

Characterizing and Predicting Postpartum Depression from Shared Facebook Data

Munmun De Choudhury Scott Counts Eric Horvitz Aaron Hoff

Microsoft Research, Redmond WA 98052
{munmund, counts, horvitz, aaron.hoff}@microsoft.com

ABSTRACT

The birth of a child is a major milestone in the life of parents. We leverage Facebook data shared voluntarily by 165 new mothers as streams of evidence for characterizing their postnatal experiences. We consider multiple measures including activity, social capital, emotion, and linguistic style in participants' Facebook data in pre- and postnatal periods. Our study includes detecting and predicting onset of post-partum depression (PPD). The work complements recent work on detecting and predicting significant postpartum changes in behavior, language, and affect from Twitter data. In contrast to prior studies, we gain access to ground truth on postpartum experiences via self-reports and a common psychometric instrument used to evaluate PPD. We develop a series of statistical models to predict, from data available before childbirth, a mother's likelihood of PPD. We corroborate our quantitative findings through interviews with mothers experiencing PPD. We find that increased social isolation and lowered availability of social capital on Facebook, are the best predictors of PPD in mothers.

Author Keywords

childbirth; emotion; health; language; postpartum; social media; Twitter; wellness

ACM Classification Keywords

H.3.4; H.5.2; H.5.3

INTRODUCTION

Childbirth is a major life event that changes the lives of parents. Beyond the joy and happiness of childbirth, a significant portion of new mothers experience changes in mood. Such postpartum changes include the "baby blues," lasting about 2-4 weeks after childbirth, and consisting of mild mood instability and anxiety. However, according to estimates from the CDC, about 12 to 20% of new mothers experience a mood disorder of greater severity and duration

called *postpartum depression* (<http://www.cdc.gov/reproductivehealth/Depression/>). PPD is marked by symptoms such as sadness, fatigue, changes in sleeping and eating patterns, reduced libido, crying episodes, anxiety, and irritability [2]. Beyond negative influence on mothers, there is evidence that PPD can bear short and long-term negative effects on the child's behavior, emotional, and social wellbeing [16].

Despite these ramifications, PPD is underreported, with estimates that as many as 50% of cases of PPD go undetected [29]. Underreporting is believed to be due to factors such as the fear of the social stigma of depression, lack of social support, or assumptions that the mood changes are a normal part of the overwhelming nature of new motherhood [7]. Additional barriers to help-seeking include lack of knowledge about predisposition symptoms, the availability of appropriate remedial/prevention services, or even privacy concerns [7].

What makes this form of medical condition even more challenging is that there are no adequate ways for prevention or early detection [39], unless a woman has had a history of depression in the past. Clinical diagnosis of PPD is based on the mother's self-reported experiences (e.g., DSM-IV criteria based on the mood module from the PRIME-MD—Primary Care Evaluation of Mental Disorders: the Diagnostic and Statistical Manual of Mental Disorders (DSM) published by the American Psychiatric Association provides a common language and widely relied upon standard criteria for the classification of mental disorders), prior depression history, life stress, behaviors reported by relatives or friends, and a mental status examination. Naturally, treatment efforts, that typically comprise medication, therapy, or both, are also more successful with early intervention; in fact, the likelihood of achieving full recovery declines as the illness lengthens [7].

Hence, there is value in innovative methods that can identify women at risk, even perhaps in the early stages of PPD, and provide them access to appropriate services and support. To the extent these methods can provide lower cost complements to traditional PPD assessments, they may help reach a larger portion of the population. Prevention efforts could alter women's lifetime trajectory of problems arising from mental illness, and avoid the serious social and medical ramifications associated with psychopathology.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

CSCW'14, February 15–19, 2014, Baltimore, Maryland, USA.

Copyright © 2014 ACM 978-1-4503-2540-0/14/02...\$15.00.

<http://dx.doi.org/10.1145/2531602.2531675>

A Digital Safety Net

We explore the use of online social networks as a lens on mood and behavior to glean insights about the postpartum experience of new mothers. Individuals are increasingly using online social networks and social media such as Facebook and Twitter to share updates about their daily ordeals, but also often to make announcements of major life milestones, including childbirth and parental milestones [4,13]. Data captured from social media can span new mothers' social activity, interactions with friends and other audiences, and emotional and linguistic expression. Consequently, it can provide a natural laboratory for researchers to study their behavior and experience of motherhood in general [4,5]. In fact, a body of work has emerged that has looked at whether the material posted on social networking site profiles accurately portrays someone's mental and physical state [5; 32]. For example, references to depression or drinking on Facebook are concurrently associated with self-reported depression rating scores [25], and postings of displayed risk behavior were found to be related to injuries as well as substance use or violence among college undergraduates [23].

Motivated along those lines, we consider the use of social media data to detect and predict PPD. The work complements earlier efforts to detect and predict postpartum changes in behavior, language, and affect from Twitter data. However, rather than rely on observed changes, in this work we gain access to ground truth on postpartum levels of depression and PPD diagnoses via both self-reports and use of a common psychometric instrument used to evaluate PPD.

Our main contributions include:

(1) We conduct an online survey to collect gold-standard labels of depression on 165 new mothers who use Facebook (scores on the PHQ-9 depression screening tool). We note here that the PHQ9 depression scores are critical as they allow us to distinguish new moms actually suffering from depression versus those that have changed behavior (e.g., posting less on Facebook) for more benign reasons like they simply are too busy with their new baby. Thereafter we characterize participants' Facebook behaviors over 50 weeks of prenatal period and 10 weeks of postnatal, totaling 600K postings on Facebook. We propose 49 different measures of mothers' activity on Facebook, including their available social capital, emotion, and linguistic style.

(2) We develop several statistical models to predict whether or not a mother will have PPD. A model that uses only prenatal data is found to explain as much as 31% of variance in the data, and improves upon a baseline model based on demographic and childbirth history data by 77%. Including a short time horizon (~1 month) after childbirth, we achieve better performance, where our model is found to explain up to 48% of variance in the data.

(3) We corroborate our quantitative findings through semi-structured interviews conducted with a sample of the mothers with PPD. We find that experiences of PPD are best predicted by increased social isolation as manifested in reduced social activity and interaction on Facebook, and decreased access to social capital. We find that emotional measures as captured through Facebook posts are not effective predictors of PPD, perhaps due to the stigma associated with depression.

We believe that this research can bring to the fore variables related to the exacerbation of PPD, thereby enabling new mechanisms to identify at-risk mothers, and provide guidance on valuable interventions. In general it could lay the groundwork for a future digital safety net to scaffold new mothers following an important phase transition in life.

BACKGROUND AND RELATED WORK

Clinical/Psychiatry Literature on PPD

A considerable body of work in psychiatry and the clinical literature is devoted to understanding PPD. Much of this work is survey-driven and relies on self-reported data. Surveys such as the Postpartum Depression Predictors Inventory (PPDI) [1] reflect meta-analyses of risk factors for PPD [2], including lack of social support, socioeconomic status, and infant temperament, among others (see [30] for more on risks and influencers of PPD). Lack of social support and social isolation in particular, along with psychological stress have been shown to influence the attitudes, emotions, and behaviors of new mothers [10,48]. In another study [46], Scott et al. found that the strongest predictors of PPD were past history of psychopathology and psychological disturbance during pregnancy, poor marital relationship, low social support, and stressful life events. Finally, Fleming et al. [11] observed that depressed mothers exhibited fewer affectionate contact behaviors (and in general lower maternal responsiveness) towards their infants postpartum, compared to non-depressed mothers.

Although not exhaustive, proxies for several risk factors of PPD, like the ones studied in prior literature, might be monitored via mothers' activities on social media like Facebook and Twitter. Social support and access to social capital might be inferred from a mother's degree of interaction with her contacts on social media. Further, infant temperament and maternal responsiveness might be measured through posts, photos, and videos the mother shares about her baby on Facebook, while stressful events in the past may have cues manifested in an individual's social media postings.

