NETWORK MAP OF ADVERSE HEALTH EFFECTS AMONG VICTIMS OF INTIMATE PARTNER VIOLENCE

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Intimate partner violence (IPV) is a serious problem with devastating health consequences. Screening procedures may overlook relationships between IPV and negative health effects. To identify IPV-associated women's health issues, we mined national, aggregated de-identified electronic health record data and compared female health issues of domestic abuse (DA) versus non-DA records, identifying terms significantly more frequent for the DA group. After coding these terms into 28 broad categories, we developed a network map to determine strength of relationships between categories in the context of DA, finding that acute conditions are strongly connected to cardiovascular, gastrointestinal, gynecological, and neurological conditions among victims.

1. Introduction

Domestic abuse is a rampant problem across the globe, contributing to severe economic, health related, and societal costs. The consequences of intimate partner violence (IPV) are devastating and systemic. In 2010, the National Intimate Partner and Sexual Violence Survey found that approximately 30% of women experience physical violence from an intimate partner during their lifetime, with 25% experiencing severe physical violence such as being slammed, hit, or beaten.[1] Although victims of IPV are not exclusively female, women are more likely than men to be the victim and sustain serious physical injury.[1,2]

IPV has been shown to cause numerous adverse health effects, ranging from minor injuries to serious disability and death.[2-4] Physical assault (including sexual violence) is associated with psychological distress such as anxiety, depression, and suicidal ideation,[5] sexually transmitted infections including HIV,[3,6] gynecological problems like pelvic inflammatory disease,[7] and unintended pregnancy and complications relating to the mother's and newborn's health.[3,8-10] Researchers have identified many long-term effects of IPV, finding evidence that victims of violence are more prone than the general populous to suffer from mental health and substance abuse disorders, gastrointestinal problems, chronic pain and physical ailments, and various neurological symptoms.[5,11] This information has not prompted further research into how professionals can prevent and treat the IPV epidemic. Holistic approaches incorporating comprehensive treatment of both physical and emotional ailments have received little attention.

Self-report data indicates that female victims of violence have poorer overall health than female victims of non-violent crimes (and women in general), presenting troubling physical symptoms like tachycardia, tension headaches, menstruation related issues, stomach problems, or skin disorders.[12] Intimate partner violence often involves episodes of physical and sexual violence. No doubt this is a contributing factor to poor victim health, and likely increases the use of healthcare services by victims of violence. For example, sexual assault victims are more likely to seek physical and mental health care within the first six months of the attack, with services increasing 15-24% during the first twelve months alone. Naturally, the corollary of this is a higher cost of health care and treatment for victims than non-victims. Emergency room records indicate un-witnessed episodes of head, neck, and facial injuries are significant markers of IPV,[13] and traumatic brain injury may be more prevalent in this population than previously suspected.[14] Unfortunately, physicians often overlook or misattribute problems associated with violence, which can result in prolonging victims' pain and wasting patient and provider resources. Proper screening and treatment of IPV is critical to ensure that victims of violence receive the necessary care and support for recovery.

While the effects of IPV are known to be serious and diverse, knowledge of specific health effects and their relation to IPV is still limited. In this study, we utilized electronic health records (EHR) to identify frequently occurring symptoms among IPV victims. Our approach is motivated by the notion that EHR data provide valuable information from health care providers that may not be obtained through self-report data. Furthermore, both self-report data and physicians' records are difficult to obtain in large amounts due to topic sensitivity. For these reasons, investigators struggle to compile available symptom data into comprehensive and systematic reviews. The consequences of violence on human health are elusive and complex, and therefore utilization of large-scale data can be useful in identifying correlates that are overlooked by other research. Here, we take a first step toward utilizing EHR data to characterize adverse health effects co-occurring with IPV, identifying statistical associations between IPV and other symptoms and determining the strength of these relationships. It is important to note that our analysis does not target any symptom in particular; rather we mine the entire EHR data (1999 through our original data query point 5/8/14) and test the association of all reported symptoms to identify those statistically significant.

