Childhood Adversity's Impact on Dynamic Mental Health During and Post Pregnancy

Jennifer Yu*[1,4,5], Mai Ali*[2,5], Rui Zhu*[1,4,5], Parinita Edke*[1,4,5] and Anna Goldenberg[1,3,4,5]

[1]Department of Computer Science, University of Toronto, Toronto, Canada
[2]Department of Electrical and Computer Engineering, University of Toronto, Toronto, Canada
[3]Department of Laboratory Medicine and Pathobiology, University of Toronto, Toronto, Canada
[4]Hospital for Sick Children, Toronto, Canada
[5]Vector Institute, Toronto,Canada

Abstract
Maternal health is one of the main sustainable development goals of the World Health Organization (WHO). Changes associated with pregnancy can be reflected in the physiological, psychological and behavioral states of women. In this study, we investigated relationships between Adverse Childhood Experiences (ACEs) and mental health symptoms such as depression and anxiety over pregnancy and into the postpartum period, as well as quality of life. Further, we examined the interrelationship between mental health symptoms and physical health during and post pregnancy, finding that the effects during pre and postnatal periods tend to differ. We hope that our analysis lays potential groundwork for exploring more complex relationships between mental health symptoms and ACEs during and post pregnancy.

Keywords
Causal Discovery, Mobile Health, Maternal Mental Health, Adverse Childhood Experiences

1. Introduction

Pregnancy brings extensive psychological and biological changes, significantly impacting maternal and fetal health. Depression is reported as the most common mental health disorder during pregnancy [1]. According to a recent study conducted by Al-abri et.al, the mean of the global prevalence of depression during the prenatal period is 28.5%, as opposed to 27.5% and 26.3% in postnatal and antenatal periods respectively [2]. Although the prevalence of depression during and after pregnancy is almost similar, prenatal mental health has received less research focus than its postpartum counterpart [3]. Along with depression, anxiety ranks as one of the most prevalent mental disorders. Depression and anxiety are more widespread among women, with a ratio of approximately 2:1 compared to men during women's reproductive years [4]. Furthermore, depression and anxiety often coexist, with 41.6% of those diagnosed with major depression also facing anxiety disorders within a year [4] [5]. Adverse childhood experience (ACE) prior to the age of 18 has been associated with several negative health outcomes in the future such as chronic obstructive pulmonary disorder, ischemic heart disease and major depressive disorder. However, there is limited knowledge of how those mental health conditions manifest during pregnancy. Lastly, the simultaneous occurrence of mental and physical health conditions, is a prevalent issue that leads to more severe health outcomes than the cumulative effects of individual conditions [6]. Although pregnancy is characterized by several physiological and behavioural changes, there is a lack of understanding regarding the specific patterns of interaction between mental and physical health during pregnancy [6].

Our research is motivated by the need to comprehensively understand the relationships between ACEs and pregnancy-related symptoms and outcomes. Existing literature primarily explores the interrelationships between pairs of variables (e.g., ACE and depression, depression and anxiety), leaving a gap in holistic understanding. The specific objectives of this study are to explore:

- How ACEs affect pregnancy related depression, anxiety, and quality of life
- The intricate relationships among mental health symptoms that occur during and post-pregnancy
- Investigate the relationship between physical and mental health during pregnancy

By illuminating these associations and patterns, our analysis could contribute to a more nuanced understanding of how ACEs impact maternal mental health. This could raise awareness of ACE at both individual and community levels so that we could inform more effective interventions to support individuals who have experienced ACEs [7].

IEEESDS'23: Data Science Techniques for Datasets on Mental and Neurodegenerative Disorders, June 22, 2023, Zürich, Switzerland
jenniferjie.yu@mail.utoronto.ca (J. Yu*); maia.ali@mail.utoronto.ca (M. Ali*); v.zhu@mail.utoronto.ca (R. Zhu*); parinita.edke@mail.utoronto.ca (P. Edke*); anna.goldenberg@utoronto.ca (A. Goldenberg)
0000-0001-9991-4117 (J. Yu*)

2. Literature Review

2.1. Relationships between ACE and maternal mental health symptoms

Numerous studies have indicated a significant association between early childhood adversity and adverse mental health outcomes in adulthood [8] [9] [10]. With respect to pregnancy, childhood abuse and history of domestic violence have been identified as risk factors for deteriorated mental health during pregnancy alongside lack of support, personal history of mental illness, unplanned or unwanted pregnancy, adverse life events, high perceived stress, pregnancy complications, and pregnancy loss [2] [3]. In a recent study investigating the relationship between early childhood adversity and pregnancy outcomes, 50% of the study population reported experiencing at least one ACE prior to the age of 18, while 17% reported experiencing three or more ACEs [11]. The results in [11] also illustrated the strong negative effects ACEs has on birth weight and gestational age. In [1], a robust association between childhood abuse and depressive symptoms during pregnancy has been established.

Walker [12] utilized a structural equation modeling (SEM) to explore the relationship between ACEs and mental health symptoms during pregnancy, highlighting potential mechanisms linking early adversity to mental health symptoms during pregnancy. Although the study did not establish causal relationships, it provided strong evidence of a direct association between ACEs and mental health symptoms. These associations were attenuated by positive factors like resilience and social support. The findings presented by Walker [12] seem to align with results reported in a similar study conducted by Lydsdottir et al. [13]. Lydsdottir et al. presented SEMs to examine the relationship between adverse experiences in childhood and adulthood, prior history of mental illness, and symptoms of mental disorders during pregnancy. Both adult and childhood adversities were significantly associated with a history of depression and mental disorders during pregnancy. On the other hand, social support was found to have a significant negative association with symptoms of common mental disorders during pregnancy which is similar to what has been reported in [12].

