Major Life Changes and Behavioral Markers in Social Media: Case of Childbirth

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ABSTRACT
We explore the harnessing of social media as a window for understanding changes around major life events in individuals and larger populations. We specifically examine patterns of activity, emotional, and linguistic correlates for childbirth and postnatal course. After identifying childbirth events on Twitter, we analyze daily posting patterns and language usage before and after birth by new mothers, and make inferences about the status and dynamics of changes in emotions expressed following childbirth. We find that childbirth causes some change for most new mothers, but approximately 15% of new mothers show significant changes in their online activity and emotional expression postpartum. Interestingly, we observe that these mothers can be distinguished by linguistic changes captured by shifts in a relatively small number of words in their social media posts. Thereafter, we introduce a greedy differencing procedure to identify the type of language that characterizes significant changes in these mothers during postpartum. We conclude with a discussion of how such characterizations might be applied to recognizing and understanding health and wellness in women following childbirth.

Author Keywords
childbirth, emotion, health, language, postpartum, social media, Twitter, wellness

ACM Classification Keywords
H.5.m [Information Systems]: Information Systems Applications – Miscellaneous.

General Terms
Algorithms; Human Factors; Measurement.

INTRODUCTION
Social media platforms including Twitter and Facebook provide a window onto the thoughts and feelings of individuals and populations. Considerable recent research has focused on exploration and mining of such data in a variety of domains, ranging from financial markets to politics, public health, and crisis mitigation [3,28,37].

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We explore the domain of personal health, specifically looking at the effects of a major life event on mood and behavior. To do so, we employ three social media-centric measures: (1) patterns of activity, (2) linguistic style, and (3) emotional expression. Patterns and levels of activity define interactions with others and overall engagement with the social landscape. Language has been shown to provide useful psychological markers [29], and prior research [36,38] has shown that usage of language has the potential to convey information about individuals' behavior, their social surroundings, contexts and crises they are in. Emotions are founded on interrelated patterns of cognitive processes, physiological arousal, and behavioral reactions [11]. They appear to serve to organize experiences and influence behavior by directing attention, and by influencing perceptions of self, others, and the interpretation and memories of events. All three of these—patterns of activity, linguistic expression, and emotion—have been used in a variety of ways to understand as well as to promote general wellness among individuals and encourage healthy behavior (e.g., [2,16,32]). Social media provides access to these dimensions of human behavior in a longitudinal manner, and thus may be an informative tool in the study of how people experience and respond to significant life events.

We use content from Twitter in our study. Twitter has a large user base, including many people who have been using the service for years. The latter allows for analyses at time scales long enough to include periods before and after one or more major life events. Furthermore, Twitter often is used to broadcast updates on daily life, as well as on external information of interest, with the goals of maintaining existing relationships with strong and weak ties, and at the same time building new ties [22]. Thus, Twitter is a natural medium for sharing news about important updates and happenings in people's lives, including childbirth, marriage, loss of a job, and such deeply traumatic experiences as death of a loved one, divorce, and a severe car accident.

We focus in this paper on the major life event of *childbirth*. We explore and present a number of measures of activity patterns, emotional expression, and linguistic style to detect changes in 85 new mothers in the postnatal phase (approximately the five months *following* childbirth), as compared to the prenatal period (approximately the five months *before* childbirth), based on Twitter postings. One contribution of the work is a method for identifying new mothers from Twitter data. We follow an iterative strategy to collect posts that are indicative of births in Twitter's Firehose stream, and then use crowdsourcing techniques to determine a high precision set of new mothers.

Our analyses, both quantitative and qualitative, show that a percentage of new mothers in our dataset (~15%), in the postnatal phase undergo significant behavioral changes compared to others, as well as to an average Twitter user. These changes include: reduced activity, reduced positive affect, heightened negative affect, and significant change in use of specific linguistic styles, including interpersonal pronouns. Furthermore, on identifying aspects of language in the Twitter posts that contribute to this change, we find that changes in usage of a narrow span of words (~1-10% of the entire language vocabulary characterizing the content of posts of the new mothers) distinguish new mothers who show significant changes across multiple measures compared to other new mothers. Such minimal yet discriminatory linguistic changes suggest that language-centric diagnostic tools might one day be developed to aid in the identification of potential postpartum disorders, thereby broadly helping to reduce non-invasively the stigma around temporary and persisting challenges with mood and mental illness.

We believe that the motivation, methodology, and direction of this research can be leveraged in a variety of areas. One scenario comprises better identification of forthcoming or new mothers who would benefit from support groups that encourage postpartum social support and mete out wellness advice to prenatal and postnatal women. In essence, these groups can strive to provide a venue where new mothers can find each other, trade baby tips and start up friendships. Broadly, through our proposed behavioral measures, we hope to introduce a line of research that can help promote health-related well-being, by reflecting and even forecasting reactions to a range of major life events, leveraging social media.

BACKGROUND LITERATURE

Understanding behavioral change has been a focus of attention for researchers in social, clinical, personality, and cognitive psychology [29,30,35,38], and more recently in the HCI [7] and social media communities [9,14]. Hence we draw upon insights from a variety of research areas on findings about behavioral patterns surrounding childbirth.

Behavior Analysis around Childbirth

Clinical and psychiatric studies around monitoring behavior of new mothers have been of interest to researchers for several decades including, for instance, the role of social support on the emotion, attitudes, and behavior of new mothers [30,34]. A considerable amount of research in this area has focused on *postpartum depression* (PPD), a type of clinical depression that affects a portion of mothers after childbirth [12,19]. For instance, Nielson et al. [24] examined demographic, obstetric, and psychosocial risk factors of postpartum depression, finding that psychological distress and perceived social isolation during pregnancy both were significant predictors of postpartum depression.

Research on psychological aspects of childbirth for mothers is challenged by the limitations of data availability and collection; obtaining relevant data can require collecting data about women from late pregnancy to months after childbirth. To date, studies have largely been based on self-reports that do not always scale to large populations, making it hard to generalize the findings about the behaviors of new mothers. To this end, social media and networking tools can provide a new window onto new mothers for studying behavioral changes at-scale without necessarily requiring active engagement with the mothers.

