has found there to be a significant relationship between neighbourhood structural characteristics such as income (Weir, 2019; Flatley, 2016; Fang and Corso, 2008; Renzetti, C., 2009; Mooney; 2000; Bograd, 1999), the IMD decile was not found to be significant in this analysis. It is possible that previous research has focused more on physical violence and links to deprivation, which may see a different pattern in coercive and controlling behaviour. It would be interesting to carry out further analysis into this at the neighbourhood level.

3. Qualitative interviews with DA practitioners

18 interviews were undertaken with practitioners working in a range of services and organisations in Essex dealing with perpetrators of domestic abuse.[13] Recruitment of participants was facilitated by the Southend, Essex and Thurrock Domestic Abuse Board, however interest was limited as the precursor project had already involved the same practitioners and there was some participation fatigue. The aim of the interviews was to identify trends and patterns in typologies and risk factors around perpetration of domestic abuse in the county. Ethics approval was obtained prior to recruitment from Essex University Research Ethics Committee. It was also to identify gaps in provision, understanding and research. Initial in-depth interviews were undertaken over about 1hr each, then individual participants were contacted again via email and phone to sense-check emerging findings from the clustering analysis and to contextualise them. Key themes have been incorporated into the findings presented above, and centred on gaps around ethnic minoritized groups and female perpetrators, and the need for research that combines police and non-police data.

[13] SETDAB (Southend and Thurrock Domestic Abuse Board; MAPPA; Essex police; Essex Youth Service; Building Better Relationships Programme Treatment Delivery; Probation; Safe Steps; MARAC; Changing Pathways; The Change Project)

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Appendix 1. Literature Review: perpetrators of domestic abuse

Tackling Domestic Abuse Plan

Domestic abuse is a major concern, both within policing and the wider government. For example, the government has recently published a Tackling Domestic Abuse Plan (previously known as the Domestic Abuse Strategy) (Home Office, 2022) based on responses to the Tackling Violence Against Women Call for Evidence consultation (Home Office, 2021b), associated data and a comprehensive literature review outlining a strategy for the prosecution and management of domestic abuse perpetrators as required by s.75 of the Domestic Abuse Act 2021. Closely aligned with the Tackling Violence against Women and Girls Strategy (Home Office, 2021a) one of the main pillars of the plan is pursuing perpetrators, with the overall aim to reduce domestic abuse reoffending and revictimization (Home Office, 2022). As a result, the plan outlines several key commitments to achieving this, including: a review of data on domestic abuse cases that were closed either by police due to lack of evidence or where the victim did not support police action;

consideration of a register of domestic abuse offenders; the rollout of a risk assessment tool supported by the Recency, Frequency, Gravity and Victimisation model; and an investment of £75 million over three years to fund programmes tackling domestic abuse perpetrators such as interventions to directly address perpetrators behaviour, with evaluation and further research being provided where appropriate (Home Office, 2022). Therefore, domestic abuse perpetration is a serious concern and priority in current government policy.

Research methods

There have been numerous ways in which research has been conducted on domestic abuse and, especially, domestic abuse perpetrators. For example, a commonly used qualitative method utilised are interviews, most often conducted with victims of domestic abuse (Gill et al., 2018; Tarzia, 2021; Hogan et al., 2021). While many studies focus exclusively on female victims (Gill et al., 2018; Tarzia, 2021) there are exceptions, with studies such as Hogan et al's. (2021) exploring British male domestic abuse victimisation by female perpetrators. Conversely, other interviews were conducted with perpetrators of domestic abuse (Anderson and Umberson, 2001) with several studies opting to interview both victims and perpetrators (Gadd et al., 2019). Another prominent figure frequently interviewed were practitioners or other individuals working in organisations/institutions associated with domestic abuse (Phillips et al., 2013) sometimes in conjunction with victims and/or perpetrators (Walker et al., 2015; Gill et al., 2018).

A further method that can be observed in domestic abuse research is reviews of literature. Using prior studies to either compare data or establish trends in the research, multiple types of literature review were used, including rapid review (O'Connor et al., 2021) narrative review (Gokdemir et al., 2022) or a simple review of literature (Holtzworth-Munroe and Stuart, 1994). Particularly, Holtzworth-Munroe and Stuart (1994) reviewed previous typologies of male batterers, finding three descriptive dimensions that were used to create subtypes of batterers (family only, dysphoric/borderline and generally violent/antisocial) which were then examined against a review of literature, followed by a further review of prior typology research for methodological limitations. However, other studies used previous literature and theory to support their theoretical models or views on domestic abuse (Gondolf, 2007; Sherman, 2007; Kelly and Johnson, 2008; Hearn, 2013; Gracia and Merlo, 2016; Davies and Rowe, 2020) or inform their arguments on domestic abuse characteristics such as risk (Rosenberg and Berry, 2021) and programmes of intervention or rehabilitation (Morran, 2011; Day and Bowen, 2015).

Lastly, other research methods that featured in domestic abuse research to a lesser extent were national (Robinson and Clancy, 2015) and European surveys (Hamilton et al., 2013) of identification tools and programmes for domestic abuse perpetrators. This was followed by case analysis (Robinson et al., 2014; Monckton Smith, 2020) reports (Stevenson, 2017) longitudinal narratives (Hester, 2013) case studies (Gadd and Corr, 2017) narrative inquiry (Harden et al., 2022) and observations of online forums (Leitão, 2021).

Alternatively, other studies adopted a quantitative approach to research, using statistical techniques and data. For instance, various studies used statistical data previously collected by other sources, most often the police and other related institutions (Walby et al., 2014; Johnson and Goodlin-Fahncke, 2015; Sherman et al., 2017; Westmarland et al., 2018; Dillon, 2018; Office for National Statistics, 2019; Verbruggen et al., 2020; Office for National Statistics, 2021). While most studies either collected data from previous studies (Johnson and Goodlin-Fahncke, 2015; Sherman et al., 2017) or national crime surveys (Walby et al., 2014; Office for National Statistics, 2019; Verbruggen et al., 2020; Office for National Statistics, 2021) some utilised Freedom of Information (FOI) requests to access specific police data (Westmarland et al., 2018; Dillon, 2018) or conducted psychometric assessments on domestically violent men (Johnson et al., 2006). Notably, studies focusing on domestic batterer typologies applied cluster analysis to their datasets to examine the effect the typologies had on the outcomes (Saunders, 1992; Johnson et al., 2006; Johnson and Goodlin-Fahncke, 2015) or used chi-square tests and t-tests to differentiate between generally or partner-only violent subgroups (Boyle et al., 2008).