We note that little prior work has focused on *predicting* PPD. This is likely because collecting longitudinal data is difficult given the resources and invasiveness required to observe mothers behavior over months and years. Online social platforms like Facebook show promise in this regard: As

numerous people have been using these tools for years, there are opportunities to track behavioral patterns over time in fine granularity—in this case, before and after childbirth of the mothers to understand and identify predictive factors behind PPD.

New Mothers' Use of Social Media/Networks

Mothers are a growing demographic on the Internet—per NielsenWire polls in 2012, 72% mothers in the US use Facebook [28]. Over the years, several studies have focused on studying mothers' use of social technologies, such as blogging [22], motherhood and parenting forums [45,36], and Facebook [13]. McDaniel et al. [22] observed that new mothers' frequency of blogging was predictive of feelings of social connection to extended family and friends, of social support, and of maternal wellbeing. Based on ethnographic studies, Gibson and Hanson [13] observed that Facebook was perceived as a valuable platform by new mothers in being able to remain socially connected with others postpartum, to construct a new identity, or to seek information and reassurance on their choices and concerns around rearing a newborn. Schoenebeck [45] found that postings made on the anonymous message board YouBeMom.com define new types of social norms and expectations shaping online mom culture.

The prior work suggests that online social technologies may be providing new mothers with mechanisms to utilize their social capital and to find a disinhibiting outlet for communication, venting, and sharing baby tips. We pursue the use of streams of online social activity to understand the role of online social support or its lack in PPD.

In related work, De Choudhury et al. analyzed Twitter postings of new mothers to detect [4] and to predict [5] extreme behavioral changes postpartum. The studies did not gain access to ground truth data on PPD outcomes, but rather relied on the sensing of extreme changes in Twitter. To the best of our knowledge, this paper presents the first of its kind study identifying predictors of postpartum depression based on new mothers' use of Facebook.

Social Media/Networks in Health and Wellness

Beyond PPD, researchers have been increasingly interested in understanding how social media activities can be used to infer the wellbeing of people, and conditions and symptoms related to diseases [36] and disease contagion, e.g., flu [48]. Facebook use has been shown to help those with lower self-esteem to attain higher social capital [47]. Moreno et al., [24] demonstrated that status updates on Facebook could reveal symptoms of major depressive episodes, while Park et al. [32] found differences in the perception of Twitter use between depressed and non-depressed users—the former found value in Twitter due to the ability to garner social awareness and engage in emotional interaction. On similar lines, De Choudhury et al. [6] examined year-long Twitter postings of individuals suffering from major depressive

disorder to build statistical models that predict the future occurrence of depression.

A common thread in this research is how computational techniques may be applied to naturalistic data that people share on today's online social platforms to infer their health condition. These techniques are rooted in findings in the social science literature, where computerized analysis of language and social network analysis has revealed markers of depression [42], anxiety, and other psychological disorders [31,43]. Weaving together these ideas, we conjecture that linguistic and activity analyses, and notions of social capital manifested in online social platforms can offer a novel methodology for augmenting traditional approaches to measuring and predicting risk for PPD.

FACEBOOK DATA COLLECTION

We conducted an online survey to collect information about PPD experiences of new mothers, and to gain access to their Facebook data for our analyses, with their consent. The survey website was active between mid-July and mid-September, 2012. It was advertised through multiple channels so as to reach a diverse population of new mothers in the US—mailing lists of new mothers within our organization and the broader community in our metropolitan area (e.g., neighborhood based mommy blogs), postings from our organization's official Twitter and Facebook accounts as well as the authors' personal Twitter, Facebook and Google+ accounts, paid Facebook ads targeting mothers in the age group 20-39 years, and finally sponsored posts on BabyCenter (babycenter.com), a popular website aimed at mothers that hosts discussion forums and parenting articles.

We recruited mothers who were owners of a Facebook account and who gave birth to a child within the last nine months or less, so that we could capture their experiences with postpartum depression while they were possibly still persistent. To incentivize participation and to acknowledge the mothers for their time and effort, they were entered into the random drawing of four \$500 Amazon gift cards.

PPD Survey

In the survey of participants, we collected demographic data of the mothers (age, family income, occupation), and data related to the child/childbirth experience, including the child's birthdate, whether the child is the first-born, and whether the mother had been diagnosed with PPD by a clinician at some point following childbirth. The survey also inquired about the different ways the mothers used Facebook—for status updates, photo-sharing, and so on.

In addition to the survey we gave participants a PHQ-9 (Patient Health Questionnaire) depression screening tool [20] to detect whether mothers were currently depressed. Specifically, the questionnaire seeks responses over the past two week period, on the frequency of experiences like “*little interest or pleasure in doing things*”; “*feeling tired or having little energy*”. Scores on the PHQ-9 range from zero to 27, where higher scores indicate the presence of more

symptomology. Per psychiatric literature [20], individuals with scores greater than or equal to 15 are considered to be moderately severe to severely depressed.

Following the PHQ-9 questionnaire, mothers were asked to optionally authorize a Facebook application, with the goal of allowing us a one-time crawl of their Facebook timeline data. For each of the mothers who opted-in, we archived a data dump of the following timeline data: status updates that they both shared and were tagged in (both content and time), captions associated with photos, videos, and links they shared or were tagged in, and *like* and comment counts on all these items (statuses, photos, videos, links, check-ins). Note that actual photos and videos were not crawled, in the interest of the participants’ privacy.

		PHQ-9 Score	
		<i>no</i>	<i>yes</i>
Self-report	<i>no</i>	137	9
	<i>yes</i>	13	15
No PPD		137	
PPD			28
Total		165	

Table 1. Mothers with PPD based on self-report and PHQ-9 depression severity scoring.

Constructing PPD Ground Truth

Running this online survey gave us 292 responses. After dismissal of incomplete surveys we obtained 267, out of which 174 also opted-in to grant us access to use their Facebook data for our research (59.58% of total responses). We wished to focus on the subset of the mothers for whom we could validate their self-reported PPD condition, as well as their PHQ-9 questionnaire scores. That is, the set of mothers who reported to have never been diagnosed with PPD, as well as scored negatively on the questionnaire; and those who reported to have had PPD following childbirth, with current PHQ-9 score to be either in the positive PPD range (persistent PPD), or in the negative PPD range (receded PPD).

Using the standard depression severity scoring of PHQ-9 as mentioned above, we present a confusion matrix of the number of mothers with self-reported PPD (yes/no) and PHQ-9 diagnosed PPD (yes/no) in Table 1. Note that per the reasoning presented earlier, we obtain 28 mothers with experiences of PPD following childbirth, while 137 with no PPD experience at any point in time. We also note here that mothers who self-reported to have no PPD, but scored positively in PPD severity in the questionnaire were ignored, since we could not be sure of their actual/true PPD experience, or the possibility that responses on the PHQ-9 questionnaire could simply be noisy. The number of mothers (28, or 16.7% of the sample population) who were detected to have had PPD is toward the higher end of the CDC estimate of mothers suffering from PPD in the United States. We acknowledge here that it might reflect a bias in our recruitment strategy—some of the ads, especially ones on babycenter.com were posted on a forum around PPD—our

goal was to ensure we are able to recruit sufficient number of mothers with PPD for reliable statistical analyses. However this number still aligns with most studies conducted around depression and mental illness [6].

Dataset Statistics

We now discuss some statistics of our dataset of mothers. First, in Table 2, we present some demographic information such as age, income, ethnicity, and top five occupation types of the mothers with and without PPD. We do not see any statistically significant differences between no PPD and PPD groups for age (based on an independent sample *t*-test); however we do observe that mothers with PPD tend to be of lower income levels ($p < 0.01$) and more likely to be “stay-at-home moms” (24%). For ethnicity, we observe that the majority of the mothers in our dataset are “Caucasian” which may indicate a bias in the respondent-driven sampling method we adopted in our survey.

