Project Summary and Key Findings

Neonatal mortality remains a major public health challenge in low- and middle-income countries (LMICs), accounting for approximately 2.5 million deaths annually, with nearly 98% occurring in these settings. In Kenya, where the neonatal mortality rate is 22 deaths per 1,000 live births, timely identification of high-risk newborns is hindered by overstretched health systems, limited specialist staff, and reliance on subjective clinical assessments. This project evaluated the feasibility, usability, acceptability, and clinical applicability of 21 predictor variables derived from a machine learning (ML) model previously validated in LMICs (AUC >0.80). The variables were grouped into five categories: Maternal Information, Pregnancy Information, Delivery Information, Neonatal Information (Delivery/Day 1), and Post-Delivery Information (Day 2). The aim was to assess their suitability within Kenyan health facilities and generate evidence to inform future AI-enabled neonatal decision-support systems aligned with Sustainable Development Goal (SDG) 3.2.

Led by Strathmore University in collaboration with the University of Bradford, the study employed a mixed-methods pre-implementation design across Kibera Community Health Centre, Nazareth Mission Hospital, and Matuu Community Health Unit. A paper-based neonatal risk predictor tool was integrated into routine clinical workflows over four months, alongside key informant interviews to identify implementation barriers.

The findings demonstrated that the predictor variables were operationally feasible and clinically relevant. High-quality data were collected from 394 newborns, with less than 1% missing data for most variables. Healthcare workers reported that the variables aligned well with routine newborn assessments, particularly gestational age, birth weight, temperature, respiratory status, and vital signs. Participants also recommended adding contextual variables such as APGAR score, mode of delivery, and duration of labour to enhance predictive performance.

Usability results were encouraging: 89% found the tool easy to learn, 86% were confident using it, and 78% reported improved identification of high-risk newborns and timelier interventions. However, only 44% indicated changes in referral practices, highlighting the need for stronger integration into routine care. Key implementation barriers included staff shortages, heavy workloads, unreliable electricity, poor internet connectivity, and continued reliance on hybrid paper–digital systems.

Overall, the study demonstrates that the neonatal risk predictor variables are feasible, usable, and appropriate for routine newborn care in Kenyan health facilities. Based on the evidence, the neonatal risk prediction project is ready to advance to a second phase involving the development and pilot implementation of a fully digital, AI-enabled neonatal decision-support tool integrated

with existing health information systems. The pilot will evaluate the solution under real-world clinical conditions, strengthen workforce capacity and digital infrastructure, and generate the evidence needed to support broader scale-up and sustainable integration into routine newborn care.