In a previous study,[15] we accessed and analyzed national EHR data through the *Explorys* platform (Explorys Inc., an IBM company), specifically utilizing the "Explorys Enterprise Performance Management (EPM): Explore" web application to identify diseases which seem to be more prevalent among victims of IPV than the general US population. *Explorys* is comprised of EHR, EMR, insurance claims, and billing data sources. A variety of national data sources contribute data to the platform, including affiliated providers, electronic medical systems, health care plans, and care settings. Over twenty major integrated healthcare systems provide data to *Explorys*, bringing together patient information from across America. Over 300,000 providers participate, gathering more than 315 billion clinical, operational, and financial data elements from approximately 50 million unique patients. Data is pooled from clinical EMRs, healthcare system outgoing bills, and adjudicated payer claims. Researchers from a wide range of disciplines use this compiled data to identify patterns and trends in diseases, treatments, and outcomes.[16]

We hoped that our analysis of the data we obtained through the *Explorys* platform would help us differentiate between those health problems which result directly from acute violence and violence related physical injuries, and those health problems which are chronic or persistent and result from multiple non-violent causes. After identifying the diseases occurring significantly more frequently among victims of IPV, we categorized the diseases into 28 broad categories, and found that IPV is predominantly associated with four types of health problems: acute; chronic; gynecological; and mental/behavior health. The results further supported our suspicions that IPV is a systematic problem with multifaceted interactions across a wide range of health issues.

To develop a better understanding of how IPV is related to negative health effects, it is potentially useful to determine the interactions and relationships between symptom categories. Analyzing these relationships may help us discover what physiological systems are more closely associated with experiencing severe consequences of IPV, and could lead to future research into the effects of IPV on the body. For this study, we decided to perform a data-driven analysis and network mapping of the same significantly occurring diseases identified previously to reveal how these terms interact. We chose network mapping because it analyzes the structural relationships and patterns within a network of 'nodes', providing a visual representation of the strength of these relationships. In this case, the nodes are each symptom category, and the connections or 'edges' between these categories indicate how frequently those given categories appear together in our coded symptoms. Through this analysis we specifically hope to identify the strength of connections between different disease categories, in an effort to investigate how these associations may be related to each other. Through this analysis we can explore the many ways IPV affects the overall health of victims.

2. Methods

2.1. *Identification of Terms Prevalent among Domestic Abuse Victims*

The flow chart for the methodology implemented in this study is shown in Figure 1. A complete and detailed description of the data acquisition performed for this study can be found in a previously published manuscript.[15] Here, we provide a brief summary.

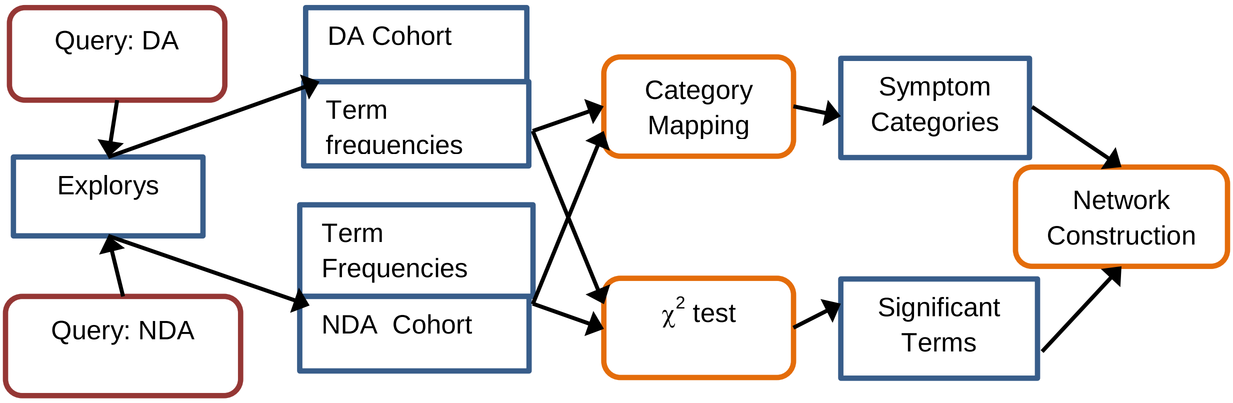

Fig 1. Flowchart for data acquisition, querying, statistical analysis, and network construction. DA: Domestic Abuse. NDA: Non-Domestic Abuse