Age	all	no PPD	PPD
Median age	31	31	30
Average age	30.36875	30.582	29.645
Income			
Median income	80,000	85,500	55,000
Average income	96,127.48	102,040.	72,724.1
		9	4
Ethnicity			
African-American	3	3	0
Asian	17	17	0
Caucasian	127	98	29
Latino/Hispanic	9	6	3
Native American	2	2	0
Other	3	2	1
Occupation			
Stay at Home Mom	50	38	12
Computer & Mathematical	21	20	1
Education, Training, & Lib.	14	12	2
Business & Financial Op.	9	9	0
Healthcare Practitioner	8	4	4

Table 2. Demographics of mothers with and without PPD.

We observe that mothers giving birth to a second or later child have considerably higher chances of having PPD (67.12%), compared to those giving birth to their first kid (37.78%). We also observe that premature childbirth had little association with PPD—among the mothers who had PPD, only 13.33% reported having given birth to a premature child, while it was 10.2% for those without PPD.

Facebook Data

We now present some characteristics of the Facebook data dump that we collected for the set of 165 mothers. For each mother, we created two separate data files—one spanning the prenatal period, and the other the postnatal period. In Figure 1, we show cumulative distributions of the duration span of prenatal and postnatal data we could collect from the Facebook dumps of the mothers. We notice that for the set of 165 mothers, we have up to 50 weeks of prenatal data, while for postnatal data, for the same set of mothers we have access to up to 10 weeks of data. Note that 50 weeks is almost close

to a year, which gives us ample data to observe manifestations of prenatal depression, or even early signs of PPD. Focusing on 10 weeks of postnatal data consistently for all mothers gives us sufficient time to observe PPD related changes following childbirth. Several studies on PPD in the clinical literature has focused on similar timeframes (e.g., O’Hara et al. [29] identified predictors of PPD at the 2nd trimester of pregnancy, while Fleming et al. in [11] studied PPD at 3 months postpartum).

Based on the above time frames, combining the prenatal and postpartum periods, we obtained 578,220 items that were posted by the 165 mothers (combining wall posts, photos, videos, links, check-ins), which had 534,123 likes and 487,072 comments. In terms of the posts received on the timelines (i.e., posts in which the mothers were tagged in by friends), there were 21,078 posts in all, with 24,259 likes and 23,830 comments.

MEASURING BEHAVIORAL CHARACTERISTICS

We now present a number of measures that we used to characterize the behavior of the mothers. Unless otherwise mentioned, we use *posts* to refer to any item shared/received on a mother’s timeline that can be a wall post, a photo, video, link or a check-in.

User Characteristics

We define seven different *user characteristics* that measure a user’s nature of activity on Facebook. The first three measures include: the *number of status updates* made by a mother; the *number of media items* (photos/videos) uploaded by a mother; and *number of wall posts she made to specific friends* on Facebook.

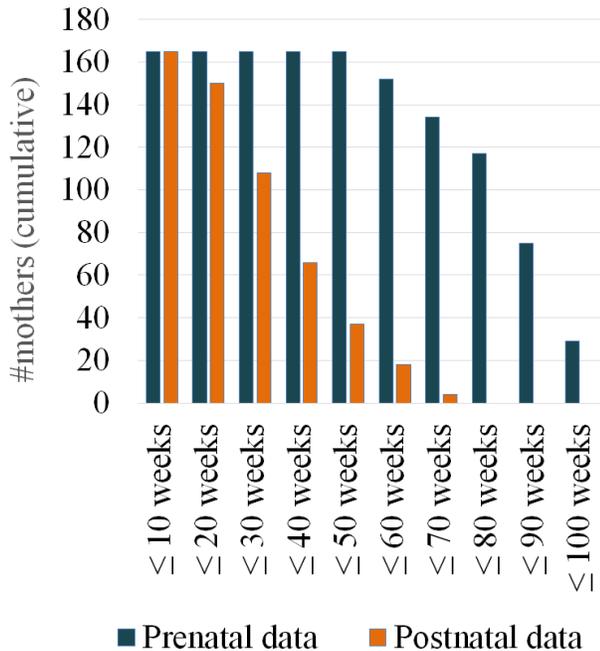


Figure 1. Cumulative distributions of durations of prenatal and postnatal Facebook data for the mothers in our dataset.

The remaining measures capture overall Facebook usage patterns of the mothers. We consider all postings made by a mother on her timeline per day (including status updates, media uploaded) as a time-series signal during the entire duration of the analysis. Based on this data, we define the remaining measures in the user-characteristics category as the different properties of this time-series signal.

A fourth measure captures the *rate of change of posting activity* over time, and is given as the normalized difference between the number of posts made on a certain day and the mean number of posts over a time window before (we consider week-long windows). A fifth measure captures the degree to which a mother’s Facebook *activity shows a negative trend*. This measure is computed from the rate of change measure as the fraction of weeks during which the rate of change is negative [17]. A sixth measure captures the entropy or *variation in the number of posts* per week over the entire prenatal period—high entropy would indicate high volatility of activity. A seventh measure is the *mean power of the number of posts per week*, in essence capturing the degree of periodicity in the frequency domain of a mother’s activity over time [17].

Social Capital

Previous research has found an inverse relationship between an individual’s access to cognitive social capital (social trust, sense of belonging, mutual aid) and depression [12]. Given Facebook’s rich friendship networks, we leveraged the following types of one-to-one social interactions as measures of a mother’s social capital, as defined as resources and support embedded within social networks: *likes on status updates* (wall posts / check-ins) made by a mother; *comments on status updates*; *likes on uploaded media* (photos/videos/links); *comments on uploaded media*; *wall posts made by friends* to a mother; *likes on wall posts made by friends* to a mother; *comments on wall posts made by friends* to a mother; *media posted by friends on wall*; *likes on media posted by friends on wall*; *comments on media posted by friends on wall*; *likes on media with specific friends tagged*; *comments on media with specific friends tagged*; *likes on wall posts to friends by a mother*; *comments on wall posts to friends* by a mother; *media in which specific friends were tagged*; and *number of friends in which a mother directed a specific communication to via tagging*.

Content Characteristics

Emotional Expression. We consider two measures of the emotional state of mothers in our dataset: *positive affect* (PA), and *negative affect* (NA), motivated from work in [35]. Measurements of PA and NA per mother are computed using the psycholinguistic resource LIWC (<http://www.liwc.net/>), whose emotion categories have been scientifically validated to perform well for determining affect in Twitter [14].

Question-centric Statuses. We also define a content characterization measure of the posts shared by mothers that captures their information/advice seeking tendency on Facebook. For the purpose, we infer whether or not a post made by a mother contains a question—that is, if the post contains a “?” marker and has one of the words “what”, “why”, “how”, “when”, “where”, “who”, “whom” etc.

Linguistic Style

We also use measures that 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 and psychological environment [35]. We again use LIWC for determining 22 specific linguistic styles, e.g.: *articles, verbs, conjunctions, adverbs, personal pronouns, prepositions, functional words, assent, negation, certainty and quantifiers*.

PPD VERSUS NON-PPD BEHAVIOR

We now present statistics characterizing and distinguishing the behavior of the mothers during prenatal and postpartum periods (combined). Table 3 presents the per-day mean, median, and standard deviation of the measures we use to characterize behavior of the mothers, combining the 50 week prenatal and 10 week postnatal periods. We also show which measures statistically distinguish the two cohorts based on independent sample *t*-tests (after adopting Bonferroni correction).

Our observations indicate that most of the user characteristics can distinguish well the behavior of the two cohorts. Specifically, for the PPD experiencing mothers, Facebook activity as measured by status updates and media items shared is lower (difference of means between prenatal and postnatal periods: 14.8% and 8.4% respectively). They also appear to be less socially interactive in reaching out to friends by tagging them in wall posts (30% lower than non-PPD mothers).