2.2. Causal discovery

In causal discovery, the goal is to identify causal relationships through the analysis of observational data. Granger causality [14] is a popular technique for examining associations among different time-series data, assuming covariance stationarity. To handle non-stationary data, windowing techniques are commonly used, but they were not applicable to our dataset due to limited time steps and lack of stationarity. The Inductive Causation (IC) algorithm [15], implemented in the PC algorithm [16], is a well-known constraint-based approach for causal discovery. The PC algorithm starts with a complete, undirected graph and iteratively removes edges based on conditional independence decisions. However, the PC algorithm assumes the absence of hidden confounders, which is challenging to guarantee in systems involving human physiology and psychology. The DAGs with NO TEARS algorithm [17], a score-based approach for learning causal graphs, formulates the structure learning problem as a continuous optimization problem over real matrices. Unlike the PC algorithm, this technique does not assume the absence of hidden confounders. Both the PC and DAGs with NO TEARS algorithms were utilized for causal relationship discovery between ACE and mental health during pregnancy. The construction and performance of both methods are presented and discussed in the following sections.

3. Methodology

3.1. Dataset

The dataset used in this study is from the Better Understanding the Metamorphosis of Pregnancy (BUMP) study [18]. The BUMP study is a longitudinal digital health study that aims to gain a deeper understanding of the pregnancy and postpartum individual-level experience through the use of wearable and mobile devices [18]. For the purposes of this study, we use data collected from 4 clinically validated surveys that measured ACE, depression and anxiety symptoms, and quality of life: the ACE survey [19], the participant Health Questionnaire (PHQ-9) [20], the General Anxiety Disorder-7 (GAD-7) survey [21], and the Participant-Reported Outcomes Measurement Information System (PROMIS) survey [22]. PROMIS survey was broken down into PROMIS-physical and PROMIS-mental according to [23].

Let $\mathscr{P}$ denote the set of participants in the form of unique user identification numbers, with $|\mathscr{P}| = 254$ individuals. Let $\mathscr{S} = \{\text{ACE, GAD-7, PHQ-9, PROMIS-physical, PROMIS-mental}\}$ denote the set of surveys in the study. Let $\mathscr{Q}_{survey}$ denote the set of questions of *survey*. For each participant $p \in \mathscr{P}$, the answers to each survey $s \in \mathscr{S} \setminus \{\text{ACE}\}$ were collected at each check-in time point $t \in \mathscr{T}$, which contains 10 check-in time point before delivery $\mathscr{T}_{prenatal}$, and 3 check-in time after delivery $t \in \mathscr{T}_{postnatal}$. The time interval between two consecutive check-in time points is approximately two weeks. $x^{(p)}_{s,q,t}$, where $p \in \mathscr{P}$, $s \in \mathscr{S} \setminus \{\text{ACE}\}$, $q \in \mathscr{Q}_s$, $t \in \mathscr{T}$, represents the answer to question q of survey s given by participant p at check-in time point t. Survey ACE was only taken once for each

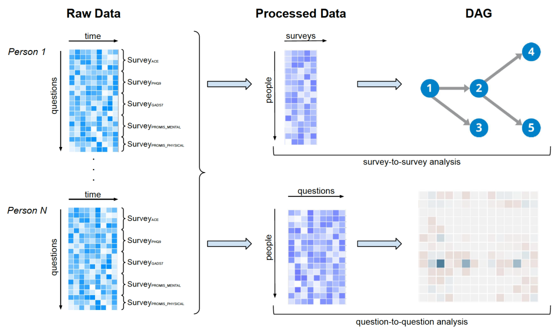


Figure 1: Algorithm Overview: a conceptual schematic diagram that shows how DAGs are generated using raw survey data. **Top left**: survey-to-survey analysis, which viewed each survey as a node. **Bottom left**: question-to-question analysis, where each question in each survey is a node.

participants. $x^{(p)}_{\text{ACE},q}$, where $p \in \mathscr{P}$, $q \in \mathscr{Q}_{\text{ACE}}$, represent the answer to question q in the ACE survey given by participant p. Lastly, missingness in the dataset occurred due to non-compliance of participants in filling out surveys at various time points t, and thus, for each participant p, we denote the available data time points as $\mathscr{T}^{(p)} \subset \mathscr{T}$.

3.2. Data preprocessing

The survey data that was collected at different check-in times was preprocessed for deploying static causal structure discovery algorithms. We employed two analysis approaches: survey-to-survey analysis and question-to-question analysis. An overview of the two approaches is presented in Figure 1. The former approach considered each survey as a node, while the latter treated each survey question as a node. In addition to these approaches, we also conducted two different analyses, 1) analyses across all time points and 2) analyses of prenatal and postnatal data. These additional analyses allowed us to gain further insights into the data and explore the effects of time on our results.