We obtained data from a population of almost 15 million patients who were adult females aged 18-65 seen in multiple different healthcare systems across the United States with unique EHR from 1999 to the present (5/8/14: original query date). These data were normalized and classified using common ontologies, searchable through the HIPAA-enabled, de-identified "Explorys Enterprise Performance Management: Explore" web application. Using SNOMED clinical terms built into *Explorys*, our search query identified 5870 records (DA cohort) of IPV victims (these records were retrieved by searching for the finding 'domestic abuse', a code option utilized by health professionals for EHR), compared to 14,315,140 records (NDA cohort) of patients who did not have any indication of IPV victimization in their EHR. Racial and age distribution for the DA and NDA cohorts are shown in Figure 2.

It is important to note that in order to protect patient privacy, data is accessible only as frequencies across the cohorts defined by these queries. Similarly, demographic information is available as summaries. For this reason, sophisticated data mining techniques such as association rule mining are not directly applicable. Here, we base our analysis on the comparison of frequencies. Of note, African Americans make up a greater proportion of the DA group than NDA, and while NDA records are relatively evenly distributed across age groups, DA records show higher relative frequencies for ages 25-44.

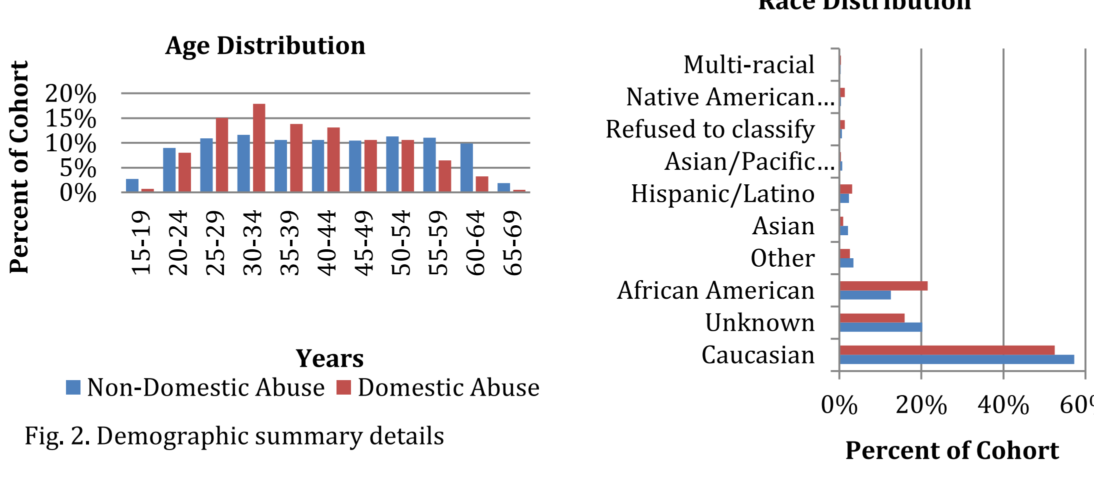

Fig. 2. Demographic summary details

Within the IPV identified records, we found 3458 symptom/diagnosis terms possibly associated with domestic abuse (i.e. the aggregated records contained 3458 medically coded symptoms, diagnoses, and findings – also referred to as "terms" in the following discussion). With a view to identifying conditions that are prevalent among victims of domestic abuse, we compared the frequency of each term in the DA cohort with its frequency in the NDA cohort. For each term, we used χ^2-test to assess the significance of its frequency in the DA cohort with respect to its frequency in the NDA cohort. To adjust for multiple hypothesis testing, we used Bonferroni correction (3458 tests were performed). This analysis suggested that 2430 of the identified terms were significantly more prevalent among IPV victims ($p < 0.05$). Two independent researchers used medical dictionaries to manually code these symptoms into broader, more general categories with high inter-rater reliability, four main classes emerged: chronic symptoms and disorders, acute injuries, mental and behavioral issues, and gynecological problems.