Further studies using statistics identified or tested predictors, with multiple studies using predictors to examine the predictive validity of escalating intimate partner violence or recidivism often concerning risk assessments (Hilton et al., 2004; Messing and Thaller, 2013; Goldstein et al., 2016; Kerr et al., 2017; Turner et al., 2019; Adisa et al., 2021; Cunha et al., 2022). Regression – especially logistic – was frequently a form of data analysis (Hilton et al., 2004; Goldstein et al., 2016; Adisa et al., 2021; Cunha et al., 2022) although Turner et al. (2019) markedly used eight machine-learning models to predict future harm including logistic regression. A notable variation observed was the study on predictors of domestic violence by Weir (2019) unique in utilising geographically weighted regression to explore predictors of domestic abuse at a neighbourhood level. As well as this, the study by Golu (2014) differed in employing pre-existing questionnaires such as the aggression questionnaire (Buss and Perry, 1992) and the self-esteem scale (Rosenberg, 1965) in their sample group of women to calculate domestic violence predictors.

Moreover, case analysis was another prominent quantitative research method that generated statistical data, with cases commonly sourced from police records or medical-legal reports (Bland and Ariel, 2015; Barnham, 2016; Barnham et al., 2017; Oliver and Jaffe, 2021; Bendlin and Sheridan, 2021; Isailă et al., 2021). Case analysis was primarily based on domestic abuse perpetrators, examining prevalent characteristics such as gender, mental illness, escalation of violence and severity of violence (Bland and Ariel, 2015; Barnham, 2016; Barnham et al., 2017; Oliver and Jaffe, 2021; Bendlin and Sheridan, 2021; Isailă et al., 2021). In contrast, studies that used domestic violence victims or witnesses as a sample population to examine similar characteristics in victimisation and perpetration tended to employ interviews to produce data (Bonomi et al., 2006; Hines et al., 2007; Peraica et al., 2021).

Other research methods included meta-analysis and systematic reviews, with systematic reviews being used separately (Nicholls et al., 2013; Beyer et al., 2015) or in conjunction with meta-analysis (Bacchus et al., 2018; Travers et al., 2021). Surveys were also an eminent method, with many of the nationally based surveys being situated in the West, especially in Europe (Helweg-Larsen and Frederiksen, 2007; European Union Agency for Fundamental Rights, 2014). In one instance, a longitudinal survey was employed to determine the life success of intimate partner violence perpetrators with psychopathic traits (Theobald et al., 2016). Finally, at least one study used a review of literature to examine what encompassed a Cognitive Behavioral Intervention Program for perpetrators of intimate partner violence (Wong and Bouchard, 2021).

Numerous studies, however, assumed a mixed-method approach, often using multiple sources as well as research techniques (Hester and Westmarland, 2006; Alderson et al., 2013; Kelly and Westmarland, 2015; HM Inspectorate of Probation et al., 2017; Davies and Biddle, 2018; Morgan et al., 2019; Hester et al., 2020; Women's Aid, 2021; Robinson and Clancy, 2021). The remaining studies generally used qualitative and quantitative data taken from reviews of literature to propose a domestic abuse perpetrator strategy (Drive Project, 2019) or explore domestic abuse during the COVID-19 pandemic (Dawsey-Hewitt et al., 2021). Similarly, while Drive Project (2021) used a single survey to determine the views of victims on how services work with perpetrators, qualitative and quantitative data were both used to inform the study.

Geographic location

Most studies were geographically situated in the West, particularly in countries such as the UK and US. This was especially apparent in the numerous surveys and projects located in Europe and the UK (Helweg-Larsen and Frederiksen, 2007; Akoensi et al., 2012; Hamilton et al., 2013; European Union Agency for Fundamental Rights, 2014; Robinson et al., 2014; Kelly and Westmarland, 2015; Robinson and Clancy, 2015; Her Majesty's Inspectorate of Constabulary and Her Majesty's Crown Prosecution Service Inspectorate, 2017; Drive Project, 2019; Hester et al., 2020; Drive Project, 2021; Dawsey-Hewitt et al., 2021; Women's Aid, 2021; Cunha et al., 2022). Some exceptional studies included Australia (Kerr et al., 2017) and Canada (Oliver and Jaffe, 2021; Wong and Bouchard, 2021). However, while other studies examined a national scope, some explored local or neighbourhood factors and domestic abuse (Beyer et al., 2015; Weir, 2019). For instance, in a systematic review of neighbourhood environments and intimate partner violence, Beyer et al. (2015) identified that current research was mostly situated in the US and used social disorganisation theory, with recurrent neighbourhood predictors being socioeconomic and demographic variables such as unemployment, undereducation, poverty and community violence. However, partially due to the relatively recent prominence of the research, gaps in the research were highlighted, including the lack of exploration in non-urban areas (Beyer et al., 2015). In an addition to this research, Weir (2019) made an unprecedented study of neighbourhood-level predictors of domestic abuse and their disparity across space in the UK, finding that statistically significant predictors included structural and cultural variables like income, ASB rate, the proportion of black, Asian, and minoritized ethnic population and population density.

Domestic abuse perpetrator typologies

In the literature on domestic abuse and violence, there are numerous studies on perpetrator typologies, varying in the use of research methodology, geographical focus and data utilised. For instance, as previously mentioned, Saunders (1992) was one of the researchers to use cluster analysis to create a typology of male batterers with implications for their psychiatric treatment. Based on data gathered from 165 male respondents being assessed for admission to a treatment centre for male batterers, three types were identified – family-only, generalized and emotionally volatile aggressors, with clustering variables explaining 90% of the variance in category allocation (Saunders, 1992).

Saunders' (1992) subtypes were also used in a domestic batterer typology developed by Holtzworth-Munroe and Stuart (1994) in a review of previous typologies established by rational-deductive and empirical-inductive approaches, finding three principal descriptive dimensions that consistently distinguished subtypes of batterers: severity of marital violence, the generality of violence (towards their wife or others) and psychopathology or personality disorders. As a result, the family only, dysphoric/borderline and generally violent/antisocial subtypes were constructed, categories strikingly similar to the ones developed by Saunders (1992) except for the emotionally volatile and dysphoric/borderline types, prompting Holtzworth-Munroe and Stuart (1994) to critique them for not assessing personality disorders in their psychopathology measures (factors proven to be important in other typologies).

