Australian Government
Australian Institute of Criminology

Trends & issues in crime and criminal justice

ISSN 1836-2206 (Online) | ISBN 978 1 925304 93 0 (Online)

No. 629 July 2021

Text mining police narratives for mentions of mental disorders in family and domestic violence events

Armita Adily, George Karystianis and Tony Butler

Abstract | In this paper, we describe the feasibility of using a text-mining method to generate new insights relating to family and domestic violence (FDV) from free-text police event narratives. Despite the rich descriptive content of the event narratives regarding the context and individuals involved in FDV events, the police narratives are untapped as a source of data to generate research evidence. We used text mining to automatically identify mentions of mental disorders for both persons of interest (POIs) and victims of FDV in 492,393 police event narratives created between January 2005 and December 2016. Mentions of mental disorders for both POIs and victims were identified in nearly 15.8 percent (77,995) of all FDV events. Of all events with mentions of mental disorder, 76.9 percent (60,032) and 16.4 percent (12,852) were related to either POIs or victims, respectively. The next step will be to use actual diagnoses from NSW Health records to determine concordance between the two data sources. We will also use text mining to extract information about the context of FDV events among key at-risk groups.

Introduction

Family and domestic violence (FDV) is a major public health problem which can result in injuries and other short- and long-term health consequences. According to the 2016 Personal Safety Survey, in Australia, an estimated one in six (1.6 million) women and one in 16 (547,600) men had experienced inter-partner violence (IPV) after the age of 15. Similar rates were reported for physical violence by a partner for women and men. Women were eight times more likely than men to experience sexual violence by a partner (5.1% versus 0.6%; Australian Bureau of Statistics 2017). IPV is one of the most common forms of violence against women in Australia and the leading cause of morbidity and mortality for women of childbearing age (NSW Department of Health 2016; VicHealth 2005).

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Furthermore, the 2016 Personal Safety Survey estimated that 1.1 million adults had experienced childhood physical abuse, with 81 percent of first incidents being abuse by a family member. Parents were the perpetrators of 78 percent of physical violence before 15 years of age. Forty percent of those who had experienced childhood abuse (978,600) also witnessed violence towards their mother and/or father by a partner before the age of 15. IPV was three times greater for those who had experience of childhood abuse than for those who did not have this experience (28% compared with 8.9%; Australian Bureau of Statistics 2017).

The cost of violence against women in Australia was estimated at $13.6 billion in 2009 (Nittis et al. 2013). FDV has an intergenerational effect, with children who have witnessed abuse experiencing multiple health problems (Bedi & Goddard 2007). Acts of violence among those in domestic and family relationships may consist of physical, sexual, emotional or psychological abuse (Australian Government Department of Social Services 2010). The most common FDV events reported to the police are: threats of assault or actual assault, malicious damage, maliciously damaging property with the intent to injure a person, stalking, intimidation, communication offences such as harassment via repeated phone calls or text messages, cruelty to animals, driving offences, sexual offences, indecent assaults and breaches of an apprehended domestic violence order (Grech & Burgess 2011).

Family and domestic violence and mental illness

Previous studies suggest a relationship between mental illness and FDV (Oram et al. 2013; Trevillion et al. 2012). However, a research gap exists on the extent of this relationship for both perpetrators and victims (Solomon, Cavanaugh & Gelles 2005; Trevillion et al. 2012; Van Dorn, Volavka & Johnson 2012). Specifically, research about the rates of mental illness among some groups who are at an increased risk of FDV is neglected (Oram et al. 2013; Solomon, Cavanaugh & Gelles 2005).

A systematic review of 41 observational and experimental studies of women and men who were 16 years or older demonstrated an increased likelihood of FDV victimisation across all categories of mental disorders (Trevillion et al. 2012). With limited high-quality research, only four studies from the systematic review were included in a meta-analysis that showed increased odds of IPV victimisation among women with depressive disorders, anxiety disorders, and post-traumatic stress disorder compared to women with no mental illness (Trevillion et al. 2012).

There is limited high-quality evidence about the extent and patterns of FDV perpetrated by people with mental disorders (Solomon, Cavanaugh & Gelles 2005). A few empirical studies suggest a higher incidence of IPV by people with mental illnesses including post-traumatic stress disorder, borderline personality disorder, psychopathic traits and adult attachment challenges (McGinn et al. 2015; Solomon, Cavanaugh & Gelles 2005). A meta-analysis of six studies with a combined sample of 222 IPV perpetrators showed that 53 percent had a history of traumatic brain injury, compared with a prevalence in the general population of between 10 percent and 38.5 percent (Farrer, Frost & Hedges 2012).

