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# Text mining domestic violence police narratives to identify behaviours linked to coercive control

George Karystianis[1*], Nabila Chowdhury[1], Lorraine Sheridan[2], Sharon Reutens[1], Sunny Wade[3], Stephen Allnutt[4], Min-Taec Kim[5], Suzanne Poynton[5] and Tony Butler[1]


## Abstract

**Background and setting** Domestic and family violence (DFV) is a significant societal problem that predominantly affects women and children. One behaviour that has been linked to DFV perpetration is coercive control. While various definitions have been proposed, it involves "acts of assault, threats, humiliation and intimidation or other abuse that is used to harm, punish, or frighten a victim" ranging from emotional to social and financial abuse. One potentially rich source of information on coercive control are police reports. In this paper we determine whether it is possible to automatically identify behaviours linked to coercive control from DFV police reports and present the prevalence of such behaviours by age and sex.

**Methods** We modified an existing rule-based text mining method to identify 48 coercive control related behaviours from 406,196 DFV reports involving a single person of interest (POI) (i.e., an individual suspected or charged with a DFV offence) against a single victim from NSW Police Force records between 2009 and 2020.

**Results** 223,778 (54.6%) DFV events had at least one identifiable coercive control behaviour with the most common behaviour being verbal abuse (38.9%) followed by property damage (30.0%). Financial (3.2%) and social abuse (0.4%) were the least common behaviours linked to coercive control. No major differences were found in the proportion of DFV events between male and female POIs or victims. The oldest POI group (≥ 65 years) had the largest proportion for behaviours related to verbal abuse (38.0%) while the youngest POI group reported the highest proportion of DFV involving property damage (45.5%). The youngest victim group (< 18 years old) had the highest proportion of DFV events involving verbal abuse (37.3%) while victims between 18 and 24 years old reported the most harassment through phone calls and text messages (3.1% and 2.4% respectively); double that of those in the oldest (≥ 65 years) victim group (1.4% and 0.7% respectively).

**Conclusions** Police data capture a wide variety of behaviours linked to coercive control, offering insights across the age spectrum and sex. Text mining can be used to retrieve such information. However, social and financial abuse were not commonly recorded emphasising the need to improve police training to encourage inquiring about such behaviours when attending DFV events.


**Keywords** Coercive control, Domestic and family violence, Text mining, Police records

*Correspondence:
George Karystianis
g.karystianis@unsw.edu.au
Full list of author information is available at the end of the article

## Introduction

Domestic and family violence (DFV) is a significant societal problem that predominantly affects women and children. In Australia, on average, one woman per week is murdered by a current or former intimate partner, and one in six women and one in 16 men are subjected to physical and/or sexual violence by a current or former partner (AIHW 2017; AIHW 2019). DFV imposes a significant economic and health burden on the community (Khalifeh et al. 2015). Estimates suggest that the annual financial burden in Australia arising from DFV against women and their children is over AUD $22 billion (~US $16.3 billion) in Australia, £66 billion (~US $89 billion) in the United Kingdom, and US $55 billion in the United States (Department of Social Services 2016; Holmes et al., 2018; Oliver 2019).

One behaviour that has been linked to DFV is coercive control (Crossman & Hardesty, 2018). Coercive control can be defined as actions that aim to exert domination and control over the other party (usually) in an intimate partner relationship. The often, subtle nature of this behaviour makes it difficult to identify and detect since it is hard to separate the processes of control that are considered coercive from those affected by it (Crossman & Hardesty, 2018).

Despite numerous definitions of coercive control in the literature, the most common features are the intention and motivation of a perpetrator to obtain "control" over a victim, the perception of such behaviour as negative by the victim, and the ability of the perpetrator to make a credible threat (Hamberger et al., 2017). Coercive control can range from physical and psychological forms of control such as verbal abuse (e.g., threats, shaming), financial (e.g., denying access to bank accounts or credit cards), and social (e.g., isolation from friends, family and children) (Slabbert & Green, 2013). Yet, limited empirical research exists into how specific behaviours and attitudes might aid understanding and measurement of coercive control, and its role in predicting physical interpersonal violence, including the severity of future violence (Hilton et al., 2022). The role of technology in coercive control has emerged in recent years with DFV practitioners increasingly highlighting how digital developments can be employed by perpetrators of coercive control to negatively impact victims (Woodlock et al., 2020).

Studies have shown that coercive control affects women more than men (Johnson et al. 2014, Myhill 2015; Hester et al. 2017). Johnson et al. (2014) showed that while the rates for men who experienced coercive control was 5.4%, the equivalent for women was four times more (22.0%), while Myhill (2015) found that the rate of women experiencing coercive control behaviours was almost 30% as opposed to 6% for men. Although women have been predominantly affected by such behaviour, it has been proposed that some forms of coercive control (e.g., verbal abuse) are equally likely to be used by both women and men (Felson and Outlaw, 2007; Graham-Kevan 2007). Further, it remains unclear how prevalent this type of behaviour is across the age spectrum. In Australia, Boxtall and Morgan (2021) reported that most women who experienced coercive control were between 25 to 34 years old (32%) followed by 18 to 24 years old (22%). Laumann et al. (2008) found that 9% of older adults experienced verbal mistreatment and 3.5% experienced financial mistreatment while from a sample of over 5,000 elders (Acierno et al. 2009), nearly 1 out of every 10 older people received some form of abuse and/or neglect. These statistics highlight the need to investigate this phenomenon more through large population samples whose demographic characteristics might assist to form a clearer picture.

