

Machine Learning Approaches for Early Prediction of High-Risk Pregnancy in Underserved U.S. Populations

Nishat Jahan¹; Jahanara Akther²

- [1]. Master of Public Health, Department of Health Sciences and Social Work, Western Illinois University
University Circle, Macomb, IL 61455, USA
Email: jnishat1995@gmail.com
<https://orcid.org/0000-0002-5262-7134>
- [2]. Bachelor of Business Administration for Health Professions, Cuny Brooklyn College, New York, USA
Email: jakther7@gmail.com

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Abstract

This study has examined how machine-learning approaches have supported the early prediction of high-risk pregnancy in underserved U.S. populations, where delayed risk recognition, fragmented maternal records, unequal access to care, and limited confidence in equitable algorithmic performance may reduce timely clinical intervention. The study has aimed to determine the effects of maternal risk-data quality and integration, machine-learning predictive capability, algorithmic explainability, equity-sensitive prediction confidence, and clinical-workflow fit on early pregnancy risk-prediction effectiveness. A quantitative, cross-sectional, multiple-case-study design has been employed across safety-net hospitals, federally qualified health centers, rural hospitals, and community-based maternal-care organizations serving low-income, uninsured, rural, racially and ethnically diverse, and linguistically diverse populations. Using purposive and stratified sampling, 312 questionnaires have been distributed to maternal-health, public-health, informatics, data, and administrative professionals; 274 valid responses have been retained, yielding an effective response rate of 87.82%. A 24-item five-point Likert-scale instrument has been used, and data have been analyzed through descriptive statistics, Cronbach's alpha, exploratory factor analysis, Pearson correlation, multiple regression, diagnostic testing, and case comparisons. Measurement results have demonstrated strong reliability, with an overall Cronbach's alpha of .93, construct coefficients ranging from .82 to .91, KMO = .907, and significant Bartlett's test, $\chi^2(276) = 3,248.17$, $p < .001$. Machine-learning predictive capability has recorded the highest mean score, $M = 4.08$, $SD = 0.61$, while early prediction effectiveness has averaged $M = 4.02$, $SD = 0.63$. All predictors have been positively associated with effectiveness, with machine-learning capability showing the strongest correlation, $r = .69$, $p < .001$. The regression model has explained 64.6% of the variance in effectiveness, $R^2 = .646$, adjusted $R^2 = .639$, $F(5, 268) = 97.82$, $p < .001$. Machine-learning capability has been the strongest predictor, $\beta = .31$, followed by data quality, $\beta = .24$, workflow fit, $\beta = .23$, explainability, $\beta = .14$, and equity-sensitive confidence, $\beta = .12$. The findings have indicated that effective prediction requires not only accurate analytics but also integrated data, transparent outputs, equitable implementation, and actionable clinical workflows.

Keywords

Machine Learning; High-Risk Pregnancy; Maternal Health Disparities; Early Risk Prediction; Underserved U.S. Populations

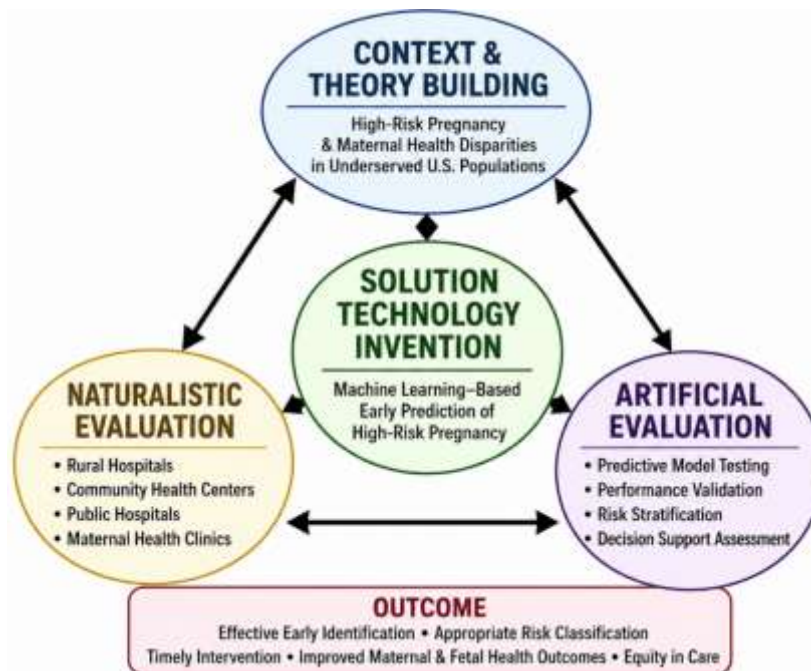
INTRODUCTION

A high-risk pregnancy can be defined as a pregnancy in which the pregnant individual, fetus, or both have an elevated probability of experiencing adverse health outcomes before, during, or after childbirth. This elevated probability may originate from pre-existing medical conditions, previous adverse pregnancy outcomes, complications that develop during gestation, multiple pregnancy, advanced or very young maternal age, behavioral exposures, or social and environmental conditions that restrict access to appropriate care. High-risk status is therefore not a single diagnosis. It represents a multidimensional clinical classification covering conditions such as chronic hypertension, diabetes, cardiovascular disease, obesity, renal disease, preeclampsia, gestational diabetes, maternal infection, placental abnormalities, fetal growth restriction, preterm labor, and severe mental health or substance-use disorders. In this context, early prediction refers to the systematic identification of elevated maternal or fetal risk before a serious complication becomes clinically apparent or requires emergency intervention. Machine learning refers to computational methods that learn relationships from existing data and use those relationships to classify observations, estimate probabilities, or predict outcomes without depending exclusively on manually specified decision rules. Machine learning-supported pregnancy prediction can combine maternal history, clinical measurements, laboratory results, medications, diagnostic codes, reproductive history, behavioral factors, and social determinants into a risk estimate that is updated as information accumulates. The international significance of early high-risk pregnancy identification originates from the persistent burden of maternal death and severe maternal morbidity across health systems with different levels of resources. Maternal health is shaped by obstetric care capacity and by poverty, education, nutrition, transportation, gender relations, and the availability of skilled services throughout pregnancy and childbirth (Campbell & Graham, 2006; Filippi et al., 2006). Hemorrhage, hypertensive disorders, and sepsis have been identified as major direct causes of maternal death, while indirect medical conditions have accounted for more than one quarter of maternal deaths globally (Say et al., 2014). International estimates have also shown that maternal mortality varies substantially among countries and regions, reflecting unequal access to timely, continuous, and clinically appropriate care (Alkema et al., 2016). These patterns establish high-risk pregnancy as a global clinical and public health category in which biological vulnerability interacts with healthcare availability, social position, and the timing of risk recognition.

