Exploring Parent-Child Dyadic Networks to Design a Smartphone-based Mindfulness Intervention for Underserved Families

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ABSTRACT

Parents from socioeconomically disadvantaged and minoritized backgrounds disproportionately experience higher rates of daily negative mood and lower levels of physical activity, negatively impacting health outcomes across the lifespan. Scalable, evidence-based interventions to promote family wellbeing and that fit into the busy lives of parents juggling many responsibilities remain beyond reach, especially for families from minoritized groups experiencing the greatest barriers to health. Mindfulness holds promise for addressing these disparities in access to evidence-based behavioral health interventions because it can be engaged upon at any given moment, can be delivered using smartphones, has higher rates of program completion relative to other evidence-based treatments, and has high rates of being integrated into daily life following study completion. In this study, we used smartphone experience-sampling and accelerometry to respectively measure mood and physical activity in 31 parent-child dyads. Parents reported negative mood and stress 10 times per day across 14 days for themselves and their child (3-8 years old). We used Group Iterative Multiple Model Estimation to construct networks describing associations among negative mood, stress, and physical activity for each parent and child dyad. Our findings suggest that we can use a complex systems approach to model the associations among mood, stress, and physical activity in parents and children in daily life. We discuss opportunities for using these parent-child dyad networks to inform the design of parent focused smartphone-based mindfulness interventions to support healthy parent-child interactions and reduce health disparities.

CCS CONCEPTS

• **Human-centered computing** → Human computer interaction (HCI); Empirical studies in HCI; • **Applied computing**;

KEYWORDS

mHealth, personal informatics, physical activity, emotion regulation

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1 INTRODUCTION

Physical activity fosters growth and development; makes people feel better, function better, sleep better; and reduces the risk of many chronic diseases [10]. Despite substantial efforts to increase population physical activity, only 25% of adults and 20% of children meet physical activity guidelines [28]. Physical activity behaviors are developed during early childhood, with patterns tracking through adolescence into adulthood [27]. Cultivating early patterns of physically active behavior through family-based interventions is policy-relevant and holds the potential to alter population health [18]. Socioecological models and family systems theories of child development highlight parents as having a significant influence on children's health and development [8], with a recent emphasis on parents' role in supporting the initiation and maintenance of children's health behaviors, such as physical activity [15]. The design of intervention strategies that support activity-promoting behavior in families necessitates an understanding of the complex, dynamic processes underlying parent-child physical activity as it unfolds during life as it is lived [6].

1.1 Parent Emotion Regulation may Compromise Child Physical Activity

Parent negative mood is an understudied, yet theoretically-relevant factor that may influence young children's physical activity. Affective processes are thought to be more strongly related to the adoption and maintenance of positive health behaviors, such as physical activity, than social-cognitive factors (e.g., motivation, self-efficacy) especially among adults [29]. Affective determinants of physical activity have also been highlighted in theoretical frameworks, including the dual-processing model, self-regulation theory, and self-determination theory [7, 13, 31]. In adults, positive and negative affect, fatigue, and arousal momentary states predict subsequent physical activity within five minutes to a few hours [20]. The link between emotions and physical activity in parents has implications for child physical activity. For example, parents' negative

mood directly impact children's physical activity and weight status [12].

1.2 Mobile Health Interventions are Scalable

Although family-based interventions are effective for enhancing health behaviors [16] high noncompliance and dropout rates (50-73%) have been observed even among the most targeted programs [16]. Dropout rates are especially high among low socioeconomic status (SES) and racially/ethnically diverse parents (50-75%) [16]. Although no single factor predicting dropout has emerged, participants identify scheduling conflicts, substantial intervention time commitment that required missed work and school, increased experiences of high stress, and heightened financial burden associated with lack of insurance coverage as reasons for low intervention completion rates [25]. There is a critical need for scalable family-based health behavior interventions that fit better into the lives of busy families and that meet the needs of underserved populations at increased risk for chronic disease and dropping out of interventions. Leveraging the ubiquity of smartphones has the potential for designing scalable and affordable family-based mobile health interventions that can be delivered when and where people are most likely to be receptive. Smartphone ownership is high among Black (83%), Hispanic (85%), and low-SES Americans (76-83%) and comparable to white (85%) and high-SES (> 84%) Americans [23]. Smartphone ownership across socioeconomic groups is increasing. Low-SES and ethnic minority individuals reach for their smartphone more often than other populations and rely more heavily on smartphones for daily internet access [22]. This proposal fills critical gaps in the mobile health (mHealth) interventions designed for low-SES and racial/ethnic minority individuals literature [26]. We will take a smartphone-based approach, answering the pressing need for mHealth interventions supporting family health behaviors that have the potential to be scalable, especially for families previously underrepresented in research and who are experiencing the highest barriers to wellness and the highest rates of chronic disease that can be mitigated by physical activity [24]. Using smartphones, participants will have the intervention in the palm of their hand, without the need to miss work, travel to the laboratory, or stay after school with their child to participate.

