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LITERATURE REVIEW: ARTIFICIAL INTELLIGENCE FOR INTERNATIONAL DEVELOPMENT

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In the international development sector, scarce resources must be deployed as efficiently as possible. As advances in computing have transformed artificial intelligence from fiction into a reality that even a smartphone can harness, academics have begun thinking rigorously about how AI can be leveraged to benefit developing countries. Their exact research questions differ across domains but generally fall into two buckets (see *Appendix*). First, can machine learning (ML) methods, particularly deep learning, make better policy-relevant predictions? ML has been around for decades, but was more recently adopted in the dev sector under the umbrella of "data science for social good." Second, can LLMs/chatbots be utilized in low resource settings to provide high-quality services or information in a cost-effective, scalable manner? This nascent literature has exploded alongside the pace of public chatbot releases and fierce debate over the safety and ethics of AI use; its seminal papers likely haven't been released yet.

This literature review explores present research on dev-relevant AI applications. Most current work falls outside the development economics discipline, appearing instead in domain-specific or computer science journals. Many are pre-prints or conference papers. With no shortage of grey literature theorizing about AI, we focus on studies with quantifiable outcomes. For ML, we consider papers comparing AI-enabled prediction with traditional methods to assess technical feasibility, though not often deploying it in real policy contexts. For LLMs, we collate experiments that measure the efficacy of chatbot interventions against a baseline. Most studies are RCTs in their pilot stages; there are few opportunities for quasi-experimental work since chatbot interventions haven't been rolled out at scale. To limit its scope, this review omits some key areas of AI research: ethics and bias; public health surveillance; and "upstream" AI uses such as training doctors and teachers rather than targeting health or education directly.

Findings in every domain suggest AI is a powerful policy tool. However, this developing-context-focused review highlights what we *don't* know as much as what we *do* know. Most obviously, cutting-edge work on AI feasibility takes place in a few advanced economies; it is very difficult to determine if findings are externally valid. Bureaucrats in poorer countries may not implement ML tools as well as academic research teams. Many existing chatbot studies use convenience samples, meaning selected participants may be unrepresentatively willing and able to use AI. In areas with little access to electricity—let alone internet bandwidth—some LLM use cases may not be viable at all. We emphasize research on AI applications tailored to the means and needs of low resource environments, but the evidence landscape remains sparse to date.

The preliminary literature is also susceptible to substantial publication bias. Unsuccessful ML work is never published. With some pilot RCTs lacking statistical power to identify effects, those reported are more likely to be significant; one can't tell if a null finding is just a result of low power. It also follows that experts are hesitant to claim AI "doesn't work" without the certainty of a well-powered study to back it up. Because fully fleshed-out impact evaluations require time, strong evidence against AI effectiveness would still be in the publication pipeline today.

There is a silver lining: even lower tech chatbots are seeing incredible performance increases each year, making them far more powerful than those tested in the studies we examine.

Literature Overview

Health

AI has many potential uses in the healthcare sector, yet poses great risk to human well-being if utilized incorrectly. Early research suggests AI health interventions are very effective. However, systematic reviews warn that the current evidence may not translate well to low resourced environments: most RCTs have been run in the USA, China, or Europe, and do not have racially or socio-economically diverse sampling frames. While developing countries can benefit greatly from AI-enabled diagnosis, decision support systems, and information dissemination, many lack the data infrastructure for predictive medicine or health system optimization.

For disease diagnosis using machine learning (ML) and computer vision, reviews report that the treatment arm—either an AI system or clinician-AI duo—outperformed the control in 75% of studies.[1] These interventions were highly specialized: specialties such as gastroenterology (digestive system) received greater attention than commonplace primary care scenarios. Lower-tech versions of these tools may perform far worse in less sophisticated clinics because most required video analysis rather than still imagery, greatly increasing their resource demands.[2]

Overworked, under-resourced clinicians may benefit greatly from chatbot-based treatment decision support,[3] an area where LLMs consistently perform as well as human doctors or even better in human-AI duos.[4] A recent paper even found AI adept in weighing competing factors (cost, patient preferences, social determinants) rather than predicting a single objective diagnosis.[5] While less-resourced health workers notionally benefit most from these tools, there are major threats to external validity: these workers may be less equipped to notice when chatbot err, which may also happen more in local languages or contexts. Moreover, most RCTs are conducted via survey vignettes rather than clinical settings for ethical and practical reasons.

AI-based info dissemination is another promising application for the developing world. Chatbot tools informing patients about their specific conditions were found to be as effective in meeting patient demand and providing satisfactory answers as human communication.[6] AI achieved human-like performance in influencing patients to undertake next-step treatments (genetic testing, influenza vaccination, referral uptake); speed of feedback after patient visit improved drastically.[7] If further research confirms that low resourced individuals are similarly able and willing to benefit from chatbot-based info—by no means a given—these tools could extend health information access to underserved and remote communities.