Behavior Analysis in Psycholinguistics

Researchers in the psycholinguistics community have explored how utterances, written texts, or other expressions of language can be used to better understand human intentions, moods, competencies, and disorders. As examples, computerized analysis of written text has revealed cues and diagnostic markers about emotional closeness of individuals [17], neurotic tendencies, and depression and anxiety among other psychiatric disorders [27,29,38]. Oxman et al. [27] demonstrated that linguistic analysis of speech samples could reliably and accurately classify patients into diagnostic groups such as those suffering depression and paranoia. Along similar lines, Tellengen [35] investigated how the structures of emotional expression can be used to assess anxiety. However, studies of depression, anxiety, or other distinctive behavioral changes in these works have been explored without regard to the context of events in the lives of individuals. One exception is the work of Spera, Buhrfeind and Pennebaker [33], who examine how expressive writing may help people cope with job loss.

Behavior Analysis around Events via Social Media

There is an extensive body of work on using social media to understand and track the emotions and behavior of large populations [18]. While some of this work has focused on public events like collective crisis situations [36], events in an individual's life (e.g., childbirth, death, job loss etc.) have not been explored in a rigorous manner. Along with the Spera et al. work [33] mentioned above, an exception is [5], wherein the authors used linguistic features to predict death related bereavement on the MySpace social network. On a similar note, the use of social media to enable the maintenance of friendships during personal moves has also been studied [31].

Social Media for Health and Wellness

Interest has been growing in opportunities to employ social media and networking, and other Internet data to encourage and promote healthy behavior and well-being [1,16,20,32]. Bahr at al. [2] studied how social networks can be leveraged to help people combat obesity. Munson et al. [21] presented an application for Facebook that promotes health interventions. Jamison-Powell et al. [15] examined discussions around insomnia on Twitter.

The breadth of work aimed at the use of social media to promote physical and psychosocial health highlights the spectrum of opportunities for creating applications that can support and encourage health-related awareness and self-reflection. In many cases, these tools would benefit from methods for identifying users who most need them. Our hope is that the techniques and methodologies that we present in this paper for measuring emotional and behavioral change around childbirth can be generalized to other health and wellness applications.

DATA

As we are interested in understanding behavioral change around the major life event of the birth of a child, our population of interest comprises new mothers: female Twitter users who are likely to have given birth to a child in a given timeframe. Although we have observed that many fathers post about the birth of a child soon after the birth, we focus maternally because it is well-established that new mothers more consistently experience a significant change in their lifestyle and habits in the postnatal period, compared to the fathers (ref. [19,25]).

Identifying new mothers on social media based on their posts, and in the absence of self-reported gender, is a challenging problem. We follow a multistage approach involving (1) constructing a candidate set of likely new mothers based on filtering a large corpus of Twitter posts for birth announcement events, and (2) identifying with high confidence a set of new mothers using gender inference and ratings from crowdworkers recruited via Amazon's Mechanical Turk (AMT). We discuss these steps in the following subsections.

Identifying Birth Events

We first construct a list of several queries to search the Twitter Firehose stream (made available to us via a contract with Twitter) for candidate users likely to be posting about their childbirth—a proxy for announcement of a birth event. We focus on searching the Twitter stream over a fixed two-month period between May 1, 2011 and Jun 30, 2011 (English language posts only), roughly the midpoint of the Twitter data that we had available. This leaves us sufficient data before and after the period to compare the prenatal and postnatal behavior of the new mothers.

To obtain the queries, we examined archives of birth announcements in four local newspapers over a period of three years from 2009 to 2012 (The Beacon-News[1], Aurora News-Register[1], Crete News[1], and Gothenburg Times[1]). Based on independent manual inspection from two researchers, we formulated a lexicon of sets of keywords and phrases that typically characterized the newspaper birth announcements. The terms resonate with intuitions that parents announce the birth of their children in canonical ways, often including mention of the labor experience and reporting on the physical details of their newborn child, including gender, weight, and height. These phrases were considered as search terms to identify birth announcements, to find candidate sets of new mothers from the Twitter stream. Examples of these identifying queries are given in Table 1. This phase yielded a candidate set of 483 unique users, who were the authors of potential birth announcement Twitter posts.

(1) birth, weigh*, pounds/lbs, inches, length/long, baby/son/daughter/boy/girl
(2) announc*, birth of, son/daughter/brother/sister
(3) announc*, arrival of, son/daughter/brother/sister
(4) are the parents of, son/daughter/boy/girl/baby
(5) welcome* home by, brother/sister/sibling*
(6) is the proud big brother/sister
(7) after, labor, born
(8) it's a boy/girl, born

Table 1. List of queries for identifying birth events on Twitter.

Identifying New Mothers through Crowdsourcing

As we are interested in mothers, inferring the gender of the above constructed candidate user set is important. Twitter does not provide a facility for users to report on their gender. Thus, we relied on cues obtained from their self-declared first names to infer the gender of the users in our candidate set. To this end, we employed a lexicon-based approach that identifies matches of the first name of the Twitter user to a large dictionary of first names collated from the United States Census data, available for download (http://www.census.gov/genealogy/www/data/1990surnames/names_files.html), as well as a publicly available corpus of Facebook users' names and self-reported gender. Because of the cross-cultural nature of Facebook, crossing these two sources worked fairly well in inferring gender of the Twitter users. We tested the accuracy of this inference mechanism by randomly selecting 100 identified users and labeling their gender manually. The lexicon-driven gender inference mechanism yielded 83% accuracy. Following gender identification, we obtained a smaller set of likely new mothers comprising 177 users.

[1] http://beaconnews.suntimes.com/, http://auroranewsregister.com/, http://cretenews.net/, http://gothenburgtimes.com/

In the final step, we task crowdworkers at Mechanical Turk (https://www.mturk.com/mturk/) with reviewing the set of likely new mother candidates and ruling out cases of false positives, in pursuit of a high precision dataset. We showed each crowdworker (min. 95% approval rating, English language proficient, and familiar with Twitter) a set of 10 Twitter posts from each user in our candidate set, such that five posts were posted right before the index childbirth post, and five after the post. Our goal was to provide crowdworkers with contextual cues to help them to judge whether the author of the posts was a legitimate new mother. Additionally, we also showed the Twitter profile bio, picture, and a link to the Twitter profile for each user. The specific question involved responding to a yes/no/maybe multiple-choice question per user, to evaluate if the user was a new mother. We thus collected five ratings per user from the crowdworkers, and used the majority rating as the correct label (Fleiss-Kappa was 0.69). For our final dataset, we considered the users with the "yes" label and this set consisted of 85 validated new mothers.