1.3 Minoritized Groups are Underrepresented in Mobile Health and Mindfulness Research

Minoritized groups are underrepresented in mobile health and mindfulness research. Mindfulness is a promising behavioral strategy to address health disparities, demonstrating effectiveness in reducing blood pressure, affective volatility, physiological stress markers, and depressive symptoms in ethnoracial minorities [1]. Despite mindfulness' promise to mitigate adverse health through facilitating behavior change, crucial barriers thwart its accessibility and dissemination among minoritized groups. Namely, certain sub-populations (e.g., individuals with low-SES and racial/ethnic minorities) have not been well represented in mindfulness research [30]. Although most mindfulness research has included predominantly white, affluent populations, these interventions may be particularly effective in marginalized populations experiencing a greater burden of illness on emotional and physical well-being and greater barriers to accessing health services [9]. Encouragingly, mindfulness-based interventions have been shown to be acceptable for underserved populations with higher program completion rates relative to other evidence-based treatments and high rates of integrating mindfulness into daily life following study completion [14]. Even more limited is the representation of minoritized groups in mindfulness-based mHealth interventions, which hold promise for increasing access to health services for minoritized groups facing increased barriers to health in the United States.

1.4 The Present Study

We constructed parent-child dyad networks to examine the interplay among parent and child negative mood and physical activity in daily life. A key aim of this study was to identify points for intervention and opportunities to design a personalized smartphone-based mindfulness intervention to alleviate parent negative mood and support child physical activity in daily life. The present study was approved by the Institutional Review Board at University of Pennsylvania. Parents/guardians provided written informed consent for themselves and their child, and children provided verbal assent prior to participation when the research team member visited the family to drop off equipment.

2 METHOD

A total of 31 parent-child dyads were recruited from the greater Philadelphia community to participate in this pilot study (see Table 1 for demographic characteristics). Parents were 18 years or older and had a child aged 3-8 years old living with them. Parents identified as African American/Black (50%), Hispanic/Latino (13%), Asian American (8%), and white (26%). Participants reported a modal yearly family income $\leq$ \$34,999. Participants' education spanned less than high school (10%), high school or GED (26%), associate's degree (21%), bachelor's degree (16%), master's degree (15%), doctorate (5%), and professional degree (5%). Participants' employment spanned not employed (37%), part-time employed (16%), and full-time employed (47%). Parents completed an eligibility screening questionnaire and then a baseline survey. Following the baseline survey, a member of the research team visited the home of the parent and child to measure height and weight, train parents on the smartphone experience-sampling protocol and drop off the accelerometers. At the end of the 14-day experience-sampling period, a research team member picked up the accelerometers

2.1 Measures

Parent mood was measured using items from the Profile of Mood States (POMS). The POMS is a validated measure of mood that has been previously used in experience-sampling studies with adults. Negative mood was measured as the average of three items "Right now I feel anxious", "Right now I feel angry", and "Right now I feel sad" on a scale from 1 to 100 [21]. Although other POMS items indexing positive mood were collected, here we focus on the items that comprise negative mood. Parent stress was measured using items adapted from the Perceived Stress Scale "Right now, I feel stressed" on a scale from 1 to 100 [11]. Child mood was measured using parent-reported items adapted from the Mood and Feelings

Table 1: Participant Demographics

Measure	Parents	Children
Age (years)	35.9 ± 6.6	5.6 ± 1.7
Gender (n)	Man = 6	Boy = 17
	Woman = 24	Girl = 14
	Additional gender category/identity = 1	
BMI (percentile)	98.5 ± 3.2	85.4 ± 19
Weight Status[a]	Normal weight = 12	Normal weight = 2
	Overweight = 2	Overweight = 3
	Obese = 17	Obese = 26

a BMI = Body Mass Index based on based on Center for Disease Control and Prevention normative data for age and biological sex assigned at birth.