The mental health of FDV perpetrators has been incorporated into FDV risk assessment tools (Chalkley & Strang 2017; Dowling & Morgan 2019; Ringland 2018; Thornton 2017). In New South Wales, the police have used the Domestic Violence Safety Assessment Tool (DVSAT) in all attended IPV events from 1 July 2015 to assess the risk of repeat offending (Ringland 2018). While the overall accuracy of DVSAT to predict the risk of repeat IPV within 12 months is low, the question relating to a perpetrator's mental health is a strong predictor of IPV risk (Ringland 2018).

Aim and method

In this paper, we describe the feasibility of text mining mentions of mental disorders from police text narratives and present the results. As a future next step, we aim to investigate the concordance between mentions of mental illnesses in the police reports and diagnostic data from the NSW Ministry of Health (NSW Health) by linking the police and health data.

WebCOPS

In New South Wales, data on criminal events are recorded in the Web Computerised Operational Policing System (WebCOPS) when the police attend these events. WebCOPS is an integrated system designed to focus on operational policing functions to enable a law enforcement organisation to capture, access and analyse crime information and intelligence on an organisation-wide basis. It is estimated that 1.5 million events are entered into WebCOPS each year (NSW Police Force 2011). Information about incidents contained in WebCOPS is available as both structured text (fixed fields) and free text (event narratives).

In WebCOPS, FDV events are identified based on the relationship between the victim and the person of interest (POI). In this study, 492,393 FDV records from between 1 January 2015 and 31 December 2016 were extracted if the victim and POI had one of the following relationships: 'spouse/partner', 'ex-spouse/ex-partner', 'boyfriend/girlfriend (including ex-boyfriend/ex-girlfriend)', 'child (including step/foster child) of victim', 'parent/guardian (including step/foster)', 'sibling', 'other member of family (including kin)' or 'carer'. The offences recorded in these events included homicides, assaults, malicious damage, breaches of an apprehended domestic violence order and other offences against another person.

Police event narratives

An event narrative is one of the features of the WebCOPS system. It is the free-text description of the event attended by the police and may be used by the police to guide the development of charge sheets in those cases where matters proceed to court. They otherwise have limited practical value and are rarely used for research purposes. They contain information about the individuals involved, a description of relevant incidents leading up to, during and following the event, along with any action taken by police. Police narratives are generally detailed, with reasonably complete accounts of the crime from the police perspective (a de-identified example is given in the *Appendix*).

To date, the police event narratives have not been used to inform the FDV debate, but they have been used in a limited fashion to enhance larger quantitative analyses of other crimes by selecting small samples of between 100 and 300 narratives and manually analysing them in order to provide information of a qualitative nature. For example, studies of offences involving small numbers of events (eg attempted abductions; Fitzgerald & People 2006) or offences confined to a particular geographic area or year have used the narratives.

However, even this approach is painstaking and uses only a fraction of the available narratives. One NSW study undertook a manual analysis of narratives relating to fraud to identify the dollar value of each fraud, the parties involved and, in the case of credit cards, how the cards were obtained. This study used 1,000 narratives, which represented only two percent out of a possible 49,457 events between 2012 and 2013 and 1.4 percent out of a possible 35,664 narratives between 2008 and 2009 (Macdonald & Fitzgerald 2014). This study suggested that 'there is no systematic way to extract information from these [police] narratives other than by manual review' (Macdonald & Fitzgerald 2014). However, the application of text-mining techniques may change this situation and allow meaningful information to be extracted from this large corpus of data.

Use of text mining to identify targeted information in free text

Text mining has been applied for over 30 years in many biomedical domains for the automatic recognition of important clinical concepts and events, with notable results (Abbe et al. 2015; Savova et al. 2010; Spasić et al. 2014). Text mining refers to the process of automatically identifying targeted information—for example, mentions of mental disorders among POIs or victims—from unstructured textual sources (Feldman & Sanger 2007; Kao & Poteet 2007) and making it accessible for subsequent analysis to support epidemiological and clinical research. Text mining employs a variety of techniques, such as named entity recognition (Bundschus et al. 2008; Hristovski et al. 2006; Jimeno et al. 2008), and text-mining outputs can be visualised using statistical and graphical techniques (eg cluster analysis) or used as variables in predictive data modelling.

