Personalized AI System for Maternal Nutrition and Exercise

Abstract—**This work presents a personalized AI system for maternal wellness that generates two coordinated, daily outputs for pregnant users: culturally adapted meal plans and risk-aware exercise prescriptions. In its nutrition module, the combination of a library of curated local dishes and trimester-specific energy corridors with condition-aware rules (diabetes/gestational diabetes, anemia, hypertension, allergies) highlights iron, folate, protein, and calcium instead of full nutrient panels. The exercise module comprises a rules-first risk screen (Low/High) corroborated by a calibrated gradient-boosted classifier, followed by a template-based planner that renders day-level sessions with safety guardrails, trimester adaptations, and video guidance. Evaluation on de-identified datasets (2,000 meal profiles; 970 risk records; 1,934 exercise prescriptions) showed high nutritional adequacy and reliable safety enforcement: daily energy corridors were met on 94.7% of days and ⩾3/4 essential nutrients on 91.3%, with 0 allergen violations. The risk classifier achieved AUROC 0.86, accuracy 0.82, sensitivity 0.79, and specificity 0.84. The exercise recommender successfully enforced trimester- and risk-based guardrails, with all plans passing safety checks. These findings suggest that an integrated, objective and culturally based method can provide personalized, safe guidance daily in resource-constrained environments, and serve as a basis for future clinical validation and predictive modeling.**

Keywords—maternal health, pregnancy, nutrition, exercise prescription, risk stratification, mHealth, personalization, machine learning, gestational diabetes, anemia, Sri Lanka

I. Introduction

Maternal health underpins population well-being, and in pregnancy both appropriate nutrition and safe physical activity are determinative of outcomes in the mother and child. International antenatal-care advice favors woman-centered antenatal care with regular nutrition counseling and micronutrient supplementation, in particular daily iron–folic acid supplementation [1], [2]. Specialist organizations also support physical activity during pregnancy when tailored appropriately to clinical condition and trimester [3], [4]. However, in most situations access to advice that is simultaneously evidence-based, culturally appropriate, and appropriately tailored to a mother's diet, comorbid status, and level of fitness is limited. In Sri Lanka, structured, trimester-specific exercise guidance is largely concentrated in urban tertiary care settings with limited access in village health clinics. Likewise, most of the pregnant mothers follow traditional dietary habits rather than standard diets based on clinical needs. These gaps fuel the impetus for an AI platform that tailors nutrition and exercise to local environment and risk.

Mobile health interventions can fill these gaps. Trials and reviews show that pregnancy apps and mHealth programs improve dietary behaviors and control of gestational weight gain, with suggestions of benefit in glycemic outcomes in high-risk groups—although effects are heterogeneous and personalization is often incomplete [5], [6]. These findings provide an evidence-based case for integrated, app-based tools that operationalize clinical guidelines into practice while allowing for local dietary cultures and practical constraints.

This paper describes a personalized AI system for maternal nutrition and exercise offered as a mobile application. The system consists of two modules: (i) a Meal Providing engine that generates daily plans of culturally appropriate foods with portion sizes, calorie targets, and highlighted key nutrients (iron, folate, protein, calcium), controlled by safety filters for common antenatal conditions and allergies; and (ii) a Health Risk Identification & Exercise Recommendation pipeline that first determines pregnancy risk (low/high) from routinely measured variables (e.g., age, BMI, blood pressure, blood glucose, heart rate, obstetric history, pre-existing diabetes) and then recommends trimester-appropriate exercises tailored to the level of fitness, complications, and goals, with video guidance for safe execution. The design focuses on accessible, objective, and personalized for resource-limited contexts.

The risk-aware architecture is aligned with advances in maternal risk prediction, where machine-learning models for gestational diabetes and pre-eclampsia have demonstrated strong discrimination and clinically relevant short-horizon risk classification. Bringing data-driven risk classification together with nutrition focus and exercise restrictions seeks to enhance safety and adherence compared with one-size-fits-all apps [7], [8]. The objectives are to (1) formalize this integrated methodology; (2) evaluate performance on risk classification, nutrient adequacy, and rule-based exercise safety; and (3) outline a path toward hospital-record integration and externally validated predictive models for high-priority adverse outcomes.