Finally, for each of these 85 assumed new mothers, we queried their Twitter timelines in the Firehose stream to collect all of their posts in two 5-month periods, corresponding to prenatal and postnatal phases around child-birth (Dec 1, 2010 – Apr 30, 2011 and Jul 1, 2011 – Nov 30, 2011, respectively). We note that these were public timelines. We discuss privacy and ethical considerations in the Discussion section.

BEHAVIORAL CHANGE MEASURES

We propose several measures to quantify the behavioral change of the new mothers.

Activity Measure. We characterize activity via a measure we refer to as *volume*, defined as the average normalized number of posts per day made by the new mothers, over the prenatal and postnatal periods.

Emotion Measures. We focus on four measures of emotional state. The first two measures, Positive Affect (PA) and Negative Affect (NA) were computed using the psycholinguistic lexicon LIWC (http://www.liwc.net/). LIWC's emotion categories are large in size, broad in usage and semantics, and have been scientifically validated to work on Internet language (see [29] for psychometric information), as well as for affect computation (see [14] for their usage in short text data, in the context of Twitter). For the third and fourth measures, activation and dominance, we utilized the ANEW lexicon [4]. This resource provides a set of normative emotional ratings for a large number of words in the English language. The approximately 2000 words in ANEW have ratings in terms of pleasure, arousal, and dominance (over a 1-10 scale); and can therefore be suitably used to measure activation and dominance measures of Twitter posts.

(1) *Positive Affect (PA).* We define a measure of *positive affect* (PA) of the new mothers, during the prenatal and postnatal periods respectively. We focus on the words in the positive emotion category of LIWC [14]. Given a post from a new mother posted during a certain day, thereafter we perform a regular expression match exercise to determine the fraction of words that match the words in LIWC's positive emotion category. This fraction gives the measure of PA per mother, per post.

(2) *Negative Affect (NA).* Like PA, we also define a measure of *negative affect* (NA) averaged over all mothers, during the prenatal and postnatal periods respectively. We again utilize LIWC for its negative affect categories: 'negative emotion', 'anger', 'anxiety', 'sadness' [14]. Based on the same word spotting technique, we measure NA per day, per mother.

(3) *Activation*. Our third emotion attribute is called *activation*. Activation measures the intensity of an emotion; hence it is an important dimension beyond PA and NA. As an example, while *frustrated* and *infuriated* are both negative emotions, *infuriated* is higher in activation. We adopt the ANEW lexicon [4] to determine the activation level of a given post for a mother, during the prenatal and postnatal periods. As with affect measurement, we follow a regular expression match exercise to spot for ANEW words in a post. Thereafter, using the corresponding activation values of each such word from ANEW, we determine a mean measure of activation per post, given a mother.

(4) *Dominance*. The fourth emotion-based behavioral attribute is called dominance. It represents the controlling and dominant nature of an emotion. For instance while both *fear* and *anger* are negative emotions, *anger* is a dominant emotion, while *fear* is a submissive emotion. We again use the ANEW resource, and follow the same technique as activation measurement to determine the mean dominance of posts from each mother.

Linguistic Style Measures. We also introduce measures to characterize behavioral change, based on the use of linguistic styles in posts by mothers, during the prenatal and the postnatal periods. Linguistic styles capture how language is used by individuals and provide information about their behavioral characteristics subject to their social environment [29]. Typically researchers [27,29,33,38] have observed the usage of linguistic features, such as parts of speech that represent references and relationships in characterizing style [8].

We again use LIWC for determining 22 specific linguistic style markers including: articles, auxiliary verbs, conjunctions, adverbs, impersonal pronouns, personal pronouns, prepositions, functional words, fillers, assent, negation, certainty and quantifiers. To determine the usage of various linguistic styles, we again use a regular expression match exercise to find the proportion of each type of linguistic style words in a post from a mother. The mean value over all posts from a mother gives the final measure, per style.

PRENATAL—POSTNATAL COMPARISON

We now explore the behavioral differences of new mothers in the prenatal and postnatal periods, using the three categories of measures defined in the previous section.

Comparison with a Background Cohort

Our first study examines variations in behavior on Twitter by the new mothers compared to the average Twitter user. For this purpose, we sample a random set of 50,000 users from the Firehose stream over the same timeframe to ensure consistency in comparison. We collect all of the posts shared for each general user over the time period, and then compute the daily behavioral measures using the methods discussed in the previous section. We refer to this sample as the *background cohort*.

We now report trend analyses of the measures over the studied time frame, contrasting the new mothers with the background cohort. In the set of trend analyses displayed in Figure 1, blue lines within each panel show the demarcation between the prenatal and the postnatal time periods; beige lines represent trends of mothers while green lines show the trends for the background cohort. For brevity and clarity, for the linguistic style category, we show only the usage of 1st person pronoun and the 3rd person pronoun which have been found to be demonstrative of particular characteristics of human emotion, including depression [29].

To quantify comparisons of these trends, we report in Table 2 the difference of means of behavioral measures, for each of the following four comparisons: the difference in behavior of background cohort between the time periods *after* and *prior* to childbirth (BA-BP); the change of behavior of new mothers between the time periods *after* childbirth with respect to *prior* (MA-MP); the change of behavior of new mothers compared to that of background cohort during the time period *prior* to childbirth (MP-BP); and the change of behavior of new mothers compared to that of background cohort during the time period *after* to childbirth (MA-BA). To further illustrate our findings from a qualitative perspective, we report a set of randomly selected example posts in Table 3, for all of the cohorts – MA, MP and BP, BA together.

The trends and difference of means of behavioral measures in Table 2 show evident distinctions between the mothers and background cohort after childbirth (MA-BA), including drops in posting volume and in PA, and an increase in NA (see Table 3 for an example of high NA post; also see the posts from the background cohort). Use of 1st person pronouns increases, while that of 2nd and 3rd person pronouns falls off. For these measures, we find that the differences between the mothers and the background cohort after pregnancy are statistically significant via independent sample *t*-tests (see Table 2 for details).