The trends and temporal characteristics of activity of these mothers also has cues attributing the differences in their experiences from those without experiences of PPD. Notably, they show a less periodic (39% lower), highly volatile (note, higher entropy: 15% higher), and raised levels of rate of change of activity over time. We note here that while periodic behavior of social media use often indicates routine nature of lifestyle [14], it is also known that lifestyle irregularities such as sleep disruption often are associated with the psychopathology of depression [37]. Our measures of high volatility and low periodicity in the case of the PPD group attempt to capture such irregularities in Facebook activity. Additionally, we observe that greater fraction of their time on Facebook, the PPD experiencing mothers tend to show a decreasing trend in their levels of activity, a finding in line with prior literature that indicates depression to be associated with social and psychological impairment [34]. Putting these together, we conjecture that PPD experiencing

	No PPD			PPD			<i>p</i>
	Mean	Med.	SD	Mean	Med.	SD	
User Characteristics							
Status updates posted	2.106	1.577	2.036	1.794	1.088	2.009	**
Media uploaded	2.822	1.901	3.338	2.585	1.822	2.484	***
Wall posts to specific friends	1.386	0.580	2.375	0.969	0.443	1.547	***
Rate of change of activity	-0.429	-0.299	0.479	-0.445	-0.240	0.639	**
Frac. time w/ -ve activity trend	0.557	0.595	0.173	0.572	0.605	0.139	*
Entropy of activity	0.710	0.818	0.310	0.817	0.877	0.214	**
Mean power of activity signal	37.274	0.702	164.3	22.381	0.463	109.0	**
Social Capital							
Likes on status updates	2.132	1.101	3.517	1.753	0.932	2.138	***
Comments on status updates	3.825	2.365	3.874	3.484	2.328	3.678	***
Likes on uploaded media	1.184	0.940	1.170	0.921	0.720	0.816	***
Comments on uploaded media	0.336	0.255	0.286	0.301	0.211	0.312	**
Likes on wall posts to friends	1.382	0.427	3.453	0.839	0.374	1.239	**
Comments on posts to friends	1.591	0.381	3.237	1.139	0.341	2.085	
Media with friends tagged	0.674	0.264	1.190	0.585	0.206	0.756	**
Likes on media w/ friends	0.270	0.132	0.503	0.274	0.113	0.492	*
Comments on media w/ friends	0.072	0.012	0.148	0.041	0.006	0.083	
Wall posts made by friends	0.213	0.009	0.538	0.166	0.000	0.457	*
Likes on wall posts by friends	0.259	0.006	0.935	0.117	0.000	0.332	
Comments on posts by friends	0.298	0.016	0.816	0.127	0.000	0.528	
Media by friends	0.141	0.000	0.325	0.108	0.000	0.466	**
Likes on media by friends	0.050	0.000	0.146	0.042	0.000	0.179	*
Comments on media by friends	0.013	0.000	0.035	0.006	0.000	0.042	
Friends with directed comm.	1.760	1.071	2.031	1.680	1.071	1.911	***
Content Characteristics							
Positive Affect	0.578	0.579	0.135	0.536	0.535	0.139	*
Negative Affect	0.408	0.416	0.134	0.435	0.451	0.112	
Question-centric Statuses	0.014	0.000	0.071	0.025	0.000	0.094	***
Linguistic Style							
1stPersonPronoun Singular	0.028	0.000	0.096	0.039	0.000	0.154	***
1stPersonPronoun Plural	0.010	0.000	0.047	0.003	0.000	0.013	***
2ndPersonPronoun	0.014	0.000	0.067	0.013	0.000	0.087	**
3rdPersonPronoun	0.017	0.000	0.046	0.010	0.000	0.058	***
Adverbs	0.030	0.004	0.106	0.031	0.002	0.091	
Article	0.032	0.003	0.102	0.020	0.005	0.041	***
Assent	0.013	0.000	0.066	0.005	0.000	0.048	**
AuxVerbs	0.044	0.010	0.110	0.086	0.012	0.224	
Certain	0.018	0.000	0.069	0.012	0.000	0.054	**
Conjunction	0.029	0.004	0.094	0.045	0.004	0.134	
Exclusive	0.007	0.000	0.022	0.017	0.000	0.056	*
Filler	0.004	0.000	0.046	0.001	0.000	0.007	**
FunctionalWords	0.300	0.092	0.730	0.325	0.056	0.883	
Inclusive	0.031	0.006	0.095	0.046	0.004	0.131	*
IndefinitePronoun	0.043	0.001	0.252	0.076	0.001	0.283	*
Inhibition	0.004	0.000	0.015	0.018	0.000	0.148	**
Negate	0.007	0.000	0.020	0.008	0.000	0.052	**
NonFluency	0.000	0.000	0.002	0.004	0.000	0.026	**
Preposition	0.082	0.018	0.273	0.068	0.012	0.167	
Quantifier	0.017	0.000	0.066	0.016	0.000	0.062	
Swear	0.007	0.000	0.036	0.012	0.000	0.134	**
Tentative	0.008	0.000	0.031	0.009	0.000	0.033	
Verbs	0.078	0.020	0.175	0.092	0.016	0.224	
<i>N</i>	137			28			

*** $p < 0.001/k$; ** $p < 0.01/k$; * $p < 0.05/k$ (after Bonferroni correction)
 $k=49$ (number of behavioral measures)

Table 3. Per-day values of the measures characterizing PPD experiencing and non-PPD mothers (combined prenatal and postpartum periods). Results of statistical significance tests (independent sample *t*-tests) comparing the two cohorts are indicated by asterisks.

mothers are posting less, suggesting a possible loss of social connectedness.

Next, PPD experiencing mothers were significantly lower than their non-PPD experiencing counterparts on our measures of social capital. For instance, PPD experiencing mothers seem to receive lower numbers of likes and comments on their status updates as well as uploaded media (17.7% and 22% respectively). They also have fewer wall posts and media made by friends. From prior literature, we know that use of social platforms online, like Facebook, likely supplements people's physical world communication and thereby helps generate and maintain their social capital [3,9]. However, in the case of individuals suffering from major depression, perceptions of levels of cognitive social capital (trust of neighbors) are considerably lower [12], potentially explaining our observation in the data.

We further observe that the PPD experiencing mothers exhibit higher expression of NA (and lower PA) compared to non-PPD mothers, consistent with depression symptoms such as mental instability and helplessness, loneliness, restlessness, exhaustion, lack of energy, and sleep deprivation [38]. However in contrast to previous work on understanding postpartum changes in new mothers using Twitter [4], we do not find these distinctions to be highly statistically significant. This may indicate a reporting bias on Facebook compared to Twitter: Since Facebook is often a platform used to connect to physical world contacts (personal and professional), individuals may be more conscious about their self-presentation, and might be less comfortable discussing emotions related to their depression in their wall posts [27]. There may also be an awkwardness factor or social stigma associated with depression, due to its sensitive nature [41] that prevents them from explicit emotional expression on Facebook.

Apart from emotion measures, the PPD experiencing mothers seem to post considerably greater content that is question-centric (78% higher), reflecting an attempt to use Facebook as a mechanism for information and advice seeking, or perhaps leveraging their available social capital to tackle the challenges of PPD [15,26]. We conjecture this could also be a manifestation of their attempt to seek social and emotional support from contacts they trust.

Finally, among the linguistic style features, we find that the presence of the first-person singular pronoun is considerably high (41.8% higher), while that of 1st person plural, 2nd and 3rd person pronouns is low in posts of the PPD-experiencing mothers (66%, 4.4%, and 43.4% respectively), reflecting their high attention to self, self-preoccupation, and psychological distancing from others [43]. PPD experiencing mothers also show lower use of articles (37% lower), indicating less attribution to things around them in their environment, another correlate of mental illness [43]. Negation, inhibition, non-fluency, and swear words also seem to be higher for this cohort compared to the other, which align with observations in prior work where negative

cognitive styles and biases have been found to be associated with depression [40].

PPD PREDICTION

Comparison of Predictive Models

Given the observed differences between the behaviors of the PPD and non-PPD experiencing mothers, we turned to predicting the onset of PPD. To start, we use the behavioral measures collected only from the prenatal period to predict whether or not a mother will have PPD during the postpartum period. We fitted a number of regression models to understand the relative value of considering different behavioral measures: user characteristics alone, social capital, content characteristics, and linguistic style, and finally a model using all of these measures. We also fitted a null model that uses all of the available demographic and self-reported attributes relating to childbirth. Prior literature shows that there is correlation between these attributes and PPD experience [2]; we sought to evaluate the additional contributions of Facebook-derived measures to the literature-identified models.