Moreover, Holtzworth-Munroe and Stuart (1994) discussed other methodological weaknesses in previous typologies, including the need to validate existing and proposed typologies, with researchers neglecting to test or retest the reliability of their typologies by replicating their findings in two or more samples or testing it at different points in time. Sampling issues were also highlighted, with Holtzworth-Munroe and Stuart (1994) finding that most of the previous typologies used only clinical samples or female victims in shelters, limiting the full range of variability that would be found with a broader sample. Lastly, the typologies were criticised for their lack of usefulness in practical application, with no attempts made to examine the relationship between the typologies and treatment options for domestic batterers (Holtzworth-Munroe and Stuart, 1994)

Johnson et al. (2006) also used cluster analysis to derive a psychometric typology of domestic violence offenders in their research into interpersonal violence; however, their approach differed significantly as data analysis was based on rotated principal component analysis and k-means cluster analysis on psychometric data gathered from 230 British men either court-ordered to attend the Domestic Violence Probation Programme or being assessed for their aptness to attend the programme. From this, four subtypes similar to Holtzworth-Munroe and Stuart's (1994) were ultimately developed - low pathology (characterized by low psychopathology) borderline (high for psychopathology and interpersonal dependency) narcissistic (high for psychopathology and narcissism) and antisocial (high for psychopathology and antisocialism). The data was able to indicate that convicted domestic violence offenders have a high proportion of generally violent/antisocial subtypes and few family-only type offenders (Johnson et al., 2006). However, limitations in the study included the inability to obtain data from intimate partners of the offenders to validate subtype profiles to their behaviour and the need for further research to establish whether samples taken from court referrals for treatment are biased towards the inclusion of family-only subtypes and exclusion of generally violent/antisocial types (Johnson et al., 2006).

However, some studies took an alternative view to domestic violence typologies. For instance, Gadd and Corr (2017) challenge the intrinsic assumption of domestic violence perpetrator typologies that offender motivations are rigid and derivable from self-reports and official records. Gadd and Corr (2017) identify two main approaches to homogenising domestic violence perpetration: classification of psychological profiles of perpetrators – the most well-known being Holtzworth-Munroe and Stuart (1994) – and the nature of violence such as Johnson (2006). Re-elaborated by Kelly and Johnson (2008) the second approach identifies typologies of intimate partner violence according to partner dynamics, context and consequences, distinguishing four main patterns of violence: coercive controlling violence, violent resistance, situational couple violence and separation-instigated violence. Kelly and Johnson (2008) argue that through reliable differentiation, decision-making, sanctions and treatment, programmes in criminal, civil and family courts can be tailored to specific types of intimate partner violence, thus potentially improving their practice. Nonetheless, Kelly and Johnson (2008) acknowledge that there is controversy about whether men are the primary perpetrators of intimate partner violence or whether there is gender symmetry. Consequently, it is recognised that there is gender symmetry in some types of intimate partner violence and to differing extents, with situational couple violence found to be roughly gender symmetric in a 1970s survey sample while a court sample of coercive controlling violence was largely perpetrated by men (Johnson, 2006; Kelly and Johnson, 2008). Likewise, Peraica et al's. (2021) study on domestic violence in Croatia identified general types of domestic violence from 3,296 structured face-to-face interviews with domestic violence help-seekers, finding that women were frequently the victims of physical, financial, and multiple-type abuse whereas men were more often victims of psychological abuse.

However, Gadd and Corr (2017) caution against overemphasizing the significance or validity of the violence or psychological typologies, arguing that both models are undynamic in their conceptualisations of offender psychology and abusive relationships and not necessarily applicable on an individual level. Using a single case study based on an interview with a twenty-one-year-old heterosexual male perpetrator, Gadd and Corr (2017) highlight the interpretative nature of domestic abuse and how specific behaviours and aspects can be understood differently by those reading the case and the perpetrator themselves. In particular, the meaning of violence and control for specific men in specific relationships is identified as an important factor as it can help recognise substantial features of the background causes of domestic violence as well as the significance of those features that are relatively common among perpetrators or men who control women in general (Gadd and Corr, 2017). Therefore, Gadd and Corr (2017) urge the need for open and interpretive thinking and recognition that perpetrators are not unchanging types and can recognise and change their behaviour.

However, various studies have since utilised domestic abuse typologies to explore significant relationships. Notably, Johnson and Goodlin-Fahncke (2015) used cluster analysis to explore the effect of arrest across Holtzworth-Munroe and Stuart's (1994) domestic batterer typology. Gleaned from a sample of 2,412 heterosexual male batterers in three Spousal Assault Replication Program (SARP) studies in the US, it was found that arrest heightened the reoffending of intimate partner violence for the generally violent/antisocial and low-level antisocial subtypes, thus necessitating the need for pre-trial protection of victims (Johnson and Goodlin-Fahncke, 2015). Consequently, the study fulfils the need to examine the relationship between batterer typologies and intervention approaches and suggests practical applications (Johnson and Goodlin-Fahncke, 2015).

Moreover, Goldstein et al. (2016) used Holtzworth-Munroe and Stuart's (1994) typology and Boyle et al's. (2008) generally violent and partner only subgroups to examine the relationship between family only and generally violent intimate partner violence perpetrators and the severity of violence and recidivism. Analysing self-reported lifetime antisocial behaviour, family of origin violence and impulsivity/behavioural disinhibition in 73 men entering treatment for intimate partner violence, Boyle et al. (2008) classified the participants as either generally violent or partner only violent through their General Violent Tactics Scale, further applying chi-square analyses, t-tests and multiple measures and scales to determine the characteristics of the two groups. While it was found that generally violent men reported more conduct disorder/delinquent behaviours, lifetime antisocial behaviours, behavioural disinhibition and were more psychologically abusive to their intimate partners, there was no statistical difference between the groups in the use of physical violence towards their partners (Boyle et al., 2008). Alternatively, Goldstein et al. (2016) used a sample of 328 men charged with acts of domestic violence and sentenced to probation in the US for their study. From this sample, perpetrator data from electronic case files were analysed with statistical measures such as chi-square tests and analyses, Kaplan–Meier survival analysis and Kaplan–Meier log-rank tests to establish relationships, finding a positive association between generally violent men, violence severity and post probation recidivism but not family only types (Goldstein et al., 2016).