Survey-to-survey analysis This analysis was performed to investigate the causal relationships between attributes that surveys measured on a population level. An overview of the analysis is presented in Appendix 2. We aggregated the question scores in each survey into survey scores. For each participant p and survey $s \in \mathscr{S}$ at time point $t \in \mathscr{T}^{(p)}$, denote $k^{(p)}_{s,t} = \sum_{q \in \mathscr{Q}_s} x^{(p)}_{s,q,t}$ as the sum of the question scores for survey s of participant p at time t. The sum was then mapped using a survey-specific mapping $\mathscr{F}_s : \mathbb{R} \to \mathbb{Z}_{\geq 0}$, where the values and numbers of mapping thresholds $n_1, \cdots, n_m$ are survey-specific, sourcing from corresponding literature[20][21][22][19]. A general example of a mapping is shown as follows:

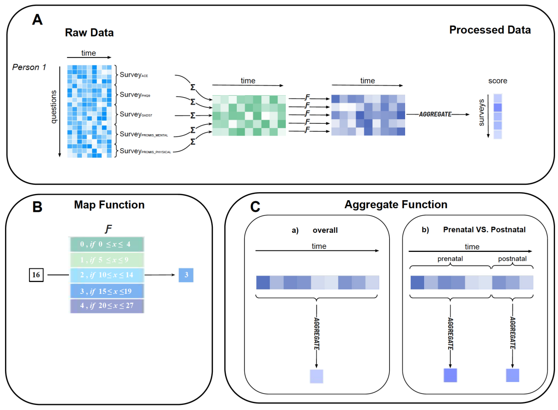


Figure 2: Survey-to-survey analysis preprocessing. A. For a participant, question scores were first summed up in each survey, then mapped to a survey score by $\mathscr{F}_s$. The survey scores were aggregated across time. **B.** An example map function $\mathscr{F}_s$ taking 16 as input, outputting 3 under the conditions. **C.** Two ways of aggregating survey scores across time: a) is across all time; b) is separated by delivery into two time intervals.

$$\mathscr{F}_s(p,t) = \begin{cases} 0, & \text{if } n_0 < k^{(p)}_{s,t} \leq n_1 \\ 1, & \text{if } n_1 < k^{(p)}_{s,t} \leq n_2 \\ \cdots & \\ m-1, & \text{if } n_{m-1} < k^{(p)}_{s,t} \leq n_m \end{cases}$$

.

Since the ACE survey was only administered once by each participant at the beginning of their involvement in the study, the mapping function for ACE does not consider time domain. However, the survey scores of the rest of the surveys for each individual were aggregated across time. For each survey $s \in \mathscr{S} \setminus \{\text{ACE}\}$ and participant $p \in \mathscr{P}$, let $d^p_s = \text{AGGREGATE}_{t \in \mathscr{T}^{(p)}}(\mathscr{F}_s(p,t))$ be the aggregated result over all the time points. Examples of AGGREGATE functions are *mean*, *median*, *max*, *min*. We used *mean* as our AGGREGATE function. Therefore, $d^p_s = \frac{1}{|\mathscr{T}^{(p)}|} \sum_{t \in \mathscr{T}^{(p)}} (\mathscr{F}_s(p,t))$. The scores of the ACE survey were unchanged. Eventually, data matrix $\mathbf{D} \in \mathbb{R}^{|\mathscr{P}| \times |\mathscr{S}|}$ was generated. The distributions of the aggregated survey score were summarized in Figure 3.

In temporal analysis, we separated the time points into prenatal and postnatal periods and calculated separate scores for each period. For participant $p \in \mathscr{P}$, if they have both pre- and postnatal check-in data available, they were involved in this analysis, and 42 participants were included. Among the 42 participants,

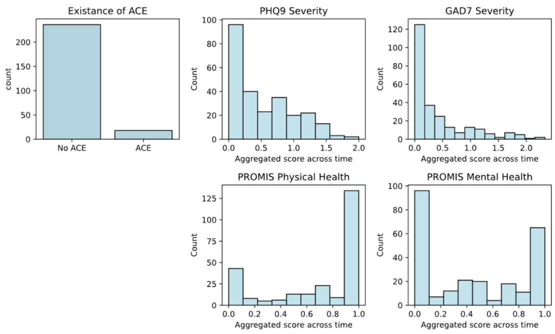


Figure 3: Distributions of all participants' survey answers across all (available) check-in time. Among the 254 participants, 236 of them did not experience ACE, and 18 of them had the experience of ACE. The distributions of the aggregated scores, averaged across all check-in times, are shown for each survey.

38 participants did not experience ACE, and 4 participants had experienced ACE. The prenatal scores were given by: $d^{p}_{s,q,prenatal} = \text{AGGREGATE}_{t \in \mathcal{T}^{(p)}_{prenatal}}(x^{(p)}s, q, t)$. The postnatal scores were given by: $d^{p}_{s,q,postnatal} = \text{AGGREGATE}_{t \in \mathcal{T}^{(p)}_{postnatal}}(x^{(p)}s, q, t)$. Two data matrices were generated based on these scores, $\mathbf{D}_{prenatal}$ and $\mathbf{D}_{postnatal}$. The data matrices were computed on the same participant cohort who had both pre- and postnatal data available. The distributions of the aggregated survey score of both pre- and postnatal check-in times were summarized in Figure 8.

Question-to-question analysis The preprocessing is similar to survey-to-survey analysis, but we directly aggregated each single question score in the surveys for an individual across time. For each survey $s \in \mathcal{S} \setminus \{\text{ACE}\}$, question $q \in \mathcal{Q}_s$, and participant $p \in \mathcal{P}$, denote $c^{p}_{s,q}$ as the aggregated result over all the time points, $c^{p}_{s,q} = \frac{1}{|\mathcal{T}^{(p)}|}\sum_{t \in \mathcal{T}^{(p)}}(x^{(p)}_{s,q,t})$. We kept the score of ACE survey unchanged. Eventually, data matrix $\mathbf{C} \in \mathbb{R}^{|\mathcal{P}| \times a}$ was generated, where $a = \sum_{s \in \mathcal{S}} |\mathcal{Q}_s|$. Similar procedures were also followed for the temporal analysis.