The mothers also show changes in behavior after childbirth, with most MA-MP measures showing statistically significant change based on *t*-tests (again, for mean

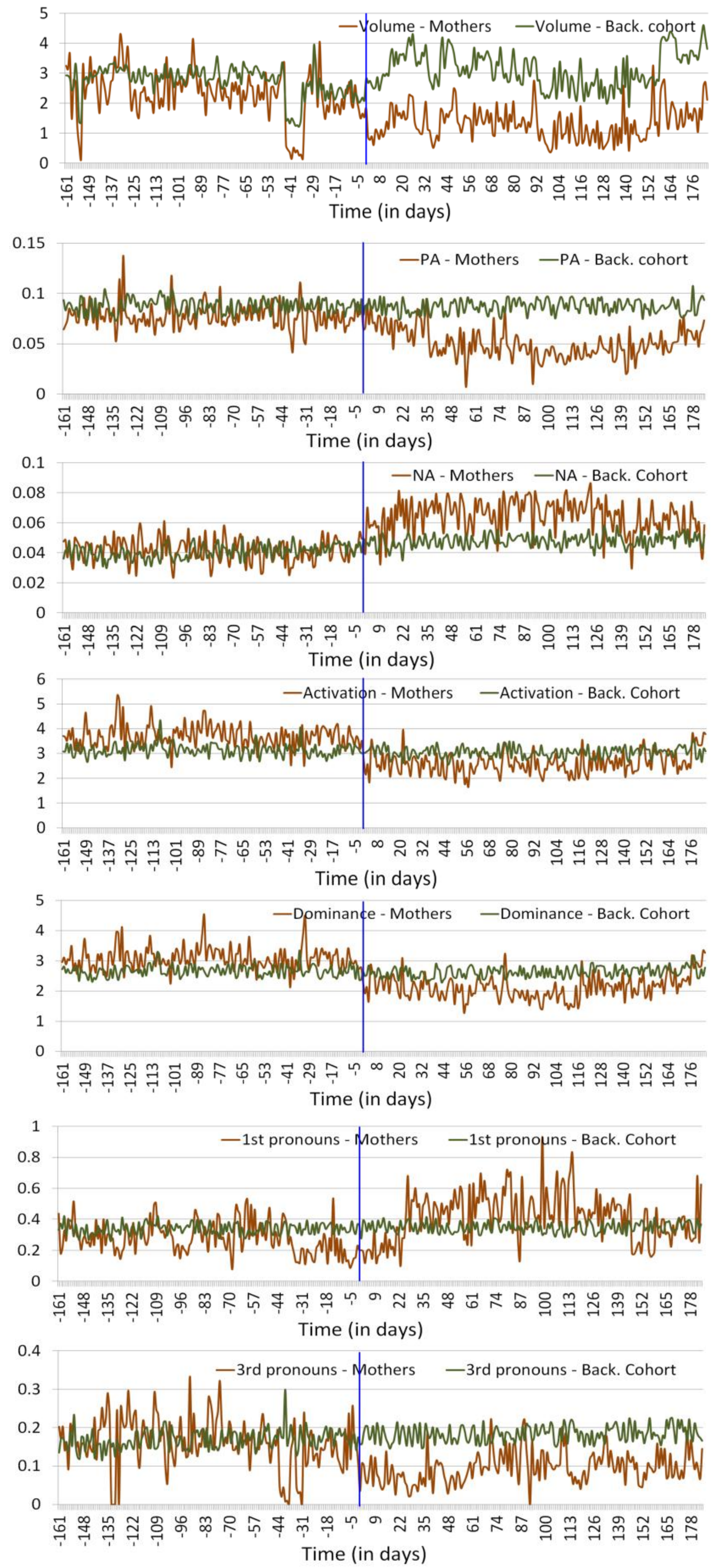

Figure 1. Comparison of behavioral measures between new mothers and the background cohort: volume (posts per day), Positive Affect (PA), Negative Affect (NA), Activation, Dominance, use of 1st person pronouns, use of 3rd person pronouns. Blue line represents the approximate time of childbirth.

amounts and directionality of change, see Table 2). The overall volumes of posting drops, indicating that on average women are posting less, suggesting a possible loss of social connectedness following childbirth. Arguably this is expected given the time demands following the birth of a child, and the example posts in Table 3 (e.g. post (4)'s reference to lack of socialization) for the MA group supports this observation qualitatively as well. Within the content they do post, however, we see a drop in PA and increase in NA, a shift potentially attributable to the mother's physical, mental and emotional exhaustion [10], as well as the sleep deprivation typical of parenting a newborn. The NA trend (and to some extent the PA trend) for the mothers during the postnatal phase exhibits much higher variance, compared to that during the prenatal phase, possibly reflecting mood swings among the new mothers [13] as well as increased anxiety or being overwhelmed frequently but inconsistently. Post (2) indicating depressing feelings and helplessness attitudes, and post (3) in Table 3 for the MA group indicating anxiety and panic attacks, further bolster this observation.

Measures	BA-BP	MP-BP	MA-BA	MA-MP
Volume	0.053	-0.837	-1.5242***	-1.3958***
PA	0.001	-0.014	-0.0483***	-0.0294***
NA	0.002	0.008	0.0325**	0.0362**
Activation	0.049	0.575	-0.6924**	-1.6539**
Dominance	-0.025	0.592	-0.7249**	-1.3473**
1st pronouns	0.006	-0.062	0.1272**	0.1698***
3rd pronouns	-0.008	-0.026	-0.1993***	-0.1868***
2nd pronouns	0.023	0.041	-0.1267***	-0.1357***
Indefinite pronouns	0.007	-0.018	0.0324*	0.0215*
Articles	0.009	0.014	0.0984**	0.1486***
Verbs	0.010	-0.044*	-0.0443*	-0.0584**
Aux-verbs	-0.007	0.019	-0.0357*	-0.0311*
Adverbs	0.025	0.033	0.0526**	0.0942***
Tentative	-0.004	0.019	0.0115	0.0112
Func. Words	-0.006	0.007	0.0072	-0.0064
Negation	-0.008	0.078*	0.0891**	0.0954***
Inhibition	0.003	-0.007	0.0316*	0.022*
Assent	0.022	-0.031	-0.0521**	-0.0694**
Certainty	-0.023	-0.037	-0.0597**	-0.0647**
Conjunction	0.048	0.083*	0.0119**	0.1391***
Preposition	0.003	0.008	-0.0173	-0.0123
Inclusive	-0.002	-0.004	0.0073	0.0194*
Exclusive	0.002	-0.007	-0.0086	-0.0099
Swear	0.005	0.022	0.0618**	0.0777***
Quantifier	-0.013	-0.019	-0.0261	-0.0363
Non-fluency	0.043	0.062	0.0913*	0.1531**
Filler	-0.002	0.008	0.0294	0.0592*

* $p < 0.01$; ** $p < .001$; *** $p < .0001$

Table 2. Difference of means computed over various behavioral measures comparing new mothers and background cohort. Note that the differences for each measure are on different scales. Each column corresponds to change of behavior between two sets: e.g., (MA-BA) implies change of MA with respect to BA. Here BP and BA represent the background cohort prior to and after the childbirth, while MP and MA represent new mothers prior to and after childbirth.