2.2. *Network Construction*

To provide a compact and visually comprehensive view of the diagnosis terms that were significantly more frequent in patients with the finding of "domestic abuse" (DA group), we created a network of diagnosis categories.

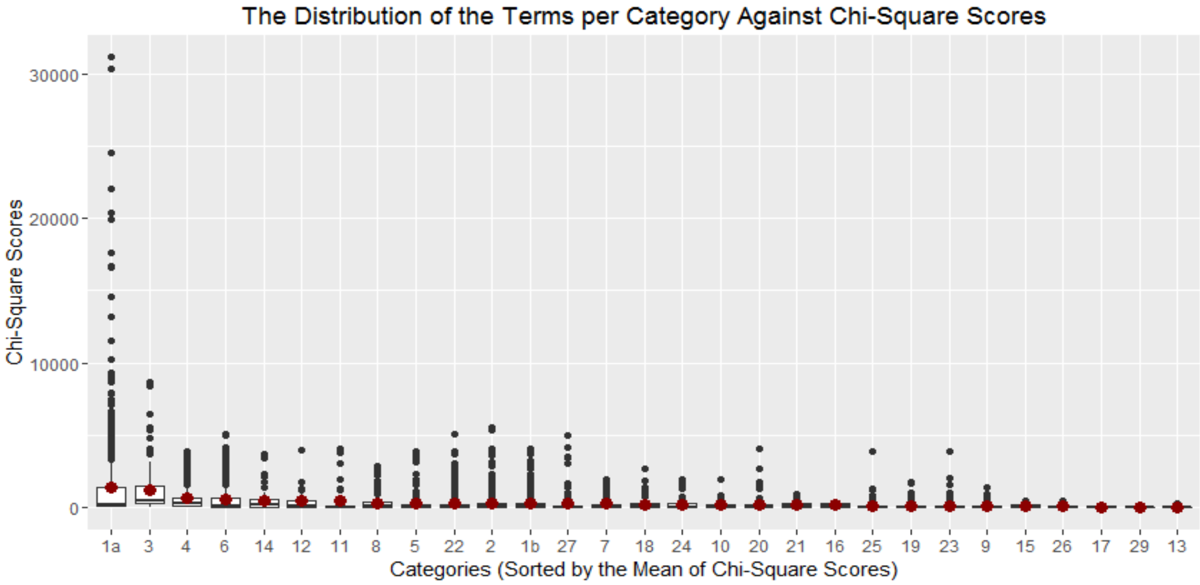

Fig. 3. Distribution of χ^2-statistics among terms assigned to each category. The distributions are shown by box plots, the mean of each distribution is shown by a red. The categories are sorted according to the mean χ^2 statistic

We first categorized the diagnosis terms by assigning each term to 28 specific categories. In this classification, assignment of a term to more than one category was allowed. Subsequently, we selected the 2429 terms that were significantly more frequent in the DA group ($p< 0.05$ based on the Chi-Square Test). We then counted the frequency of each category among these 2429 terms. The distribution of χ^2-statistics for the terms assigned to each category is shown in Figure 3.