Mentions of mental disorders

In our study, we aimed to examine the feasibility of using text mining to identify mentions of mental disorder for POIs and victims in all FDV events from WebCOPS between January 2005 and December 2016. In an attempt to capture all possible terms relating to mental disorders in the free-text police narratives, we used the full list of the mental illnesses contained in the World Health Organization's (2017) *International classification of diseases for mental and behavioral disorders* (tenth revision; ICD-10). After consultation with experts in the field of mental health, we manually inspected a random sample of 200 events (training set) to compile a dictionary of terms commonly used to describe the mental illnesses classified in ICD-10 and included commonly used misspellings (eg 'schitzophrenia') and other descriptive terms (eg 'abuses alcohol', 'anger issues') that could indicate the presence of a mental disorder. We also included traumatic brain injury, dementia, intellectual disability and mentions relating to:

- unspecified mental illness (eg 'victim is suffering from a severe mental disorder');
- psychotropic medications by name or drug class (eg 'victim takes Valium'; 'accused takes a number of antidepressants'); and
- drug prescription abuse, substance abuse, and drug-induced disorders.

Extraction and mapping of mentions

Our approach to the recognition of terms relating to mental disorder was to engineer rules based on commonly observed syntactical patterns in our training set. Combined with the compiled dictionary of commonly used terms for mental disorders, the rules are triggered when the related pattern (using a preposition, verb and noun phrases) is encountered in text to identify and classify mental disorders in relation to a POI or a victim (eg 'victim suffers from schizophrenia' [indicating a mental illness of the victim], 'defendant did not take his antidepressant' [indicating a mental illness of the POI]). To generate our rules, we used the General Architecture for Text Engineering (GATE) software (Cunningham 2013).

Since the extracted mental disorder mentions from the narratives are highly variable (eg synonyms and misspellings), the terms were mapped onto the named ICD-10 categories. This was done automatically through a heuristic algorithm that relies on groups of terms that are representative of various ICD-10 categories. If a given mention matched one term from a specific ICD-10 category, then it was mapped to that category. The mapping was done at four levels, with level 1 being the most generic and representing the mental disorder categories specified by ICD-10 along with another eight categories added for this study (a total of 26 categories). Where a mental disorder mention was more specific, it was mapped to a lower-level ICD-10 subcategory, with the level 2, level 3 and level 4 mapping having 62, 98 and 27 subcategories, respectively. The mapping was done manually by a domain expert in the field of psychiatry. For the purposes of reporting the results, we present the level 1 and level 2 ICD-10 mappings only.

We added eight customised level 1 categories to the 18 ICD-10 categories for cases where no direct mapping of a mention was available. Four of these eight categories involved mentions of psychotropic medications:

- medications—antidepressants;
- medications—antianxiety;
- medications—antipsychotics; and
- medications—neuroleptics.

For example, in event narratives where a medication class (eg antidepressant medication) or a brand name (eg Zoloft) was specified, we mapped these mentions to the level 1 category 'medications—antidepressants'.

The other four customised categories were:

- drug prescription abuse;
- substance abuse (unspecified);
- traumatic brain injury; and
- unspecified drug-induced disorder.

For example, those cases where we recognised that either the victim or the POI had an unknown mental disorder or an unknown drug-induced mental disorder were mapped to the level 1 categories of 'unspecified mental disorder' or 'unspecified drug-induced disorder', respectively.

We evaluated our rule-based method on a randomly selected sample of 100 FDV events. After mapping and eliminating any duplicate mental disorder mentions from each narrative, we evaluated our performance at the event level. We compared the text mined and manually extracted mentions of mental disorder in the sample of 100 FDV events by using the standard definitions of:

- precision—true positives against true and false positives;
- recall—true positives against true positives and false negatives; and
- F1-score—a harmonic mean between precision and recall (Ananaidou, Kell & Tsujii 2006).

The F1-scores returned were greater than 80 percent, suggesting reliable results, with 87 percent and 81 percent for the identification of the mental disorder mentions for POIs and victims respectively. Our results demonstrated high precision (98% and 87% for POIs and victims respectively), indicating the identification of only a small number of false positives. Recall was the same for both victims and POIs (79%). However, these values should be taken with caution, since the number of mental disorder mentions that were not identified was very small (9 for victims and 33 for POIs).