In Australia, several jurisdictions have enacted legislation to criminalize coercive control by targeting specific forms of control. Tasmania focused on the criminalization of economic and emotional abuse or intimidation in 2004, while New South Wales (NSW) defined coercive control as "*a form of domestic abuse involving repeated patterns of abusive behaviour – which can include physical, sexual, psychological, emotional or financial abuse – the cumulative effect of which is to rob victim-survivors of their autonomy and independence.*" (Department of Communities and Justice, 2020).

Data sources on coercive control are hard to access, with information likely to exist in medical or counselling records, however, these are not readily accessible (Buchanan & Humphries, 2021). One potential source of information on coercive control behaviours is collected by the police when they attend and report on DFV events. During these encounters, the police record demographic and other characteristics of perpetrators and victims called "fixed fields" (e.g., age, sex, ethnicity, offence type, relationship between perpetrator and victim, the setting). They also write a detailed free text narrative on the event, often several pages long, describing key event information derived from observations and reports from victims, perpetrators and other witnesses such as the observed mental state of perpetrators and victims, reports of mental illness, stated threats, injuries and abuse types. A recent study showed that a variety of behaviours and attitudes that might comprise coercive control behaviours are recorded and documented in text narratives by the responding police officers in a DFV event (Hilton et al., 2022), while Elzinga et al. (2010) concluded that is possible to identify potential jihadists from a large dataset of police reports.

In NSW, the text narratives can be used in court proceedings should a matter progress in the legal system, yet they mostly remain unused and thus, represent an untapped resource. If unlocked, they could provide insights and new knowledge on DFV, including coercive control. Barriers preventing the use of the narratives include: the highly sensitive nature of the data and strict access protocols, a lack of awareness of the rich information contained within the narratives, their voluminous nature, and an absence of those with the necessary skills to automatically process large numbers of such data. Indeed, the NSW Bureau of Crime Research and Statistics stated "*there is no systematic way to extract information from these [police] narratives other than by manual review*" (Macdonald & Fitzgerald 2014). However, sophisticated, automated approaches are now available that can be used to unlock important information effectively and reliably by processing large-scale textual data.

One such approach to processing text is text mining which has been applied for more than 30 years in different areas to provide unique insights by identifying concepts of interest from unstructured text, extracting terms and establishing new associations and links among them and fill gaps in missing information (Friedman et al., 2004; Savova et al., 2010; Spasic et al., 2014; Karystianis et al., 2015; Abbe et al., 2016; Wang et al., 2018). Examples have been made to automatically analyze police narrative reports (Chau et al., 2002; Ananyan, 2004; Ku & Leroy, 2008; Elzinga et al., 2010; Poelmans et al., 2011; Kuang et al. 2017; Karystianis et al., 2018; Haleem et al. 2019; Karystianis et al., 2019; Birks et al. 2020; van der Laan & Tollenaar 2021; Halford et al. 2022). Examples where text mining has been used on police reports include efforts to identify the names of offenders, illicit drugs, and weapons with varying degrees of success in terms of system performance (Chau et al., 2002; Ananyan 2004). Poelmans et al. (2011) classified police reports as DFV or non-DFV-related by employing an unsupervised clustering technique, while efforts to recognize drugs, weapons and facial features from witness narratives through rule and dictionary-based approaches returned encouraging results (Iriberi & Leroy 2007; Ku et al., 2008). Karystianis et al. (2018, 2019) successfully applied a rule-based approach combined with manually crafted dictionaries to extract mental illness mentions for perpetrators and victims, abuse types, and victim injuries from DFV police text narratives. Recently, Halford et al. (2022) used a language model (i.e., BERT) to identify key details from police text records related to anti-social behavior. Other research attempts involved the use of deep learning methods to recognize mental health related events (Haleem et al. 2019) and machine learning to cluster crime classes (Kuang et al. 2017), and residential burglaries (Birks et al. 2020) from police narratives and cybercrime from police registrations (Van der Laan & Tollenaar 2021).

In this study, we implemented text mining to determine the feasibility of automatically extracting forms of abuse which can be classified as coercive control behaviours from 526,787 DFV police text narratives from 2009 to 2020 and present the prevalence by age and sex.

## Methods

### Data

We selected all events that were flagged as DFV under the Crimes (Domestic and Personal Violence) Act 2007 (NSW) that occurred between 1 January 2009 and 31 March 2020 from the NSW Police Force (NSWPF). Non-criminal events (e.g., those recorded as DFV—no offence) were excluded from the sample. This data does not feature a variable that flags the presence of coercive control, as coercive control was not an offence when this data was collected. A total of 526,787 DFV events were used. We also received the following fixed fields for these events: the age and sex of the individuals involved, the premises type (i.e., a standardized value used by NSWPF to describe the setting the alleged event took place e.g., residential premise, public place, etc.) and the relationship between the POI (Person of Interest)—an individual suspected or charged with committing an DFV offence by the police—and victim. The dataset contained events that in some cases had more than one POI or victim involved. However, the implemented text mining methodology was unable to associate the extracted "mention" to a specific POI or victim, if more than one individual POI or victim were present in the DFV event. Thus, in the current analysis, results are presented only for events that involved a single POI and a single victim resulting to a total of 406,196 events out of 526,787 (77.1%) with a total of 182,676 unique POIs.

