Child Health in Rural Bangladesh: Peer Mentor Matching through Artificial Intelligence and Matching Algorithms

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In 2015, the United Nations identified "good health and well-being" as one of the Sustainable Development Goals (SDG) with one of the nine outcome targets promoting improvements in health during early childhood. Those goals arose since children's cognitive and non-cognitive skills are heavily influenced by their environment during the early stages of life while a lack of progress impedes well-being. The first 1,000 days of a child's life are particularly crucial, as poor childcare and insufficient investments during this period can impede both physical and brain development (Doyle, 2020). The situation is especially concerning in low- and middle-income countries (LMICs), particularly in South Asia and sub-Saharan Africa, where the number of children under 5 affected by stunting and wasting exceeds 160 and 50 million, respectively (Black et al., 2013). Moreover, poor parenting, such as suboptimal breastfeeding, can also increase the risk of child mortality in the first two years of a child's life (Black et al., 2013). However, addressing this problem is challenging and requires carefully designed interventions for LMICs because several financial, cultural, and social barriers limit women's access to health clinics in remote villages. As such, child health programs aimed at women are a possible way to improve the outcomes for children

Peers might have a strong influence on an individual's behavior (Falk & Ichino, 2006; Chadi et al., 2022; Hoffmann et al., 2022) and assimilation of information given during meetings of parents. Therefore, to increase availability, the involvement of non-experts in health care settings is becoming increasingly common in LMIC (Patel et al., 2017; Haushofer et al., 2020; Islam et al., 2022; Barker et al., 2022); however, the impact of non-expert delivered advice remain underwhelming compared to expert-delivered advice.[1] One reason is that patients may feel uncomfortable interacting and sharing private information with strangers, which can increase the likelihood of them prematurely dropping out of the program, even if it is not the best decision for them or their child (Cronin et al., 2020). To improve the effectiveness of non-expert-delivered interventions and keep patients engaged, it is crucial to carefully match patients with suitable non-expert peers.

We ask the following questions: Can we match non-expert peers to improve the impact on child health outcomes? In particular, how should one match new mothers (mentees hereinafter) with experienced mothers who could become non-expert child health service providers (mentors hereinafter) in this context? In line with those questions, we consider settings where a set of mentors is to be matched with another set of mentees. Each mentor has a strict preference ranking over mentees, and vice versa. The existing literature on mental health interventions relies on random matching between mentors and mentees. We investigate whether we can improve upon such matches. Conventional matching mechanisms select a match between mentors and mentees based on submitted preference reports. Economists generally recommend strategy proof mechanisms where agents have no incentive to misreport their preferences (Gale & Shapley, 1962; Shapley & Scarf, 1974). Yet real agents might have imperfect information about others, making them uncertain about the

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[1]For comparison, see Rahman et al. (2008); Cuijpers et al. (2016); Singla et al. (2017).

level of satisfaction they would actually receive from a given match. Further, boundedly rational agents have been shown to fail to report preferences accurately, even in strategy proof mechanisms (Stephenson, 2022). In contrast, machine learning based recommendation algorithms, such as those employed by Netflix and Spotify to match users with fitting content, use information about agents and the content to infer preferences and select suitable matches (Ren et al., 2021; Biswas et al., 2022; Patro et al., 2020). It remains ambiguous which of these approaches is more effective in practice.

Therefore, in this project, we will carry out a randomized controlled trial to evaluate the impacts of different matching mechanisms in child health in a LMIC, Bangladesh. Bangladesh is a suitable place to test our conjectures because it has a critical shortage of health workers (experts) in comparison to the number of mentees who require intervention, especially in rural areas (Sadiq & Ahmed, 2020). Bangladesh scores one of the lowest in the world on health worker availability (Ullah, 2021) and, in fact, Bangladesh only has 9.9 doctors, nurses, and midwives per 10,000 people, which falls significantly below the worldwide median of 48.6 (WHO, 2021). Therefore, in this low-resource setting, our proposed intervention aims to create a social support system for new mothers — who often need prompt advice, support, and encouragement to succeed — through experienced mothers from the same community, who are willing to guide and support new mothers in need.

1 Experimental design

Child Connect (CC). In this program, the mentees will receive personalized support on a 1:1 basis, at either the mentee's or mentor's home. Each session will last up to 60 minutes. Child Connect will focus on promoting positive parenting skills (e.g., understanding when a child is hungry, sleepy, anxious, or requires medical attention, ways to burp or massage a baby, how often to breastfeed, signs that baby is not getting enough breast milk, ways to play with children using household items, etc.) and improving parental self-esteem. Mentees will also be able to contact mentors outside the sessions when required (either by visiting the mentor's home or calling them). This program will be a personalized 1:1 version of the Chilean program "Nobody is Perfect", which is focused on providing group sessions and uses randomized matching (Carneiro et al., 2023). To minimize contamination, our unit of randomization will be at the village level. CC will be delivered to mentees via one of the five treatment arms summarized in Table 1.

Table 1: Experimental Design

Treatment	CC	Preference Reporting	Predicted Preferences
Control			
RM	✓		
EM	✓	✓	
IM	✓		✓
Expert	✓		

Note: Treatments *RM* corresponds to random matching, *EM* to explicit matching (preference based), *IM* to implicit matching (machine learning), and *Expert* to random matching with an expert in child health.