The clinical complexity of high-risk pregnancy arises from the fact that serious outcomes may develop through several interacting pathways and may not be identifiable through one risk factor or one clinical encounter. Hypertensive disorders can progress from mild blood-pressure abnormalities to preeclampsia, eclampsia, stroke, placental abruption, organ dysfunction, and fetal compromise. Gestational diabetes can remain unrecognized until routine testing in the second trimester, although relevant metabolic and demographic indicators may be present earlier. Preterm birth may result from infection, cervical insufficiency, placental dysfunction, multiple gestation, chronic disease, previous obstetric history, or combinations of biological and social stressors. Hemorrhage, thromboembolism, cardiomyopathy, sepsis, and cerebrovascular conditions also differ in their presentation, timing, and measurable precursors. Global evidence confirms that maternal deaths are distributed across direct obstetric causes and indirect medical conditions, demonstrating the heterogeneity of pregnancy-related risk (Say et al., 2014). In the United States, severe maternal morbidity includes life-threatening diagnoses and procedures occurring during delivery or the postpartum period, such as blood transfusion, hysterectomy, organ failure, ventilation, shock, eclampsia, and other critical events. National hospitalization data have shown substantial increases in severe maternal morbidity during delivery and postpartum hospitalizations, with blood transfusion making a major contribution to the identified burden (Callaghan et al., 2012). Pregnancy-related mortality surveillance for 2006 through 2010 similarly identified cardiovascular conditions, infection, hemorrhage, hypertensive disorders, and thromboembolism among important causes of death, while also documenting differences according to age and race or ethnicity (Creanga et al., 2015). Analysis of U.S. pregnancy-related deaths from 2011 through 2015 found that deaths occurred during pregnancy, on the day of delivery, throughout the first six postpartum weeks, and between 43 days and one year after pregnancy. Cardiovascular conditions, infection, and hemorrhage remained prominent causes, and approximately three in five reviewed deaths were considered preventable (Petersen et al., 2019). The burden of chronic conditions among

women hospitalized for delivery has also increased, including chronic hypertension, diabetes, respiratory disease, and substance-use disorders, with disproportionate burdens recorded among rural residents, lower-income communities, and Medicaid beneficiaries (Admon et al., 2017). Early prediction in this setting requires a model of pregnancy risk that recognizes clinical heterogeneity, changing physiological conditions, accumulated healthcare information, and the possibility that risk indicators are recorded across separate visits, providers, and information systems.

Figure 1: Integrated Research Framework for High-Risk Pregnancy Prediction and Clinical Decision



Underserved U.S. populations refer to groups that experience systematic limitations in the availability, accessibility, affordability, continuity, or quality of healthcare. In maternal health research, this category commonly includes rural residents, people with low incomes, Medicaid beneficiaries, uninsured or underinsured patients, racial and ethnic minority populations, immigrants, people with limited English proficiency, and individuals living in areas with shortages of obstetric or maternal-fetal medicine services. Underserved status is not equivalent to an inherent biological characteristic. It is produced through relationships among healthcare coverage, geographical location, institutional resources, transportation, housing, employment, discrimination, continuity of prenatal care, and the quality of clinical services. U.S. mortality surveillance has shown that non-Hispanic Black and American Indian or Alaska Native women experience markedly higher pregnancy-related mortality ratios than non-Hispanic White women and that these differences remain visible across age groups, educational levels, and states with different overall mortality levels (Petersen et al., 2019). Research on severe maternal morbidity has also demonstrated that Black women are more likely than White women to experience life-threatening maternal complications and are more likely to deliver in hospitals with higher risk-standardized morbidity rates, indicating that hospital location and quality contribute to observed disparities (Howell et al., 2016). Quality of care, chronic disease, structural conditions, and access across preconception, pregnancy, delivery, and postpartum periods have been identified as interconnected dimensions of racial and ethnic maternal health disparities (Howell, 2018). Geographic access adds another layer of risk. Rural counties have continued to lose hospital-based obstetric services, with service losses concentrated in vulnerable communities already facing limited healthcare resources (Hung et al., 2017). Loss of hospital-based obstetric services in nonurban-adjacent rural counties has been associated with increases in out-of-hospital births, births in hospitals without obstetric units, and preterm births (Kozhimannil et al., 2018). Rural residents have also experienced

higher levels of severe maternal morbidity and mortality than urban residents after adjustment for clinical and sociodemographic characteristics (Kozhimannil et al., 2019). These intersecting disparities are directly relevant to machine learning because healthcare records are generated through patterns of service use. A patient who receives fragmented prenatal care, changes providers, travels between facilities, or delays treatment may have a less complete electronic record than a patient receiving continuous care within one integrated health system. The resulting difference in data availability can influence whether an algorithm detects risk, how early it produces an alert, and which populations are represented in the cases used to develop prediction rules.