Measure	β	SE	t-Statistic
Intercept	2.4196 ***	0.036	6.709
Age ¹	0.0142 *	0.025	0.174
Ethnicity ¹	0.0079	0.025	0.031
Occupation ¹	-0.174 **	0.023	-0.756
Income	-0.046 ***	0.112	-2.691
First child ¹	-0.636 **	0.025	-2.519
Premature child ¹	0.2711	0.023	1.133
Deviance			115.218
Log likelihood			-57.609
pseudo-R ²			0.1398
Estimated dispersion parameter			0.919
Number of observations			156
Error degrees of freedom			149

¹ binary variable coded as 1/0

age: ≤ 30 years $\rightarrow 0$; >30 years $\rightarrow 1$

ethnicity: Caucasian $\rightarrow 1$; Other $\rightarrow 0$

occupation: Stay-at-home mom $\rightarrow 1$; working mom $\rightarrow 0$

Table 4. Performance of demographics model.

For all of our models in this section, we use stepwise logistic regression models, in which the independent variables are the different behavioral measures, and the response variable is whether or not a particular mother reported the onset of PPD following the birth as well as scored in the depression range on the PHQ-9 questionnaire. Particularly, we make use of the “forward selection” approach of stepwise regression—we start with a (modified) simple null model, and then incrementally test the addition of variables spanning various categories based on appropriate model comparison criteria (e.g., deviance/log likelihood in this case). The advantage of such a descriptive model as this is that, it allows us to determine the relative importance of each measure in predicting PPD, although we acknowledge that it would not support higher-order interaction between variables without considerably more data than is available through our dataset. Note that we use a measure called deviance² to evaluate

goodness of fit, since this model has no direct analog of the proportion of variance explained by the predictors (R^2) in OLS. However we do provide, for each model, a competing analogous index: pseudo R^2 [21]. Because this statistic does not mean what R^2 means in OLS regression (the proportion of variance explained by the predictors), we suggest interpreting this statistic with caution.

Performance of Demographics Model

We begin with a discussion of a modified null model, which we call the demographics model, in order to help us make a stronger claim about the predictive utility of the behavioral measures. The demographics model uses the variables: age, ethnicity, occupation, income, whether or not the childbirth in context of our survey was the first child of the mother, and if it was a premature child. The results of this model are given in Table 4. We notice that the variables occupation, household income, and whether or not it was a mother's first child were significant, with small to moderate beta coefficients. Overall this model explains about 14% of variance in the data (per the value of pseudo R^2).

Measures	β		SE	t-Stat
+ User characteristics (Model 1)				
Intercept	1.303	***	0.084	17.497
status updates	-0.428	**	0.031	-11.86
media uploaded	-0.622	***	0.029	-16.66
income	-0.165	*	0.052	-3.2044
wall posts to friends	-0.468	**	0.031	-9.235
Entropy of activity	0.639	***	0.142	15.48
first child	-0.284	**	0.204	7.3729
occupation	-0.176	*	0.196	-2.2193
Mean power of activity	-0.283	**	0.125	-4.4306
age	0.096	*	0.138	-2.385
Deviance				100.784
Log likelihood				-50.392
pseudo- R^2				0.183
Estimated dispersion parameter				0.87
Error degrees of freedom				142
+ Social capital (Model 2)				
Intercept	0.208	**	0.107	2.4132
likes on status updates	-0.328	*	0.041	-9.8713
likes on uploaded media	-1.405	***	2.306	-0.6124
Media uploaded	-0.639	***	0.032	-10.395
commt. on stat. updates	-1.209	***	0.094	-13.798
comments on media	-0.473	**	0.391	-3.866
wall posts by friends	-0.435	**	0.495	-4.873
status updates	-0.592	**	0.029	-7.953
first child	-0.184	*	0.183	1.3308
#frnds in directed comm.	-1.261	***	1.143	-14.782
Deviance				84.588
Log likelihood				-42.294
pseudo- R^2				0.242
Estimated dispersion parameter				0.81
Error degrees of freedom				126
+ Content Characteristics (Model 3)				

¹ In logistic regression analysis, deviance is used instead of sum of squares calculations, like in linear regression [21]. It is a measure of the lack of fit to the data in a logistic regression model—lower numbers are better. Deviance is calculated by comparing a given

Intercept	0.249	**	0.052	5.1092
media uploaded	-0.635	***	0.149	-9.394
commt. on stat. updates	-1.038	***	0.583	-14.248
Question-centric status	0.493	**	0.204	2.7366
status updates	-0.441	**	0.352	-10.395
first child	-0.146	*	0.738	1.284
Positive Affect	-0.076	*	0.218	-0.3827
wall posts by friends	-0.483	**	0.193	-6.253
entropy of activity	0.459	**	0.314	8.948
Negative Affect	0.037		0.459	0.0814
Deviance				79.644
Log likelihood				-39.822
pseudo- R^2				0.279
Estimated dispersion parameter				0.79
Error degrees of freedom				123
+ Linguistic style (Model 4)				
Intercept	-0.032	*	0.058	-0.127
1 st Person Singular	1.924	***	7.179	0.472
1 st Person Plural	-0.392	**	2.224	-0.287
2 nd Person Pronoun	-4.824	***	5.262	-0.744
3 rd Person Pronoun	-3.209	***	2.933	-0.899
Article	-4.085	***	9.368	-0.405
Certain	-1.771	**	4.303	-0.329
Question-centric status	0.364	**	0.251	1.560
#frnds in directed comm.	2.534	***	6.034	0.748
commt. on stat. updates	1.783	**	1.686	0.435
Swear words	2.029	**	3.161	0.2067
Deviance				61.32
Log likelihood				-30.668
pseudo- R^2				0.355
Estimated dispersion parameter				0.72
Error degrees of freedom				100

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 5. Performances of different stepwise logistic regression models. We incrementally add variables spanning the four categories: user characteristics, social capital, content characteristics, and linguistic style, to the demographics model. E.g., Model 3 includes variables of content characteristics, along with those of the demographics, user characteristics, and social capital models. Top 10 terms per model according to their β values are shown.

Performance of Stepwise Regression Models

Next we explore the performance of a number of models that are incrementally added to the variables in the demographics model: user characteristics, social capital, content characteristics, and linguistic style. In Table 5, we report the results. On adding the user characteristics variables to the demographics model, it performs slightly better than the demographics model, explaining about 18% of the variance in the data. The deviance¹ of this model is 100.784 compared to 115.218 by the demographics model. Lower number of wall posts made to friends, acting as a proxy of the degree of the mothers' social interactions, was found to be a better predictor of PPD experience. As also found in the previous

model with the saturated model – a model with a theoretically perfect fit (the intercept only model in this case).

section, high volatility (entropy) and low periodicity of activity indicated greater likelihood of PPD.

Next we discuss performance of the model that adds the social capital variables to the above model. This model shows considerable improvement in performance over the previous ones, explaining 24% of the variance in the data, as well as showing greater model fit through reduction in deviance (84.58). Reduced number of comments on status updates and uploaded media, as well as fewer likes and less commentary on media posted by friends on wall increased a mother’s likelihood of PPD. Aside from this form of direct feedback and acknowledgment from one’s social network, we also observe that lower degrees of communication initiated by friends, such as fewer wall posts made by friends was predictive of having PPD.

Our third model that added the content characteristics to the previous model yielded only marginal boost in performance explaining about 27% variance in the data—the deviance reduced to 79.64. We did not observe much effect from the two affect measures, especially negative affect, confirming our findings in the previous section that Facebook affective expression is not characteristically different in the two cohorts.