Mentees in the *control* group will not be matched with mentors to receive parenting advice through Child Connect. In treatment *RM*, mentees will be randomly matched to mentors (the status quo in the literature with non-expert mentors, e.g., as in Patel et al. (2017)). In treatment *EM*, mentees will be matched by explicitly asking for a preference

ordering of mentors for mentees and vice versa using the top trading cycle. In treatment *IM*, mentees will be matched based on an implicit machine-learning (ML) matching algorithm as an artificial intelligence application using the demographic information of the mentors and mentees. Finally, in treatment *Expert*, mentees will be randomly matched with an expert in child development (the status quo in the health literature, e.g., see Rahman et al. 2008). As we conjecture that *EM* and *IM* matching would lead to better outcomes than *RM*, we believe *RM* will allow us to estimate the lower-bound impact of the provision of advice for child development, while treatment *Expert* will allow us to estimate the upper-bound impact. We will work with two experts throughout the intervention (for both delivering CC in treatment *Expert* and training non-expert mentors in *RM*, *EM*, and *IM*). Our experts will be from the University of Rajshahi — one of the largest public universities in Bangladesh. We aim to obtain IRB approvals from the University of Rajshahi and the Royal Holloway University of London.

Sampling. We will conduct this study in 200 randomly selected villages in the Rajshahi Division of Bangladesh, in Rajshahi and Natore districts. We will collaborate with the local NGO, SARCH, to implement the intervention and conduct the fieldwork. Following Patel et al. (2017) – a study on home visits to provide health services to participants on a one-on-one basis –, we computed the required cluster and sample sizes in each arm with an improvement in mental health outcome by -7.53 (from Patel et al. 2017) at 5% significance level with 80% power. We found that a minimum of 36 clusters and 180 mentees (with 5 mentees per cluster) are required in each arm to satisfy this requirement. To ensure we satisfy this requirement, we will randomly invite and enroll 200 respondents per treatment arm. Therefore, our intervention will be implemented on a sample of 1,000 mentees selected from 200 villages, with 40 villages per arm.

In treatments *RM*, *EM*, and *IM*, we will recruit the same number of non-expert mentors as the number of mentees to facilitate treatment delivery on a one-on-one basis (200 per arm, 600 in total). Mentors will be recruited from the same villages as mentees. We will closely follow Patel et al. (2017) for recruitment and training of non-expert mentors. All mentors and mentees will be adults, between the ages of 18 and 60.

2 Data and Timeline

For Child Connect data will be collected at baseline, one month after the intervention ends, and every six months afterward until the child reaches two years. That is, we will follow up at 7 months, 13 months, and 19 months after the intervention ends, covering early-childhood development in the first 700 days (or two years). We wish to start the project in November 2025 and finish by October 2027.

At baseline, we will measure a range of individual and household characteristics. These questions include but are not limited to age, gender, education, income, household size, occupation, if they migrated from other villages recently, savings, informal borrowings, working hours, household assets, intra-village cluster sizes, etc. In addition, we will measure the new mothers' knowledge of parenting using a series of questions on how often children should be fed, how to find out if children are hungry, how often should they sleep, etc.

Malnutrition and growth. (1) weight-for-age, (2) height-for-age, (3) weight-for-height, (4) mid-upper-arm circumference-for-age, and (5) head circumference-for-age. To construct these z-scores, we need measures of weight (in grams), height (in cm), mid-upper-arm circumference (in cm), head circumference (in cm), age (in months), and gender of children.

Socioemotional, physical, and cognitive development. Measures of communication skills, gross-motor skills, fine-motor skills, personal-social skills, and problem-solving

skills using the Ages and Stages Questionnaire III (ASQ-3). Questions are answered by mothers, but can be partially validated by enumerators during the interview (e.g., whether the child can grab a finger, follow a finger when moved around, make sounds, respond to calls, smile at strangers, etc.). We will also measure the emotional and behavioral strengths and difficulties of children using the Strengths and Difficulties (SDQ) questionnaire.

Mechanisms—Childcare quality, mothers' healthy diet, and financial channels. (1) Daily time-investment on children, such as playing, story telling, chanting rhymes, etc., through time-diary (measured in minutes). (2) Frequency of breastfeeding per day (recorded through a time-diary). (3) The number of times mothers sought expert help in the previous month (via health center or mentor) when they were unsure about what to do. (4) Calories, carbohydrates, protein, and fat content present in mothers' breast milk (can be analysed objectively through lactation labs). (5) Cleanliness (how often mother bathes children, wash clothes, frequency of own hand washing and daily showering, etc.). (6) Financial help or informal borrowings from mentors or non-family members (e.g., to buy medicine for children, pay doctor's fees, etc.).

Health outcomes of mentees and mentors. Using validated scales, we will measure (i) depressive symptoms (PHQ-9 scale), (ii) emotional regulation (DERS-SF scale), (iii) anxiety disorder (GAD-7 scale), (iv) perceived sleep disturbance (Pittsburgh sleep quality index), (v) physical functioning and quality-adjusted life years (SF-12 and EQ-5D scales).

3 Fieldwork

Collaborator. We will collaborate with a Bangladeshi non-profit organization, the Society for Amelioration of Rural Communities and Households (SARCH), to implement the intervention and collect data. The PI has previously worked on two RCTs with this organization.

Requested funding. A total of USD 142,998.12. This includes five enumerators' salary for 8 months ($40,206.18), two expert psychotherapists' salary for 4 months ($39,587.64), 600 non-expert mentors' remuneration based on sessions completed ($12,371.11 or $2.58 per session per mentor, which is above the average daily income of $2.10 in this region), all travel related costs of enumerators and child development experts for 24 months ($22,268.04), two field visits by the PI ($6,185.57), salary of one full-time RA based in Bangladesh for 24 months ($12,371.13), and one part-time RA based in the UK ($10,008.45).

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