### Coercive control behavioural schema

After consulting with two forensic psychiatrists (SW, SA) with significant experience in assessing coercive control for the courts, "hands-off" (i.e., non-physical) abuse types that have been linked to coercive control, including property damage, were selected for extraction. These behaviours were categorized into five groups that are consistent with the current literature on DFV: financial abuse, social abuse, property damage, verbal abuse, harassment (Slabbert & Green, 2013). Behaviours that could not be categorised were assigned into a sixth group (i.e., other abuse). A total of 48 abuse types were identified (Table 1).

**Table 1** Coercive control categories and subcategories with examples identified from police text narratives

| Coercive control category | Subcategory type | Examples from text narrative |
|---|---|---|
| Harassment | Stalking, unspecified | The accused was charged with stalking |
| | Stalking through vehicle | Continued to follow the victim with their car |
| | Stalking at known location | Defendant has parked their vehicle a short distance away from the victim's residence |
| | Trespassing | Forced their way into the house |
| | Harassment, unspecified | Has been continuously harassing the victim |
| | Harassment [phone calls] | Received several phone calls from the accused |
| | Harassment [text messages] | Victim received over 200 messages |
| | Harassment [emails] | Received approximately 100 emails |
| | Harassment [social media] | Sent Facebook threatening messages |
| | Harassment [unwanted gifts] | Has repeatedly given the victim flowers and chocolates |
| | Harassment [letters/notes] | Has been leaving letters and notes |
| | Harassment at known location | Victim asked the accused to leave the house multiple times |
| | Blackmail | Defendant blackmailed the victim to give them money |
| | Unauthorized information dissemination | Recorded them without their permission |
| Social abuse | Acts of self-harm by the POI | Defendant started to cut their own wrists |
| | Illegal use of tracking device | Placed a tracking device on the victim's vehicle |
| | Unauthorized sharing/dissemination of private intimate materials | The defendant shared an intimate video without the victim's permission |
| | Statements of surveillance | I need to know what days you are home and what days you are out |
| | Internet search of private details | Conducted several Internet searches about the victim's address |
| | Privacy violation | Defendant went through the victim's phone |
| | Controlling behaviour | Has become very possessive of the victim |
| | Premises lock out | Refused to let the victim into the house |
| | Home isolation | Isolating the victim in the house |
| | Isolation [family] | Not allowing the victim to see their family |
| | Isolation [children] | Does not allow victim to see their children |
| | Isolation [friends] | Does not allow the victim to socialise |
| Financial abuse | Deprivation of basic necessities | Deprived the victim access to clothes |
| | Employment control | Did not allow the victim to go to work |
| | Financial control | The accused controlled the complainant's money |
| | Withholding of personal effects | Grabbed the victim's wallet |
| Property damage | Arson | Attempted to set fire to the premises |
| | Property damage | Charged with malicious damage |
| Other abuse | Intimidation with an object | Picked up a knife and threatened the victim |
| | Intimidation to harm | Was going to kill the victim |
| | Intimidation, unspecified | Was charged with intimidation |
| | Obsession with victim | They were obsessed with the victim |
| Verbal abuse | Threat to harm animals (e.g., pets, farm animals) | Has threatened to harm the dog |
| | Threat to harm a third person | They said they were going to kill the whole family |
| | Threat to take the children away | Threatened to take the baby away |
| | Verbal abuse | Continued to yell abuse at the victim |
| | Threat to self-harm | I am going to cut myself |
| | Threat to commit suicide | He threatened suicide |
| | Direct threat to damage property | I'm going to smash the car |
| | Direct threat to kill | I am going to kill you |
| | Direct threat to sexual assault | I am going to rape you |
| | Direct threat to harm animals | I will kill your dog |
| | Direct veiled threat to harm | Watch your back |
| | Direct threat to harm a third person | Your dad is going to get shot |

### Text mining

We used an existing text mining methodology to identify coercive control related behaviours in the DFV narrative sample (Karystianis et al., 2019). This method has been already evaluated and applied to 492,393 DFV police narratives for the identification of all abuse types. This approach uses rule-based language expression patterns and term dictionaries to recognize a wide range of abuse types from 'hands-off' to "hands-on". Since the focus of this study was to capture behaviours linked to coercive control and not physical in nature, we only used expression patterns that identified non-physical abuse types (e.g., stalking via car, harassment [text messages], controlling behaviour). The following steps were added:

1. Expanded existing dictionaries to include additional behaviours linked to coercive control;
2. Restructured rules to capture "hands-off" abusive behaviour;
3. Aggregated multiple abuse mentions in each event to achieve document level annotation (e.g., if one event has several mentions of isolation from family and friends, at the document level, this was reported as one mention of social abuse with its subcategories being "isolation [family]" and "isolation [friends]").