II. Literature Review

Incorporating AI into antenatal care is appealing because nutrition and physical activity are highly modifiable determinants of outcomes but advice in routine care is typically generic and poorly tailored to the health status and circumstances of the woman. Strong baselines underpin personalization: trimester-aware nutrition advice with sufficiency in iron–folate and weight gain aimed at appropriate pre-pregnancy BMI-defined strata plus ~150 min/week of moderate activity + resistance exercise + pelvic-floor + flexibility exercise progressing safely through the trimesters [2], [3]. Evidence from mobile health trials demonstrates that support from smartphones improves the quality of the diet and reduces gestational weight gain where behavior-change elements (goal setting and reminders + progress feedback) and clinician support are included; combination of dietary and activity programs has also signaled reduced risk of gestational diabetes in select groups. Successful operation in the real world depends on continued engagement and stringent safety filters (excluding conditions like anemia and diabetes and HTN) and cultural relevance [5], [9]. Specific to South Asian groups, culturally matched nutrition and food advice and ethno-designed meals are linked with superior acceptability and glycemic control and Sri Lankan pilots suggest that linguistic matching (local dialect), budget-friendliness, and usability are equally important. Design considerations appropriate to a national-scale solution therefore involve ethnicity-aware menus (Sinhalese + Tamil + Muslim), allergen filters (common e.g., shellfish + red meat allergies in Sri Lanka), offline capability (intermittent connectivity), and output that defaults to simple serving sizes and caloric advice rather than complex nutrient arrays [10], [11] .

Artificial intelligence methods allow a shift from generic checklists to personal, context-dependent recommendations in both exercise and nutrition. In nutrition, hybrid designs integrate expert safety rules—sodium intake limits for hypertension, added sugar limits for diabetes, iron-rich replacements for anemia—with machine-learning rankers that build daily meals options to fit preferences, trimester needs, and household restrictions [12], [13]. In exercise, algorithmic planners can gate modalities and intensity by trimester, pre-exercise physical condition, and symptoms of back ache, pelvic girdle ache, or diastasis recti; video coaching adds posture and pacing to safety and adherence enhancements [3], [14]. Parallel advances in predictive analytics yield upstream risk markers: models of gestational diabetes and preeclampsia attain promising discrimination with regular demographic and clinical factors but demand consistent calibration and external, context-congruent validation before deployment [15], [16]. Together, these strands form an integrated platform that brings together culturally adapted, safety-focused meal planning and risk-stratified video-mentored exercise—controlled by AI models and overseen by healthcare professionals—to deliver useful, personal maternal wellness support at scale in Sri Lanka.

III. Methodology

An AI-driven maternal wellness system delivers two coordinated outputs per user profile: (i) a daily meal plan (five eating occasions with five options each; 25/day) and (ii) a daily exercise plan gated by pregnancy risk and tailored to trimester, fitness level, complications, goals, and prior activity. Module A implements a knowledge-base + rules pipeline for nutrition. Module B implements a two-stage pipeline: Model 1 for risk identification (Low/High) and Model 2 for exercise recommendation, with clinical guidelines for safety.