3.3. Causal structure discovery algorithms

We used causal structure discovery algorithms to find a graph $G = (V, E)$, where V is the set of nodes defined and E is the set of edges representing the causal relationship between variables. The graph should be a *directed acyclic graph* (DAG), where the edges have orientations and there are no directed cycles or directed loops. We applied two causal structure discovery algorithms to our dataset: PC algorithm [24][25] and DAG with NO TEARS [26] to output a DAG.

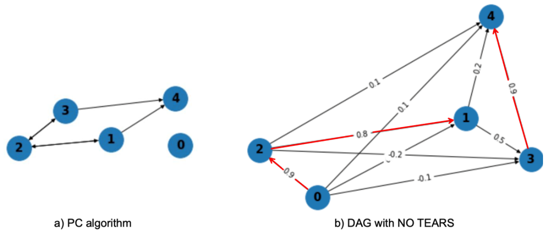


Figure 4: Survey-to-survey analysis. **a)** is a CPDAG generated by extending the skeleton from the PC algorithm. **b)** is a DAG generated by the DAGs with NO TEARS algorithm. (Node 0: ACE; Node 1: Depression; Node 2: Anxiety; Node 3: Mental Well-being; Node 4: Physical Well-being)

The PC algorithm [24] is a constraint-based method that tests for conditional independence between d-separation sets to determine the skeleton of the graph. This skeleton can be extended to a completed partially directed acyclic graph (CPDAG) within the equivalence class of the underlying DAG, where ambiguous causal directions are represented by arrow-to-arrow connections. However, the CPDAG is not a DAG since it cannot distinguish certain observational equivalence classes. To accommodate the independence test's limitation with continuous values, we rounded the scores obtained from previous steps. The implementation of the PC algorithm utilized the *pcalg* package [25]. DAG with NO TEARS[26] is a score-based method. Let data matrix be $\mathbf{X} \in \mathbb{R}^{n \times d}$. It optimizes for a loss function under the constraint that the graph should be a DAG:

$$\begin{gathered} \min_G \; Loss(W) \\ \text{subject to } G(W) \in DAGs, \end{gathered}$$

where $W \in \mathbb{R}^{d \times d}$ is the weighted adjacency matrix inducing $G(W)$. Since a sparse DAG is desired, the $Loss(W) = \frac{1}{2n}\|\mathbf{X} - \mathbf{X}W\|^2_F + \lambda\|W\|_1$. The discrete constraint can be replaced by a smooth constraint $h(W) = tr(e^{W \odot W}) - d = 0$ as proposed by [26]. Solving the constraint optimization problem yields a DAG, which is what we desired.

4. Results

The results obtained using the PC and DAG with NO TEARS methods utilized for investigating the relationship between ACEs and mental health symptoms during pregnancy and postpartum are presented in this section. Due to the measured and unmeasured confounders, we cannot attribute causality to the associations we uncovered, they provide valuable insights into the dynamic

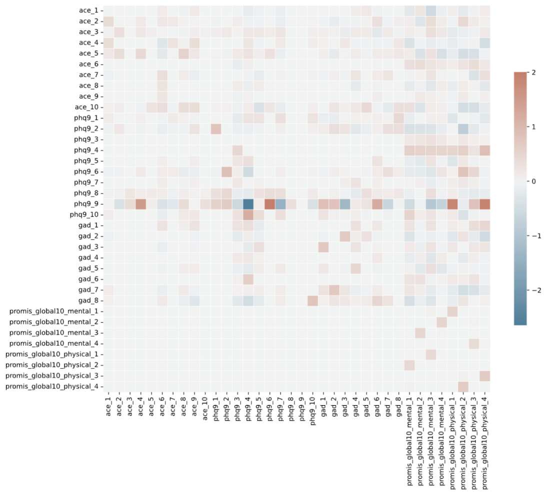


Figure 5: Question-to-question analysis: DAG generated from the DAG with NO TEARS algorithm. The direction of the edges is from variables on rows to columns. The variables are: questions in ACE, PHQ-9, GAD-7, PROMIS-mental, and PROMIS-physical.

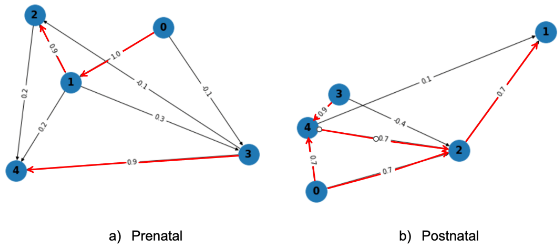


Figure 6: Survey-to-survey analysis with temporal separation: DAG generated from the DAG with NO TEARS algorithm - a.) Prenatal vs. b.) Postnatal. (Node 0: ACE; Node 1: Depression; Node 2: Anxiety; Node 3: Mental Well-being; Node 4: Physical Well-being)

relationship between ACEs and mental health symptoms during pregnancy and postpartum.

The survey-to-survey results are shown in Figure 4. Figure 4a shows the results of the PC algorithm, where it can be observed that ACE has no connections with other nodes. This is likely because of the highly unbalanced nature of the ACE data in the dataset, which comes from the fact that only a few individuals have experienced significant levels of adverse events in their childhood. Therefore, we hypothesize that this unbalanced data distribution leads to the ACE variable being independent of all other variables, the skewness of the data affecting the results of the independence tests.