The method was implemented through the General Architecture for Text Engineering (GATE), a family of open-source text analysis tools and processes (Cunningham et al., 2013).

#### *Dictionaries*

We selected 14 dictionaries from our previous work (Karystianis et al., 2019) that were used as semantic anchors in our approach to identify non-physical abuse type behaviour (Additional file 1: Table S1). The dictionaries contain systematic variations such as plurals, past and present tenses of words, acronyms and abbreviations. The original dictionary comprising threats was split into twelve additional dictionaries, each one describing a specific threat class (Additional file 1: Table S1). These were expanded manually to include several variations (e.g., "your kids are going to have no father", "your kids are going to have no mother") and surface expressions ("you're dead" to "you are dead" or "your dead"). After consultation with the two domain experts, an additional set of nine dictionaries was crafted to include non-physical abuse types such as various forms of harassment (e.g., texting, calling), social media abuse and a list of individuals related to a victim that were mentioned as potential targets in POIs' threats (Additional file 1: Table S1).

#### *Rules*

The method makes use of rules based on common syntactical patterns observed in the narrative text, specifically referring to the perpetration by the POI of a coercive control related behaviour (e.g., "POI sent over 300 text messages to the victim's phone"). The syntactical patterns included:

- Frozen syntactical expressions as anchors for certain elements built through specific verbs (e.g., "POI stalked the victim");
- Noun phrases and prepositions;
- Semantic placeholders identifiable through the application of the manually crafted dictionaries (e.g., all possible synonyms describing a POI, such as "POI," "perpetrator," and "offender").

The rule scope was expanded resulting in 618 rules for 48 different coercive control related behaviours (~12 rules per behaviour type).

### Evaluation

The implemented methodology has been previously evaluated against a set of 100 randomly selected domestic violence narratives with reliable performance at the document (i.e., event narrative) level in identifying various abuse types (Karystianis et al., 2019). With precision (the number of true positives against the number of true positives and false positives), recall (the number of true positives against the number of true positives and false negatives) and F1-score (the harmonic mean between precision and recall) values of 90% suggesting reliable performance results, an evaluation was deemed unnecessary since we did not include new abuse types. To ensure consistency in the methodology's performance, we apply the method on 50 additional, randomly selected narratives from our data sample which were manually inspected for sources of false positives and negatives. No errors were observed in that sample.

### Ethics

Ethics approval was obtained from the University of New South Wales Human Research Ethics Committee (reference HC16558).

## Results

DFV police attended events occurred in residential premises in almost nine out of ten (86.9%; 352,842) instances, followed by outdoor/public places (6.9%; 28,092), and business/commercial areas (2.3%; 9399) (Additional file 1: Table S2). The most common relationship between POIs and victims was spouse/partner with 14.8% (60,277) and boy/girlfriend (including ex-boy/girlfriend) with 14.6%

(59,580) (Additional file 1: Table S3). 34.0% (138,264) of DFV events had a relationship status of "unknown/not stated".

Overall, 223,778 (54.6%) DFV events involved at least one behaviour linked to coercive control. The most common was verbal abuse (38.9%; 87,088) followed by property damage (30.0%; 67,021), other (19.6%; 43,884) and harassment (7.9%; 17,693). Financial (3.2%; 7,097) and social abuse (0.4%; 995) were the least prevalent. The most common subcategory of coercive control linked behaviours was property damage (29.9%; 66,948) followed by verbal abuse (29.6%; 66,276) and intimidation to harm (9.3%; 20,805) (Table 2). Other subcategories ranked within the top fifteen most common ones were direct threats to kill the victim (4.6%; 21,948) and various types of harassment like calls (2.5%; 5,686) or text messages (2.1%; 4,741). Less commonly reported behaviours such as financial control, harassment with gifts, letters or emails and social isolation (i.e., isolation from family, friends) had a frequency of less than 1% (Table 2).