	Disease Classification Category	**Percent (%)**
1b	Acute Condition	34.1%
1a	Acute Injury	23.1%
2	Chronic	16.2%
6	Disorders	15.6%
19	Cardiovascular	8.6%
8	Pregnancy Related	7.5%
7	Gynecological	7.5%
22	Musculoskeletal	6.2%
4	Mental Health	5.9%
18	Gastrointestinal	5.6%
9	Allergy	5.0%
3	Substance Abuse	4.8%
5	Other	4.6%
20	Nervous system	4.5%
27	Skin related (not burns)	4.0%
21	Respiratory	3.9%
23	Eyes, Ears, Nose & Throat	3.8%
24	Excretory	3.1%
14	Personal History	2.2%
11	Congenital/Hereditary	1.6%
25	Endocrine	1.6%
13	Neoplasm	1.3%
26	Immune System	1.3%
12	Nutrition	1.2%
10	Procedure	0.8%
16	Neuropathy	0.8%
15	Family History	0.7%
17	Diabetes	0.6%

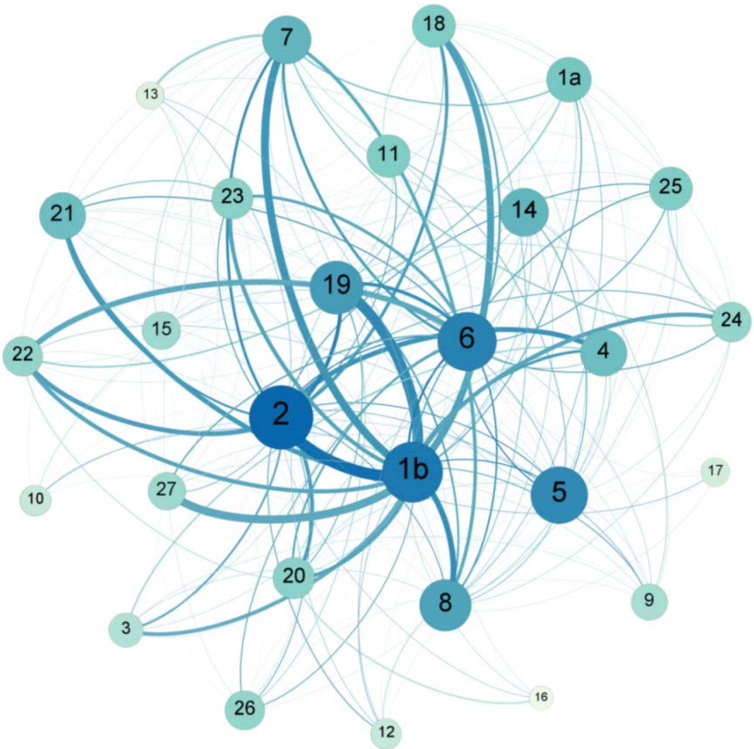

Fig. 4. Network Map of the 28 categories made up of 2429 symptom terms found to be significantly more prevalent among victims of IPV than the general population. Larger nodes indicate higher coding frequency of the category by itself, while thicker edges reveal the strength of relationship between two nodes by signifying the frequency of any two categories being coded together on a single symptom term. Darker nodes appear more frequently among the pairs than lighter nodes. Percentages of total diagnoses found to be significantly frequent in patients with a DA finding for each individual symptom category also shown.

To assess the co-occurrence of each pair of categories in the DA group, we counted the number of terms among these 2429 terms that are assigned both categories. Note that this co-occurrence frequency is not to be confused with co-morbidity of diagnoses; this number rather reflects the likelihood that a diagnosis significantly more frequent in patients with DA will belong to both categories. In total, 208 pairs of categories were assigned together to at least one of the 2429 terms.

After counting frequencies of categories and pairs of categories among the terms that are significantly frequent in the DA group, we visualized the frequencies as a network using GePhi 0.9.0 Beta (Fig. 4). In the figure, the size of each node represents the frequency of the respective category among the terms that are significantly frequent in the DA group. The thickness of each edge represents the number of terms that are assigned both of the respective categories.