By inspecting the evaluation set, we discovered a limited number of false positives of mental disorders for either POIs or victims. In some cases, false positives were due to ambiguous syntax which meant that the rules assigned the mental disorder to the wrong person. For example, in the sentence ‘POI has the potential to become violent with the victim due to her alcoholism’, ‘alcoholism’ was extracted incorrectly as a mental disorder of the victim instead of the POI. In other cases, the rules incorrectly identified a mental disorder in a specific situation due to a mention that mapped to a term in the mental disorder dictionary (eg ‘as a result of the glass on the floor the defendant had cut herself’ [false positive for POI]).

One source of false negative cases involved syntactical patterns that were not seen in the training sets and therefore were not incorporated in the rule design (eg ‘The victim also stated to the police that during her time with the POI she was intoxicated as she knows that she has an alcohol addiction’ [false negative: mental disorder mention for victim]). In other cases, the rules ignored a mental disorder mention because there was no semantic anchor specifying the role of the individual (eg ‘Her child’s behaviour is because of a condition ADHD’ [false negative: mental disorder mention for POI]). In such cases, we chose not to engineer any additional rules in order to protect the system’s precision and hence to avoid the generation of numerous false positives for other individuals (eg witnesses, children at risk, friend, neighbour) that could be involved in an FDV event or experience a mental disorder.

Results

Mentions of mental disorder in police narratives

Of the total of 492,393 FDV events in WebCOPS, 77,995 (15.8%) had mentions of mental disorders for the POIs or the victims. Of all events with mentions of mental disorders, 76.9 percent (60,032 events) had mentions for POIs only, 16.4 percent (12,852 events) had mentions for victims only and 6.5 percent (5,111 events) had mentions of mental disorders for both POIs and victims (Table 1).

Table 1: WebCOPS family and domestic violence events with mentions of mental disorder (*n*=77,995), Jan 2005 – Dec 2016

	Number of events	%	Number of unique mental disorder mentions in events	%
POIs only	60,032	76.9	81,942	79.3
Victims only	12,852	16.4	21,290	20.6
POIs and victims	5,111	6.5	–	–
Total	**77,995**	**100**	**103,232**	**100**

As shown in Table 2, about one-third of the mentions of mental disorders for POIs (26,598; 32.5%) and almost a quarter of the mentions for victims (4,851; 22.8%) were noted by the attending police officers but not specified. The most frequent mentions of mental disorders related to 'mood [affective] disorders' (eg bipolar disorder, depression) for both POIs (15,330, 18.7%) and victims (4,946, 23.2%). Twelve percent of POIs (9,848) and 10.4 percent of victims (2,224) had mentions of 'behavioural and emotional disorders with onset usually occurring in childhood and adolescence' (eg 'anger issues', 'loses control'). There were more frequent mentions of 'intentional self-harm' for POIs (3,271) than for victims (949). However, the rate of mentions was higher for victims than POIs (4.5% vs 4.0%).

For victims of FDV events, the third-highest number of reported mentions was for 'anxiety, dissociative, stress-related, somatoform and other nonpsychotic mental disorders' (2,261; 10.6%). For POIs, the number of reported mentions of 'anxiety, dissociative, stress-related, somatoform and other nonpsychotic mental disorders' was higher (3,755; 4.6%). Overall, there were more mentions of 'intellectual disability' for POIs (1,517) than for victims (939). However, the rates of these mentions were higher for victims (4.4%) than for POIs (1.9%). Mentions of 'traumatic brain injury' (eg 'the victim has suffered a brain injury due to a car accident') were reported for nearly one percent of both POIs and victims (688 and 250 mentions respectively).

Table 2: WebCOPS self and third-party unique mentions of mental disorders at the first level of ICD-10 for persons of interest (POIs, *n*=81,942) and victims (*n*=21,290), Jan 2005 – Dec 2016