Our fourth model utilizes the different markers of linguistic style as additional variables in the regression model, explaining more than 35% of the variance in the data, as well as improving on the demographics variable only model (null model) by 153% per the value of pseudo R^2 with the lowest deviance so far: 61.32. Interpersonal pronouns are good predictors as observed in the previous section: higher use of 1st person singular pronouns indicated greater likelihood of PPD, along with lower usage of 2nd, 3rd person pronouns, and articles. Note that this model combines all of the 49 behavioral measures for regression.

	χ^2	<i>p-value</i>
Model 1 vs. demographics model	14.434	<i>3.4e-004</i>
Model 2 vs. Model 1	16.286	<i>6.3e-004</i>
Model 3 vs. Model 2	4.944	<i>7.6e-002</i>
Model 4 vs. Model 3	18.324	<i>8.2e-006</i>

Table 6. Model deviance of the different stepwise logistic regression models from Table 5. Significance is judged at $\alpha=.001$ confidence level. On being assessed upon a chi-square distribution, significant values (in italics) indicate that the addition of variables in a certain model (e.g., Model 2) considerably improved fit to our data compared to the previous model (e.g., Model 1).

Specifically, in this model we note that increased levels of both 1st person singular pronoun use and the frequency of question-centric statuses indicate vulnerability to PPD. One explanation could be that certain mothers might be turning to Facebook to pose questions and inquiries about concerns they might be experiencing themselves, which in turn hints at high self-attentional focus, and a known attribute of depression [43]. Furthermore, lowered usage of 2nd person pronouns in statuses probably indicate less desire for social

interaction: hence likely garner fewer comments from friends, thereby leading to decreased access to social capital.

Finally, we briefly discuss the correlations between pairs of predictors in this final model (Model 4). We find that the mean correlation is 0.09 which indicates that there is minimal collinearity in the variables. We also present results of model deviance of the various models (Models 1 to 4), assuming that the difference in deviances across models approximately follows a χ^2 distribution. In Table 6, we report the results of comparison and boost in explanatory power of the incremental addition of variables in the models. The model utilizing all measures (i.e., Model 4, in Table 5) is found to provide considerable (and the most) explanatory power. Compared to the demographics model (null model), it gives $\chi^2(149-49, N=156) = 115.218 - 61.32 = 53.89; p < 10^{-7}$.

Postnatal Time Horizon and Best Model

So far we have investigated predicting new mothers’ likelihood of PPD using data from the prenatal period alone. However, clinical literature on PPD marks the typical onset of PPD at about *one month following childbirth* [2,30]. Hence a few weeks of Facebook activity data in the early postnatal phase may contain valuable clues about future PPD experience that can be additionally leveraged to boost prediction performance.

	Prenatal	+10d	+20d	+30d	Postnatal
Dev.	61.32	57.39	52.58	46.61	58.15
LL	-30.668	-26.3	-20.34	-17.24	-28.84
psd. R^2	0.355	0.383	0.439	0.484	0.372
<i>s_{fit}</i>	0.72	0.68	0.62	0.57	0.703
<i>N</i>	156	156	156	156	156
Error df	100	100	100	100	100

Table 7. Performance of models with varying postnatal time horizon. Last column corresponds to a model with month-long postnatal period data only.

Thus we now consider harnessing evidence, incrementally, for an additional period of up to a month following childbirth for each mother (apart from prenatal period). We do not report the details of the models here; however performance is summarized in Table 7. We find that as more information derived from the postnatal period, our model improves in performance monotonically. Best performance is given by the prenatal period + 30 days model, where our predictive power increases considerably, explaining about 48% of variance in the data, and improving over our prenatal only model (Model 4) by 36% and by 246% over the null model, in terms of variance explained. This is also explained in terms of model deviance: $\chi^2(100, N=156) = 61.32 - 46.61 = 14.71; p < 10^{-4}$. We additionally tested a model that uses simply the month-long postnatal period data—yielding a pseudo R^2 of 0.37. This model appears to be marginally better (not statistically significant) compared to the prenatal only model (Model 4) with model deviance: $\chi^2(100, N=156) = 61.32 - 58.15 = 3.17; p < 0.08$.

In essence we conclude that the prenatal period *does* provide PPD-predictive information that together with a brief period

of postnatal observations, improves our predictions considerably. This aligns with findings in the clinical literature where typically prepartum depression is known to be a good indicator of PPD, along with post-childbirth anxiety and stress [2].

VALIDATION INTERVIEWS

To corroborate our findings with a qualitative sense of Facebook use by PPD experiencing mothers, we conducted six semi-structured interviews with a random sample drawn from our dataset of 28 PPD experiencing mothers. The interviewee mothers were asked generally about their diagnosis of PPD, timeline of the persistence of the condition, coping strategies they adopted, availability of social and emotional support during the experience, prior mental illness history, and the role of Facebook during the entire experience.

We coded the data into various themes, and overall the mothers indicated numerous instances where our findings were validated. First, in terms of Facebook use, a participant reported how she was not using Facebook during her PPD experience to upload media (photos and videos) related to her newborn daughter—a culture typical of new mothers otherwise:

You know, I exclusively stayed away from using Facebook during the [PPD] time; it was only when I really needed to, maybe sometimes to find out about a specific friend. I wasn't even doing the whole "OMG look at my cute baby" pictures thing, like you know, a lot of the new mommies do. I didn't feel as much connection with my baby, actually it was almost like I was angry, that she came in my life, and suddenly everything changed, I was a different person. (Mom B)

Another mother suffering from PPD indicated a similar experience about how the ill effects of PPD were obstructing her normal lifestyle, and thereby lowering her tendency to be active on Facebook:

[PPD] was a terrible time: I would feel exhausted the whole day—I would wake up in the morning after a whole night's sleep, and still not feel fresh and feel like I lack energy to do anything, even stuff about the baby. Posting on Facebook was naturally less during the whole time, until I was on meds and started to feel better. (Mom D)

Secondly, almost all mothers (5 out of 6) indicated that they refrained from reporting their emotion or their mental state in general during the PPD experience, naturally due to its sensitive nature, and to avoid the risk of facing judgment, scrutiny or stigma—an aspect also revealed by our analyses:

When I was first diagnosed, no one except my immediate family knew. Yes I would post less [on Facebook], but when I did, it would never be about how I was feeling, or the bad times I was going through. I actually made sure no one knew about my feelings or thoughts. Doesn't mean I didn't do the occasional posting, but it was hardly anything which would engage my friends, like, I was trying to be less interactive purposefully, and just posting rather objectively. (Mom C)

Some mothers even reported that the social stigma associated with mental illness was precluding them from expressing their emotionality on Facebook (3 out of 6):

It is not like I want privacy in a crazy way or something, but I just thought PPD is such a terrible thing: how could I let my friends know about it? What would they think? Maybe I was lacking something—something was wrong with me? That I was not normal? All those thoughts came to me—and obviously I made a decision: I don't want people who I actually know in real life, to know about it. (Mom E)

Finally, we found evidence of a variety of negative experiences from mothers with PPD around receiving social and emotional support from Facebook (4 out of 6):

I initially thought: oh great! Facebook will be a nice place to connect with my mommy friends and get some help maybe? Turns out I was so wrong. In some sense, several of these mommies I connected with, I mean not all, but they were so inconsiderate and judgmental about me and my condition. I wanted help, not how they thought I was. Clearly I started feeling that maybe I wouldn't be able to get as much help from them as I thought I would. Those Facebook pages around motherhood were slightly better—though kinda same story continued. (Mom C)

On similar lines, another participant reported on using Facebook as a means of seeking information on issues and concerns at hand; however they felt those postings garnered relatively lesser social support and feedback, especially because of mismatch of their particular PPD context or the maternity experience in general:

[I] wasn't really doing the "oh shit I am feeling terrible" thing on Facebook. But I did used to post quite a few questions as and when they popped up, maybe sometimes about what I am going through, or whether I should do X over Y—stuff like that—though I made it a point it was sort of obscure, like I didn't want folks to know that "hey this is what is happening to me". But I felt people were still a little surprised by that—not many people were responding on those, like they would on say, the baby pictures. It was like they weren't really expecting me to ask those questions, or maybe just trying to stay away from the whole thing. (Mom B)

These interviews, together with our empirical findings, i.e., the Facebook predictors of PPD, indicate three important characteristic aspects of PPD-suffering mothers—(1) their degree of social activity on Facebook is lower, and Facebook posts are often objective in nature or geared toward seeking feedback on concerns and questions; (2) due to the fact that many Facebook contacts are also physical world friends and acquaintances, mothers preferred not to disclose emotionality around their depressive state or feelings relating to helplessness and insecurity; and (3) that they received little social and emotional support (note the *negative* beta weights in the social capital model in Table 5) and were less able to leverage social capital from Facebook. In essence, through the lens of Facebook use, we also observe how social disapproval as well as hardship and stigma related to mental illness weigh on PPD suffering mothers.