3. Results

The results of the data-driven analysis and network mapping are illustrated in Figure 4. The Acute Conditions (1b) and Chronic (2) categories appear to be the most significant in our network map, showing the greatest frequency of occurrence among the coded terms. Chronic (2) exhibits strong connections to Acute Conditions (1b), and fair connections to Mental Health (4), Cardiovascular (19), Nervous System (20), and Musculoskeletal (22). It should be noted that the strong connection between chronic and acute conditions is due to ambiguity of the symptom terms, resulting in the possibility of a term being coded as both chronic and acute because it could be either, depending on the patient's situation. Acute Conditions (1b) has strong connections to Chronic (2) and Cardiovascular (19), with more moderate connections to Gynecological (7), Gastrointestinal (18), Skin Related (27), and Pregnancy Related (8). It also has fair connections to Substance Abuse (3), Nervous System (20), Respiratory (21), Musculoskeletal (22), Eyes, Ears, Nose & Throat (23), and Excretory (24).

Disorders (6) shows some significance in coded frequency, with a moderate connection to the Musculoskeletal (22) category. The Cardiovascular (19), Gynecological (7), Pregnancy Related (8), and Gastrointestinal (18) nodes may also be somewhat significant, but their primary connection is with Acute Conditions (1b), which is itself a significant node in the network overall (Cardiovascular is also fairly connected to Chronic (2), another independently significant node).

Interestingly, although the Acute Injures (1a) node indicates relatively significant frequency of coding, this category is mostly isolated, demonstrating only weak connections.

4. Discussion

4.1. *General*

The results of our analysis and network mapping are fairly consistent with current knowledge of IPV. We found that chronic and acute conditions as well as acute injuries were frequently coded to the symptoms that are more prevalent among victims of IPV. We also found that the categories showing the most individual frequency (chronic and acute conditions) shared strong connections with physiological systems that have been shown to be impaired at a higher rate among IPV victims, including gynecological and pregnancy related issues, as well as gastrointestinal, cardiovascular, and neurological symptoms.[17-19] It is not surprising that 'chronic' and 'acute conditions' had the most significant frequency of coding, since most ailments that require medical attention are either established diseases or emergency issues. 'Acute conditions' shows many strong connections, because most acute conditions would be coded with whatever body system(s) they were related to. 'Chronic' is similarly highly connected, for the same reason. These two categories show a strong connection to each other because the symptoms were often ambiguous, and coded as both chronic and acute because there was not enough information in the symptom term to differentiate it between the categories.

Nodes that represent 'gynecological' and 'pregnancy related' symptoms appear to be fairly significant, which is expected when considering the nature of IPV. Physical and sexual abuse from IPV can be very damaging to the body,[17,20] resulting in trauma, infection, and the contraction of sexually transmitted infection.[6] Victims are at greater risk of experiencing sexual coercion from an intimate partner as well as birth control sabotage, and often fear talking to their partner about pregnancy prevention.[6] Studies have also shown increased risk to mothers' and newborns' health when IPV is experienced during pregnancy, such as miscarriage and low birth weight.[8,10] Pregnancy itself can also be a risk factor for IPV.[21]

We were surprised to see that the node that represents 'mental health' related symptoms was not a significant "hub" in the network. The node itself is significant, i.e., it appears moderately prevalent in the general frequency count, but lacks strong connections. This independence is explained by the fact that most symptoms labeled as 'mental health' would be unlikely to fall into other categories except for 'chronic', since many mental health issues happen to be chronic in nature but generally would not directly interact with other physiological systems.

Stress may be an important factor in the patterns we identified in the network map and analysis. There is a broad research literature describing the interactions between IPV and stress,[17,22,23] as well as the effects of stress on the body.[24-26] IPV causes an increase in cortisol, one of the body's stress hormones, which in turn might cause detrimental impacts on the victim's immune system. This can manifest in a variety of ways, but often affects gastrointestinal and circulatory system functioning. Stress resulting from IPV may also seriously increase the risk of a negative event during and following pregnancy.[27,28] Interestingly, the nodes that represent these categories showed significant frequency in the network of IPV victim health symptoms. It is difficult to verify if stress is the underlying factor in the higher significance and connection of these categories, but it may be possible in future studies to incorporate cortisol-level measurements in the search query. Many of the significant categories in our network map showed strong connections to 'chronic' and 'acute conditions', which only further demonstrates the severity of the negative health effects associated with IPV.