**Table 2** Number of DFV events (n = 223,778) with the extracted coercive control related behaviours

| Coercive control subcategory | Frequency of DFV events | % |
|---|---|---|
| Property damage | 66,948 | 29.9 |
| Verbal abuse | 66,276 | 29.6 |
| Intimidation to harm | 20,805 | 9.3 |
| Intimidation, unspecified | 20,124 | 9.0 |
| Direct threat to kill | 10,361 | 4.6 |
| Withholding of personal effects | 6,557 | 2.9 |
| Harassment [call] | 5,686 | 2.5 |
| Harassment [text message] | 4,741 | 2.1 |
| Intimidation with an object | 2,873 | 1.3 |
| Stalking, unspecified | 2,797 | 1.2 |
| Harassment, unspecified | 2,280 | 1.0 |
| Threat to damage property | 2,254 | 1.0 |
| Threat of self-harm | 2,232 | 1.0 |
| Direct veiled threats to harm | 2,147 | 1.0 |
| Suicide threats | 2,035 | 0.9 |
| Threat to harm a third person | 1,040 | 0.5 |
| Controlling behaviour | 666 | 0.3 |
| Trespassing | 603 | 0.3 |
| Financial control | 527 | 0.2 |
| Direct threat for sexual assault | 396 | 0.2 |
| Harassment [email] | 371 | 0.2 |
| Harassment at known location | 346 | 0.2 |
| Harassment [letter] | 328 | 0.1 |
| Harassment [gift] | 297 | 0.1 |
| Threats to take the children away | 201 | 0.1 |
| Threat to harm animals | 120 | 0.1 |
| Isolation [children] | 106 | < 0.1 |
| Harassment [social media] | 98 | < 0.1 |
| Privacy violation | 92 | < 0.1 |
| Stalking at known location | 86 | < 0.1 |
| Locking the victim out of the premises | 84 | < 0.1 |
| Obsession with the victim | 82 | < 0.1 |
| Property damage [arson] | 73 | < 0.1 |
| Stalking via car | 58 | < 0.1 |
| Direct threat to harm animals | 17 | < 0.1 |
| Isolation [family] | 15 | < 0.1 |
| Isolation [friends] | 15 | < 0.1 |
| Employment control | 13 | < 0.1 |
| Direct threat to harm a third person | 9 | < 0.1 |
| Acts of self-harm | 8 | < 0.1 |
| Use of device to track the victim | 5 | < 0.1 |
| Isolation [home] | 2 | < 0.1 |
| Blackmail | 1 | < 0.1 |
| Non-consensual sharing of intimate material | 1 | < 0.1 |
| Direct statement of victim surveillance | 1 | < 0.1 |
| Unauthorized dissemination of victim's information | 1 | < 0.1 |

### Persons of Interest

Almost one out of five (19.8%) DFV events with a coercive control related behaviour involved a female POI, 79.1% of events involving a male POI, and < 1% (2,228) had no recorded sex. Both male and female POIs showed similar rates across the main categories of coercive control linked behaviours including harassment (Table 3). Social abuse was the least common type at 0.5% male and 0.3% female POIs respectively (Table 3). While POIs aged between 25 to 44 years old had the largest number of DFV events (n = 121,419) among all five aged groups, proportionally POIs younger than 18 years old had the most occurrences of property damage with 45.6%. Despite POIs in the 25–44 years age group having the highest rates of financial abuse (3.4%), no major difference proportionally was observed across the other groups. The oldest POI group (65 years and older) had the highest proportion of DFV events for verbal abuse (49.6%) and other (26.3%) (Table 3).

In the 15 most common subcategories of coercive control related behaviour, property damage [non-arson] (29.0%) was the most common in male POIs. Verbal abuse was most prevalent among female POIs (33.6%), and higher than in males (28.7%) (Fig. 1). Male POIs had a larger proportion of DFV events with unspecified intimidation (9.6%) then female POIs (6.3%). Various types of harassment (e.g., text message, calls) for both male and female POIs were uncommon, and identified in only 2.0% of reports (Fig. 1). A full breakdown of the subcategories across female and male POIs is shown in Additional file 1: Table S4.

**Table 3** Number of DFV events with male and female POIs across the five age groups within the six categories of behaviour linked to coercive control (n = 223,778)

| | **Coercive control related behaviours** | | | | | | ***p-value*** |
|---|---|---|---|---|---|---|---|
| Gender | Verbal abuse | Property damage* | Other abuse | Harassment | Financial abuse | Social abuse | < 0.001 |
| Male (n = 177,139) | 67,907 (38.3) | 51,489 (29.1) | 36,725 (20.7) | 14,218 (8.0) | 5,962 (3.4) | 838 (0.5) | |
| Female (n = 44,411) | 18,499 (41.7) | 14,579 (32.8) | 6,799 (15.3) | 3,317 (7.5) | 1,077 (2.4) | 140 (0.3) | |
| Age group | | | | | | | |
| < 18 (n = 19,991) | 6,667 (33.4%) | 9,109 (45.6%) | 3,194 (16.0%) | 549 (2.8%) | 438 (2.2%) | 34 (0.2%) | < 0.001 |
| 18–24 (n = 41,287) | 14,486 (35.1%) | 14,978 (36.3%) | 7,584 (18.4%) | 2,806 (6.8%) | 1,283 (3.1%) | 150 (0.4%) | |
| 25–44 (n = 121,419) | 47,764 (39.3%) | 33,882 (27.9%) | 24,307 (20.0%) | 10,715 (8.8%) | 4,181 (3.4%) | 570 (0.5%) | |
| 45–64 (n = 35,498) | 15,962 (45.0%) | 7,520 (21.2%) | 7,569 (21.3%) | 3,199 (9.0%) | 1,057 (3.0%) | 191 (0.5%) | |
| > = 65 (n = 2,730) | 1,353 (49.6%) | 394 (14.4%) | 719 (26.3%) | 162 (5.9%) | 71 (2.6%) | 31 (1.1%) | |