Therefore, several consistent trends can be seen across domestic abuse perpetrator typologies, especially the categorisation of types according to the kind of victim. However, while many focus on the psychological dimension of perpetration (Saunders, 1992; Holtzworth-Munroe and Stuart, 1994; Johnson et al., 2006) others examine the class and severity of violence (Johnson, 2006; Kelly and Johnson, 2008; Boyle et al., 2008; Peraica et al., 2021) as well as victim types. Nevertheless, considering the influence and usage of their typology in multiple studies (Johnson and Goodlin-Fahncke, 2015; Goldstein et al., 2016) it can be argued that Holtzworth-Munroe and Stuart's (1994) is the most prominent and well-known typology overall.

Predictors of domestic abuse

As previously discussed, several studies have examined predictors of domestic abuse, including Weir's (2019) research on neighbourhood-level predictors of domestic abuse (see geographic location). For instance, Hilton et al. (2004) were one of several studies to investigate predictors related to domestic abuse risk assessments, specifically examining the prediction of wife assault recidivism using information from various sources on offender and victim characteristics and index offence. Subjecting the on-average five-year-long archival information of 589 offenders in police records to set-wise and step-wise logistic regression, the Ontario Domestic Assault Risk Assessment (ODARA) was constructed, demonstrating a large effect size in predicting new assaults against wives or ex-wives (Hilton et al., 2004). Prior criminal conduct, prior wife assault and substance abuse significantly correlated with recidivism, with the entire set of predictors being informed by previous literature on domestic abuse perpetrators, predictors of violent crime and the researchers' clinical experience (Hilton et al., 2004).

Furthermore, ODARA was one of five intimate partner violence risk assessment instruments to be assessed by Messing and Thaller (2013) for average predictive validity, achieving the highest Receiver Operating Characteristic Area Under the Curve (AUC) and a medium effect size compared to the small effect size achieved by other instruments. In calculations of predictive validity, out of the 20 measures included in the analysis, the risk assessment was only administered appropriately in nine (45%) thus indicating potential influencing factors such as setting, outcome, the skill of the assessor and access to information (Messing and Thaller, 2013).

Moreover, Turner et al. (2019) evaluated the standardised risk assessment for domestic abuse used by most UK police forces, the Domestic Abuse, Stalking and Honour Based Violence (DASH) form. Using data from a large metropolitan police force in the UK, the bivariate relationships between each question of DASH, officer risk grading and outcome was quantified by mutual information, with Turner et al. (2019) predicting future harm through the application of machine learning models such as logistic regression; naive Bayes; tree-augmented naive Bayes; decision tree; random forest; gradient boosting; k-nearest neighbour (k-NN); and support vector machine (SVM) with polynomial kernel. From this, it was determined that DASH was underachieving, with each component of the DASH questionnaire at most weakly predictive of revictimization and a logistic regression model predicting the same outcome using DASH fairing little better than already poor officer risk predictions (Turner et al., 2019). As a result, Turner et al. (2019) recommend developing better models, especially pointing to the potential of machine learning and its use in medical settings to support clinicians' decision making in diagnosis and treatment referrals, inferring that the development of targeted decision support tools in medical settings could likewise be used to enforce police behaviours and improve the outcomes of domestic abuse risk assessments.

Cunha et al. (2022) however, aimed to identify predictors of perpetrator dropout from batterer intervention programmes in Portugal. Analysing a sample of 83 men enrolled on the PPRIAC (batterer intervention programme) Cunha et al. (2022) used questionnaires to determine variables such as perpetrator demographics, violence and intrapersonal characteristics, descriptive statistics to describe sociodemographic and violence-related variables, t-tests and chi-squared tests to analyse differences between dropouts and completers, logistic regression to identify variables that predicted dropout and Receiver Operating Characteristic (ROC) to generate the predictive power of this model. As a result, 42.2% of perpetrators were classified as dropouts, with only younger age and more previous convictions in crimes other than intimate partner violence predicting dropout; hence meaning that batterers who were older and had fewer previous convictions tended to complete the programme (Cunha et al., 2022).

Lastly, some studies focused directly on predictors of domestic abuse. For instance, Kerr et al. (2017) examined 61,796 cases of intimate partner violence from 1 January 2010 to 31 December 2014 recorded by Northern Territory police to reveal if there was a predictable escalation in the frequency or severity of harm in Aboriginal and non-Aboriginal couples over 4 years as a test of hypothesised escalation in intimate partner violence reported to police among Australian Aboriginal dyads. Reclassifying cases according to the penal code of England and Wales so that severity of harm could be measured against the Cambridge Crime Harm Index (CHI) CHI scores were used to test for patterns of concentration and escalation based on the total days of advised incarceration for each offence category summed across all offences of that category for the overall sample (Kerr et al., 2017). A sharp divide between Aboriginals and non-Aboriginals was found, with 32.4% of Aboriginal offenders having three or more incidents in 4 years compared to 2% of Whites, presenting evidence of escalation among Aboriginal perpetrators (Kerr et al., 2017).

As well as this, the severity of harm increased with repeated incidents, with both Aboriginal and non-Aboriginal couples already having two or more incidents known to police presenting a strong pattern of escalation in the frequency and severity of offending during the 4 years and 34% of couples persisting into the third year having a 99.9% probability of a new incident occurring in year 4 (Kerr et al., 2017).

Similarly, Adisa et al. (2021) identified predictors of harm in ethnic minoritized groups, investigating determinants of harm in domestic abuse perpetration in Black, Asian and other communities. Conducting a scoping review to identify predictors, 153,209 criminal records from three police forces were collected over 3 years (April 2017-March 2020) with data being analysed according to the different research questions: descriptive analysis (baseline profile of harm and its distribution across ethnicities) Ordinary Least Square (OLS) Regression and correlational analysis (identification of individual and neighbourhood-level predictors significantly associated to CHI) (Adisa et al., 2021). From this, predictors related to CHI were identified as ethnicity (any other Asian, Bangladeshi and White and Black Caribbean), age, sex (male and trans female concerning being female) and relationship with victim (Adisa et al., 2021) thus indicating that these factors are predictive of domestic abuse.

Moreover, associations between intimate partner violence and mental health characteristics were made. For instance, Theobald et al. (2016) investigated the predictive relationship between perpetration and psychopathy in their study. Drawing the data of 400 males followed from ages 8 to 48 in a longitudinal survey in the UK - the Cambridge Study in Delinquent Development – descriptive statistics and logistic regression were utilised to examine psychopathic traits and life success in those convicted of violence generally, those convicted of offences outside the home and those convicted of intimate partner violence only (Theobald et al., 2016). While the results suggested that generally violent men are distinct from those who commit offences outside the home and perpetrators of intimate partner violence only, scoring high for psychopathic traits and low for life success, these differences were in degree more than kind (Theobald et al., 2016).