IMPLICATIONS

Technology Design

The ability to identify characteristic and predictive factors of PPD presents technology design opportunities for new and expectant mothers. Like other technologies designed for motherhood in general, including systems that enable pregnant women to share baby activity levels with their intimate social groups [18], “smart baby monitors” [19] that help mothers document milestones of their child's development, we envision tools that leverage mothers' activity on online social platforms for the purpose of estimating their risk to PPD. Such tools, including software/smartphone applications and services, can serve as early warning systems. They can provide pregnant women and new mothers with personalized information on their risk of encountering significant behavioral changes, in the form of PPD, per their Facebook or other social network/media activity.

To be clear, we do not envision these tools as standalone diagnostic tools, but instead as part of a broader awareness, detection, and support system. For instance, this technology could be part of diary-centric systems that capture a self-narrative about postpartum life. Such an application is loosely akin to affective computing systems for depression treatment, which have been shown to be engaging and effective [8]. As part of this mix of this PPD detection and support system, predictions made from Facebook data could assign a personalized “PPD risk score” to mothers. In operation, if inferred likelihoods of forthcoming extreme changes surpass a threshold, mothers could be warned or otherwise engaged in order to reach out for social support or medical attention. In short, we hope analytic approaches based on social media data can play a role in helping PPD suffering women find timely and appropriate support from health care professionals and other mothers.

Ethics and Policy

We envision the systems described above to be designed as privacy preserving applications that are deployed by and for individuals, thereby honoring the sensitive aspect of revealing mental health related information to them. Closely intertwined with this privacy issue is the challenge of interventions. Can we design effective interventions for people, whom we have inferred to be vulnerable to a certain mental illness (PPD in this case), in a way that is private, while raising awareness of this vulnerability to themselves and trusted others (doctors, family, friends)? In extreme situations, when an individual's inferred vulnerability to a mental illness is alarmingly high (e.g., if the individual is suicide-prone), what should be our responsibility as a research community? For instance, should there be other kinds of special interventions where appropriate counseling communities or organizations are engaged?

In short, finding the *right* types of interventions that can actually make a positive impact on people's behavioral state as well as abide by adequate privacy and ethical norms is a

research question on its own. We hope this work triggers conversations and involvement with the ethics and clinician community to investigate opportunities and caution in this regard.

Furthermore, there are several other ethical and policy related dimensions to research that utilizes social network activities to make inferences about their mental and behavioral health. Up to what point can such inferences about illness or disability be deemed to be safe for an individual's professional and societal identity? How do we ensure that such measurements do not introduce new means of discrimination or inequality in society given that we now have a mechanism to infer such traditionally stigmatic conditions which are otherwise chosen to be kept private? These and other potential consequences such as revealing nuanced aspects of behavior and mental health conditions to insurance companies or employers make resolution of these ethical questions critical to the successful use of these new data sources.

To summarize, we believe that it is important to bring the possibilities to the fore, so as to leverage the benefits of these methods and ideas to enhance the quality of life for people, as well as to stimulate discussion and awareness of the potential role that policies could play in supporting the identities and practices that individuals suffering mental illness develop in the face of social disadvantage.

CONCLUSION

In this paper, we examined the feasibility of using Facebook as a tool to detect, characterize, and predict postpartum depression in new mothers. First we conducted an online study to gather self-reported diagnoses of PPD, along with scores on a common depression screening instrument (PHQ-9 questionnaire) to evaluate 165 mothers on their PPD experience. Thereafter, based on their activity, interactions, emotional and linguistic expression on Facebook over more than a year, we characterized differences between mothers with PPD and without PPD. Finally, we adopted a mixed methods approach in which first we developed a series of statistical models leveraging these measures, to predict PPD in our dataset, and then corroborated our findings through six semi-structured interviews with our participants.

We found that experiences of PPD were best predicted (best model explained 48% variance in the data) by increased social isolation as manifested in reduced social activity and interaction on Facebook, and decreased access to social capital. Since Facebook friend networks typically include offline social ties spanning friends and coworkers, and due to the stigma associated with mental illness in general, we find that emotional measures were less effective predictors.

Our work is of course not free from limitations. Analyses focused on data from online social platforms may suffer due to challenges of selective self-presentation. In other words, Facebook or Twitter alone may not represent with high fidelity the complex realm and circumstances that define the

PPD experience. Moreover, this work has focused on a somewhat limited set of mothers who are active on Facebook and are concentrated in a particular ethnic community with upper middle class lifestyle. It remains to be seen in future work how we can generalize our findings to a larger population for whom we online data is less available and therefore manifests less of the PPD experience. We also note here that the diagnosis of PPD itself may change Facebook behavior, something we saw some evidence of in the qualitative findings. While we cannot test this broadly here, understanding how medical diagnoses impact social media behavior is an interesting possibility for future work. Further, although we characterized online social capital of the mothers in this paper through their Facebook use, and found that it was a good predictor of PPD, quantifying offline social capital could provide valuable inputs to our findings as well.

Finally, we emphasize here that, like any statistical model, our model is likely to yield false positives. Because we used a descriptive approach in this paper, the exact false positive rate is not known, but we note that the findings of this research should be interpreted with caution, especially in terms of what the medical community could do leveraging them. In particular we recommend against focusing on a single measure such as the amount of Facebook activity, as there could be alternative explanations (e.g., mothers could post less simply because they are now dealing with new time constraints or simply have changed their priorities and are less interested in Facebook). Instead we recommend triangulating with a variety of measures and validating with known diagnostic instruments, like the PHQ9, so as to distinguish between those changing their behavior for benign versus worrisome reasons. Finally, we again stress that this research is intended not as a standalone diagnostic tool, but as a mechanism to complement current diagnoses by giving psychiatrists and caregivers access to a novel and rich non-intrusive data source about people's behavior.