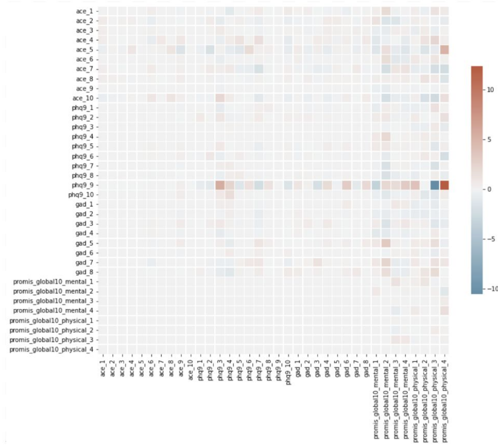
The second result in 4b is from the DAGs with NO TEARS algorithm. Based on the consultation with domain experts, it was determined that the DAG with NO TEARS algorithm yields more reasonable results. Therefore, we utilized this algorithm for further analyses. For better interpretation, we focused on strong connections (weight > 0.7, average of edge weights in both prental and postnatal graphs). Though the learned graph is fully connected, we see that the strongest relations are from ACE to Anxiety (0.9) to Depression (0.8) to Mental Well-being (0.5) to Physical Well-being (0.9). These findings are consistent with previous studies [12, 13].

As for the results of the question-to-question level analysis, the weighted adjacency matrix generated from the DAG with NO TEARS is shown in Figure 5. Notably, question 9 from the PHQ-9 survey exhibits stronger edge weights than other questions, which can be observed as dark red regions (weight ≈ 2) in Figure 5. This question pertains to suicide risk and asks individuals about thoughts of self-harm or feeling better off dead in the past two weeks. Compared to other questions in the surveys, this particular question reflects an extremely severe symptom if answered affirmatively. Detailed descriptions of each survey question can be found in Appendix 1.2. Based on Figure 5, PHQ9-q9 (the suicide risk question) is particularly strongly positively associated with ACE-q4 (feeling that no one in your family loved you), PHQ9-q6 (feeling bad or like a failure), PROMIS_GLOBAL10_PHYSICAL-q1 (rating physical health) and PROMIS_GLOBAL10_PHYSICAL-q4 (rating your pain on average) and negatively associated with PHQ9-q4 (trouble falling or staying asleep, or sleeping too much). The association between increased risk of suicide (PHQ9-q9) and childhood adversity has been previously presented in [27], particularly the positive correlation between neglect which is captured in ACE-q4 and risk of suicide attempts [28].

Please note that we ensured that semantic similarities were not confounding our analysis. To that extent, domain experts assisted in determining semantically similar questions, as shown in Appendix 1.4. For instance, question 5 in GAD-7 inquires about restlessness, while question 8 in PHQ-9 asks about excessive fidgeting or restlessness. Correlations between semantically similar questions were removed from the analysis and not considered.

The results on the comparison between prenatal and postnatal survey-to-survey analysis are shown in Figure 6. First, we note that the associations differ between prenatal and postnatal stages. We also found that ACE is associated with depression and anxiety both pre- and post-nataly (edge weights 0.9 and 0.7 in the prenatal and postnatal periods, respectively). These findings are consistent with [4] and[5]. Interestingly, while there is a strong association between ACE and depression in

a) Prenatal



b) Postnatal

Figure 7: Question-to-question analysis: DAG from the DAG with NO TEARS algorithm - a.) Prenatal b.) Postnatal.

the prenatal stage (edge weight of 1.0), there is no such direct association in the post-natal period. In fact, in the postnatal period ACE and depression are independent given anxiety, i.e. ACE directly affects anxiety (edge weight of 0.7) which in turn affects depression (edge weight of 0.7). It is satisfying to note that in both prenatal and postnatal states, there is a stable association between mental health and physical health, as indicated by the PROMIS Global 10 survey (weight of 0.9 in both graphs) indicating that the analysis was able to recover some of the expected associations in the two states we examined. While we acknowledge the limitations of our dataset, the identified differences may be interesting to explore in future research.

5. Discussion

In this paper we focused on understanding relations between measurements, specifically ACE and mental health, during pregnancy as well as post-nataly. Our findings indicate that the way ACE affects mental health may differ during the pre and postnatal stages. The caveat of any such study is in the frequency of the extreme measures. Since some of the values, especially extreme ones, tend to be rare, their presence/absence can skew the independence tests that causal analysis is based on quite severely. In addition, while we have administered some of the expected surveys to identify depression and anxiety as well as other factors, there are a myriad of unmeasured factors that may influence the association and dependency between reported variables that may result in a direct dependency link in the graph, obscuring the potential unmeasured confounding. Thus, while our results indicate that the relation effect of ACE on mental health differs during the pre- and postnatal periods, further in depth studies are recommended to facilitate understanding of the direct vs indirect effects in these scenarios. We hope that ultimately this work is a first step in offering insights to developing clinical interventions that can improve maternal mental health during pregnancy and reduce the risk of serious prenatal and postpartum mental health conditions in addition to overall well-being.

6. Acknowledgment

*This work is done based on equal contributions from JY, MA, RZ,and PE. JY, MA, RZ, PE are generously supported by 4YouandMe. AG is further supported by CIFAR AI chair as well as the Varma Family Chair.