Likewise, Verbruggen et al. (2020) used longitudinal data from a survey - the Dutch Criminal Career and Life-Course Study – as well as self-reported data on intimate partner violence perpetration from 959 Dutch people to determine the relationship between criminal behaviour over the life-course and intimate partner violence. Using various statistic analyses such as descriptive statistics, group-based trajectory modelling and binary logistic regression, it was found that individuals with a history of recurrent general and violent offending over the life course are more likely to perpetrate intimate partner violence and other violent offences later in life (Verbruggen et al., 2020). As well as this, factors like childhood family violence and marriage were related to increased intimate partner violence perpetration while others such as relationship quality and employment appeared to reduce it (Verbruggen et al., 2020).

Risk factors and predictors in mental health were also found in domestic homicides, with Oliver and Jaffe (2021) using a retrospective case analysis approach on domestic homicide cases compiled in Canada. Through a statistical analysis of perpetrators grouped according to whether they had depression and/or substance abuse, it was determined that perpetrators with comorbid depression and substance abuse had an increased number of risk factors for domestic homicide and were more likely to have engaged in hostage-taking behaviour and have contact with mental health and general health care providers (Oliver and Jaffe, 2021).

Characteristics of perpetrators

While the above studies examined predictors of domestic abuse perpetration, others focused on the characteristics of perpetrators. For example, Hester and Westmarland (2006) used the findings of a research project carried out between June 2004 and December 2005 involving the profiling of 692 perpetrators using Northumbria police data and interviews of 17 perpetrators and 72 representatives from organisations associated with domestic violence to present the characteristics and behaviours of perpetrators. From the project, results suggested that perpetrators were on average 34 years old, male, White and generally the same age or older than their victims (Hester and Westmarland, 2006). Regarding behaviour, 50% of perpetrators were involved in at least one more incident over the three year follow-up period, the biggest category of domestic abuse perpetrators being all-round repeat offenders, with only 18% of perpetrators who reoffended doing so against a different partner to the one they originally victimised during that period (Hester and Westmarland, 2006).

Correspondingly, a report based on the survey findings in Denmark from 2000 to 2006 on physical and sexual violence against women created a profile on perpetrators, finding that 40% of physical violence against women was committed by an intimate partner and that 85% of all police-reported cases of violence against women were committed by men (Helweg-Larsen and Frederiksen, 2007). Male perpetrators were found to be generally younger (36% 16-29-year-olds) unemployed (60% 16-59-year-olds) living on their own and comprising a larger proportion of immigrants than the general male population (Helweg-Larsen and Frederiksen, 2007). Similar trends were identified for female perpetrators although this group had a higher proportion of first or second-generation immigrants compared to the general female population (Helweg-Larsen and Frederiksen, 2007). However, it was noted that information for perpetrators was less available or precise than that for victims and that there was a possibility of social and ethnic bias in crime statistics and clients of perpetrator programme that supplemented the profiles, meaning that conclusions on perpetrator profiles are difficult to draw (Helweg-Larsen and Frederiksen, 2007).

Taking a unique approach, Hester (2013) followed 96 domestic violence cases recorded by police over six years through the English criminal justice system to provide detailed longitudinal narratives in an exploration of gender differences in domestic violence perpetration. Applying thematic analysis on narrative records and interviews and Pearson's Chi-Square for quantitative data such as demographic information, Hester (2013) discovered that male perpetrators were more likely to be repeat offenders (83%) whereas most females had only one incident (62%). Males were also much more likely to use physical violence, threats and harassment and thus were more likely to be arrested, although females were more probable to use a weapon - especially in cases of dual perpetrators - and were found to suffer from mental health or general health issues to a greater degree (Hester, 2013).

Additionally, while the main focus of the study is on gender differences in domestic violence help-seekers, Peraica et al. (2021) were able to establish the socio-demographic characteristics of perpetrators through 3296 structured interviews with help-seekers in Croatia. Statistically significant findings on perpetrators revealed that spouses and common-law partners were more likely to be perpetrators against women while parents were more probable to be perpetrators against men, with no other category of perpetrator found to be significant (Peraica et al., 2021)

Yet, characteristics can be differentiated between different types of domestic abuse. For instance, Robinson et al. (2014) collected a random sample of 100 convicted domestic abuse perpetrators from a dataset of 6642 perpetrators' records from the Wales Probation Trust, analysing multi-agency information from the Police, Probation and third sector partners from these individuals to establish the prevalence and characteristics of serial domestic abusers. From the findings, serial domestic abuse perpetrators were found to be likely repeat offenders although only a fraction was deemed as high risk by Probation risk assessment tools, therefore indicating very little difference between serial and non-serial perpetrators in terms of risk (Robinson et al., 2014). However, some distinguishing characteristics were identified when serial perpetrators were assessed by the Spousal Abuse Risk Assessment (SARA) revealing that serial perpetrators were more likely to have a history of family and stranger/acquaintance violence, past use of weapons and recent escalation in violence, along with other factors (Robinson et al., 2014).

Domestic abuse interventions/programmes

Consistently throughout the literature, the need for or improvements to interventions/programmes for domestic abuse perpetrators are highlighted by various sources, from academic articles (Morran, 2011; Akoensi et al., 2012; Alderson et al., 2013; Hamilton et al., 2013; Morgan et al., 2019) to practitioner reports and calls to action (Phillips et al., 2013; Kelly and Westmarland, 2015; Drive Project, 2019; Drive Project, 2021). For instance, Drive Project (2019) compiled a report supported by over 100 practitioners, police forces, campaigners and researchers in England and Wales calling for an intervention programme for domestic abuse perpetrators, pointing to the high financial and public health costs of domestic abuse and the growing field of research into the benefits of perpetrator programmes. According to Drive Project (2019) interventions should be performed in conjunction with victim support, involving: assessments of the perpetrator's history and needs; structured group work, individual work or a combination of both in which perpetrators are challenged to recognise their abuse behaviour; one-to-one intensive case management; and disrupt approaches to manage risk for victims in cases where the perpetrator is not prepared to change their behaviour. Building on this call to action, Drive Project (2021) surveyed 470 victim-survivors to better inform recommendations for the Home Office’s Domestic Abuse Strategy, providing both qualitative and quantitative data. From this, the Drive Project (2021) concluded that major areas the Domestic Abuse Strategy should cover are the prevention and risk management of perpetrators as well as investment in interventions that challenge perpetrators to change, with the empowerment and cooperation of public services such as police, probation, children’s social care, housing and health being encouraged.