Questionnaire (MFQ) [2]. The MFQ is a validated measure of parent-reported child mood and has been previously used in experience-sampling studies with children [4]. Parents reported "Right now, how is your child's mood?" on a scale from 1 (extremely bad) to 100 (extremely good). Physical activity was assessed during the 14-day experience-sampling period using an ActiGraph GT9X Link (ActiGraph; Pensacola, FL) activity monitor. The GT9X activity monitor is a small (3.5 x 3.5 x 1 centimeters), light (14 grams), noninvasive device used for physical activity data collection in the field. Parents and children were instructed to wear the activity monitor on their non-dominant wrist and to remove the activity monitor for water-based activities (e.g., swimming, showering, bathing). Each GT9X activity monitor was initialized with a start and stop time and date to record data only during the 14-day experience sampling period. Triaxial accelerometer data were collected using a 30 Hz sampling rate with the screen turned off to conserve battery life for the duration of the 14-day experience-sampling period. All data were downloaded using ActiLife software (v.6.13.3). After data download, parent physical activity was converted to vector magnitude counts in 60-s epochs and child physical activity was converted to vector magnitude counts in 1-s epochs using the agcounts package in R. Given the different characteristics of physical activity behavior in adults and children, it is recommended to use shorter epoch lengths to accurately capture short bouts of movement in young children [3]. Vector magnitude is the square root of the sum of the squares of each axis of the data:

$$\sqrt{Vertical_{axis}^2 + Longitudinal_{axis}^2 + Lateral_{axis}^2} \quad (1)$$

Vector magnitude incorporates the vertical (up-down), longitudinal (forward-backward), and lateral (left-right) axes. Prior work has shown that vector magnitude is a more valid representation of physical activity than the more common approach of using only the vertical axis [19]. This approach also allows for characterizing nonexercise activity (e.g., fidgeting) that does contribute to overall energy expenditure, which is more common among young children, as part of physical activity. Although there is no present consensus on how best to measure children's physical activity due to a paucity of validation studies in this age group, we used three-dimensional system with short epoch length to align with current evidence and the behavioral perspective that young children's physical activity patterns are omnidirectional and occur in short bursts [19].

2.2 Analysis

To provide insight into the processes through which parent and child mood and physical activity interact, we modeled the parent-child dyad as a complex system of interacting components. We tested whether a complex systems model captures the intervention processes influencing child physical activity. In this way, we were able to examine specific points for future interventions (e.g., optimizing interventions to reduce parent negative mood to increase child physical activity may necessitate intervening on parent exposure to stress and parent sleep). Ultimately, the complex systems model developed for this proposal can then be scaled to design a parent-focused mindfulness intervention delivered via smartphone to alleviate negative mood. We modelled experience-sampling data using a unified structural equation modeling (uSEM) approach called Group Iterative Multiple Model Estimation (GIMME) [5]. This approach resulted in the construction of a network that describes the contemporaneous and lagged associations among parent and child mood and physical activity. The choice of GIMME over alternative approaches is motivated by three strengths of the approach. First, GIMME allows the construction of networks of interacting constructs at the sample level as well as the dyad level, allowing the consideration of dyad-specific networks but also a sample-level network that may be of interest to the broader literature to inform population-health efforts. Second, model selection relies on a data-driven, automatic search procedure, circumventing the need for a priori assumptions of network structure. Third, GIMME's search procedure has proven capable of recovering true effects with few spurious effects [5].

3 RESULTS

3.1 Compliance

High rates of compliance with the protocol were observed: 97% of the parent-child dyads completed all 14 days of the study, with an overall response rate to the smartphone prompts of 80%. These results support feasibility of deploying smartphone-based mHealth interventions among low-SES ethnoracial minority families.