The activation and dominance measures also drop during the postnatal phase indicating a decrease in arousal, again potentially attributed physical and mental exhaustion or some form of "maternity/baby blues." Maternity blues typically exhibits as a heightened emotional state that can affect 80% or more of new mothers following the birth of a baby [25]. We conjecture that new mothers are likely to experience overwhelming fatigue from handling daily tasks around taking care of the baby and thus are more likely to express moods of low intensity (low activation) and more submission (low dominance). For instance, posts (1), (2) and (3) for the MA group in Table 3 (note words like "miserable," "frustrated," "disappointing") show that mothers are describing their perceived helplessness in caring for their babies, and consequently appear to be expressing negativity of low arousal and dominance.

Mothers after childbirth (MA)
1) `[high NA]` Ugh, my daughter hates her bassinet. I hate disappointing her. What a miserable day.
2) `[low activation]` My baby is only catnapping during the day. That's so sad and depressing. I feel helpless
3) `[low dominance]` Anxiety/panic attacks need to eff off!!!!!!!!!!!!!! I'm trying to lead a somewhat normal life with my baby!!!! #frustrated #miserable
4) `[high 1st person pronoun use]` No lie I fuckin miss all socializing..... my daughter keeps me occupied and exhausted. I have all my moments of the day
Mothers before childbirth (MP)
1) Derek & I sat on our screened in back porch listening to the thunderstorm & rain! So peaceful! Just to think in 35 hours we'll be parents!
2) Pregnant for the first time and I'm afraid I won't be able to stand the labor pain. Husband trying to reassure me, but he seems scared too. Thoughts????
3) I'm completely thrilled at the prospect of becoming a mother but the weight gain is bothering me :(:(. Do I just need to get over myself'? Am I the only one :S
4) Days are getting busy!!! Need to start packing for the hospital, in case the baby is coming early!
Background cohort (BP, BA)
1) @some_user lol they would have called the police girl. ooh and ma make chicken and rice tonight. I was like oooh she is gonna be mad…
2) I've waited too long for that and I'm okay if I have to wait again for 1 or 2 weeks maybe. But please don't let me down.
3) Whenever someone tells me they're a fan of Lady Gaga, I smile and just go "Me too!" but in my mind I'm like <some_url>

Table 3. Example posts from MA, MP, BA and BP cohorts.

Similarly, the use of certain linguistic styles, particularly, 1st person pronouns increases, while use of 3rd person pronouns drops, possibly reflecting the emotional distancing many new mothers go through after childbirth [19,30]. The example post (4) in Table 3 for mothers after childbirth indicates this qualitatively as well. In this post, the particular mother appears to be experiencing exhaustion and pain, thereby exhibiting attention drawn to herself; hence subsequently is found to use more first-person singular pronouns.

Though shown only in Table 2, we also observe increased use of articles, adverbs, conjunctions, swear, and negation style categories during postnatal phase for the set of assumed new mothers following childbirth with respect to the background cohort, as well as themselves before the birth of their child. Prior literature supports high usage of these styles with expression of negative emotion, or illness [6,29,38] that might correspond to the circumstances of some of the new mothers.

On the other hand, the difference of mean values of measures in Table 1, along with the example posts in Table 3, confirms an expected lack of change in the background cohort. Finally, the trends in Figure 1 reveal slight differences between the mothers and the background cohort *before* childbirth, suggesting an effect for pregnancy reflected in social media behavior (perhaps due to insomnia, exhaustion, physical discomfort etc.). In fact, these aspects are apparent in the posts for the MP group in Table 3, where mothers are discussing concerns around weight gain (post (3)), labor pain (post (2)), and preparations prior to the birth-related hospital trip (post (4)). In essence, pregnancy is likely to disrupt mothers' normal social media activities to some extent, explaining the seemingly minor differences with respect to the background cohort. However several of these differences are not found to be statistically significant (see Table 2), likely because the variance across the mothers is notably high (see, for example, the high variance in use of 3rd person pronouns in Figure 1).

In summary, we note here broadly that *t*-tests of means for various measures have shown statistically significant differences between pairs of cohorts. However we notice that it is possible that with our small sample size, these significant effects could be a result of a handful of extreme-change mothers who have shown considerable behavioral anomaly, i.e., they changed more than others. Identifying these mothers specifically may have implications in terms of detecting any seemingly serious behavioral disorder via development of new services and applications. Hence we focus more deeply on identifying individual level changes in our sample of new mothers in the following subsection.

Individual-level Comparison

To start, Figure 2 shows heat map visualizations of individual-level change for two measures: positive affect and activation. For brevity considerations, we focus on these two measures as illustrative examples of variance in change across the new mothers, though we note that most

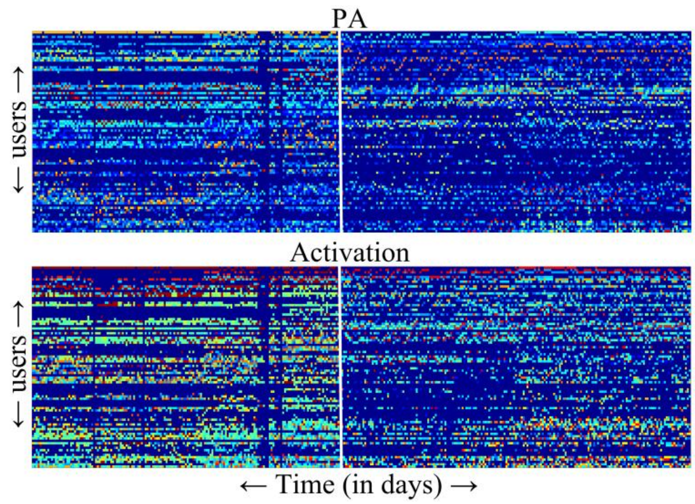

Figure 2. Heat map visualizations show individual level changes for positive affect and activation in the postnatal period, in comparison to the prenatal phase. New mothers are represented in rows, time (in days) by columns. The colormap uses an RGB scale where red represents greater values while blue represents smaller values of each measure. The white line demarcation in each heat map shows the estimated time of childbirth.

measures showed similar patterns, as evidenced by the changes in the aggregated measures shown in Figure 1 and Table 2. The heat maps show decreases in PA and activation following childbirth for many mothers, but also give a sense of the variability across mothers, with some changing very little and some changing in the opposite direction of the majority.