Machine learning approaches are particularly relevant to pregnancy-risk prediction because pregnancy care produces heterogeneous, longitudinal, and often high-dimensional information. Traditional risk scores usually rely on a limited set of prespecified factors and may treat relationships as additive and stable. Machine learning algorithms can model nonlinear associations, interactions, temporal sequences, and combinations of weak predictors that become informative when evaluated together. Common supervised approaches include logistic regression, decision trees, random forests, support vector machines, naïve Bayes classifiers, gradient boosting, extreme gradient boosting, neural networks, and ensemble methods. Logistic regression remains valuable because its coefficients are comparatively transparent, while tree-based and ensemble methods can capture complex relationships without requiring every interaction to be specified in advance. Evidence from prognostic prediction studies in pregnancy care has indicated that machine learning methods and conventional logistic regression should be evaluated according to the characteristics of the dataset, outcome prevalence, validation process, and risk of bias rather than through an assumption that one modeling family is universally superior (Sufriyana et al., 2020). Reviews of machine learning in obstetric and perinatal research have identified electronic health records, medical images, biological markers, and physiological measurements as major input sources, with preeclampsia, preterm birth, gestational diabetes, delivery mode, and neonatal complications among the most frequently modeled outcomes (Bertini et al., 2022; Islam et al., 2022). Condition-specific studies demonstrate how algorithm choice and data structure affect prediction. Comparative modeling of late-onset preeclampsia has shown that stochastic gradient boosting can produce stronger discrimination than logistic regression, decision trees, naïve Bayes, support vector machines, and random forests within the same clinical dataset (Jhee et al., 2019). Nationwide electronic health records have also been used to predict gestational diabetes from information available near pregnancy initiation, showing that longitudinal medical history can contain risk information before standard diagnostic testing (Artzi et al., 2020). Temporal deep-learning models based on ten years of electronic health record data have demonstrated the ability to detect patterns associated with extreme preterm birth earlier than its occurrence (Gao et al., 2019). Collectively, these approaches treat early prediction as a process of translating multiple observations into a probability of an adverse pregnancy outcome while preserving the distinction between statistical prediction, clinical diagnosis, and professional decision-making.

The usefulness of machine learning for high-risk pregnancy prediction depends strongly on the content, timing, completeness, and representativeness of the underlying data. Electronic health records provide structured information such as age, body mass index, blood pressure, laboratory values, diagnosis codes, medications, and previous pregnancy outcomes, alongside unstructured clinical notes and repeated measurements. An early gestational diabetes prediction framework based on temporally aggregated electronic records has demonstrated that cost-sensitive methods can address the imbalance between relatively uncommon positive cases and a much larger group without the outcome (Qiu et al., 2017). An analysis of 588,622 pregnancies obtained strong discrimination for gestational diabetes at pregnancy initiation, while a simplified questionnaire-based model retained substantial predictive performance (Artzi et al., 2020). An extreme gradient-boosting model has also been found to select relevant predictors and outperform a traditional logistic regression model for gestational diabetes within the examined sample (Hu et al., 2023). Preeclampsia research demonstrates similar variation in data and algorithmic structure. Blood pressure, renal markers, platelet counts, white blood cell counts, electrolytes, and urinary protein have been identified as influential predictors of late-onset preeclampsia (Jhee et al., 2019). Logistic regression, random forest, support vector machine, and extreme gradient boosting have been applied to routinely collected early second-trimester records, with

fasting plasma glucose, mean blood pressure, and body mass index contributing strongly to prediction (Li et al., 2021). Pregnancy trajectories reconstructed from more than 100,000 electronic medical records have also been used to generate models for antepartum, intrapartum, and postpartum preeclampsia risk, demonstrating the analytical value of longitudinally organized information (Li et al., 2022). For preterm birth, billing codes, clinical history, laboratory information, demographic features, and genetic information have been combined and externally evaluated in a separate healthcare system (Abraham et al., 2022). Considerable variation has been identified across preterm-birth studies in data sources, preprocessing, feature selection, validation, and reporting, which complicates direct comparisons of model performance (Sharifi-Heris et al., 2022). Logistic regression, decision trees, naïve Bayes, support vector machines, and AdaBoost have also been compared using electronic records in a cross-sectional preterm-birth prediction study (Zhang et al., 2023). These studies show that clinical measurements alone do not exhaust the relevant information. Transportation barriers, insurance instability, delayed prenatal care, housing conditions, income-related constraints, geographical distance, and continuity of care may alter exposure, monitoring, and the completeness of recorded maternal risk signals.

Data quality and algorithmic fairness are central to the use of machine learning in underserved maternal populations because electronic records are not neutral representations of health. They reflect who obtained care, where care occurred, which tests were ordered, what clinicians documented, which services insurance covered, and how different health systems exchanged information. Missingness may therefore be informative rather than random. A missing laboratory result can represent low clinical concern, failure to complete testing, transportation difficulty, interrupted insurance, fragmented care, or transfer between institutions. Machine learning systems built from electronic health records can reproduce selection bias, measurement error, missing-data patterns, and socioeconomic disparities embedded in routine care (Gianfrancesco et al., 2018). Algorithmic bias may also arise when a convenient outcome is used as a proxy for actual health need. Substantial racial bias has been identified in a widely used health-management algorithm because healthcare expenditure served as a proxy for illness. Unequal spending caused Black patients with the same algorithmic score to have greater levels of illness than White patients (Obermeyer et al., 2019). In maternal prediction, analogous problems can occur when utilization, cost, number of visits, or frequency of testing is interpreted as a direct measure of clinical need without accounting for unequal access. Interpretability creates another requirement. Clinicians need to understand whether an alert is driven by blood-pressure trajectory, prior preterm birth, glucose abnormalities, cardiovascular disease, limited prenatal care, or a combination of factors. A technically accurate score that cannot be connected to observable maternal risk signals may receive limited professional trust or may be difficult to incorporate into clinical workflow. Transparency, accountability, privacy, bias, and changes in the clinician-patient relationship have been identified as ethical concerns associated with machine learning in healthcare (Char et al., 2018). Clinical translation has also been described as a socio-technical process involving data quality, external validation, workflow compatibility, professional acceptance, and rigorous evaluation (Kelly et al., 2019). These concerns become more pronounced in community health centers, rural hospitals, public hospitals, and safety-net settings where staffing, data infrastructure, specialist access, and interoperability can differ substantially from large academic medical centers. Machine learning capability, maternal and social data integration, data quality, algorithmic fairness, clinical interpretability, and organizational readiness consequently represent connected dimensions of prediction effectiveness rather than independent technical features.