Mental Health and Parenting

Mental health challenges are also endemic to under resourced communities. Work on chatbot dialogue tools as stand-ins for behavioral therapy finds promising ameliorating effects on depression, but more ambiguous impacts on anxiety. While treatments are cost-effective, there is little consensus on optimal "dosing," treatment duration, or persistence of effect. Chatbots can also enable behavioral change using info and nudges, with demonstrated ability to promote healthy lifestyles but also untested potential in cases like household saving. As in the health sector, the primarily advanced-economy-based work must be replicated in developing settings.

Early parenting interventions can have high-leverage impacts on child outcomes over a lifetime, yet scaling up human-mediated interventions incurs exorbitant labor costs, creating demand for cost-effective and scalable AI chatbots hosted on platforms like WhatsApp. Most research to evaluate their viability is at the pilot stage. “Small n” studies find parents willing to engage with chatbots and to sustain engagement,[8] but their sampling frame is not very representative: convenience methods such as voluntary social media sampling may select for respondents that are more able and willing to engage with LLMs than average population members, let alone parents in the developing world. “Technical difficulties” were among the most common complaints, also boding poorly for low resourced households with less technology access.

Low statistical power and varied research design also present inferential challenges. A 15-minute chatbot treatment pilot in Argentina had no significant effect on child disruptions,[9] but it is uncertain whether a true effect was obscured by low treatment dosage and sample size. A rare full-scale AI-related intervention in Uruguay (n=1,360) delivered chatbot access in a bundle of services, making it impossible to infer what portion of the treatment effect can be attributed to AI.[10] Similarly, a pilot RCT in South Africa explored AI’s complementarity with other parenting treatments, yet doesn’t benchmark them to a human-mediated baseline arm.[11]

Education

LLMs are massive info repositories able to answer content-based questions or simulate teacher-student interactions with varying sophistication. Given chatbots’ potential use in education, several meta-analyses and systematic reviews collate papers that, to this point, have exhibited mixed results. Meta-analysis combining different study results using random effects models has found randomized and quasi-randomized chatbot treatments to have a significant positive impact on learning outcomes. Effect sizes are larger at higher education levels and interventions less than 10 weeks—concerningly, it is possible that novelty effects wear off—but some papers found the impacts to be insignificant for primary and secondary education.[12]

Limited research conducted specifically in the developing world includes a descriptive study in Sierra Leone finding that teachers had very low take-up of WhatsApp-hosted chatbots; an RCT in Brazil demonstrating that teachers could pass off some grading tasks to AI without student performance declining due to less feedback; and a World Bank project in Nigeria identifying promising early results for a chatbot-based afterschool learning intervention.[13]

For language learning, meta-analyses found significant positive treatment effects for grammar, listening, and writing.[14] However, more work is necessary to see if these results are generalizable to the developing world: learners were relatively advanced, studying English, and well-resourced. In mathematics, early evidence was more mixed. An RCT in Ghana (n = 1,000) supplementing students with 1 hour of weekly WhatsApp chatbot access for 8 months exhibited strongly positive results through the first year. Yet, a smaller US-based evaluation identified only less student confidence in problem-solving once their chatbot aide was removed.[15]

AI may also help less-resourced students overcome logistical obstacles or identify pupils close to dropping out. A pair of RCTs showed chatbots can help 1st-gen US college students manage complicated filings and meet proactively with counselors, though the “light touch” intervention didn't appear to impact graduation outcomes.[16] Researchers have also used deep learning to predict student dropout in Massive Open Online Courses (MOOCs), curricula that democratizes info access but makes it difficult to identify at-risk students.[17] Using user activity data, the authors build a model predicting the students most likely to drop the program, thus directing more teacher attention on these students. Two papers based on Latin American data suggested that dropout prediction is feasible in traditional classroom settings as well.[18]

Agriculture

With most developing economies still primarily agricultural, sectoral efficiency gains can drive poverty alleviation and facilitate structural transformation. The most promising AI use cases in low resource environments rely on the superior prediction capabilities of ML: pestilence diagnosis, yield forecasting, and soil quality measurement.[19] Robotics and sensor-driven farm management, though feasible in advanced economies, are a distant reality in most of the developing world. And while ag-enabling chatbots possess great appeal, few papers have explored their practical feasibility—let alone take-up or efficacy in low resource environments.[20]

In developing settings, limited tech access forces farmers to rely on phone cameras instead of drones and rules out complex remote sensing systems. A study in East Africa nevertheless showed that a mobile-based computer vision app—with offline functionality—could diagnose disease in cassava crops as well as human experts and far better than the average farmer.[21] Similar models can detect disease/pest infestation in banana crops, though this neural network-based approach hasn't yet been scaled down to the size that a mobile phone can support.[22]

Analysts in developing economies can employ satellite imagery mixed with ML methods to map crop yields and soil quality at a scale ranging from smallholder plots to entire countries.[23] While this information can inform policymakers or be disseminated to the local level, researchers must think further about how it can be systematically operationalized. One proposal is to use ML-based yield estimates to rapidly test the impact of seed or fertilizer interventions.[24]

Prediction Problems: Data, Targeting, Governance, and Microcredit

AI also enables a broad rethinking of predictive ML tools for governance and policymaking in the developing world. A robust literature tackling "prediction policy problems"[25] shows encouraging technical viability, but traditional impact evaluation of these methods hasn't yet caught up.