References

[1] A. L. Shamblaw, R. E. Cardy, E. Prost, K. L. Harkness, Abuse as a risk factor for prenatal depressive symptoms: a meta-analysis, Archives of Women's Mental Health 22 (2018) 199–213. URL: https://doi.org/10.1007/s00737-018-0900-8. doi:10.1007/s00737-018-0900-8.

[2] K. Al-abri, D. Edge, C. J. Armitage, Prevalence and correlates of perinatal depression, Social Psychiatry and Psychiatric Epidemiology (2023). URL: https://doi.org/10.1007/s00127-022-02386-9. doi:10.1007/s00127-022-02386-9.

[3] A. Biaggi, S. Conroy, S. Pawlby, C. M. Pariante, Identifying the women at risk of antenatal anxiety and depression: A systematic review, Journal of Affective Disorders 191 (2016) 62–77. URL: https://doi.org/10.1016/j.jad.2015.11.014. doi:10.1016/j.jad.2015.11.014.

[4] R. C. Kessler, W. T. Chiu, O. Demler, E. E. Walters, Prevalence, severity, and comorbidity of 12-month DSM-IV disorders in the national comorbidity survey replication, Archives of General Psychiatry 62 (2005) 617. URL: https://doi.org/10.1001/archpsyc.62.6.617. doi:10.1001/archpsyc.62.6.617.

[5] N. H. Kalin, The critical relationship between anxiety and depression, American Journal of Psychiatry 177 (2020) 365–367. URL: https://doi.org/10.1176/appi.ajp.2020.20030305. doi:10.1176/appi.ajp.2020.20030305.

[6] V. Khachadourian, A. Kodesh, S. Levine, E. Lin, J. D. Buxbaum, V. Bergink, S. Sandin, A. Reichenberg, M. Janecka, Maternal psychiatric diagnosis and comorbidities around pregnancy, Biological Psychiatry 89 (2021) S96. URL: https://doi.org/10.1016/j.biopsych.2021.02.251. doi:10.1016/j.biopsych.2021.02.251.

[7] National Center for Injury Prevention and Control Division of Violence Prevention, Fast facts: Preventing adverse childhood experiences, 2022. URL: https://www.cdc.gov/violenceprevention/aces/fastfact.html.

[8] R. F. Anda, V. J. Felitti, J. D. Bremner, J. D. Walker, C. Whitfield, B. D. Perry, S. R. Dube, W. H. Giles, The enduring effects of abuse and related adverse experiences in childhood, European Archives of Psychiatry and Clinical Neuroscience 256 (2005) 174–186. URL: https://doi.org/10.1007/s00406-005-0624-4. doi:10.1007/s00406-005-0624-4.

[9] V. J. Felitti, R. F. Anda, D. Nordenberg, D. F. Williamson, A. M. Spitz, V. Edwards, M. P. Koss, J. S. Marks, Relationship of childhood abuse and household dysfunction to many of the leading causes of death in adults, American Journal of Preventive Medicine 14 (1998) 245–258. URL: https://doi.org/10.1016/s0749-3797(98)00017-8. doi:10.1016/s0749-3797(98)00017-8.

[10] R. E. Norman, M. Byambaa, R. De, A. Butchart, J. Scott, T. Vos, The long-term health consequences of child physical abuse, emotional abuse, and neglect: A systematic review and meta-analysis, PLoS Medicine 9 (2012) e1001349. URL: https://doi.org/10.1371/journal.pmed.1001349. doi:10.1371/journal.pmed.1001349.

[11] M. V. Smith, N. Gotman, K. A. Yonkers, Early childhood adversity and pregnancy outcomes, Maternal and Child Health Journal 20 (2016) 790–798. URL: https://doi.org/10.1007/s10995-015-1909-5. doi:10.1007/s10995-015-1909-5.

[12] H. A. Walker, Maternal Adverse Childhood Experiences and Mental Health Symptoms in Pregnancy: Behavioural and Social Mediators, Ph.D. thesis, University of Victoria, 2019.

[13] L. B. Lydsdottir, L. M. Howard, H. Olafsdottir, H. Einarsson, T. Steingrimsdottir, J. F. Sigurdsson, Adverse life experiences and common mental health problems in pregnancy: a causal pathway analysis, Archives of women's mental health (2019).

[14] A. Shojaie, E. B. Fox, Granger causality: A review and recent advances, 2021. URL: https://arxiv.org/abs/2105.02675. doi:10.48550/ARXIV.2105.02675.

[15] J. P. Verma, Emotions understanding model from spoken language using deep neural networks and mel-frequency cepstral coefficients, in: Proceedings of the Sixth Conference on Uncertainty in Artificial Intelligence, 1990, pp. 220–227.

[16] C. G. Peter Spirtes, R. Scheines, Causation, Prediction, and Search, MIT Press, 2000.

[17] X. Zheng, B. Aragam, P. Ravikumar, E. P. Xing, Dags with no tears: Continuous optimization for structure learning, 2018. URL: https://arxiv.org/abs/1803.01422.

[18] S. M. Goodday, E. Karlin, A. Brooks, C. Chapman, D. R. Karlin, L. Foschini, E. Kipping, M. Wildman, M. Francis, H. Greenman, L. Li, E. Schadt, M. Ghassemi, A. Goldenberg, F. Cormack, N. Taptiklis, C. Centen, S. Smith, S. Friend, Better understanding of the metamorphosis of pregnancy (bump): protocol for a digital feasibility study in women from preconception to postpartum, npj Digital Medicine 5 (2022) 40. URL: https://doi.org/10.1038/s41746-022-00579-9. doi:10.1038/s41746-022-00579-9.