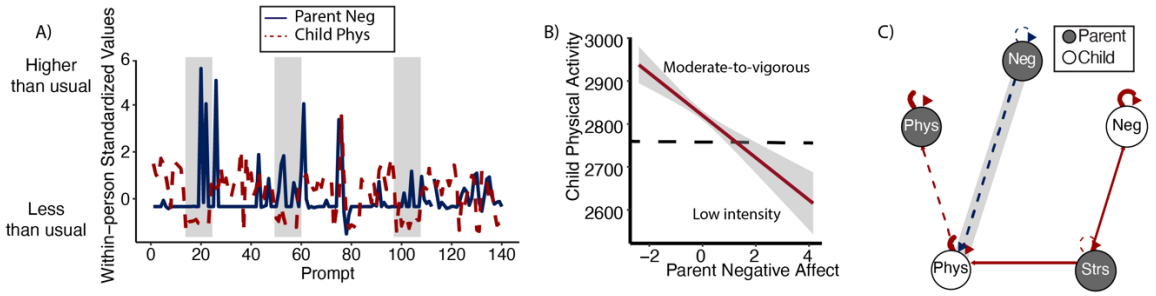

Figure 1: Momentary variations in parent negative affect and objectively measured child physical activity in daily life. Panel A depicts data from one parent-child dyad showing substantial within-person variability in parent negative mood collected 10 times per day across 14 days. The grey bars indicate moments when higher than usual parent negative mood are followed by moments of lower than usual child physical activity (physical activity was lagged to line up with the corresponding negative mood report time stamp). Panel B depicts multilevel model results testing the association between parent negative mood and child physical activity in 31 parent-child dyads. 95% confidence intervals are represented in grey. As hypothesized, moments of higher than usual parent negative affect are followed by moments of lower than usual child physical activity, which represents a substantial decrease in moderate-to-vigorous physical activity (~ 300 vector magnitude counts). The black dashed line represents approximate cut-point for moderate-to-vigorous (above) and low intensity (below) physical activity in children. Panel C depicts one parent-child dyad's GIMME network showing the moment-to-moment associations among parent physical activity, parent negative mood, child physical activity, and child negative mood. Parent nodes are grey and child nodes are white. Positive associations (edges) are shown in red and negative associations (edges) are shown in blue. Solid lines indicate same-moment associations and dashed lines represent previous-moment associations. Thickness of lines indicate strength of associations. As hypothesized, the complexity of parent-child interactions in negative affect and physical activity can be modeled using GIMME, highlighting the feasibility of constructing well-fitting models that articulate the interplay between parent-child affect and physical activity across time. As hypothesized, parent negative affect (grey node) is associated with subsequent lower child physical activity (white node) as indicated by the blue dashed edge (highlighted by the grey box). Arrows show the direction of relationships. Neg = negative affect; Phys = physical activity; Strs = stress.

3.2 Descriptive findings

We show substantial variability in parent negative mood and child physical activity in one parent-child dyad (see Figure 1A). Preliminary analyses on these data using multilevel modeling indicate that parent negative affect and child physical activity are coupled as hypothesized such that higher parent negative affect is associated with lower child physical activity (see Figure 1B). Results from GIMME analyses capture the complex, potentially bidirectional interplay between parent and child mood and physical activity in one example parent-child dyad (see Figure 1C). We show that the associations among parent-child emotions and behaviors vary across dyads. Although these results are descriptive in nature, our preliminary data show that 1) we can use a complex systems approach to describe the associations between parent and child emotions and behaviors in daily life and 2) smartphone-based mindfulness interventions may seek to target parent negative mood to increase child physical activity. We provided figures below to further describe our results of this pilot study.

4 DISCUSSION

Findings from our pilot study show support for the feasibility of using smartphone-based mHealth interventions in low-SES and ethnoracial minority families. Our preliminary results support the hypothesized association between parent negative mood and child physical activity. Namely, moments of higher than usual parent negative mood are associated with lower than usual child physical activity. Our preliminary data show that a complex systems approach can be used to characterize the interplay among parent and child emotions and behaviors in daily life. Together, these findings suggest that a smartphone-based mindfulness intervention aiming to increase child physical activity may use strategies that will alleviate parent negative mood in daily life.

For example, mindfulness interventions for parents can decrease parent over-reactivity to parent-child relationships by helping parents tolerate normative emotional fluctuations (e.g., temper tantrums) by children as well as alleviate their own negative mood. Practically speaking, a parent-focused mindfulness intervention may involve aspects of focusing on helping parents cultivate states of mindfulness through teaching strategies such as focusing on the body/breath, monitoring activity of the mind, and developing non-judgmental awareness of daily experiences. By cultivating these mindful states for as little as 10 minutes daily, parents may experience reduced negative mood as shown in prior work [17]. In particular, the mindfulness content should be designed alongside parents to represent the daily experiences of marginalized populations who experience higher rates of discrimination and daily stress. At present, there is limited mindfulness content targeted towards parenting behaviors, parenting stress, and emotional reactivity in parent-child relationships. However, the practices of body awareness, non-judgemental awareness, and gratitude common

to mindfulness have potential to reduce parent negative mood to support child physical activity in daily life.

By finding ways to support parents' emotion regulation—by helping them reduce daily negative affect—may help parents recover in the face of stressful parenting moments, disengage from negative emotions, and flexibly adapt to the current moment by selecting healthful choices for themselves and their child. For example, parent mindfulness may influence child physical activity by altering the extent to which parents transmit their emotions to their child, increasing parents' ability to regulate their emotions during daily stress, increasing parental motivation to initiate and maintain behavior change in daily life.

Next steps include examining how these complex networks of child and parent affect and physical activity change following a smartphone-based mindfulness intervention. Importantly, this network approach will allow us to capture not just the direct effect of parent negative mood on child physical activity but also indirect effects that filter through parent stress, parent physical activity, and child negative mood. Resulting from these next steps will be a generalizable framework with which investigators may capture complex bidirectional associations between parent and child behaviors and daily experiences that are important for theory but difficult to quantify.

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