AI-enabled datasets can supplement sparse government- or IGO-sponsored poverty data, better informing policy practitioners. ML approaches to satellite data, remote sensing, or street-level imagery have allowed academics to create granular poverty maps, specifically in Africa and South Asia, that often compare favorably to laborious household surveys.[26] However, ML does not automatically perform better in every case. One study finds ML prediction to underperform traditional methods in classifying poverty in Mexico because the data features extracted from satellite imaging—complex indices of vegetation level and urban buildup—are only weakly predictive of poverty. Other authors determine that remotely sensed data are worse predictors of changing poverty rates than enhanced GDP indicators, but this is at the country level where traditional data is more comprehensive and satellite data is less informative.[27]

AI prediction techniques may also help identify the ideal population segments for sampling, a technique called “targeting.” Work in Iraq and Togo shows that ML analysis of mobile phone data identified poor households as well as traditional survey methods; performance was even better when combining data types.[28] An assessment of an Italian tax rebate found that if the program was targeted to households that an AI model predicted would benefit most, instead of a random subset within an income bracket, the aggregate impact could have been far greater.[29]

ML tools have regulatory applications for overstretched governments, using existing metadata to optimize water use inspections or harnessing satellite datasets to identify informal, polluting brick kilns in Pakistan. One study showed AI analysis of budget data to identify public corruption at twice the rate of random audits.[30] Additionally, readily available satellite imagery has enabled real-time disaster prediction and targeted humanitarian assistance. ML-based flood warning systems and drought prediction outperform traditional models when tested head-to-head. AI can also track migration flows via social media, an application tested with Syrian refugees.[31]

ML methods may also unlock greater microfinance access in developing countries through improved prediction and use of novel data in credit scores, helping entities without traditional credit histories obtain funding.[32] While ML consistently yields better credit scoring in emerging market settings, alternative data such as phone-based transactions, social media history, and psychometric evaluations have, to date, been exploited only in advanced economies.

<u>**Policy Takeaways for Developing Contexts**</u>

For policymakers in developing countries, AI is a promising new tool in their evolving dev toolkits—one with potential to scale far more cheaply than traditional human-based interventions. However, the dev community has further research to do before large-scale fixed investments in AI capabilities become prudent for less resourced countries or their donors.

ML-based prediction tools are the best place to start: there is more existing research; they are an incremental upgrading of existing tools rather than a high-risk, high-reward paradigm shifter; and they are a more accessible way for governments to begin building technical AI chops. Moreover, the WB and IMF have ML experts that can provide TA to jumpstart the process. The greater challenge is thinking creatively about which ML applications benefit their societies most.

In the current funding environment, officials should not rush to roll out LLMs beyond the pilot scale. Unlike with ML, we can say little with confidence about what they can (and can’t) do. Even research in the best-explored sectors (health and education) may not be externally valid; the behavioral dynamics of chatbot interactions are mostly unexplored. Yet, we cannot ignore the potential of LLMs to catalyze dramatic change. The good news is that a flood of evidence is imminent: smaller, more powerful chatbots were popularized in 2022-2023, and there are undoubtedly many publications in the academic pipeline.

Development economists can help in three ways: rigorously evaluating chatbot interventions in diverse settings, as J-PAL is spearheading with its recent call for proposals; raising alarm about publication bias and pushing initiatives like the AEA RCT registry; and exploring econ-specific phenomena like general equilibrium effects and structural dynamics of chatbot usage.

Appendix

Literature Summary

Domain	Use Cases	ML or Chatbot	Developing World Focus	Early Findings	Limitations + Concerns
Health	ML-enabled diagnosis; decision support; patient information and outreach	Mixed	Low	Positive (high)	Sampling frames not diverse; priority to specialty use cases; survey vignettes.
Mental Health + Parenting	Substituting talk therapy for depression/anxiety; encouraging behavioral change; parenting coaching and advice	Chatbot	Moderate	Positive (moderate)	Convenience samples; technical challenges; low power; disentangling AI from bundled treatment arms
Education	Supplement classroom study; simulate student-teacher interaction; grading tasks; overcome logistical obstacles; predict drop-out	Mostly Chatbot	Moderate	Positive (low)	Result heterogeneity (length, grade level, conflicting findings)
Agriculture	Diagnosing crop disease; predicting yields or soil quality with satellite imagery	ML	Moderate	Positive (high)	Only demonstrates feasibility; unclear how impacts accrue to local level
Prediction Problems	Poverty mapping; program targeting; disaster and humanitarian forecasting; regulatory capacity; microcredit	ML	High	Positive (high)	Only demonstrates feasibility

For the column titled *Early Findings*, “low,” “moderate,” and “high” reflect a loose qualitative assessment of consistency of results. “Low” consistency indicates that while results are primarily positive, there are also many null findings.

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