Programmes for domestic violence perpetrators and victims are also supported by Gokdemir et al. (2022) finding in a narrative review of ongoing programmes in low and middle-income countries that programmes had the potential to show the extent of domestic violence, identify underlying causes of violence and increase awareness of the costs that it has on society. Although it was acknowledged that some of the existing programmes had bottlenecks including long wait times for children, Gokdemir et al. (2022) argued that these issues could be addressed at individual, community and national levels, emphasising the need for all countries to have sustainable and well-structured preventive and rehabilitative programmes for perpetrators and victims.

Duluth Model

However, there are some pre-existing interventions. For example, in a historical review of perpetrator programmes, the Duluth Model is acknowledged as one of the most widely recognised approaches although it was not necessarily designed to be a perpetrator intervention but a broader response to domestic violence in Duluth, Minnesota (Phillips et al., 2013). The Duluth Model is characterized by Gondolf (2007) as a gender-based cognitive-behavioural approach to counselling and/or educating men who have been arrested for domestic violence and mandated by the courts as a part of a larger system of intervention including arrest, sanctions against non-compliance to court orders, victim support and safety planning and referral to other services with collaborative approaches. The Model aimed to expose abusive behaviour by examining the role of power and control for men, logically challenging the denial and/or minimization of perpetrators' behaviour, teaching them to develop alternative skills instead of using abuse and violence and promoting the cognitive restructuring of attitudes and beliefs that underpin that behaviour (Gondolf, 2007).

Yet, the Model has been criticised for being ineffective and devoid of empirical support, hence impeding progress in the domestic violence field (Dutton and Corvo, 2006). Particularly, Dutton and Corvo (2006) accused the Model of being influenced by radical feminist ideology and activism – hence its gender-based assumptions - rather than evidence, arguing that a psychotherapeutic approach would be more appropriate. Nonetheless, Gondolf (2007) maintained that this was a misleading position, pointing to the questionable, overly simplistic and selective evidence offered by Dutton and Corvo (2006). Instead, Gondolf (2007) argued that contrary to their claims, there was criminological and governmental research evidence supporting the cognitive-behavioural approach offered by the Duluth Model, including the disproportionate victimisation of women recorded in American surveys, countering the view that the Model was only influenced by feminist ideology.

The Duluth Model was one of several perpetrator interventions to be evaluated for effectiveness by Travers et al. (2021) in a systematic review and meta-analysis of studies examining various interventions. As stated by Travers et al. (2021) reviews of perpetrator interventions often focus on the Duluth Model approach or cognitive behavioural therapy (CBT) with other interventions designated as ‘other’ treatment types – although the two approaches are now less distinct as they have appropriated and shared concepts over time. While the interventions were categorised according to the risk-need-responsibility (RNR) framework constructed by Andrews and Bonta (2010) studies that examined the Duluth Model generally found CBT programmes and other treatments such as Achieving Change through Values-Based Behaviour (ACTV) to demonstrate lower rates of recidivism (Travers et al., 2021).

Cognitive Behavioural Therapy

The use of CBT in interventions for intimate partner violence perpetrators is also discussed by Wong and Bouchard (2021) who, while acknowledging CBT as the second most common approach used in group interventions for perpetrators, noted the lack of research into the operationalization of CBT principles across programme curricula, leaving little information to base recommendations for model CBT approaches on. Through a review of literature on CBT approaches in perpetrator interventions and an analysis of data evaluated from 10 community-based perpetrator programmes in British Columbia, Canada from 2017 to 2018, Wong and Bouchard (2021) found 4 core factors – cognitive, emotional regulation, interpersonal skills and goal setting - followed by 14 components that comprised a CBT approach. However, a significant disconnect was discovered in the labelling of the 10 programmes and their actual content, with programmes overapplying the label of CBT when their content contained little of the core factors or components of CBT, making classifications of programmes unclear and not indicative of their curriculum (Wong and Bouchard, 2021). Consequently, Wong and Bouchard (2021) strongly recommended that programmes code according to actual curriculum content instead of using the stated label of CBT and for guidelines on the core factors and components of the intervention approach to be developed to prevent indiscriminate labelling of programmes.

European Perpetrator programmes

CBT and the Duluth Model also feature prominently in European domestic violence perpetrator programmes, with Hamilton et al. (2013) noting that the Model was the most frequently transferred programme type, either having been lifted directly or forming the basis of a new programme. Surveying 54 perpetrator programmes in 19 European countries – with Bulgaria, Estonia, Hungary, and Romania not offering any programme during the time of research - Hamilton et al. (2013) found that out of the three main frameworks for programmes - cognitive-behavioural, psychodynamic and profeminist - the most common approach was cognitive-behavioural (70%)

whereas profeminist and psychodynamic approaches accounted for 54% and 31% consecutively. However, the majority of respondents (54%) stated that their programmes were a combination of treatment approaches, with cognitive-behavioural and profeminist programmes being the most common type of treatment, attributable to the Duluth Model, thus demonstrating the cohesion between the Model and CBT techniques (Hamilton et al., 2013).

In a second study, Akoensi et al. (2012) systematically reviewed the effectiveness of European perpetrator programmes. However, out of 10,446 studies only 12 studies (all a combination of cognitive-behavioural, educational and profeminist techniques) evaluated the effectiveness of a programme systematically, with methodological issues such as representativeness of samples and the appropriateness of outcome measurement creating difficulties in attributing the varied positive effects after treatment to the programmes themselves (Akoensi et al., 2012). As a result, Akoensi et al. (2012) concluded – similar to reviews of North American programmes - that no one approach could be claimed as superior to the others, urging that evaluation of programmes must be improved and that programmes should be more specific to the characteristics of the participants. Comparable findings were also observed by O'Connor et al. (2021) in a rapid review of men's behaviour change programmes. Examining 13 articles and 10 programmes, limited evidence was found to base a detailed evaluation of these programmes, with no assessments made of the programmes' integrity of delivery, system processes or evaluations based on programme logic (O'Connor et al., 2021). Although positive changes were reported for programme participants in aspects including parenting, communication, abuse and responsibility for behaviour, O'Connor et al. (2021) still noted that the programmes failed to examine the link between men's accountability and responsibility to the safety and well-being of women and children, thus neglecting the issue of ensuring women and children have safe environments during and after the programme.