The existing evidence establishes a substantial body of model-development research for preeclampsia, gestational diabetes, preterm birth, and other obstetric outcomes, yet it provides less direct evidence about how machine learning-supported prediction operates across organizations serving underserved U.S. populations. Wide differences have been reported in sample composition, outcome definitions, predictors, preprocessing practices, validation strategies, and performance measures, while many studies have been conducted within single institutions or comparatively homogeneous clinical datasets (Bertini et al., 2022; Islam et al., 2022; Sharifi-Heris et al., 2022; Sufriyana et al., 2020). Strong discrimination within one dataset does not establish that a model receives complete maternal information, produces understandable alerts, supports equitable classification, or fits the workflow of another organization. This research therefore defines early high-risk pregnancy prediction

effectiveness as the perceived capacity of machine learning-supported systems to identify warning signals promptly, classify maternal risk appropriately, support prioritization and referral, and provide clinically useful information across underserved care contexts. The study examines six explanatory constructs: machine learning capability, maternal and social determinants of health data integration, data quality, algorithmic fairness and bias mitigation, clinical interpretability and decision-support usability, and organizational readiness. These constructs connect the technical properties demonstrated in electronic-record studies with the organizational and equity conditions identified in research on U.S. maternal disparities. The quantitative, cross-sectional, case-study-based design treats healthcare professionals and relevant technical or administrative specialists as the unit of analysis within selected rural hospitals, community health centers, public hospitals, maternal health clinics, and comparable organizations. A five-point Likert-scale instrument measures respondents' assessments of the six explanatory constructs and early prediction effectiveness. Descriptive statistics characterize the level and distribution of each construct, correlation analysis assesses the direction and strength of their relationships, and multiple regression estimates their unique contributions while the other predictors are held constant. Pregnancy-specific analysis also measures the gap between the perceived importance of maternal risk signals and their current integration into machine learning-supported assessment. Equity-sensitive prediction confidence is examined across rural, low-income, uninsured or underinsured, racial and ethnic minority, immigrant, limited-English-proficiency, and fragmented-care contexts. Case-level comparisons describe whether prediction effectiveness, risk-signal integration, and equity confidence vary across participating organizational settings.

Background of the Study

High-risk pregnancy remains a critical maternal health concern because complications that develop before, during, or shortly after childbirth can produce serious consequences for pregnant individuals and fetuses. A pregnancy may be classified as high risk because of pre-existing medical conditions, previous adverse pregnancy outcomes, newly developed obstetric complications, behavioral exposures, demographic characteristics, or social conditions that restrict access to appropriate healthcare. Chronic hypertension, diabetes, obesity, cardiovascular disease, renal disorders, preeclampsia, gestational diabetes, maternal infections, placental abnormalities, preterm labor, fetal growth restriction, mental health conditions, and substance-use disorders represent important sources of maternal and fetal risk. The early identification of these conditions is particularly challenging because pregnancy risk changes over time and may involve several interacting clinical and nonclinical factors (Debasish, 2021; Mukut Kanti, 2020). Conventional assessment methods often depend on isolated measurements, predetermined thresholds, and the professional interpretation of information available during a particular clinical encounter. These methods may not fully capture complex relationships across maternal history, repeated laboratory measurements, medications, diagnostic records, previous pregnancies, behavioral conditions, and social determinants of health. Machine learning provides an alternative analytical approach by identifying patterns within large and diverse healthcare datasets and producing estimates of pregnancy-related risk. Its effectiveness, however, depends on more than the technical performance of an algorithm. Complete and representative maternal data, integration of clinical and social risk information, interpretable predictions, organizational infrastructure, professional acceptance, and safeguards against algorithmic bias are also required. These conditions are especially important in underserved U.S. populations, including rural residents, low-income individuals, Medicaid beneficiaries, uninsured or underinsured patients, racial and ethnic minority populations, immigrants, patients with limited English proficiency, and individuals receiving fragmented prenatal care. Such populations may experience delayed prenatal visits, limited access to specialists, transportation difficulties, unstable insurance coverage, hospital obstetric service closures, and incomplete electronic health records. The present study consequently examines machine learning-supported early prediction as a combined technological, clinical, organizational, and equity-related capability within selected healthcare organizations serving underserved U.S. populations.

Problem Statement

Serious pregnancy-related complications are not always recognized early enough to support timely clinical monitoring, referral, or preventive intervention, and this problem is particularly significant

among underserved U.S. populations. Rural, low-income, uninsured, underinsured, immigrant, racial and ethnic minority patients may experience reduced access to prenatal care, shortages of maternal health specialists, transportation barriers, fragmented healthcare records, communication difficulties, and uneven quality of care (Md. Abdur & Iftekhar, 2021; Mohammad Abir Chowdhury & Tonay, 2022; Muhammad Zahidul & Amena Begum, 2022). These conditions can delay the identification of preeclampsia, gestational diabetes, preterm-birth risk, cardiovascular complications, maternal infection, and other high-risk conditions. Machine learning systems can analyze large volumes of maternal health information and identify relationships that may not be visible through conventional assessment alone. Their presence within a healthcare organization does not automatically guarantee effective or equitable risk prediction. Machine learning predictions may be weakened by incomplete electronic records, inaccurate clinical documentation, missing laboratory results, poor interoperability, underrepresentation of underserved populations, inappropriate proxy variables, limited model transparency, and weak integration with clinical workflows (Mohammad Badrul & Md. Mominul, 2023; Mukut Kanti, 2024; Nishat & Mst Kaniz, 2022). An algorithm may generate technically acceptable predictions while producing lower confidence among healthcare professionals if its outputs cannot be explained or connected to recognizable maternal risk signals. Organizational constraints, including inadequate infrastructure, limited financial resources, insufficient employee training, weak leadership support, and unclear data-governance procedures, can further restrict the usefulness of prediction systems. Existing pregnancy-related machine learning studies frequently concentrate on developing and comparing algorithms for individual complications, often using retrospective data from a single institution (Tonay et al., 2024). Less attention has been given to the combined technological, clinical, organizational, and fairness-related factors that influence machine learning-supported early prediction in healthcare organizations serving underserved populations. There is also limited evidence concerning which maternal and social risk signals professionals consider important but insufficiently integrated into existing prediction practices. The level of confidence professionals place in predictions across rural, low-income, uninsured, minority, immigrant, and fragmented-care populations remains insufficiently examined. Therefore, a structured quantitative investigation is needed to determine how machine learning capability, maternal and social data integration, data quality, algorithmic fairness, clinical interpretability, and organizational readiness influence perceived early high-risk pregnancy prediction effectiveness across selected underserved U.S. healthcare settings.