*Property damage includes property damage [non arson] and arson

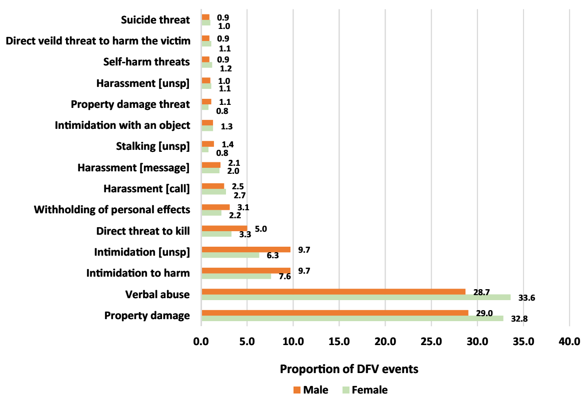


**Fig. 1** Top fifteen most common subcategories of coercive control related behaviour for male and female POIs (n = 223,778). *unsp* unspecified

In terms of age, the oldest POI age group had the highest proportion of behaviours related to verbal abuse (38.0%), various forms of intimidation (unspecified (10.2%), intimidation to harm (14.1%) and direct threats to kill the victim (7.6%). Almost half of the DFV events involving the youngest POI group reported property damage (45.5%). Less frequent coercive control subcategories, showed POIs aged between 25 to 44 years old to withhold personal effects of victims in 3.2% of reports, and harass victims through phone calls (2.8%), and text messages (2.4%). Despite the low rate, self-harm (1.4%) and suicide threats (1.4%) were mostly performed by the youngest POI group (Additional file 1: Table S5).

### Victims

The total number of DFV events with a coercive control related behaviour that involved male victims was 23.8% and for female victims 74.1%; 2.1% (4,526) had no recorded victim sex. The proportion of coercive control related behaviours across events was similar in male and female victims (Table 4). Across subcategories related to coercive control behaviours, the distribution for female and male victims were similar. However, unspecified intimidation was more common in females, and verbal abuse more common in males (Fig. 2). For a full breakdown of the subcategories across female and male victims, see Table 6 in the Supplementary Material. Age wise, the oldest and youngest victim groups had the highest proportion of DFV events that reported verbal abuse with 47.5% and 44.0% (Table 3). Social abuse remained uncommon with the proportion of DFV events across age groups being less than 0.5%. Property damage was the highest in the 45 to 64 year old age group (34.1%) while harassment was the most prevalent in the 18 to 24 year old group (9.1%) (Additional file 1: Table S7).

## Discussion

Identifying behaviours linked to coercive control from a large dataset of police narratives is possible through the application of text mining. The method employed was developed to highlight broader abuse types in the DFV context, however, we have shown that it is feasible to modify this approach to recognize hands-off abuse which can be classified as coercive control. Although police narratives of DFV are a rich source of information and detail several behaviours that suggest coercive control such as financial and social abuse, these are not frequently recorded. However, police narratives can capture a wide range of coercive control related actions including stalking, harassment and cases that involve property damage, verbal abuse and intimidation across all age groups and in both sexes.

Existing evidence concerning who is most likely to perpetrate behaviours linked to coercive control is mainly derived from victims' experiences through in-depth interviews and ad-hoc surveys (Campbell et al. 2003; Frye et al. 2006) that allow for anonymous reporting. In the

**Table 4** Number of DFV events with male and female victims across the five age groups within the six categories of behaviour linked to coercive control (n = 223,778)

| | Coercive control related behaviours | | | | | | p-value |
|---|---|---|---|---|---|---|---|
| | Verbal abuse | Property damage* | Other abuse | Harassment | Financial abuse | Social abuse | |
| Gender | | | | | | | |
| Male (n = 53,327) | 20,880 (39.2) | 17,636 (33.1) | 9,790 (18.4) | 3,563 (6.7) | 1,279 (2.4) | 179 (0.3) | < 0.001 |
| Female (n = 165,925) | 65,112 (39.2) | 46,920 (28.3) | 33,564 (20.2) | 13,773 (8.3) | 5,758 (3.5) | 798 (0.5) | |
| Age group | | | | | | | |
| < 18 (n = 13,350) | 6,338 (47.5%) | 2,208 (16.5%) | 3,280 (24.6%) | 871 (6.5%) | 583 (4.4%) | 70 (0.5%) | < 0.001 |
| 18–24 (n = 37,847) | 14,394 (38.0%) | 10,346 (27.3%) | 7,949 (21.0%) | 3,424 (9.1%) | 1,561 (4.1%) | 173 (0.5%) | |
| 25–44 (n = 111,509) | 42,637 (38.2%) | 33,081 (29.7%) | 21,704 (19.5%) | 9,852 (8.8%) | 3,686 (3.3%) | 549 (0.5%) | |
| 45–64 (n = 48,668) | 19,139 (39.3%) | 16,588 (34.1%) | 8,838 (18.2%) | 2,880 (5.9%) | 1,068 (2.2%) | 155 (0.3%) | |
| > = 65 (n = 8,093) | 3,558 (44.0%) | 2,383 (29.5%) | 1,617 (20.0%) | 345 (4.3%) | 156 (1.9%) | 34 (0.4%) | |