REFERENCES

1. Beck, C.T. (1998). A checklist to identify women at risk for developing postpartum depression. *Journal of Obstetric, Gynecologic, & Neonatal Nursing*, 27, 39-46.
2. Beck, C.T. (2001). Predictors of Postpartum Depression: An Update. *Nursing Research*, 50 (5), 275-285.
3. Burke, M., Kraut, R., & Marlow, C. (2011). Social capital on Facebook: Differentiating uses and users. In *Proc. CHI 2011*. 571-580.
4. De Choudhury, M., Counts, S., & Horvitz, E. (2013). Major Life Changes and Behavioral Markers in Social Media: Case of Childbirth. In *Proc. CSCW 2013*.
5. De Choudhury, M., Counts, S., & Horvitz, E. (2013). Predicting Postpartum Changes in Emotion and Behavior via Social Media. In *Proc. CHI 2013*.
6. De Choudhury, M., Gamon, M., Counts, S., & Horvitz, E. (2013). Predicting Depression via Social Media. In *Proc. ICWSM 2013*.
7. Dennis, C., and Chung-Lee, L. Postpartum Depression Help-Seeking Barriers and Maternal Treatment Preferences: A Qualitative Systematic Review. *Birth*, (2006), 33(4), 323-331.
8. Doherty, G., Coyle, D., & Sharry, J. (2012). Engagement with Online Mental Health Interventions: An Exploratory Clinical Study of a Treatment for Depression. In *Proc. CHI 2012*.
9. Ellison, N. B., Steinfield, C., & Lampe, C. (2011). Connection strategies: Social capital implications of Facebook-enabled communication practices. *New Media & Society*, 13(6), 873-892.
10. Fleming, A. S., Klein, E. and Corter, C. (1992). The Effects of a Social Support Group on Depression, Maternal Attitudes and Behavior in New Mothers. *J. Child Psychology and Psychiatry*, 33: 685-698.
11. Fleming, Alison S.; Ruble, Diane N.; Flett, Gordon L.; Shaul, David L. (1988). Postpartum adjustment in first-time mothers: Relations between mood, maternal attitudes, and mother-infant interactions. *Developmental Psychology*, vol 24(1), pp. 71-81.
12. Fujiwara, T., & Kawachi, I. (2008). A prospective study of individual-level social capital and major depression in the United States. *Journal of Epidemiology and Community Health*, 62(7), 627-633.
13. Gibson, L. & Hanson, V.L. "Digital Motherhood": How Does Technology Support New Mothers? In *Proc. CHI 2013*.
14. Golder, S. A., & Macy, M. W. (2011). Diurnal and Seasonal Mood Vary with Work, Sleep and Daylength Across Diverse Cultures. *Science*. 30 Sep 2011.
15. Gray, R., Ellison, N. B., Vitak, J., & Lampe, C. (2013, February). Who wants to know?: question-asking and answering practices among Facebook users. In *Proc. CSCW 2013*. 1213-1224.
16. Halligan, S.L., Murray, L., Martins, C., and Cooper, P.J. Maternal depression and psychiatric outcomes in adolescent offspring: A 13-year longitudinal study. *Journal of Affective Disorders* 97 (2007), 145-154.
17. Hamilton, J. D. (1994). *Time Series Analysis* (Vol. 2). Princeton: Princeton University Press.
18. Hui, M., Ly, C., and Neustaedter, C. MammiBelli: Sharing Baby Activity Levels Between Expectant Mothers and Their Intimate Social Groups. In *Proc. EA CHI 2012*, 1649--1654.
19. Kientz, J. A., Arriaga, R. I., & Abowd, G. D. (2009). Baby Steps : Evaluation Of A System To Support Record- Keeping For Parents Of Young Children. In *Proc. CHI 2009*. 1713-1722.
20. Kroenke K, Spitzer RL, Williams JB (2001). The PHQ-9: validity of a brief depression severity measure. *J Gen Intern Med*. 16(9):606.
21. McCullagh, P., and J. A. Nelder. *Generalized Linear Models*. New York: Chapman & Hall, 1990.
22. McDaniel, B.T., Coyne, S.M., and Holmes, E.K. (2012) New Mothers and Media Use: Associations between Blogging, Social Networking, and Maternal Well-Being. *Maternal and Child Health Journal*, 16(7), 1509-17.
23. Moreno MA, Parks MR, & Zimmerman FJ, et al. (2009). Display of health risk behaviors on MySpace by

- adolescents: Prevalence and associations. *Archives of Pediatrics and Adolescent Medicine*. 163(1):35–41.
24. Moreno MA, Jelenchick LA, & Egan KG, et al. (2011). Feeling bad on Facebook: Depression disclosures by college students on a social networking site. *Depressions and Anxiety*. 28(6):447–455.
 25. Moreno, M. A., Christakis, D. A., Egan, K. G., Brockman, L. N., & Becker, T. (2011). Associations between displayed alcohol references on Facebook and problem drinking among college students. *Archives of Pediatrics & Adolescent Medicine*. 166(2):157-63.
 26. Morris, M. R., Teevan, J., & Panovich, K. (2010). What do people ask their social networks, and why?: a survey study of status message Q&A behavior. In *Proc. CHI 2012*.
 27. Newman M, Lauterbach D, Munson SA, Resnick P., Morris, M. (2011). It's not that I don't have problems, I'm just not putting them on Facebook: Challenges and Opportunities in Using Online Social Networks for Health. In *Proc. CSCW 2011*.
 28. NielsenWire. Infographic: The Digital Lives of American Moms. <http://www.nielsen.com/us/en/newswire/2012/digital-lives-of-american-moms.html> May 11, 2012.
 29. O'Hara, M. W., Neunaber, D. J., & Zekoski, E. M. (1984). Prospective study of postpartum depression: prevalence, course, and predictive factors. *Journal of abnormal psychology*, 93(2), 158.
 30. O'Hara, M.W. (1995). Postpartum Depression: Causes and Consequences. *New York: Springer-Verlag*.
 31. Oxman T.E., Rosenberg S.D., & Tucker G.J. (1982). The language of paranoia. *American J. Psychiatry* 139:275–82.
 32. Park, M., McDonald D., & Cha, M. (2013). Perception Differences between the Depressed and Non-depressed Users in Twitter. In *Proc. ICWSM 2013*.
 33. Paul, M., & Dredze, M. (2011). You are what you tweet: Analyzing Twitter for public health. In *Proc. ICWSM 2011*.
 34. Paykel, E. S., & Weissman, M. M. (1973). Social adjustment and depression: a longitudinal study. *Archives of General Psychiatry*, 28(5), 659.
 35. Pennebaker, J.W., Mehl, M.R., and Niederhoffer, K.G. (2002). Psychological aspects of natural language use: Our words, ourselves. *Annual Review of Psychology* 54: 547-477.
 36. Plantin, Lars, and Kristian Daneback. 2009. "Parenthood, information and support on the internet. A literature review of research on parents and professionals online." *BMC Family Practice* 10(1):34.
 37. Prigerson, H. G., Monk, T. H., Reynolds, C. F., Begley, A., Houck, P. R., Bierhals, A. J., & Kupfer, D. J. (1995). Lifestyle regularity and activity level as protective factors against bereavement-related depression in later life. *Depression*, 3(6), 297-302.
 38. Rabkin, J. G.; & Struening, E. L. 1976. Life events, stress, and illness. *Science*, 194(4268), 1013-1020.
 39. Righetti-Veltama, M., Conne-Perréard, E., Bousquet, A., & Manzano, J. (1998). Risk factors and predictive signs of postpartum depression. *Journal of affective disorders*, 49(3), 167-180.
 40. Robinson, M. S.; & Alloy, L. B. 2003. Negative cognitive styles and stress-reactive rumination interact to predict depression: A prospective study. *Cognitive Therapy and Research*, 27(3), 275-291.
 41. Roeloffs, C., Sherbourne, C., Unützer, J., Fink, A., Tang, L., & Wells, K. B. (2003). Stigma and depression among primary care patients. *General hospital psychiatry*, 25(5), 311-315.
 42. Rosenquist, J. N., Fowler, J. H., & Christakis, N. A. (2010). Social network determinants of depression. *Molecular psychiatry*, 16(3), 273-281.
 43. Rude, S.; Gortner, E.; & Pennebaker, J. 2004. Language use of depressed and depression-vulnerable college students. *Cognition and Emotion*, 1121-1133.
 44. Sadilek, A., Kautz, H., & Silenzio, V. (2012). Modeling Spread of Disease from Social Interactions. In *Proc. ICSWM 2011*.
 45. Schoenebeck, S.Y. The Secret Life of Online Moms: Anonymity and Disinhibition on YouBeMom.com. In *Proc. ICWSM 2013*.
 46. Scott KD, Klaus PH, Klaus MH.(1999). The obstetrical and postpartum benefits of continuous support during childbirth. *J Womens Health Gend Based Med*. vol 8(10):1257-64.
 47. Steinfeld, C., Ellison, N., Lampe, C. (2008). Social capital, self-esteem, and use of online social network sites: A longitudinal study. *J. of Applied Developmental Psychology*, 29, 434-445.
 48. Tarkka, M.-T. & Paunonen, M. (1996). Social support and its impact on mothers' experiences of childbirth. *Journal of Advanced Nursing*, 23: 70–75.