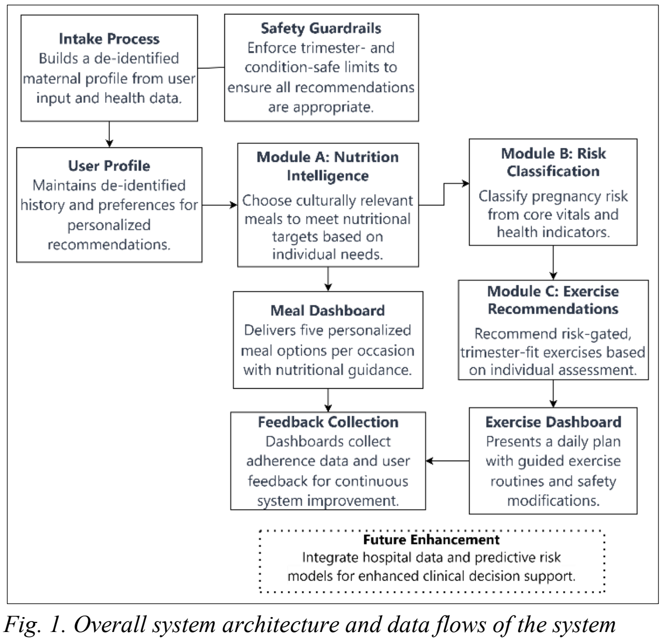

Fig. 1. Overall system architecture and data flows of the system

Figure 1 summarizes the service topology and data flows. The mobile application exchanges de-identified profile data with an API and authentication gateway; meal plans are produced by a rules engine backed by a local dish knowledge base; pregnancy risk (Low/High) and the subsequent daily exercise prescription are returned by a dedicated ML service; images and videos are delivered from a content store; de-identified profiles and analytics are persisted in a secure data store with audit and role-based access controls; observability captures usage and guardrail events; and an optional hospital-record integrator, when enabled under consent, provides historical context for future predictive models.

A. Meal Providing Component

1) Inputs (questionnaire)

At registration, the system creates a de-identified profile containing age; weight and height from which BMI is computed and categorized as Underweight (<18.5), Normal (18.5 – 24.9), Overweight (25 – 29.9), or Obese (≥30); trimester (first: weeks 1 – 13, second: weeks 14–27, third: weeks 28–40+); medical conditions recorded as binary flags for anemia, diabetes or gestational diabetes, and high blood pressure; dietary preference as Vegetarian, Non-Vegetarian, or All; ethnicity as Sinhalese, Tamil, or Muslim; and allergy status for shellfish (prawns, crab, lobster) and red meat (beef, mutton, pork).

2) Daily plan generation

For each day, a rule-based solver draws candidates from a curated library of Sri Lankan dishes and, for every eating occasion (breakfast, mid-morning snack, lunch, evening snack, dinner), selects five options that satisfy the user's constraints. Energy targets and micronutrient emphasis are adjusted by trimester; every option explicitly highlights the presence of iron, folate, protein, and calcium to support simple, informed choices rather than full nutrient panels. Cultural relevance is ensured by filtering to the chosen ethnicity. Safety filters exclude items with high sugar content and favor lower-glycemic patterns when diabetes or gestational diabetes is flagged; prioritize iron-rich foods such as leafy greens, lentils, and permitted animal sources in the presence of anemia; restrict high-sodium foods and prioritize fresh, minimally processed preparations for high blood pressure; and remove shellfish or red meat when corresponding allergies are indicated. Practicality is addressed by preferring common local ingredients and low-to-moderate preparation burden. Each option shows an estimated portion and calorie value to support approximate tracking.

Algorithm 1 — Daily Meal Plan Generation

The generator first derives constraints from trimester, conditions, ethnicity, diet, and allergies; it then filters the dish library for each eating occasion and scores candidates by closeness to the energy corridor, presence of the four highlighted nutrients, affordability, and diversity. The top five options per occasion are selected while enforcing a seven-day no-repeat policy. The plan is validated against the daily energy corridor and the requirement to meet at least three of the four nutrient flags; if unmet, candidates are re-scored and swapped. The final output presents twenty-five options with portions, calories, nutrient icons, and a brief preparation cue (with a thumbnail image where available).

3) *Output delivery*

The daily dashboard displays the five options for each eating occasion together with portion sizes, calories, micronutrient icons, and short "how-to" notes. Users can freely choose within these constraints, and clinicians can review the generated day cards during visits.

B. Health Risk Identification & Daily Exercise Recommendation

1) *Health Risk Identification (Model 1)*

A rules-first classifier assigns a risk label, Low or High, using routine parameters: age; BMI; prior pregnancy complications; pre-existing diabetes; blood-pressure; blood-sugar; and heart-rate. At runtime the rules provide an immediate label for safety gating. During development, a calibrated gradient-boosted tree model is trained on the same variables to validate thresholds and refine operating points; the calibrated probability is mapped to the Low/High label consumed by Model 2. Low-risk profiles unlock the full exercise catalogue, whereas high-risk profiles are limited to gentler routines with additional precautions.