*Property damage includes property damage [non arson] and arson

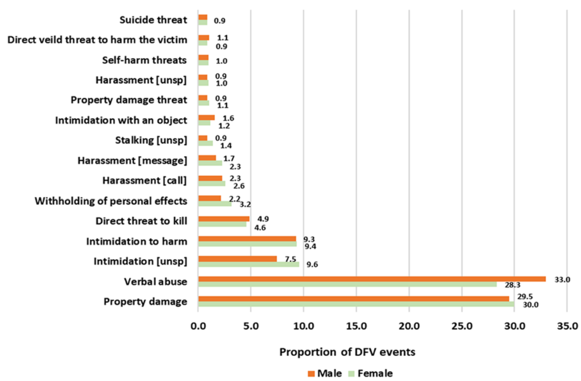


**Fig. 2** Top fifteen most common subcategories of coercive control related behaviour for male and female victims (n = 223,778). *unsp* unspecified

UK, 21% of women and 9% of men reported experiencing emotional and financial abuse (Office for National Statistics 2016). In Sweden, 41% of women and 37% of men were subjected to social isolation (i.e., friends and family) from their partners (Morgan and Bjrkert 2006) while in Australia 78% of women DFV survivors were harassed through technology facilitated abuse in the form of text messages and phone calls, with 56% reporting that their partners used mobile technology to check their location, and 17% reporting the use of GPS technology by their parent to track their movements (Woodlock 2016).

Since coercive control is often a subjective phenomenon, particularly when it relates to text or verbal communication attributing a negative meaning to behaviours that can be interpreted differently when reading a police record, it is not surprising to discover that certain behaviours like financial control, harassment at a known location, and privacy violations are less likely to involve the police and so, they will not be picked up in police-based reporting. This is evidenced in the prevalence of less than 1% we observed for such behaviours. One reason for this is the focus of attending police officers in a DFV event on victim safety and observing and recording visible injuries and property damage while noting down distress statements, along with key information such as the mental health status of POIs and victims and whether children or any witnesses were present and in (immediate) danger. As police orient towards the detection of criminal offences, cases and instances of coercive behaviour, despite their inclusion in legal definitions of DFV, are not recorded. Victim's safety takes primacy over other factors in DFV events, and consequently, more subtle and less obvious forms of abuse are less likely to be inquired about.

Current tools for collecting information on FDV events used by police focus more on physical assault than on indicators of coercive control. This is reflected in the present work with property damage (including arson) (29.9%) which, excluding verbal abuse, was the most prevalent type in DFV. Less common forms of coercive control might not contain sufficient detail in police narratives to allow them to be surfaced by text mining (Myhill 2019), as illustrated by the low event frequency around several explicit subcategories (e.g., isolation from family and friends, employment control, acts of self-harm, stalking the victim via a vehicle) which were reported in less than 0.1% of events. Further, certain forms of coercive control are not perceived as such by victims and so are less likely to be reported to police, particularly in the face of more apparent abuse such as a physical assault or direct threat to kill and harm the victim. Studies have shown that applying comprehensive question banks to ask victims about their experiences of various forms of coercive control tend to produce higher reported rates of these abuse types (Boxall & Morgan, 2021). Nevertheless, it is clear that a number of police DFV records do report coercive control behaviours when responding to a DFV event, although this was not a widespread practice.

Given the growing body of research that attests to the damaging impact of coercive control towards physical and mental health, and its link with violent behaviour and sexual assaults (Stark & Hester, 2019), it is pertinent to update tools that allow the capture of such behaviours by police and assist in the early identification of victims moving away from free-text discussion and non-flexible assessment tools that return weak predictive values (Ringland 2018; Dowling and Morgan 2019). The advent of computational text mining methods offers promising opportunities for analysing police data, particularly in the DFV space (Neubauer et al., 2023). However, considering that victims might be unable to recognize that they are subjects to this form of abuse, careful and sensitive questioning by the police is necessary. Improving police training to highlight their responses on these lesser known concepts would prove beneficial by focusing on DFV related behaviour that is more difficult to measure than physical and sexual abuse. The present study identified several categories of coercively control behaviour based on existing literature and can be used to inform future tool development and training content.

Based on these findings, police information collection and recording practices can be altered. For example, when attending DFV events, police officers can include standardized questions devised by experts in DFV and forensic psychiatry to capture behaviours linked to coercive control. Considering that many DFV events have no recorded offence since no physical harm or damage was observed, it could be helpful if a separate section was included in the narrative focusing on detailing these types of behaviours. This is particularly important given recent legislative developments in NSW that aimed at creating a stand-alone offence of coercive control (NSW Department of Communities and Justice, 2022).

The sex differences observed in our work reflected that seen in the literature with more female than male victims, and male perpetrators more likely to engage in intimidatory acts and acts that reflected an obsession with the victim (Australian Bureau of Statistics 2017; Leemis et al., 2022; Office for National Statistics, 2020). Specific forms of harassment, such as messaging, and phone calls, had similar prevalence across the sexes. The literature indicates that although men and women may employ a similar range of domestically abusive tactics, men are more frequently intimidatory toward current and former female partners (Australian Bureau of Statistics 2017; Office for National Statistics 2020; Gilchrist et al., 2017). According to our findings, male victims (33.0%) reported a slightly higher risk of property damage than female victims (28.3%). However, there have not been many studies that conduct direct comparisons between male and female POIs behind the motivation of DFV occurrence (Langhinrichsen-Rohling et al., 2012; Karystianis et al., 2022).

