violence. Another method explores the role of emergency vs. elective C-section deliveries on the study of C-sections as an adverse outcome of delivery. These studies together enable further understanding of processes and diseases that are specific to women or differentially impact women. In harmony with the focus of PSB, the session emphasizes methodological advances and applications in data science, emphasizing reproducibility and validation.

2. Session Summary

The session includes three full-length papers competitively selected for inclusion that are focused on exploring problems associated with the complex problem of intimate partner violence, including patterns and injury prediction (2 distinct papers) and another study focused on deconstructing Cesarean sections into emergency versus elective to better understand this complex health outcome. We selected these important contributions that are applicable to utilize big datasets on studying women's health outcomes.

2.1. *Full-length papers*

In *Co-occurrence Patterns of Intimate Partner Violence,* the authors present a method that learns patterns of survivors of intimate partner violence (IPV) [11]. The main data-source for their study is the National Intimate Partner and Sexual Violence Survey (NISVS). The algorithm then clusters IPV into 5 different subgroups, and the authors compare these algorithm-chosen subgroups to traditional categories of IPV including physical violence, psychological aggression, sexual violence and micro-aggression. An important finding of their pattern analysis and co-occurrence pattern mining is that physical violence often co-occurs with psychological aggression and co-occurs less often with micro-aggression. In addition, the authors found that sexual violence tended to be a mutually exclusive form of IPV. Furthermore, this exclusive nature of sexual violence was so strong that it formed a single connected component in their subsequent network analysis. Overall, the findings from this study underscore the importance of breaking down IPV into type of IPV (e.g., physical violence, psychological aggression, sexual violence and micro-aggression) as these different types of IPV have different co-occurrence patterns and could be important for subsequent studies that link IPV to other health outcomes. The authors results suggest that their method effectively clusters types of IPV patients into subgroups that pertain to the type of IPV experienced by the patient and underscore the importance of co-occurrence patterns in IPV.

In *Intimate Partner Violence and Injury Prediction from Radiology Reports,* **Chen et al.** present an algorithm to predict which patients will experience injury as a result of IPV[12]. Because there are different types of IPV and not all IPV results in an injury to the partner, this method would be useful in determining *a priori* what patients will be likely to experience injuries as a result of IPV. This study differs from the previous study in that **Chen et al.'s** algorithm utilizes data from a large academic hospital's violence prevention support program from Jan 2013 - Jun 2018. For information on the subsequent injuries, the authors also had access to the patients' radiology reports. The authors develop a machine learning model assess IPV patients for risk of injury. Their method was successfully able to predict IPV 1.34 years before entrance into a violence prevention program with 95% sensitivity and 71% specificity. There are future plans to deploy their model as a clinical risk model for early detection of IPV.

In *Not All C-sections are the same: Investigating Emergency vs. Elective C-section Deliveries,* **Canelón et al.** present a method that utilizes Electronic Health Records (EHR) data to breakdown Cesarean sections (C-sections) into emergency vs. elective C-sections [13]. This breakdown is important because C-sections are often deemed an 'adverse outcome' across the board. However, there can be situations where it is the best outcome for a particular patient. Therefore, detailing out the important difference between a patient with an elective or planned C-section (e.g., in the case of a patient with complex comorbidities) versus an emergency C-section (e.g., as the result of an amniotic fluid embolism) is important when determining if the C-section is an adverse delivery outcome or not. In this study, the authors confirm that they adequately capture the differences between emergency and elective C-section by comparing the rates on weekday versus weekend, observing the expected drop in elective C-sections on the weekends. In addition, they modeled emergency deliveries in general as an adverse outcome and found that the following patient characteristics increased the risk of an emergency delivery: preterm birth, being younger than 25, identifying as Black/African American, Asian, or Other/Mixed, after adjusting for pregnancy number and C-section number for each patient. Interestingly, later pregnancies and repeat cesareans decreased the risk of an emergency delivery, and identifying as White, Hispanic, and Native Hawaiian/Pacific Islander patients appeared to lower the risk of an emergency delivery. The same risk factors and trends were found also for Cesarean deliveries (when looking at emergencies as the outcome) except that Asian patients did not have an increased risk of an emergency delivery in the C-section population, and Native Hawaiian/Pacific Islander patients did not have a reduced risk in this group. Overall, modeling the relationship between emergency vs. elective deliveries is important to understanding the relationship between other comorbidities and risk factors for C-sections. In addition, it is important for breaking down C-sections into those that are likely adverse events (e.g., emergencies) versus those that are due to comorbidities or other patient health issues (e.g., elective or planned).