We cannot accurately assess whether this network map reveals subtle patterns or cycles, because our data is a compilation of records that incorporate data without the dimension of time. If we could find a way to apply temporal filters, we might be able to identify a progression of health events common among victims of IPV that would further illustrate exactly how IPV leads to negative health over the victim's lifetime. This will enable health care practices and professionals to more accurately identify, assess, and treat IPV and related illnesses, ultimately utilizing knowledge of how IPV impacts health to improve treatment decision making processes. Analyzing this data will help explore how EHR can be utilized for research. Our findings may demonstrate that it is possible to improve standard screening procedures and treatment plans for victims of violence as well as patients in other circumstances, simply by examining electronic health records. The significant correlations that can be found through this method provide valuable information for both clinical and research applications.

4.2. *Limitations*

Although studies have shown that approximately 1 in every 4 women will experience IPV at some point during their lifetime,[1] the data collected by *Explorys* does not reflect this observation. This is likely due to a variety of factors, and may be most influenced by the underreporting and inadequate screening of IPV victims. Although our query returned NDA records from all 50 states, as well as Puerto Rico, Guam, and APO/FPO (military bases), it returned DA records from only a dozen location categories. The relative distribution of records across these location categories for both DA and NDA cohorts are shown in Figure 5. It would be interesting to examine the laws and regulations of the states that returned EHR for the DA group. It is possible that local regulations influence the likelihood of domestic abuse being screened and recorded by medical professionals.

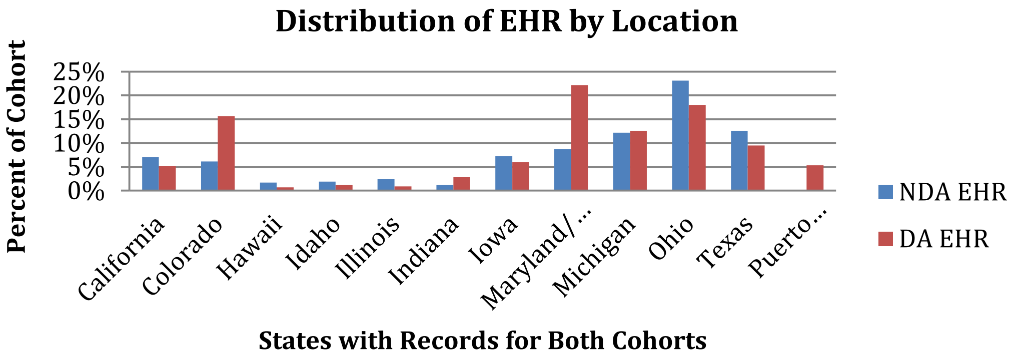

Fig. 5. . Distribution of location categories for the domestic abuse (DA) and non-domestic abuse (NDA) cohorts.

It is interesting to note that the distribution of EHR for the NDA cohort does not correspond with the distribution of the US population as measured by the 2010 US Census Bureau (comparison not shown here, but NDA EHR showed disproportionately high distribution in Texas, Ohio, Michigan, Maryland/DC, Iowa, Idaho, Hawaii, and Colorado compared to relative census population distributions). This difference may reflect the sampling of medical facilities providing data to *Explorys*. These trends are worth investigating to better understand how inherent confounds of the data may influence query results. Many of the records pertaining to this subset of the population may not have been captured by our queries, and thus potentially were not included in our network map and data analysis. This means that it is very likely that records in our NDA group actually belong in the DA group, which would seem to muddy the analysis. However, we feel that due to this underreporting, our DA group likely represents the most severe cases of domestic abuse, and thus highlights the most obvious symptom connections. Further analysis could help us tease out more subtle victim symptom characteristics. This information could then be used to develop targeted queries in the future that may help us to identify high-risk IPV victims through related EHR diagnoses, even if domestic abuse is not listed as a finding. While we were able to extract some demographic characteristics of the cohorts (Fig. 2), the nature of the data does not permit us to match demographics to specific records. However, as Fig. 5 illustrates, there are serious gaps in EHR data for the DA group, and it is not possible to identify confounds resulting from demographics with such limited data.