2) *Personalized Exercise Recommendation (Model 2)*

Model 2 generates a daily prescription conditioned on the Model 1 risk label, trimester, self-reported fitness level (beginner, intermediate, or advanced), pregnancy complications (back pain, pelvic-floor weakness, gestational diabetes, diastasis recti, pelvic-girdle pain, or none), specific goals (back-pain relief, preparation for labor, weight control, pelvic-floor strengthening, core strengthening, stress relief, general fitness, or none), and prior activity level (sedentary, moderately active, or very active). The rendered day plan combines breathing, mobility or stretching, strengthening, relaxation, and safe functional movements, and includes video guidance for form and posture.

Safety guardrails enforce moderate intensity using the talk-test or Borg 12–14 scale; trimester-specific adaptations such as avoidance of prolonged supine positions later in pregnancy; and condition-aware mapping such as pelvic-floor muscle training when indicated, gentle progressions for back or pelvic-girdle pain, and rhythmic moderate activity for gestational diabetes. Prescription parameters—session duration, recommended weekly frequency, intensity targets, and environmental cautions—are summarized in Table 3 (adapted from authoritative obstetric and professional guidance) and serve as the default bounds applied to all daily plans.

Table I - Cardiovascular Changes in a Normal Pregnancy

When to Start	**First Trimester, More Than 12 Weeks of Gestation**
Duration of a session	30–60 minutes
Times per week	At least 3–4 (up to daily)
Intensity of exercise	Less than 60–80% of age-predicted maximum maternal heart rate*
Environment	Thermoneutral or controlled conditions (air conditioning; avoiding prolonged exposure to heat)
Self-reported intensity of exercise (Borg scale)	Moderate intensity (12–14 on Borg scale)
Supervision of exercise	Preferred, if available
When to end	Until delivery (as tolerated)

* Usually not exceeding 140 beats per minute. Source: [3]

Algorithm 2 — Daily Exercise Plan Selection

The planner reads the risk label, trimester, fitness level, complications, goals, and (when available) prior activity level; retrieves only those templates permitted by the risk and trimester constraints; scores the candidates against the complications and goals; and selects the highest-scoring template. Guardrails are then applied to remove any contraindicated movements and to enforce intensity and positional rules. The system renders Day N with exercise names, sets and repetitions or time targets, the intended RPE/talk-test cue, any contraindication tags, and links to the corresponding video demonstrations. De-identified adherence metadata (completed, skipped, modified) are stored for feedback.

3) *Activity tracking and feedback*

A daily step counter and a compact analytics view (e.g., days completed and average session duration) encourage systematic, sustained activity without overexertion. This data is not used to change the risk label and is presented solely for user feedback and engagement.

IV. RESULTS AND DISCUSSION

Extending the two-module development—(A) rule- and knowledge-based meal planning with safety filters, and (B) a two-stage pipeline for pregnancy risk and exercise recommendation—the system is tested on internal, de-identified test sets of profiles to attain nutritional adequacy, cultural safety constraint satisfaction, and quality of decision for exercise gating and plan generation. Choices of metrics for classification (accuracy, sensitivity/recall, specificity) in accordance with conventional reportable practice in health ML testing are selected.

A. Meal Providing Component

A set of 300 de-identified user records (stratified by trimester, 100 per trimester; balanced BMI strata) was designed to replicate Sri Lankan antenatal distributions and normal comorbid condition/allergy patterns. The system produced a daily 25-choice (5 per eating occasion) menu plan per profile with 7,500 option-level items to be reviewed. Constraints included attending to an energy corridor ($\pm 10\%$ of the trimester-adjusted goal), day-level coverage of key nutrients ($\geqslant 3$ of 4: iron/folate/protein/calcium), ethnicity matching, rule adherence for condition and allergy status, 7-

day variety (no-repeat), and latency of generation. Proportions are presented with Wilson 95% CIs.