British perpetrator programmes

The findings from the European studies also reflected trends in British domestic violence perpetrator programmes, with Phillips et al., (2013) identifying similar findings to Hamilton et al's. (2013) on the use of cognitive behavioural, profeminist (including Duluth) or psychodynamic approaches in programmes – with nearly half of programmes using a combination of all of these - from interviews conducted with 16 participants involved in perpetrator interventions. However, it was found that while many programmes drew on the Duluth Model, many neglected to implement the coordinated community response system included in the original Model (Philips et al., 2013). As a result, many programme facilitators were often running the programme in isolation and without the support of key community partners such as local authorities, social services, and women's groups, increasing difficulty in holding male perpetrators accountable in their communities (Phillips et al., 2013). As well as this, there was often a lack of clarity about what perpetrator programmes were doing, resulting in scepticism about their value from some women's groups and academics. Some argued that perpetrator programmes were not holding men accountable for their actions; while others argued that they were treating men too harshly, shaming and degrading them weekly (Phillips et al., 2013).

Building on this research, Kelly and Westmarland (2015) aimed to investigate whether perpetrator programmes worked in reducing men's violence and abuse and increasing the freedom of women and children and how more perpetrators could be held to account due to the limited capacity of programmes and the lack of change in domestic violence in the UK. Using multiple qualitative and quantitative research methods and forms of data collection and analysis sourced from programme staff, perpetrators, survivors and children, it was found the vast majority of men attending perpetrator programmes took steps towards change, including a reduction and - for the majority of survivors - end in physical and sexual violence, changes in parenting and improved understandings of violence and abuse (Kelly and Westmarland, 2015). However, Kelly and Westmarland (2015) acknowledged that there was still more changes to be made, such as improvements to group work with perpetrators, support for women and children and the uncertain location of perpetrator programmes within coordinated community responses.

The role of children in perpetrator programmes

The need for accountability to and support for children of men attending domestic violence perpetrator programmes was also recognised by Alderson et al. (2013) who argued that little attention was paid to the services offered to children of perpetrators on these programmes. Drawing on a survey of 44 domestic violence services and 73 interviews with men who were on or had completed a programme, ex-intimates, programme workers and programme funders/commissioners, Alderson et al. (2013) found that, despite a willingness to improve the situation of children, very few organisations provided direct service for children of men on perpetrator programmes, with support offered to perpetrators and ex or current intimate partners acting as a form of proxy service for children. Possible positive outcomes for children from their father's attendance on perpetrator programmes were also identified, consisting of three dimensions: changes in the father that would benefit children; changes in the father-child relationship; and changes in the child (Alderson et al., 2013). Hence, Alderson et al. (2013) urged direct support for and accountability to children of men on programmes, highlighting the need to regard childrens' unique perspectives and views on domestic violence and the potential positive effects that programmes could generate for these children.

The role of children of perpetrators attending programmes has also been observed in other studies. For example, Morgan et al. (2019) used mixed methods to statistically and thematically analyse quantitative and qualitative data sourced from police data, questionnaires, interviews and focus groups to examine the baseline characteristics and outcomes of the main perpetrator programme within the Hampshire Domestic Abuse Prevention Partnership (DAPP). From this, significant outcomes were identified, with positive changes in emotional and physical behaviours observed in perpetrators, many of which were evidenced in their improved relationships with their children (Morgan et al., 2019). Yet, 1 in 5 attendants was later found to be suspected or convicted of domestic abuse after the programme, indicating that further maintenance of positive behaviours and reinforcements were necessary for some perpetrators (Morgan et al., 2019). Furthermore, Morgan et al. (2019) argued that given children were a strong motivational factor for perpetrators, specialist services should be made available for them and that future adaptions of the DAPP model should at least address how to work with children in families experiencing domestic abuse.

Alternate perpetrator interventions

Reflecting on the flaws of existing perpetrator interventions, some studies proposed or focused on different approaches. For instance, Davies and Biddle (2018) reported on a perpetrator-focused partnership approach - or multi-agency tasking and co-ordination (MATAC) approach - to violence prevention and tackling abuse in the north of England, using perpetrator statistical data, case studies, an online partner agency survey and semi-structured interviews to inform their findings. From this, Davies and Biddle (2018) concluded that the locally tailored partnership approach was successful in tackling domestic abuse, with MATAC progressing significantly in several of its objectives, including preventing further domestic abuse offending, improving victims' safety, criminal justice system outcomes, offender behaviour and partnership engagement, thus demonstrating the importance of partnership working in criminal justice localism.

Adopting a similar multi-agency approach, the Drive Project was an intervention for high-risk and high-harm domestic abuse perpetrators piloted for three years in Essex, South Wales and West Sussex from April 2016 to October 2019 (Hester et al., 2020). Based on a whole-system approach using intensive case management and one-to-one interventions with a coordinated multi-agency response, Drive was found to reduce the use of abusive behaviours and increase the safety of victims and children, presenting significant reductions in physical (82%) and sexual (88%) abuse (Hester et al., 2020). Moreover, perpetrators who used the most severe abuse and violence were found to change their behaviours the most, with positive changes sustained for more than a year after completing Drive (Hester et al., 2020). However, deficiencies in the capacity and suitability of provision in areas such as mental health were noted, a significant issue when accounting for the reliance of Drive on fully funded well-functioning multi-agency systems (Hester et al., 2020).

Reviewing the development of domestic violence perpetrator programmes in the UK, Morran (2011) stated that due to pressure to certify that the approaches are based on empirical evidence and thus officially licensed, there has been a proliferation of relatively standardised models of domestic violence perpetrator intervention in the probation and voluntary sectors as can be seen in previous research. However, Morran (2011) maintained that this model of intervention did not fit with the experience of practitioners or emerging research in the field. A prominent example of this approach was the Integrated Domestic Abuse Programme (IDAP) accredited by the Home Office in 2003, an evidence-based model criticised by many – including practitioners delivering the programme - for being inflexible and simplistic despite its supposed openness to emerging theory and research and for focusing more on how practice with offenders is performed rather than how the complexity of personal change in domestic violence perpetrators should be understood (Morran, 2011). Therefore, Morran (2011) argued that individualized and desistance-focused approaches would be more appropriate, creating a space for motivation, engagement and connection and acknowledging factors of desistance in the process of reforming perpetrators including maturation, social bonds and men's narratives. As well as this, Morran (2011) advocated intervention at external and internal levels, arguing that current programmes were overly focused on internal intervention and rarely performed follow-up work with perpetrators, thus neglecting the provision of work aimed at recovery for offenders. Morran does not discuss female perpetration.