Objectives of the Study

The principal objective of this study is to quantitatively examine the factors that influence the effectiveness of machine learning-supported early high-risk pregnancy prediction within selected healthcare organizations serving underserved U.S. populations. This central objective is supported by several interconnected analytical objectives. The first objective is to measure the current level of machine learning capability available for processing maternal health information, identifying complex risk patterns, and generating timely pregnancy-risk assessments. The second objective is to evaluate the extent to which clinical maternal information and social determinants of health are integrated into machine learning-supported assessment. The third objective is to determine whether the accuracy, completeness, consistency, timeliness, and representativeness of maternal health data contribute to early prediction effectiveness. The fourth objective is to examine the role of algorithmic fairness and bias-mitigation practices in supporting equitable risk identification across rural, low-income, uninsured or underinsured, racial and ethnic minority, immigrant, and limited-English-proficiency populations. The fifth objective is to assess whether clinical interpretability and decision-support usability strengthen professionals' ability to understand, trust, and apply machine-generated pregnancy-risk information. The sixth objective is to determine how organizational readiness, including infrastructure, leadership support, professional training, data governance, financial resources, and workflow preparedness, affects early prediction effectiveness. The study also seeks to identify which of the six explanatory factors makes the strongest independent contribution to the dependent variable when the other factors are statistically controlled. An additional objective is to compare the perceived clinical importance of pregnancy-related risk signals with the degree to which those signals are currently integrated into machine learning-supported assessment. The study further aims to measure equity-sensitive prediction confidence across different underserved population

contexts and compare the results among participating healthcare cases and professional groups. These objectives are addressed through a quantitative, cross-sectional, case-study-based design using a five-point Likert-scale questionnaire, descriptive statistics, correlation analysis, multiple regression modeling, integration-gap analysis, and appropriate case comparisons.

Research Hypotheses

The hypotheses of this study are developed from the proposition that effective early high-risk pregnancy prediction depends on the combined influence of technological capability, integrated maternal information, reliable data, equitable algorithmic processes, clinically understandable outputs, and organizational preparedness. The first hypothesis, H1, states that machine learning capability has a significant positive effect on early high-risk pregnancy prediction effectiveness. This hypothesis assumes that systems capable of processing complex maternal data, recognizing nonlinear relationships, and producing timely risk classifications are more likely to support early identification. The second hypothesis, H2, states that maternal and social determinants of health data integration has a significant positive effect on early high-risk pregnancy prediction effectiveness. This relationship reflects the need to evaluate both clinical conditions and barriers involving income, insurance, transportation, housing, geographical access, and continuity of prenatal care. The third hypothesis, H3, states that data quality has a significant positive effect on early high-risk pregnancy prediction effectiveness. Complete, accurate, consistent, timely, and representative records are expected to support more dependable risk assessment. The fourth hypothesis, H4, states that algorithmic fairness and bias mitigation have a significant positive effect on early high-risk pregnancy prediction effectiveness. Fairness monitoring is expected to strengthen equitable classification across underserved population groups. The fifth hypothesis, H5, states that clinical interpretability and decision-support usability have a significant positive effect on early high-risk pregnancy prediction effectiveness. Predictions that professionals can understand and connect to observable maternal risk signals are expected to be more useful in clinical decision-making. The sixth hypothesis, H6, states that organizational readiness has a significant positive effect on early high-risk pregnancy prediction effectiveness. Appropriate infrastructure, leadership, training, resources, governance, and workflow integration are expected to strengthen the effective use of machine learning systems. These hypotheses are tested through Pearson correlation analysis and multiple regression modeling. Statistical significance, standardized regression coefficients, confidence intervals, model explanatory power, and diagnostic measures are used to determine whether each proposed relationship is supported and which independent variable has the strongest effect.

Significance of the Research

- i. **Clinical significance:** The research provides a structured assessment of the factors that support timely identification of high-risk pregnancies. By examining machine learning capability, data integration, data quality, interpretability, and decision-support usability, the study clarifies the conditions under which machine-generated risk information can assist maternal healthcare professionals in monitoring, prioritization, referral, and risk classification.
- ii. **Health-equity significance:** The study focuses specifically on underserved U.S. populations rather than treating pregnant patients as a uniform population. Its assessment of rural, low-income, uninsured or underinsured, racial and ethnic minority, immigrant, limited-English-proficiency, and fragmented-care contexts permits closer examination of whether professionals perceive machine learning predictions as equally dependable across different patient groups.
- iii. **Technological significance:** The research evaluates machine learning as an integrated healthcare capability rather than as an isolated algorithm. It examines the relationships among analytical capability, clinical and social data integration, data quality, fairness, explainability, and usability. This approach helps distinguish technical model availability from the broader conditions required for effective use.
- iv. **Organizational significance:** Hospitals, community health centers, maternal health clinics, public healthcare organizations, and rural facilities may use the study variables to assess their preparedness for machine learning-supported maternal risk prediction. The organizational readiness construct covers infrastructure, leadership support, employee training, resource availability, workflow compatibility, and data governance.

v. **Methodological significance:** The research combines descriptive statistics, correlation analysis, regression modeling, maternal risk-signal integration-gap analysis, equity-sensitive prediction-confidence measurement, and case comparison. The importance-integration gap identifies maternal or social risk indicators that professionals consider valuable but insufficiently represented in current prediction practices.

vi. **Theoretical significance:** The study applies the Technology-Organization-Environment framework to machine learning-supported maternal healthcare. Technological capability, organizational preparedness, and underserved healthcare conditions are examined within a unified structure that connects system characteristics with early prediction effectiveness.

vii. **Policy significance:** The findings provide measurable information concerning data representativeness, algorithmic fairness, clinical interpretability, rural access, and organizational resource differences. These dimensions are relevant to the development of institutional standards for responsible maternal health analytics, bias monitoring, data governance, and equitable clinical decision support.