Measure	Small effect	Medium effect	Large effect
Activity	38	29	*20*
Emotion	17	4	*12*
Style	43	3	*18*

Table 4. Effect sizes (based on Cohen's *d*) over the three types of measures. Numbers indicate the number of new mothers showing changes following childbirth of each effect size.

We formalize the individual-level differences across mothers by computing Cohen's *d*, per mother and per measure, in order to distinguish sets of mothers with small, medium and large effect sizes (considered as $d >= .2$, .5., and .8 respectively) . That is, for each mother individually, we computed the effect size of the change in their scores on the measures before and after childbirth in order to determine the extent to which they changed. We report the number of mothers with changes of the three effect sizes in each of the three measure categories in Table 2. In order for a mother to be included in an effect size category, she had to change at that level across *all* measures within the category. Thus the numbers in Table 2 do not sum to our total number of 85 mothers, as some mothers did not change even at small effect size amounts.

To summarize, from Table 2 we observe that, although there is a substantial number of mothers with large effect sizes for each measurement category, activity and linguistic style measures show relatively larger number of mothers with large effect size changes. While fewer mothers undergo such changes for the emotion measures, on combining across all measure types, it turns out that the 12 mothers who show large effect changes for emotion measures also show large effect changes for the activity and the style measures. This set of 12 mothers then is the set of mothers whose behavior changes the most in the postnatal period across all measures, and stands out as having changed more broadly and more substantially than the other mothers studied in our data. For comparison purposes, we perform the same exercise to determine the set of mothers who show small effects consistently across all measure types, which comes to 15 mothers.

SIGNIFICANT CHANGE POSTPARTUM

In this final section, we explore in depth, the behavioral change of the mothers with large effects.

Mothers w/ small effects
1) I know some drs say it's ok to be on meds while breastfeeding but it kind of freaks me out cause it isn't proven longterm for baby's health.
2) Days are passing by as I watch my son grow! Can't wait for more and get together with the daddy!! Wish he was here
3) Just adjusting to having a new baby, new job and we just moved town. Need to calm down. Tips/suggestions on parenting, mothers??
4) Ugh... returning to work. I'm trying to enjoy these last few days with my baby...but all I can think about is that I will be leaving him for 10 hrs a day
5) I'm taking expressed breastmilk from the fridge on outings in the diaper bag and keeping it cool with an ice pack. Someone tried it?
Mothers w/ large effects
1) This is my first baby, feel so blessed!! But angry abt being sick all the time. I guess my hormones haven't taken nicely to this big change?
2) Starting to feel lost. I'm missing my love, my baby. Feel angry n disappointed in myself. Idk what to think or do....
3) My first time being alone with my baby and I cant stop crying. What is wrong with me? Am I depressed? Im just over here balling my eyes out
4) My DS doesnt sleep more than 3 hrs at a time and cries often and is so difficult to calm down. Cant remember when was the last time I slept
5) Feel like having a breakdown! ...like the WORST mother... feel so terribly that this poor child is stuck with this horrible monster mother..

Table 5. Randomly sampled posts from mothers with small and large effect sizes.

In the light of the two behaviorally distinct sets of mothers identified (large and small effect sizes), we first present a more rigorous qualitative examination of data characterizing the mothers with small and large effect sizes. We present *randomly sampled* example posts from the two cohorts in Table 5. A qualitative comparison of the nature of content shared by the two cohorts reveals that the mothers with large effects exhibit signals that are likely indicative of a lowered sense of social support ("Starting to feel lost.."), generally unhappy postings ("Feel angry n disappointed…", and even possible mental instability ("Feel like having a breakdown!", "balling my eyes out", "horrible monster mother"). Feelings expressed include anger, frustration and depression (posts (1), (3), (5)), lack of a sense of connectedness (posts (2), (3)), as well as physical discomfort and concerns about the baby (post (4)). On the other hand, the content from mothers with small effect sizes, although aligned with topics relating to bringing up the baby and expressing some sense of negativity ("Just adjusting…Need to calm down."), is less emotion-laden. For instance, we find that these mothers are using Twitter to invite comments and suggestions on their problems around typical adjustments to having a new baby–work-life balance, issues with breastfeeding and so on (posts (3), (5)).

Language Differences

Next we quantify these seemingly qualitative differences through a comparison of the overall language change (change in usage of stop word eliminated unigrams) of the set of mothers with large effects, with respect to the set of mothers with small effects, as well as the background cohort. The goal is to be able to determine *what* language accounts for the distinctive change of behavior among the mothers with large effects.

To this end, we first use the Euclidian distance measure to compute a numerical distance score between the usage frequencies of unigrams in the two sets (one corresponding to the prenatal phase, the other to the postnatal period) for each group. (We experimented with other distance measures like cosine similarity and Janssen-Shannon divergence, which showed similar results.) The word usage distributions are then sorted by the absolute amount of change, regardless of direction since Euclidian distance is a symmetric measure. Table 6 lists the unigrams showing the most change in usage for each of the three groups in the postnatal period, compared to the prenatal phase. In order to get a sense of the directionality of change, we compare the relative volumes postpartum with respect to prenatal, and show the +ve or –ve direction of change as ↑ or ↓ respectively. Again, note that these are relative changes, meaning that the top changing words for the background cohort do not necessarily change as much as those for the mothers with large effect changes.

We observe that the type of unigrams that change significantly vary substantially across the three groups. The background cohort's changes are mostly in words related to commonplace details of daily life (e.g., *tonight*, *here*, *morning*, *tomorrow*). For mothers with small effects, there is some evidence of going through the early childbirth phase (e.g., *fired*, *wait*, *days*). This reinforces our qualitative observation from Table 5 wherein we found these mothers using Twitter to seek support and feedback on their problems around typical baby upbringing issues. On the other hand, for the mothers with large effects, many words are emotional in nature (e.g., *aww, blessed, love*), again confirming the qualitative observations from Table 5 – see the usage of *blessed* in post (1) and the general affectionate postings (2) and (5) towards the baby.