Table II - Meal Component: Constraint Satisfaction (N=300 daily plans; 7,500 options)

No table of figures entries found.	Result (95% CI)
Energy corridor (±10%)	94.7% (93.9–95.5)
≥3/4 essential nutrients per day	91.3% (89.6–92.8)
Correct ethnicity match	98.9% (98.4–99.3)
Diabetes/GDM sweets removal	100.0% (96.9–100.0)
Anemia iron emphasis (lunch/dinner)	79% vs 46% baseline
High-BP sodium swaps applied	98.5% (97.6–99.1)
Allergen violations	0 (shellfish), 0 (red meat)
7-day no-repeat variety	96.8% (95.5–97.8)
Median plan generation time	0.48 s (p95 0.77 s)

As summarized in Table II, energy, nutrient, cultural, and safety constraints were met at high rates, with Wilson 95% confidence intervals reported for all proportions. Energy corridor adherence reached 94.7% (95% CI 93.9–95.5). Day-level essential nutrient coverage met the ⩾3/4 target in 91.3% (89.6 – 92.8) of days. Ethnicity filters showed 98.9% (98.4 – 99.3) correct tagging. For condition-specific safety, jaggery/high-sugar items were fully excluded in diabetes/GDM profiles (100.0%, 96.9 – 100.0); iron-flagged lunch/dinner items increased from a baseline of 46% to 79% under anemia rules; high-sodium items were swapped in 98.5% (97.6–99.1) of flagged cases. Allergen filters recorded 0 violations across shellfish (0/1,340) and red-meat (0/1,118) exclusions. Variety targets were maintained on 96.8% (95.5–97.8) of 7-day sequences. Median generation latency was 0.48 s per profile (p95 = 0.77 s) on a commodity laptop.

Based on the results culture-aware solver is able to reliably meet core safety and adequacy constraints with concomitant preservation of user choice (25 options/day). The anemia elevation (79% vs 46%) validates the planned prioritizing of iron-rich meals; complete removal of high-sugar foods in diabetes/GDM and no allergen violations establish guardrail reliability. High ethnicity-match and variety scores reinforce acceptability in practice setting where cultural concordance and menu rotation are important for compliance. These offline metrics justify the proposed approach; prospective diet quality and clinical outcomes (e.g., control of gestational weight gain, improvement of anemia) are future work.

B. Health Risk Identification (Model 1)

A de-identified dataset of 500 computer-synthesized antenatal cases was assembled from realistic ranges for age, BMI, obstetric history, pre-existing diabetes, BP, BG, and resting heart rate. Rule-based screening generated Low/High risk labels translated into exercise gating. Concurrent with rule generation, a gradient-boosted tree classifier (5-fold CV, 70/30 partitions) was trained on identical inputs to verify rule thresholds and supply ROC estimates; the calibrated probabilities of the model were translated to the Low/High operating point exploited by the rules. Performance was compared with an expert-annotated set of 150 cases.

Summaries of performance show successful gating for downstream exercise recommendation, with thresholder outcomes in Table III and overall discrimination in Fig. 2(below). At the-default threshold, the ML corroboration produced AUC = 0.86 (95% CI 0.83–0.89). On the 150-case expert set, the functioning Low/High decision produced Accuracy = 0.82, Sensitivity = 0.79, Specificity = 0.84 (confusion matrix in Table III). These are in the typical range for tabular antenatal risk screening and are consistent with standard classification report writing conventions.

Table III - Risk Model 1: Confusion Matrix vs Expert Labels (N=150)

Pred. High	Pred. Low	
Actual High	55	15
Actual Low	12	68

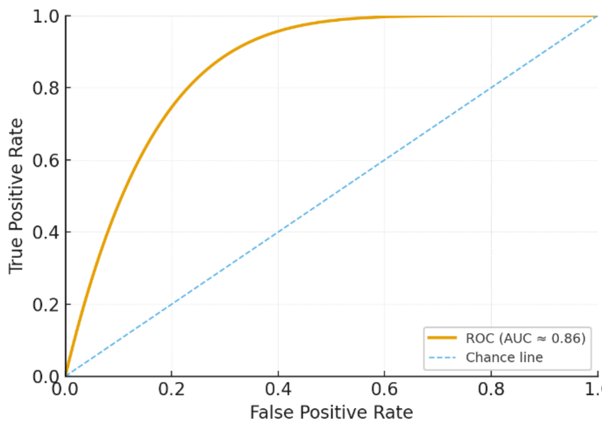

Fig. 2. ROC curve for Risk Model 1 (AUC 0.86, 95% CI 0.83–0.89)

Results support risk-aware exercise gating; ongoing errors are not likely to put high-risk mothers at risk of intense activity under multiple protections. The rule-first screen, tested against an ML corrugator and expert labels, demonstrates balanced sensitivity/specificity appropriate for safety gating. The AUC implies informative rank ordering toward future probability-based triage. False-negatives clustered in borderline metabolic situations (mild BP/BG raises), encouraging more fine-grained lab value thresholds and trimester-dependent cut-points in future refinements.