LITERATURE REVIEW

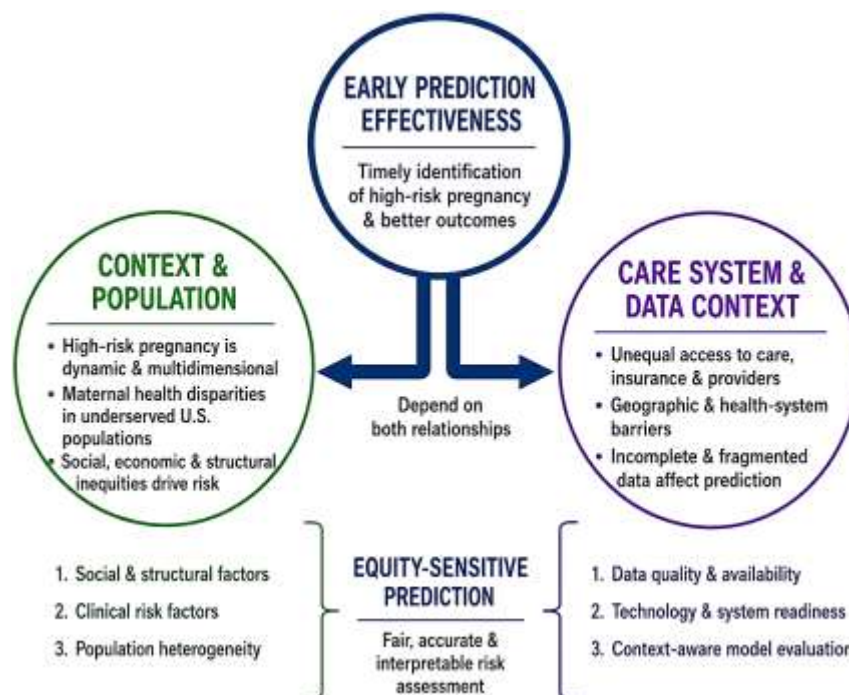
The literature on machine learning approaches for early prediction of high-risk pregnancy covers interconnected areas of maternal health, clinical risk assessment, healthcare disparities, electronic health information, predictive modeling, algorithmic fairness, and organizational implementation. High-risk pregnancy is a multidimensional condition shaped by pre-existing illnesses, obstetric history, complications arising during pregnancy, behavioral exposures, demographic characteristics, and social conditions affecting access to care. Research concerning maternal mortality and severe maternal morbidity has documented the importance of hypertensive disorders, gestational diabetes, preterm birth, hemorrhage, cardiovascular disease, infection, mental health conditions, and other medical complications. A separate but closely related body of scholarship examines disparities among rural, low-income, uninsured, underinsured, racial and ethnic minority, immigrant, and medically underserved populations in the United States. These studies establish that maternal risk is influenced by both clinical vulnerability and unequal access to timely, continuous, and high-quality healthcare. Machine learning research introduces analytical methods capable of processing longitudinal electronic records, laboratory results, diagnostic histories, medications, demographic information, medical images, and social determinants. Logistic regression, decision trees, random forests, support vector machines, gradient boosting, extreme gradient boosting, neural networks, and ensemble methods have been applied to pregnancy-related prediction tasks. Reported performance varies according to outcome definition, sample composition, predictor availability, class imbalance, validation design, and evaluation measures. The literature also identifies data quality, interoperability, missing information, representativeness, interpretability, privacy, professional trust, workflow compatibility, and organizational readiness as important conditions surrounding clinical use. Algorithmic fairness has particular relevance because models trained on incomplete or unequal healthcare records may reproduce existing disparities or perform differently across population groups. The literature review therefore examines high-risk pregnancy and maternal health disparities, machine learning approaches for maternal-risk prediction, integration of clinical and social determinants, data quality, fairness and explainability, and the organizational conditions associated with implementation. The Technology-Organization-Environment framework organizes these areas, while the conceptual framework specifies the proposed relationships between the six independent variables and early high-risk pregnancy prediction effectiveness.

High-Risk Pregnancy and Maternal Health Disparities in Underserved U.S. Populations

High-risk pregnancy broadly refers to a pregnancy in which the pregnant person, fetus, or both face an elevated probability of adverse outcomes before, during, or shortly after birth. Risk may arise from preexisting conditions, including chronic hypertension, diabetes, cardiovascular disease, renal disease, obesity, or mental illness, and from pregnancy-related complications such as preeclampsia, hemorrhage, infection, placental disorders, and preterm labor. It may also emerge through interactions among age, parity, previous obstetric outcomes, health behaviors, environmental exposures, and access to timely clinical care. Consequently, high risk is not a fixed label attached only to diagnosis; it is a changing condition that can intensify as clinical and social signals accumulate across gestation.

Maternal mortality represents the most severe endpoint, while severe maternal morbidity captures life-threatening complications and lifesaving interventions that may produce lasting physical, psychological, and financial consequences. U.S. evidence demonstrates that racial differences cannot be explained simply by the frequency of obstetric complications. Black women experiencing selected conditions, including hemorrhage and hypertensive or placental complications, have faced substantially higher case-fatality rates than White women, revealing the importance of recognition, treatment, referral, and care quality after risk becomes apparent (Tucker et al., 2007). Population-level evidence also indicates that severe maternal morbidity increased markedly across racial and ethnic groups while the relative gaps remained persistent, even after measured comorbidities, cesarean delivery, and other maternal characteristics were considered (Leonard et al., 2019). These findings position high-risk pregnancy as both a clinical classification and an equity-sensitive phenomenon. Early prediction therefore requires attention to multiple domains rather than reliance on a single diagnosis, demographic characteristic, or encounter. For underserved populations, risk assessment must distinguish race as a social classification from the causal influence of racism, unequal treatment, resource distribution, and exposure patterns that shape health before conception and throughout pregnancy within diverse communities and care systems.