Domestic abuse is not always noted in a patient's medical records, either because the patient does not reveal that she is a victim, or because medical professionals overlook recording this detail. Research has demonstrated that primary care IPV screening is inadequate and needs attention.[29] Domestic abuse is not considered a 'diagnosis' or 'condition', but is rather described in the *Explorys* database as a 'finding'. This is a reflection of how the medical community labels IPV, and explains why notating this 'finding' may not be a priority when updating a patient's medical records. Since this study most likely captured records with the most severe cases of IPV, where evidence of the abuse was obvious, the current network map may not reflect the more subtle connections associated with less severe instances of IPV. However, the results of our network map and analysis demonstrate how extensive the consequences of IPV may be on victims' health, and further illustrate the vital importance of thoroughly screening for IPV and accurately noting patient findings by members of the medical community. It may be possible to utilize this data to develop more accurate screening procedures in the future.

Utilizing EHR data is challenging, and the currently available query systems leave gaps in data quality. Data is noisy, and we lack the ability to control for a myriad of confounds. Current records allow for the possibility of patients being counted more than once when determining frequencies, and longitudinal data is missing. However, due to the necessity to maintain the strictest levels of privacy, we cannot track specific (though still de-identified) patient records to see how health changes over time. We are exploring how to utilize other tools in *Explorys* and other query and analysis techniques to capture longitudinal data. Examining the changes in symptom presentation in relation to the first appearance of DA on a patient's medical record is a key step to understanding the etiology and health consequences of violence victimization more fully. This could also be an instrumental step in implementing effective risk assessments. However, even at this point, the knowledge gained from the analysis of EHR data can still lead to vast improvements in health care and policy development, and improved queries may improve the quality of data. The techniques demonstrated in this study have implications not only for the care of intimate partner violence victims, but for the health of the entire population as a whole.

5. Conclusion

EHR data is a vital resource in advancing the knowledge of health care professionals. By analyzing the data we can create networks that show how different symptom and disease categories are related to each other, revealing associations which may indicate deeper root causes for deteriorating health. In this study, we were able to examine what health factors are associated with IPV, and how these factors interact. This gives us a more complete and compelling picture of the negative health effects of IPV. With further research it may be possible to develop improved methods and diagnostic tools for successful intervention and treatment, improving victims' quality of life throughout their lives.

Analysis of EHR data gives health providers the information to improve quality of service, especially for victims of IPV. However, it is so important for screening procedures to improve, so that victims are accurately identified and given appropriate medical care. Our network mapping and data analysis demonstrate only a fraction of the far-reaching health consequences of IPV, which cannot be ignored from a medical perspective. We know that many of the victims of IPV were not represented in our DA data set, because they haven't been identified as such in their medical records. It is absolutely imperative that we push to improve screening so that these devastating health effects can be mitigated and prevented. The data from our analysis may help with future research into how we can better identify victims who hesitate to come forward by identifying the tell-tale signs and relationships of their symptoms and conditions. It is clear that mining EHR will reveal many associations between previously independent conditions. Our future research will replicate these analysis techniques with independent datasets to confirm the efficacy of these methods. Doctors and health care providers can use this information to improve the prescription of effective treatment preventions, and identify trends across populations. If we can use this information to develop more effective screening tools and treatments, we will drastically increase the quality of life and healthcare experienced by victims of IPV, and through this the wellbeing of society as a whole.

6. Acknowledgements

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