Directionality of change in these words in Table 6 is critical. Considering the drops in PA and increases in NA shown earlier, along with the qualitative observations from Table 5, the observation from Table 7 that many of the changes of the emotion words are in a negative direction for the mothers with large effects, seems reasonable. For instance, use of *haha* and *lol*, frequently used terms of joviality expression in social media, are seen to drop sharply for mothers with large effect size. In fact, the example posts in Table 5 weighing heavy on negativity and social isolation make it further apparent why these mothers are not using these joviality words.

Background cohort	Mothers w/ small effects	Mothers w/ large effects
now **(↓)**, shit **(↑)**, back **(↑)**, that **(↑)**, day **(↓)**, life **(↑)**, time **(↓)**, them **(↑)**, me **(↑)**, you **(↑)**, fuck **(↑)**, today **(↓)**, sleep **(↑)**, tonight **(↓)**, love **(↓)**, good **(↓)**, here**(↓)**, her **(↓)**, morning **(↑)**, tomorrow **(↑)**, go **(↑)**, know **(↑)**, him **(↓)**, people **(↓)**	#past (↑), duh (↑), people (↓), photo (↑), post (↑), decision (↓), reunite (↓), women (↑), story (↑), time (↑), asap (↓), do (↑), life (↓), wait (↑), fired (↑), days (↑), happy (↓)	haha (↓), blessed (↑), lol (↓), #lifecangetbetter (↑), awesome (↓), monthly (↑), fantastic (↓), cuddle (↑), home (↑), love (↓), sick (↑), aww (↑), scary (↑)

Table 6. Top unigrams showing the most change (in usage frequency) in the postnatal period, compared to the prenatal phase, for background cohort, mothers with small effects, and mothers with large effects.

Unigram Difference Analysis

Motivated by the noticeable differences in language use among various groups, we explored the question of determining the number of unigrams whose change in usage frequencies actually renders the mothers with large effects significantly different from the background cohort and those with small effects. For the purpose, we introduce a greedy unigram elimination exercise for the mothers with large effects. Starting with unigrams exhibiting the most change (in usage frequency) in the postnatal phase compared to prenatal, we eliminate in a greedy iterative manner unigrams from the lexicon of all unigrams for this group, computing the Euclidian distance at each elimination step, with respect to the other two groups. Naturally, as more unigrams with big change are eliminated, the Euclidian distance of language of the mothers with large effects consistently approaches that of the other two groups. The iteration(s) at which the distance becomes equal to that of the mothers with small effects (or the background cohort) can be taken as an indicator of language change in the postnatal period compared to the prenatal phase.

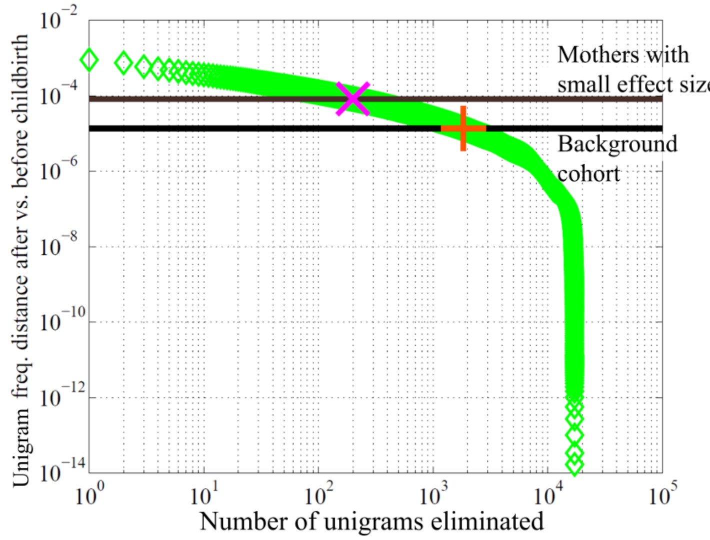

Figure 3. Unigram difference technique to determine empirical thresholds defining the language change corresponding to the mothers with large effects, with respect to those with small effects and the background cohort.

The results of this greedy unigram elimination exercise and the two unigram difference measures identified during this process are shown in Figure 3. The first difference measure is observed when, after the elimination of top 199 unigrams with biggest change, the distance of language usage frequencies of mothers with large effects becomes the same as that of those with small effects. Further, we also encounter a second difference measure following the elimination of the top 1837 unigrams with most change, wherein the language distance of the mothers with large effects becomes equal to that of the background cohort.

The two unigram difference measures suggest that the deviations observed for the mothers showing large effect size changes are captured by a rather small number of unigrams (merely 1.16% of entire unigram vocabulary compared to mothers with small effects; 10.73% with respect to the background cohort), or in other words, *a narrow span of language*. This tells us that the changes in the activity, emotion and stylistic measures we observed earlier appear to be subject to big changes in the usage frequencies of a only few words. Plausibly, an exciting future direction would be to utilize these thresholds, as well as the unigrams that drive significant change, in a language model-based prediction framework to forecast unusual behavioral change of individuals over time.

DISCUSSION

Theoretical Implications

Through a case study around childbirth, we have demonstrated how the measurement of behavior in social media can help us analyze changes around important life events. We found that, for a certain number of mothers (14-15%), activity goes down, PA goes down, NA goes up, activation and dominance go down together, and the use of 1st person pronouns goes up, while that of 3rd person pronouns goes down. We also notice that certain mothers consistently show these dynamics over the entire postnatal period of our analysis. In essence, we find that there are new mothers who are exhibiting signs of decreased social interactions, as manifested through social media, along with a number of changes in emotional expression in a generally negative direction. A peek into psycholinguistic research literature will reveal that these behavioral markers have been associated with depression of individuals [6]. In particular, isolation and loneliness are known risk factors for depression and lowered self-esteem.