[19] V. J. Felitti, R. F. Anda, D. Nordenberg, D. F. Williamson, A. M. Spitz, V. Edwards, M. P. Koss, J. S. Marks, Relationship of childhood abuse and household dysfunction to many of the leading causes of death in adults: The adverse childhood experiences (ace) study, American Journal of Preventive Medicine 14 (1998) 245–258. URL: http://www.ajpmonline.org/article/S0749379798000178/fulltexthttp://www.ajpmonline.org/article/S0749379798000178/abstracthttps://www.ajpmonline.org/article/S0749-3797(98)00017-8/abstract. doi:10.1016/S0749-3797(98)00017-8.

[20] K. Kroenke, R. L. Spitzer, J. B. Williams, The phq-9: Validity of a brief depression severity measure, Journal of General Internal Medicine 16 (2001) 606. URL: /pmc/articles/PMC1495268//pmc/articles/PMC1495268/?report=abstracthttps://www.ncbi.nlm.nih.gov/pmc/articles/PMC1495268/. doi:10.1046/J.1525-1497.2001.016009606.X.

[21] R. L. Spitzer, K. Kroenke, J. B. Williams, B. Löwe, A brief measure for assessing generalized anxiety disorder: the gad-7, Archives of internal medicine 166 (2006) 1092–1097. URL: https://

pubmed.ncbi.nlm.nih.gov/16717171/. doi:10.1001/ARCHINTE.166.10.1092.
[22] R. D. Hays, B. D. Schalet, K. L. Spritzer, D. Cella, Two-item promis® global physical and mental health scales, Journal of Patient-Reported Outcomes 1 (2017). URL: /pmc/articles/PMC5934936//pmc/articles/PMC5934936/?report=abstracthttps://www.ncbi.nlm.nih.gov/pmc/articles/PMC5934936/. doi:10.1186/S41687-017-0003-8.
[23] V. Slavin, J. Gamble, D. e. a. Creedy, Measuring physical and mental health during pregnancy and postpartum in an australian childbearing population - validation of the promis global short form, BMC Pregnancy Childbirth (2019).
[24] P. Spirtes, C. Glymour, R. Scheines, Causation, Prediction, and Search, 2nd ed., MIT press, 2000.
[25] M. Kalisch, B. M. E. Ch, Estimating high-dimensional directed acyclic graphs with the pc-algorithm peter b ¨ uhlmann, Journal of Machine Learning Research 8 (2007) 613–636.
[26] X. Zheng, B. Aragam, P. Ravikumar, E. P. Xing, Dags with no tears: Continuous optimization for structure learning (2018). URL: https://github.com/xunzheng/notears.
[27] S. R. Dube, R. F. Anda, V. J. Felitti, D. P. Chapman, D. F. Williamson, W. H. Giles, Childhood abuse, household dysfunction, and the risk of attempted suicide throughout the life span, JAMA 286 (2001) 3089. URL: https://doi.org/10.1001/jama.286.24.3089. doi:10.1001/jama.286.24.3089.
[28] J. Kingree, M. P. Thompson, N. J. Kaslow, Brief report risk factors for suicide attempts among low-income women with a history of alcohol problems, Addictive Behaviors 24 (1999) 583–587. URL: https://www.sciencedirect.com/science/article/pii/S0306460398001099. doi:https://doi.org/10.1016/S0306-4603(98)00109-9.

Appendix

1.1. Github Repo Link

The code for the project can be accessed with the following link: https://github.com/smilejennyyu/BUMP_causality

1.2. Survey questions

ACE questions

1. Did a parent or other adult in the household often … Swear at you, insult you, put you down, or humiliate you? or Act in a way that made you afraid that you might be physically hurt? Yes/No
2. Did a parent or other adult in the household often … Push, grab, slap, or throw something at you? or Ever hit you so hard that you had marks or were injured? Yes/No
3. Did an adult or person at least 5 years older than you ever… Touch or fondle you or have you touch their body in a sexual way? or Try to or actually have oral, anal, or vaginal sex with you? Yes/No
4. Did you often feel that... No one in your family loved you or thought you were important or special? or Your family didn't look out for each other, feel close to each other, or support each other? Yes/No
5. Did you often feel that … You didn't have enough to eat, had to wear dirty clothes, and had no one to protect you? or Your parents were too drunk or high to take care of you or take you to the doctor if you needed it? Yes/No
6. Were your parents ever separated or divorced? Yes/No
7. Was your mother or stepmother: Often pushed, grabbed, slapped, or had something thrown at her? or Sometimes or often kicked, bitten, hit with a fist, or hit with something hard? or Ever repeatedly hit over at least a few minutes or threatened with a gun or knife? Yes/No
8. Did you live with anyone who was a problem drinker or alcoholic or who used street drugs? Yes/No
9. Was a household member depressed or mentally ill or did a household member attempt suicide? Yes/No
10. Did a household member go to prison? Yes/No

PHQ-9 questions

Over the last 2 weeks, how often have you been bothered by the following problems? (Not at all, Several days, More than half the days, Nearly every day)

1. Little interest or pleasure in doing things
2. Feeling down, depressed, or hopeless
3. Feeling tired or having little energy.
4. Trouble falling or staying asleep, or sleeping too much.
5. Poor appetite or overeating.
6. Feeling bad about yourself or that you are a failure or have let yourself or your family down
7. Trouble concentrating on things, such as reading the newspaper or watching television.
8. Moving or speaking so slowly that other people could have noticed or the opposite - being so fidgety or restless that you have been moving around a lot more than usual.
9. Thoughts that you would be better off dead or of hurting yourself in some way.
10. If you checked off any problems, how difficult have these problems made it for you to do your work, take care of things at home, or get along with other people?