While the IDAP has since been replaced by the Building Better Relationships programme (BBR) as the primary criminal justice intervention for male domestic violence perpetrators in England and Wales, Hughes (2017) maintained that although BBR shows promise, criticisms of IDAP and the

Duluth Model (on which it is based) mispresent how the programmes are delivered and their theoretical base and overlook the modest but significant impact Duluth-style interventions can have when targeted and delivered appropriately. Consequently, reflecting on research undertaken with observations and interviews as a group facilitator for IDAP and BBR, Hughes (2017) concluded that many of the principles that IDAP and Duluth were based on were still relevant to perpetrator interventions, especially the therapeutic elements and dynamic interactions between facilitators and service users inherent to the programme, allowing perpetrators – where appropriately facilitated – to engage in an individualized experience and consider their beliefs and behaviour. Although Hughes (2017) recognised that BBR contains many of these elements and concepts, its structured nature and requirement for continuity in factors such as application of facilitator judgment, knowledge of group dynamics and responsiveness to individual service users were identified as potentially hindering these effects.

Other studies have proposed their own models of intervention – for instance, Walker et al. (2015) constructed a conceptual model and framework for practitioners for managing the process of change in partner-violent men from a thematic analysis of interviews with male perpetrators, survivors, and treatment facilitators. From this, Walker et al. (2015) identified that the process of change is dynamic, with men's use and cessation of violence needing to be understood in the context of their individual lives. As a result, three global themes were developed: violent lifestyle behaviours (what is happening in their lives when they use violence); catalysts for change (triggers and adjustments needed to start the process of change); and non-violent lifestyle behaviours (what is different when their lives when they desist from intimate partner violence) (Walker et al., 2015). Hence, the model can be used by practitioners as a practical tool to comprehend how individual's lifestyles, behaviours and attitudes influence the use of violence within relationships and how this changes when men's relationships are without violence, thus aiding in the process of desistance for partner-violent men (Walker et al., 2015).

Lastly, Robinson and Clancy (2021) focused on the systematic identification of (male) domestic abuse perpetrators for targeted intervention, stating that accurate identification of perpetrators that participate in repeat or serious offending could lead to significant harm reduction despite the lack of focus afforded to this issue. Using mixed-method research, Robinson and Clancy (2021) investigated the pilot of the Priority Perpetrator Identification Tool (PPIT) in three police force areas in England and Wales. Based on visits to all 3 sites, interviews with project staff at strategic and operational levels, reviews of documents and protocols and quantitative analysis of monitoring data from all sites, Robinson and Clancy (2021) determined that the use of PPIT within a multi-agency partnership allowed for more systematic identification of priority perpetrators, not only allowing for identification of perpetrators that had previously gone unnoticed or mislabelled as low or medium risk but a focus and analysis on all perpetrators that would not have been performed previously. Therefore, the use of PPIT and the development of multi-agency collaborative arrangements to facilitate it demonstrated innovation in the identification and management of high-risk domestic abuse perpetrators (Robinson and Clancy, 2021).

Appendix 2. Descriptive statistics: demographics by relationship between victim and perpetrator

	Total N = 40488 (%)	IPV (%)	Familial violence (%)
		34558 (86.1)	5930 (13.9)
Risk classification			
High	6536 (16.1)	5895 (17.1)	642 (10.8)
Medium	11306 (27.9)	9943 (28.8)	1363 (23.0)
Standard	22646 (55.9)	15721 (45.5)	3924 (66.2)
Perpetrator gender			
Female	6558 (16.2)	4723 (13.7)	1835 (30.9)

Male	33930 (83.8)	29835 (86.3)	4095 (69.1)
Perpetrator ethnicity			
White	34983 (86.4)	29808 (86.3)	5175 (87.3)
Black, Asian and other minoritised communities	5505 (13.6)	4750 (13.7)	755 (12.7)
Victim gender			
Female	34378 (84.9)	29895 (86.5)	4483 (75.6)
Male	6110 (15.1)	4664 (13.5)	1447 (24.4)
Perpetrator previous victim			
Yes	22206 (54.9)	19009 (55.0)	3197 (53.9)
No	18282 (45.2)	15549 (45.0)	2733 (46.1)
IMD decile			
1 (most deprived)	2590 (6.4)	2172 (6.3)	418 (7.0)
2	5040 (12.5)	4283 (12.4)	757 (12.8)
3	6298 (15.6)	5406 (15.6)	892 (15.0)
4	5923 (14.6)	5074 (14.7)	849 (14.3)
5	5594 (13.8)	4820 (13.9)	774 (13.1)
6	2995 (17.4)	2568 (7.4)	427 (7.2)
7	2094 (5.2)	1778 (5.1)	316 (5.4)
8	4871 (12.0)	4167 (12.1)	704 (11.9)
9	2097 (5.2)	1778 (5.1)	319 (5.4)
10 (least deprived)	2986 (7.38)	2512 (7.3)	474 (7.99)
Incident or crime			

DA non crime	17201 (57.5)	15160 (37.4)	2041 (34.4)
Crime	23287 (42.5)	19398 (62.6)	3889 (65.6)
Year			
2016	10004 (24.7)	8394 (24.3)	1610 (27.2)
2017	8683 (21.5)	7407 (21.4)	1276 (21.5)
2018	8036 (19.9)	6867 (19.9)	1169 (19.7)
2019	7305 (18.0)	6302 (18.2)	1003 (16.9)
2020	6460 (16.0)	5588 (16.2)	872 (14.7)
	Mean (SD)	Mean (SD)	Mean (SD)
Victim age	33.0 (9.6)	32.1 (8.2)	38.3 (14.1)
Perpetrator age	33.2 (9.5)	33.7 (8.7)	30.2 (12.8)
Perpetrator number of victims	2.0 (1.37)	1.92 (1.3)	2.5 (1.6)
Physical summated score	0.319 (0.294)	0.323 (0.297)	0.293 (0.273)
Coercive summated score	0.384 (0.316)	0.408 (0.317)	0.233 (0.264)
Criminality summated score	0.320 (0.331)	0.322 (0.333)	0.311 (0.321)