Mental disorder	Number of mentions (POIs)	%	Number of mentions (victims)	%
Unspecified mental disorder	26,598	32.5	4,851	22.8
Mood [affective] disorders	15,330	18.7	4,946	23.2
Behavioural and emotional disorders with onset usually occurring in childhood and adolescence	9,848	12.0	2,224	10.4
Mental and behavioural disorders due to psychoactive substance use	6,790	8.3	1,259	5.9
Schizophrenia, schizotypal, delusional, and other non-mood psychotic disorders	5,771	7.0	1,032	4.8
Anxiety, dissociative, stress-related, somatoform and other nonpsychotic mental disorders	3,755	4.6	2,261	10.6
Intentional self-harm	3,271	4.0	949	4.5
Substance abuse (unspecified)[a]	2,852	3.5	370	1.7
Pervasive and specific developmental disorders	1,775	2.2	501	2.4
Intellectual disability	1,517	1.9	939	4.4
Disorders of adult personality and behaviour	1,340	1.6	420	2.0
Injury of unspecified body region	800	1.0	265	1.2
Traumatic brain injury[a]	688	0.8	250	1.2
Mental disorders due to known physiological conditions	559	0.7	649	3.0
Medications—antidepressants[a]	400	0.5	130	0.6
Symptoms and signs involving cognition, perception, emotional state and behaviour	189	0.2	79	0.4
Medications—antipsychotics[a]	142	0.2	16	0.1
Medications—antianxiety[a]	91	0.1	24	0.1
Other degenerative diseases of the nervous system	62	0.1	52	0.2
Unspecified drug-induced disorders[a]	57	0.1	1	0.0
Chromosomal abnormalities not elsewhere classified	53	0.1	39	0.1
Behavioural syndromes associated with physiological disturbances and physical factors	31	0.1	23	0.1
Systemic atrophies primarily affecting the central nervous system	11	0.0	6	0.0
Diseases of the nervous system	6	0.0	3	0.0
Prescription drug abuse[a]	5	0.0	1	0.0
Medications—neuroleptics[a]	1	0.0	0	0.0

a: Additional customised category created for this study with no direct mapping to ICD-10 categories

At the second level of categorising the mentions of mental disorder (Table 3), 'major depressive disorder, single episode' ranked first for both POIs and victims, although the rates were higher for victims, with 8,944 (18.7%) and 3,269 (22.2%) mentions respectively. As shown in Table 3, mentions of first-person and third-person reports of 'alcohol abuse' ranked second among POIs (5829, 12.2%) and fifth among victims (1,180, 8.0%). 'Dementia, unspecified' was mentioned 644 times for victims (4.4%) and 546 times for POIs (1.1%).

Table 3: WebCOPS self and third-party mentions of the top 10 mental disorders at the second level of ICD-10 for persons of interest (POIs, *n*=47,831) and victims (*n*=14,694), Jan 2005 – Dec 2016

Mental disorder	Number of mentions (POIs)	%	Number of mentions (victims)	%
Major depressive disorder, single episode	8,944	18.7	3,269	22.2
Alcohol abuse	5,829	12.2	1,180	8.0
Bipolar disorder	5,449	11.4	1,553	10.6
Other behavioural and emotional disorders with onset usually occurring in childhood and adolescence	4,888	10.2	776	5.3
Schizophrenia	4,880	10.2	849	5.8
Attention-deficit hyperactivity disorder	3,980	8.3	1,312	8.9
Other anxiety disorders	2,446	5.1	1,714	11.7
Pervasive developmental disorder	1,721	3.6	477	3.2
Specific personality disorders[a]	1,310	2.7	372	2.5
Intellectual disability, unspecified	1,225	2.6	779	5.3
Dementia, unspecified[b]	546	1.1	644	4.4

a: Not in the top 10 mental disorders for victims

b: Not in the top 10 mental disorders for POIs

As previous studies have shown, psychiatric patients across all diagnostic categories experience a high prevalence of FDV (Howard 2012; Oram et al. 2013; Trevillion et al. 2012). Similar to the results of the systematic review conducted by Trevillion et al. (2012), our analysis has suggested a high prevalence of major depression among victims of FDV (Table 3).

Veracity of the mentions of mental disorder in the WebCOPS narratives

The self and third-party mentions of mental disorder in the WebCOPS narratives of FDV events have never been validated. This will be an important step if mentions of mental disorders in the narratives are to be used for reporting purposes. The NSW Police Force do not have access to health records and are thus unable to establish the veracity of any mental health mentions recorded when they attend an FDV event, due to data privacy and confidentiality issues. Automated technologies (ie text mining) do not take into consideration sensitive information within the police narratives that can be used to identify an individual. Using these kinds of technologies could help mitigate this issue.

We plan to examine the concordance between mentions of mental disorder in the police narratives and diagnoses recorded in the NSW Ministry of Health's administrative data collections such as the inpatient and emergency data collections for the cohort of POIs and victims of FDV events. This will require linking these two data sources. We will examine the true rates of mental disorder among the POIs and victims of FDV using this diagnostic health data.