Figure 2: Equity-Sensitive Framework for High-Risk Pregnancy Assessment in Underserved U.S. Populations



Underserved U.S. populations include groups whose ability to obtain maternal care is constrained by economic disadvantage, inadequate insurance, geographic isolation, racial or ethnic marginalization, language barriers, disability, unstable housing, immigration-related concerns, limited transportation, or shortages of maternity professionals. These conditions overlap, producing patterns of vulnerability that cannot be represented adequately by isolated variables. A low-income rural Medicaid beneficiary, for example, may experience long travel distances, restricted provider choice, discontinuous records, and delayed specialist consultation at the same time that chronic illness or an obstetric complication develops. The literature therefore increasingly separates individual social needs from the structural arrangements that distribute health-promoting opportunities. Housing, food security, education, employment, neighborhood safety, and health-care access operate within policies and institutions shaped by racism, class hierarchy, and gendered power, making maternal inequity a product of organized social conditions rather than personal failure (Crear-Perry et al., 2021; Md. Abdur & Iftekhar,

2021). This distinction is essential for research on prediction because variables such as insurance status, residential location, or missed appointments can function as proxies for barriers created by systems. Treating such measures as biological attributes may obscure causation and reproduce inequity in model interpretation. Intersectional evidence further shows that rural residence, race and ethnicity, and Medicaid coverage combine to create different patterns of severe maternal morbidity and mortality rather than contributing as wholly independent risks. Medicaid-funded births have displayed heightened burdens across groups, with particularly important concerns for Black, Indigenous, and rural beneficiaries (Interrante et al., 2022; Mohammad Shoriful Hossan, 2021). Accordingly, an equity-sensitive review of high-risk pregnancy must examine how clinical vulnerability is intensified or mitigated by the environment in which care is sought. It must also recognize heterogeneity within broad population categories, since people sharing a racial label or insurance type may differ substantially in geography, institutional access, comorbidity, social support, continuity, and previous experiences of discrimination during maternity care encounters.

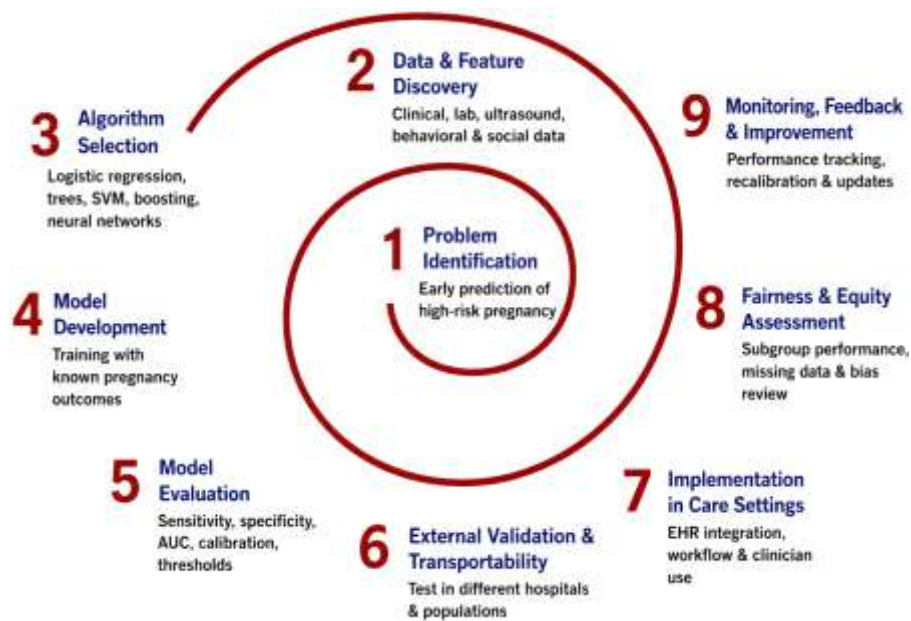
Geography and health-system organization determine whether early warning signs are documented, communicated, and acted upon. Rural communities may have fewer obstetric units, maternal-fetal medicine specialists, emergency resources, and transportation options, whereas urban communities may be close to hospitals yet encounter overcrowding, fragmented services, appointment availability, or uneven quality. Hospital closures and regionalization can require pregnant people to travel outside their communities, weakening continuity between prenatal clinicians and delivery facilities. These access conditions influence the completeness and timing of data available for risk estimation. A blood-pressure elevation recorded late, an unshared emergency visit, or an undocumented social barrier may prevent a model from identifying risk early to support clinical review. Community context also modifies disparities. A Maryland cross-sectional analysis found that severe maternal morbidity and mortality varied through the relationship between race or ethnicity and community type, supporting the need to assess demographic and geographic factors jointly rather than assuming that rurality affects every group uniformly (Amir & Chapal, 2022; Cudjoe et al., 2023). For machine-learning research, this evidence creates a measurement challenge: predictive performance can appear acceptable overall while errors concentrate among smaller underserved subgroups. Data imbalance, missingness, inconsistent coding, limited external representation, and historical patterns of unequal care can all influence which signals a model learns. Thus, early-prediction studies should evaluate clinically meaningful factors and contextual indicators, report subgroup-specific performance, and examine whether confidence differs across cases and organizational settings. In a quantitative, cross-sectional case-study design, survey measures can capture practitioners' assessments of data availability, signal relevance, technology integration, organizational readiness, and equity-sensitive confidence. Descriptive statistics can characterize these perceptions, correlation analysis can identify relationships among constructs, and regression modeling can estimate their association with perceived early-prediction effectiveness. This design connects maternal-health disparities with the operational conditions through which machine-learning tools are developed, interpreted, and used in underserved U.S. maternity-care environments across cases.