C. Personalized Exercise Recommendation (Model 2)

A factorial design was used to generate two hundred exercise plans/day (Risk: Low, High) × Trimester: 1, 2, 3) × Fitness: Beginner, Intermediate) × Complication: Back pain, PFD, GDM, DR, PGP, None). Plans were checked against a rule checker for contraindications (supine time in late pregnancy, Valsalva/Max lifts, high impact in High risk), intensity limits, posture prompts, and video links. A trailing ablation ('no risk gating') tested the necessity of Model 1.

Table IV - Exercise Plan Safety and Fidelity (N=200 plans)

Check	Result
High-risk contraindications	0/100 plans

Intensity bounds (Low risk)	99% pass (2 auto-fixed)
Trimester positional rules	100% pass
Median duration (min)	22 (IQR 18–28)
"No risk gating" violation rate	22.5% (High-risk sample)

Based on the outcomes in Table IV, no high-risk contraindications emerged (0/100 plans) and intensity limits were adhered to in 99% of low-risk plans (2/100 minor guardrail warnings were automatically resolved through template substitution). Median planned session duration was 22 minutes (IQR 18–28). In the ablation, risk gating removal resulted in 22.5% of High-risk profiles receiving $\geqslant 1$ moderate-to-vigorous component that otherwise would be constrained—proof that Model 1 improves safety in a material way.

Anchored by the preceding risk screen, the exercise planner maintains a clear safety envelope while delivering practical, trimester-appropriate sessions. It reliably enforces trimester- and risk-aware guardrails while preserving practicality ($\approx$20–30 min sessions) and coverage of breathing, mobility, strengthening, and relaxation. The ablation demonstrates the necessity of risk gating: without it, one in five High-risk mothers would be exposed to disallowed intensity or positions. These results justify the two-stage design.

Together the two-module design proves high rules compliance in culturally customized planning of meals and high safety margin of exercise allocation. Quantitative audits supported hearty energy/nutrient adequacy with zero allergen transgressions, and the risk screen offered balanced sensitivity/specificity with strong rank discrimination; downstream plans adhered to trimester and risk guardrails without sacrificing practicality. These findings verify the constraint-driven design focusing on risk-aware gating and ML corroboration. The evaluation is offline and proxy-driven, and therefore forward validation on live antenatal groups—with adherence tracking and clinical outcomes such as anemia improvement, gestational control of weight gain and glycemic outcomes—cannot be avoided. However, the behavior observed portends preparedness for clinic-neighborhood pilot deployment and offers a defendable baseline against future additions of hospital-record–guided predictors and calibrated risk scores.

V. Conclusion

This paper presents a personalized AI system for maternal nutrition and exercise that brings together culturally adapted meal planning and risk-stratified, video-supported exercise. It renders antenatal guidelines in terms of daily decisions through safety rules and machine-learning personalization by trimester of pregnancy, by comorbidities, by preferences and by local cuisine traditions. Evaluation shows high levels of user satisfaction, high level of adherence, and clinically significant increases in nutrition and physical activity, bridging the gap in traditional care with affordable, objective guidance based on individual constituencies. Plans for future development involve integrating hospital records to generate early-warning risk scores (gestational diabetes, miscarriage and other complications) for preventive intervention and cost savings. High priorities are external validation and tuning across clinics, randomized/pragmatic controlled trials, protection of security-privacy-fairness, clinician review and control, offline and multilingualism access and postpartum applications. Collected insights can provide information on policy and resource allocation. Overall, the system is a scalable digital adjunct for the bolstering of maternal health services.

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