GAD-7 questions

Over the last 2 weeks, how often have you been bothered by the following problems? (Not at all, Several days, More than half the days, Nearly every day)

1. Feeling nervous, anxious, or on edge
2. Not being able to stop or control worrying
3. Worrying too much about different things
4. Trouble relaxing
5. Being so restless that it's hard to sit still
6. Becoming easily annoyed or irritable
7. Feeling afraid as if something awful might happen
8. If you checked off any problems, how difficult have these made it for you to do your work, take If you checked off any problems, how difficult have these made it for you to do your work, take care of things at home, or get along with other people?

PROMIS 10 questions

You are about to start a survey that asks about your overall health. It is 10 questions and will take about 1 minute to complete. Question 3, 7, 9, and 10 belong to PROMIS-physical. Questions 2, 4, 5, and 8 belong to PROMIS-mental.

1. In general, would you say your health is: Excellent, Very good, Good, Fair, Poor
2. In general, would you say your quality of life is: Excellent, Very good, Good, Fair, Poor (Mental)
3. In general, how would you rate your physical health? Excellent, Very good, Good, Fair, Poor (Physical)
4. In general, how would you rate your mental health, including your mood and your ability to think? Excellent, Very good, Good, Fair, Poor (Mental)
5. In general, how would you rate your satisfaction with your social activities and relationships? Excellent, Very good, Good, Fair, Poor (Mental)
6. In general, please rate how well you carry out your usual social activities and roles. (This includes activities at home, at work and in your community, and responsibilities as a parent, child, spouse, employee, friend, etc.) Excellent, Very good, Good, Fair, Poor
7. To what extent are you able to carry out your everyday physical activities such as walking, climbing stairs, carrying groceries, or moving a chair? Completely, Mostly, Moderately, A little, Not at all (Physical)
8. In the past 7 days, how often have you been bothered by emotional problems such as feeling anxious, depressed or irritable? Never, Rarely, Sometimes, Often, Always (Mental)
9. In the past 7 days, how would you rate your fatigue on average? None, Mild, Moderate, Severe, Very severe (Physical)
10. In the past 7 days, how would you rate your pain on average? Put it on a 10-point scale from No pain to Worst pain imaginable (Physical)

1.3. Summary of pre- and postnatal check-in survey scores

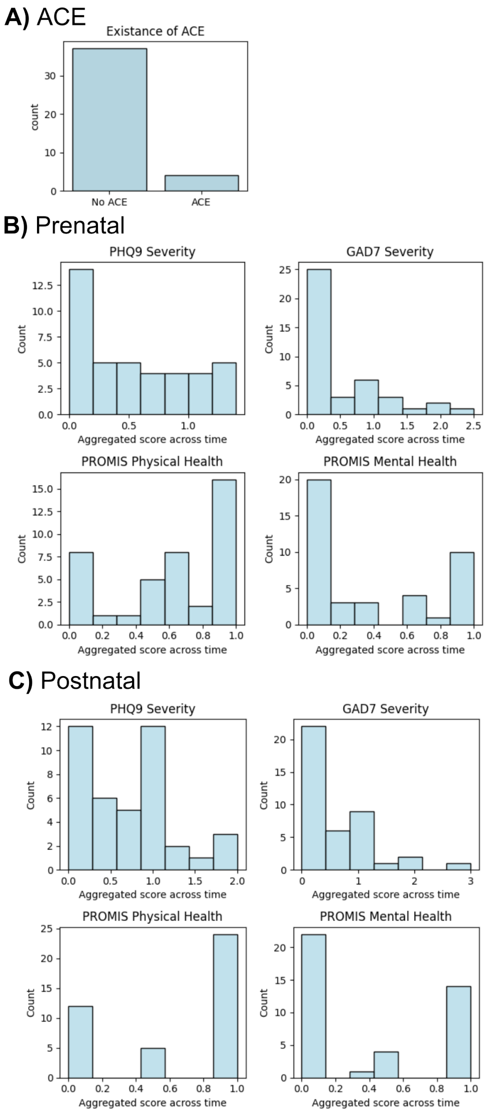


Figure 8: Distributions of survey answers across pre- and postnatal check-in time. Only 42 participants, who had at least one postnatal check-in done, were included. **A.** The distribution of ACE experience. 38 participants did not experience ACE, and 4 participants had experienced ACE. **B.** The distribution of the aggregated score across prenatal check-in times. **C.** The distribution of the aggregated score across postnatal check-in times.

1.4. Semantic Similarity for survey questions

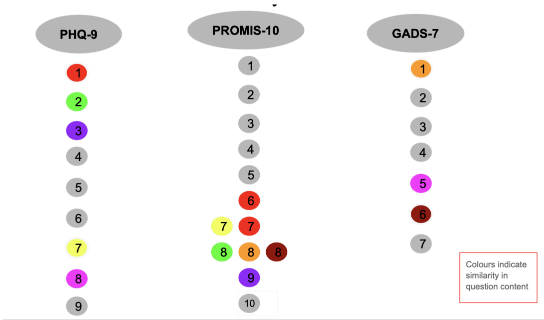


Figure 9: Semantic similarity for questions from the 3 surveys. The colours indicate similarity in question content.