Use of text mining of the WebCOPS narratives to extract qualitative features of FDV events

Currently we are designing rules to extract informative descriptors about the characteristics of the POIs and victims (eg at-risk groups such as new migrants, veterans, those in a same-sex relationship, and those in a carer relationship) and about the features of FDV events (eg warning behaviours such as stalking, abusive telephone calls/text messages, property damage, and substance use) from the WebCOPS narratives. Linking these descriptors to the NSW Health data will allow us to examine these qualitative features from the WebCOPS narratives for those with a verified mental disorder.

Discussion

Contribution to the field

We have demonstrated the feasibility of text mining for identifying targeted information from a large amount of free-text WebCOPS narratives. We continue our study by exploring the utility of the police narratives in generating new knowledge regarding predictors of FDV events and the role of key health characteristics (eg mental disorder) in FDV events. It is anticipated that text mining a large-scale set of police event narratives will generate insightful information to the police and other organisations that provide FDV services. This study also suggests that information in the police narratives can potentially be used for public health monitoring purposes such as examining trends over time.

Future directions and implications for policy and practice

Reducing FDV reoffending is one of the NSW state priorities (NSW Government 2018). Our study is consistent with this aim in that it helps to better understand and identify pathways leading to FDV events, thus contributing to improved prevention activities. The priority now being given to FDV in New South Wales and nationally is unprecedented, with the establishment of a NSW ministry devoted to this issue and the appointment of its Minister for the Prevention of Domestic and Family Violence and Sexual Assault. In 2014, Australian of the Year was awarded to a victim of FDV to highlight this problem. Similarly, the National Plan to Reduce Violence against Women and their Children has been developed to tackle this problem, with a strong emphasis on prevention (Australian Government Department of Social Services 2010).

Our future plan to link health data and police data will enable us to examine whether text mining of the police narratives correctly identifies mental health problems in FDV events. This evaluation will generate new knowledge to contribute to the debate on the potential benefits of access to health information (eg a diagnosis of a mental disorder) in FDV situations by the police. This could allow increased attention to be given to those situations where it is identified that a POI or victim possesses a health risk factor and could allow a more efficient allocation of police resources. Knowledge about the mental health status of the POIs and victims of FDV would also be insightful for other services whose aim is to reduce reoffending.

The utility of the WebCOPS data, particularly the free-text police narratives, has never been examined in a public health paradigm. The proposed exploratory study will, for the first time, take a 'big data' approach to increase our understanding of a pernicious social problem (FDV) by improving our knowledge about the characteristics and patterns of these related events.

There is significant potential for the approach taken in this study to be applied to other areas such as sexual offences, fraud, and other violent offences, and for the scope of the data linkage to be expanded to include other information sources (eg housing, welfare, and Medicare data).

Acknowledgements

We wish to thank Professor Peter Schofield (Hunter New England Health), Lee Knight (School of Population Health, UNSW), and Clara Galdon, and Dr Christie Wallace and Dr Chris Devery (NSW Police Force) for their contributions.

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Appendix

An example of a de-identified event narrative extracted from the COPS system

TIME/DATE:	About 12:00am on Monday 1st July 2014
LOCATION:	XXXX
VICTIM:	XXXX (NAME)
DOB:	XXXX
ADDRESS:	XXXX
INJURIES:	Scratch to left cheek

POI:	XXX (NAME)
DOB:	XXXX
ADDRESS:	XXXX
INJURIES:	Nil

WITNESS:	XXXX (NAME)
DOB:	XXXX
ADDRESS:	XXXX

RELATIONSHIP TO VICTIM/POI: The accused is the mother of the victim.

ILS/FIREARM INFORMATION: ILS system checked - nil find - Firearms

CAD MESSAGE DETAILS:

INFT DAUGHTER XXXX?OLD DAUGHTER XXXX (NAME) HAS ENETERED AA AND IS?GITTING HER XXXX AMBO?DECLINED. NIL WEAPONS OR GUNS. NIL?AVOS. NK?ALCOHOL?OR DRUGS. ***CHKS OTW***

HISTORY OF RELATIONSHIP AND DURATION:

The accused, XXXX (NAME) is the mother of the victim, XXXX (NAME). The victim does not live with the accused. The victim currently lives in XXXX with her father. The accused lives at XXXX. The victim is currently visiting her mother and grandparents on school holidays. Her grandparents live at XXXX.