Age differences between the POI and victim groups could reflect a tendency for older people to use non-physical means of abuse compared to younger perpetrators (Robert et al., 2013; Wijeratne and Reutens 2016). We found out that the youngest POI group was most likely to use property damage (45.5%). This difference (of 31.1%) was particularly marked when this POI group was compared against the oldest POI group, with 14.4% of events involving property damage. There was a relationship between age and the use of technology to harass the victim (phone calls, text messages), with younger age groups being more likely to abuse technology in this manner as well as being more likely to engage in emotional abuse in the form of suicide and self-harm threats.

Although the different incidence rates of coercive control behaviours across the sexes and between the various age groups found in this study could reflect true differences in their use, they could also be explained by reporting differences. For instance, in perpetrators less than 18 years old, recording of coercive control linked behaviours may be normalized or minimized instead of being reported to the police. This could explain the comparatively lower rate of non-physical behaviours for this group (e.g., harassment, 2.8%; social abuse; 0.2%) against the higher rate of behaviours like property damage (33.4%). Furthermore, people who are targeted by family members will also be less likely to report to the police than those with more distant relationships to the perpetrator. Thus, the accurate reporting (and recording) of coercive control behaviours can be influenced by many factors including attitudes towards and previous interactions with police, and fear of reprisals.

## Limitations

Our study comes with several limitations. The lack of an operationalized definition for coercive control behaviour did not assist in the identification of such behaviours from police text narratives. Therefore, knowledge from the literature along with expert input was necessary to determine which behaviours within a DFV context may be used to coercively control a victim. Consequently, potential behaviours that might have been considered a criminal act in other jurisdictions could be missing from our study and applied methodology. As the focus of this work is to present the behaviours linked to coercive control from DFV police narratives through an age and sex perspective, interpretating our results through a relationship lens could lead to different conclusions. In addition, the text mining approach has minor error sources that have been discussed extensively (Karystianis et al., 2019). It is possible that within this dataset, certain coercive control behaviours might not have been captured by our pipeline and thus, the abuse type frequencies (i.e., the number of DFV events) could be under-reported.

The NSWPF are not trained to accurately inquire about coercive control. Since they focus on the reporting of key policing information around a DFV event such as the mental health status of POIs and victims, drug and alcohol use, visible injuries and damage (among other things), these recording practices are likely to have influence the outputs of this research. Behaviours such as financial control, various forms of harassment (e.g., text messages, calls, social media posts) or social isolation are often ambiguous in nature, making it difficult for police officers to note down such actions that initially might seem irrelevant to a DFV call. This could also contribute to an under-reporting of such behaviours that the research literature identifies as linked to coercive control. There is also the debate involving the accurate identification of the primary aggressor in a DFV setting by the police. Considering the forms of coercive control are less visible, this might lead to an inappropriate linking of assumption to connect specific behaviours to certain ages or sexes (Nancarrow et al. 2020).

## Conclusions

Coercive control is a subjective behaviour that requires careful definition. Already a point for discussion across various states of Australia with significant differences in how it should be defined, coercive control is clearly linked with the perpetration of DFV. Because coercive control is reported to be widespread, this study sought to identify key behaviours related to coercive control by employing a tested text mining approach on half a million police recorded DFV events. Although several types of coercive control related behaviours were extracted, less known abuse types such as harassment via phone calls, text messages, surveillance and social isolation were not particularly prevalent in our dataset, likely due to these not being the primary focus of police when attending FDV events. While abuse types that have traditionally been linked to DFV were readily identified and occurred frequently within the police records, some limitations might have prevented the recognition and thus the presentation of coercive control behaviours in more detail. This emphasises the need to improve police training and inquiry into coercive control to encourage seeking, identifying and recording such behaviours when attending DFV events, making it the first step towards incorporating automated tools that can retrieve DFV information within text-based police records.

### Abbreviations

| | |
|---|---|
| DFV | Domestic and family violence |
| NSWPF | New South Wales Police Force |
| POI | Person of interest |

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40163-024-00200-2.

**Additional file 1.** Additional tables.

### Author contributions

GK: Study conception and initialization, literature review, application of the text mining method, result interpretation, manuscript preparation and revision. NC: Study initialization, statistical analysis and revision of the manuscript. LS: Literature review, results interpretation and revision of the manuscript. SR: Results interpretation and revision of the manuscript. SW: Classification schema creation and revision of the manuscript. SA: Classification schema creation and revision of the manuscript. MTK: Data collection and revision of the manuscript. SP: Study conception, revision of the manuscript. TB: Study conception and initialization, results interpretation, revision of the manuscript. All authors read and approved the final manuscript.

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### Availability of data and materials

Our dataset is not available due its sensitive nature and strict access protocols.

## Declarations

### Competing interests

The authors declare that they have no competing interests.

### Author details

[1]School of Population Health, University of New South Wales, Sydney, Australia. [2]Private Psychology Practice, New South Wales, Sydney, Australia. [3]New South Wales Justice Health and Forensic Mental Health Network, Sydney, Australia. [4]School of Psychiatry, University of New South Wales, Sydney, Australia. [5]New South Wales Bureau of Crime Research and Statistics, Sydney, Australia.

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## Publisher's Note