An exciting implication and future direction is the possibility of leveraging social media for unobtrusive diagnostic measures of emotional disorders in new mothers, such as postpartum depression (PPD). Such modeling can be extended in future work to making predictions *in advance of birth* about those mothers who are at high risk of suffering with an emotional disorder following the birth of the child they are carrying. Our detected group of approximately 15% of new mothers who showed broad and significant changes in behavioral and emotional expression following childbirth aligns with published reported rates of PPD in the United States [19]. The next step would involve validating these or similar social media-based measures with ground truth data on PPD. Establishing ground truth would also help address another diagnostic challenge: distinguishing actual depression from typical maternity blues. The literature suggests that maternity blues is transitory and usually ebbs within a couple of weeks after childbirth [25], and since large effect changes among some mothers were observed over a longer period of time (PPD can last up to an year following childbirth [10,19]), we may be seeing evidence of more than maternity blues changes, but we need ground truth data to justify this observation.

In the light of these observations, anonymous aggregated measurements of behavioral change of new mothers can thus inform governmental agencies, support groups, or the medical community at large of population-scale measurements of PPD.

Design Implications

Our approach and findings pave the way to several potential design implications. These include the development of automated services and tools for new mothers that can help monitor behavior and emotion in a nuanced manner, based on their social media activity. For instance, the tool could be a smartphone application that connects to the social sites the mother uses, and computes various measures over time to reveal trends in a private manner. On an individual level, monitoring some of these trends itself can serve as a self-narrative and help behavioral reflection. It could even act as an early warning mechanism to mothers with noticeably anomalous behavioral change, something especially relevant in the case of those mothers who might not be aware of their risk of PPD. By logging these trends, such an application could act as a diary-type data source to aid doctors or other trained professionals. In essence, emotional markers indicated by the tool may enable adjuvant diagnosis of postnatal disorders, complementary to survey based approaches such as the Edinburgh Postnatal Depression Scale [25], and help diagnosis or early intervention on the part of the caregivers (e.g., via psychotherapy treatments) for better health and wellness of women following childbirth.

Privacy and Ethical Considerations

Concerns regarding individual privacy, including certain ethical considerations, may arise with analyses of social media as they ultimately leverage information that may be considered sensitive, per centering on behavioral and emotional health [23]. Our hope is that our methodology can leverage publicly available data, paired with anonymous analyses whenever possible, to generate applications that are used in complete privacy by individuals. As mentioned earlier, in our case, all data are public and, with the exception of the relatively benign Mechanical Turk task of verifying Twitter users as moms who had recently given birth, all analyses were conducted anonymously. As suggested in our design implications, the privacy of the user can be honored with user-centric design of applications that restrict the sharing of such information to the user herself and optionally to a trained medical practitioner or support group. Nevertheless, this type of research, and consequently the type of findings it generates, needs to be considered with caution, and we encourage continued discussion of the topic by the research and practitioner community.

Limitations

We discuss some limitations of our measures and the techniques and tools used to compute them. For instance, we acknowledge the seeming inconsistency that ANEW was used for arousal and dominance, while LIWC was used for valence separated into positive and negative affect. This is because while LIWC is a promising resource used extensively for PA/NA computation [14], it does not support activation and dominance measures. The inconsistency of usage of two different lexica can therefore be attributed as a limitation of the availability of adequate linguistic tools.

Additionally, a lexicon-driven approach of determining emotions of users has some limitations. First, it takes into account merely self-reported affective words, and it is not known how effectively they truly reflect the psychological state of the individual. Second, it does not take into account negation that could be used in conjunction affective words (e.g., "not happy"). In our context, we argue that while these limitations may add a bit of noise to our data, they do not invalidate our findings because: (1) we consider posts of a particular user over a long time period, and given the large numbers of posts (often in thousands), we observe reasonably accurate psychological reflections of the users; and (2) we are interested in relative comparison across the prenatal and postnatal periods. Hence issues with a lexicon driven detection of emotion (e.g., use of negation) are likely to equally impact both periods. However, population scale measurements of behavior around childbirth would perhaps need advanced computing techniques of detecting emotion, such as through supervised and unsupervised learning techniques.

In terms of our findings, we acknowledge the small size of our data sample of new mothers. As early research in this domain, our work is a proof-of-concept and our purpose was to focus on a high-precision set of Twitter users with explicit evidence (on Twitter) of having given birth to a child. Our findings on this sample, quantitative and qualitative, align with observations in the psycholinguistic literature on behavioral changes around events (e.g. collective trauma [29]), which shows promise about their generalizability in larger populations, and are likely not simply an artifact of the statistical methods we used.

Moreover, while we learn that the changes in behavior in certain new mothers are often driven by a narrow range of words whose usage exhibit large change in postnatal period, it is not clear what would be the likely reasons at play behind the significant drop or rise of these words. These unobserved causes could include socio-economic factors, financial problems and so on. Availability of additional offline data of this nature can more comprehensively shed light on the underlying drivers of the behavioral changes.

Future Directions

Our studies show general promise in how activity patterns and language use in the social media posts of new mothers can reveal nuances of their behavioral and emotional change following a significant life event. By way of this specific set of behavioral phenomena on new mothers, we have thus attempted to lay the foundation for what we believe will be a rich line of research on harnessing signals from online social media activity to predict and forecast behavioral changes in individuals and for populations, and perhaps even provide valuable and timely interventions.

Opportunities therefore remain in terms of exploring social media-based measurement of other types of life events. These include loss of a job or financial instability (for understanding population scale unemployment dissatisfaction, or economic indicators); death related grief and bereavement or loss of safety after a trauma (to help individuals cope with surprising emotions and improve their quality of life) and so on.

CONCLUSION

Social media tools provide unique platforms to individuals for personal expression, allowing them share updates about their daily lives, including important life events. We conducted a case study on detecting behavioral changes of new mothers following childbirth, utilizing almost a year of their posts on Twitter. After obtaining a list of 85 new mothers via identifying birth-indicative Twitter posts as well as leveraging crowdsourcing tools, we proposed three categories of measures – activity, emotion and linguistic style to capture behavior of the mothers over the prenatal and postnatal periods. Our empirical studies provided two major findings. First, we observed that approximately 15% of the new mothers show significant change compared to other mothers and to a random set of Twitter users. Second, on examining what types of words characterize the language change of these new mothers, we were able to narrow down to a small set of 1-10% words that contributed towards the change of these mothers as expressed linguistically on Twitter. These sets of words define a distance measure, demarcating certain new mothers from the general population that might be used to detect behavioral health concerns postpartum and help promote wellness among new mothers.

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