CHILDREN: Nil

PRIOR HISTORY OF VIOLENCE INCLUDING STALKING & INTIMIDATION: Nil

CURRENT OR PREVIOUS PROTECTION ORDERS: Nil

DOCS ORDERS: Nil

FAMILY COURT AND PARENTING ORDERS: Nil

MOST RECENT INCIDENT:

The accused, XXXX (NAME) is the mother of the victim, XXXX (NAME). The victim does not live with the accused. The victim currently lives in XXXX. The accused lives at XXXX. The victim is currently visiting her mother and grandparents on school holidays. Her grandparents live at XXXX.

About 12:00am on XXXX, the victim was in her bedroom in her grandparent's house. Her aunt informed her that the accused was in the kitchen and wanted to speak with her. The victim was tired due to the time of night but did not want to be rude and went to speak to the accused. The victim entered the kitchen and as soon as she entered the room she could smell alcohol. The accused was sitting at the kitchen table. The accused asked the victim to make her a cup of tea to which the victim did. The victim then sat across the kitchen table from the accused. The accused then asked the victim to get her grandmother to come out to speak to them. The victim told the accused that her grandmother was sleeping and she had to work in the morning. The accused then told the victim 'shut the fuck up or I'll pour the tea on your face'. The accused repeated saying this three time. The victim then took the tea cup from the accused to put it in the kitchen sink.

The accused grabbed the victim's left wrist and grabbed the cup off her. The accused then got up and grabbed the victim's jumper with her left hand and forced her right forearm to the victim's throat. The accused has then pushed the victim against the kitchen wall. The victim has the pushed the accused back but the accused kept hold of the victims jumper. The accused has then hit the right side of the victim's face with her left hand. The victim fell to the kitchen floor and covered her face with her hands. The accused started to scratch the victim's face and hands. The accused then began to pull the victim's hair and punching her. The accused has also kicked the victim to her face. The victim sustained a scratch and red mark to her left cheek.

The victim's aunt entered the kitchen and separated the accused and victim. The aunt and grandfather then took the accused outside the premises and contacted Police.

About 12:30am on the same night, Police attended the location. Police observed the accused at the side of the premises knocking on the window calling for the victim. Police observed the victim top be carrying a wine case which appeared to be half empty. Police could also smell intoxication liquor on the accused.

Police spoke to and obtained details from the victim and witness. The accused was arrested and conveyed to XXXX Police Station. On arrival, the accused was introduced to the custody manager and was put into time out due to the intoxication level of the accused. When the accused was fit to be spoken to, she was explained her right under Part 9 Law Enforcement (Powers and Responsibilities) Act 2002. The accused was asked if she was willing to participate in an electronically recorded interview to which she declined.

The accused is now charged with the matter.

HR14 A/Sgt XXXX (NAME) in attendance

INJURIES / MEDICAL TREATMENT / DAMAGE TO PROPERTY:

The victim had a scratch to her left cheek

EVIDENCE AND EFFECTS OF ALCOHOL & DRUGS: The accused was moderately intoxicated

MENTAL HEALTH & OTHER HEALTH ISSUES: Nil

FIREARMS / DANGEROUS WEAPONS: Nil

FEARS HELD BY VICTIM: Feared for her safety

FEARS HELD BY POLICE: Fear for the victim's safety

ACTIONS TAKEN BY POLICE: Nil.

ACTIONS OUTSTANDING: Nil

Dr Armita Adily is a Research Fellow at the Justice Health Research Program, School of Population Health, UNSW Sydney.

Dr George Karystianis is a Research Fellow at the Justice Health Research Program, School of Population Health, UNSW Sydney.

Professor Tony Butler is the Program Head, Justice Health Research Program, School of Population Health, UNSW Sydney.

General editor, *Trends & issues in crime and criminal justice* series: Dr Rick Brown, Deputy Director, Australian Institute of Criminology. Note: *Trends & issues in crime and criminal justice* papers are peer reviewed. For a complete list and the full text of the papers in the *Trends & issues in crime and criminal justice* series, visit the AIC website at: aic.gov.au

ISSN 1836-2206 (Online) ISBN 978 1 925304 93 0 (Online)

https://doi.org/10.52922/ti04930

GPO Box 1936
Canberra ACT 2601, Australia

Tel: 02 6268 7166