3. Discussion

Informatics and 'Big Data Analytics' algorithms as applied and developed specifically for women's health questions such as those presented in this session enable novel approaches of existing data from diverse sources including EHR and survey data sources. These methods can be used for early prediction of IPV (over 1-year before violence occurs) and these methods have potential to be implemented in clinics for early identification of at-risk patients. Before these methods can be implemented, care must be taken that these machine learning algorithms have not 'learned' any features or other signals that may be indicative of patterns of care that may be biased against women or other minority or otherwise disadvantaged groups. However, the work presented in this session does represent important first steps towards early risk prediction for a complex issue such as IPV.

Overall, the research presented in this session focuses on different clinical questions that pertain to women and women's health, including IPV and C-section as an adverse outcome following delivery or birth. The studies presented explore the complexity and the need to take these larger groups (either IPV or C-sections) and further break them down into meaningful subclusters, in the case of IPV that would be breaking it down into physical violence vs. sexual violence and so forth. In the case of C-sections, it requires breaking it down into emergency vs. elective C-sections. This highlights the complexity of these outcomes and the importance of developing novel informatics algorithms to study these important women's health outcomes. The overarching goal will be to use these findings and algorithms to improve clinical care in the form of enhanced understanding of risk factors or to predict patients at risk for IPV for early identification at the point of care.

References

1. NIH. Consideration of Sex as a Biological Variable in NIH-funded Research [Internet]. . *Available from:* https://orwh.od.nih.gov/sites/orwh/files/docs/NOT-OD-15-102_Guidance.pdf. 2015.
2. Esposito L. 7 Major Gaps in Women's Health Research [Internet] Available from: https://health.usnews.com/health-care/patient-advice/slideshows/7-major-gaps-in-womens-health-research. 2017.
3. X-Linked Recessive Disorders [Internet] Available from: https://www.sciencedirect.com/topics/neuroscience/x-linked-recessive-disorders. 2020.
4. Louis GMB, Yeung E, Kannan K, et al. Patterns and Variability of Endocrine-disrupting Chemicals During Pregnancy: Implications for Understanding the Exposome of Normal Pregnancy. *Epidemiology.* 2019;30:S65-S75.
5. Feghali M, Venkataramanan R, Caritis S. Pharmacokinetics of drugs in pregnancy. Paper presented at: Seminars in perinatology2015.
6. Davidson L, Boland MR. Enabling pregnant women and their physicians to make informed medication decisions using artificial intelligence. *Journal of Pharmacokinetics and Pharmacodynamics.* 2020:1-14.
7. Boland MR, Polubriaginof F, Tatonetti NP. Development of a machine learning algorithm to classify drugs of unknown fetal effect. *Scientific reports.* 2017;7(1):1-15.
8. Duan R, Boland MR, Moore JH, Chen Y. ODAL: A one-shot distributed algorithm to perform logistic regressions on electronic health records data from multiple clinical sites. Paper presented at: PSB2019.
9. Maybin JA, Boswell L, Young VJ, Duncan WC, Critchley HO. Reduced transforming growth factor-β activity in the endometrium of women with heavy menstrual bleeding. *The Journal of Clinical Endocrinology & Metabolism.* 2017;102(4):1299-1308.
10. Husseini-Akram F, Haroun S, Altmäe S, et al. Hyaluronan–binding protein 2 (HABP2) gene variation in women with recurrent miscarriage. *BMC women's health.* 2018;18(1):143.
11. Hacaliefendioglu A, Ylmaz S, Koyuturk M, Karakurt G. Co-occurrence Patterns of Intimate Partner Violence. Paper presented at: PSB2021.
12. Chen IY, Alsentzer E, Park H, et al. Intimate Partner Violence and Injury Prediction From Radiology Reports. *PSB.* 2021.
13. Canelon S, Boland MR. Not All C-sections Are the Same: Investigating Emergency vs. Elective C-section deliveries as an Adverse Pregnancy Outcome. *PSB.* 2021.