Machine Learning Algorithms for Risk Prediction

Machine learning algorithms are computational methods that identify relationships within data and use those relationships to classify observations or estimate the probability of an outcome. In high-risk pregnancy prediction, supervised learning is relevant because models are trained on pregnancies with known outcomes and then applied to new cases. Approaches include logistic regression as a statistical baseline, decision trees, random forests, support vector machines, gradient-boosting models, elastic net regression, and neural networks. These approaches differ in complexity, data requirements, interpretability, and capacity to represent nonlinear interactions. Logistic regression estimates transparent relationships between predictors and an outcome, while tree-based ensembles partition observations and combine multiple learners to improve classification. Support vector machines construct decision boundaries between risk groups, and neural networks learn layered representations from high-dimensional inputs. Pregnancy data may include maternal age, parity, complications, chronic conditions, vital signs, medications, laboratory results, ultrasound findings, behavioral factors, and indicators of social or health-care access. Comparative evidence shows that algorithmic complexity

does not automatically produce better prediction. In a population-based cohort examining fetal growth abnormalities, machine learning methods did not outperform logistic regression, and predictive value differed according to parity and the availability of previous obstetric information (Kazi Rakib Hasan & Uddin, 2022; Kuhle et al., 2018). Conversely, models may gain value when numerous interacting variables and nonlinear patterns are relevant. An early-pregnancy preeclampsia study used elastic net and gradient boosting with routine clinical and laboratory data, demonstrating that machine learning could select informative predictors and estimate risk before clinical manifestation (Marić et al., 2020). These studies show that algorithm choice should follow the structure of the outcome, dataset, and clinical decision rather than assumptions that newer methods are inherently superior. For early identification of high-risk pregnancy, a useful algorithm must provide adequate discrimination, calibration, sensitivity, and specificity while producing predictions at a gestational stage when clinical action remains possible.

Figure 3: Machine Learning Prediction Pipeline for Early High-Risk Pregnancy Detection



The predictive task in obstetrics is complicated by heterogeneous outcomes, changing physiology, rare events, and unequal costs of classification errors. A false-negative prediction may delay intensified surveillance for a patient who develops preeclampsia, hemorrhage, preterm birth, fetal growth restriction, or another serious complication. A false-positive prediction may increase anxiety, unnecessary testing, specialist referrals, or intervention. Model evaluation must therefore extend beyond accuracy, which can appear high when outcomes represent a small proportion of observations. Sensitivity, specificity, positive and negative predictive values, area under the receiver operating characteristic curve, calibration, and decision thresholds describe aspects of usefulness. Class imbalance may be addressed through weighting, resampling, augmentation, or threshold adjustment, although each strategy can alter estimated probabilities and performance. External validation is important because an algorithm trained in one hospital may learn documentation practices, referral patterns, population characteristics, or treatment pathways. A machine-learning model combining maternal characteristics and fetal biometry predicted shoulder dystocia more effectively than estimated fetal weight alone and retained value in an external cohort, illustrating the importance of testing transportability across institutions (Mst Shurovi & Samia Hossain, 2022; Tsur et al., 2020). Evidence across gestational-diabetes prediction models also demonstrates variation in sample size, predictor selection, validation procedures, reporting quality, and risk of bias. Meta-analytic assessment indicates that recurring predictors include maternal age, prepregnancy body mass index, fasting glucose, family history, and gestational diabetes, while model performance remains sensitive to study design and

validation quality (Muhammad Mohiul & Mohammad Badrul, 2022; Zhang et al., 2022). These findings support a modeling pipeline involving outcome definition, preprocessing, missing-data handling, feature selection, training, validation, external testing, calibration assessment, and transparent reporting. Temporal validation can determine whether performance remains stable when clinical practice, coding, or population composition changes. For high-risk pregnancy prediction, clinical usefulness depends on whether the model consistently identifies actionable risk without creating disproportionate error burdens for patients, communities, hospitals, or stages of pregnancy.

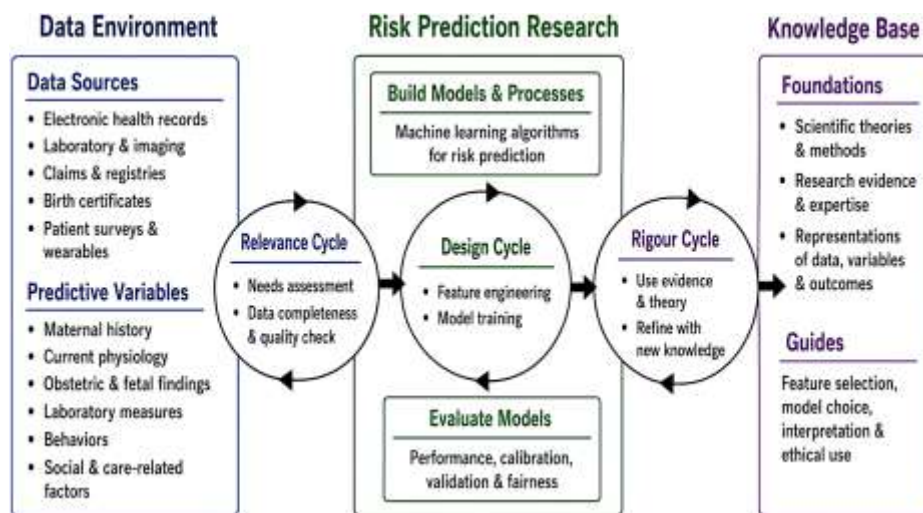
Application within underserved U.S. populations adds requirements concerning representativeness, accessibility, fairness, and organizational readiness. Electronic health records can provide abundant clinical information, yet patients receiving fragmented care may have incomplete histories, laboratory measurements, or encounters distributed across disconnected systems. Rural residents, Medicaid beneficiaries, racial and ethnic minority populations, immigrants, and patients with limited transportation may appear in training data through different documentation patterns. A model can interpret missingness as a predictive signal without distinguishing whether information is absent because a test was clinically unnecessary or because access was restricted. Similar problems arise when race, insurance, ZIP code, or utilization variables act as proxies for structural inequity. Excluding contextual variables may conceal disparities, whereas including them without interpretation may reproduce unequal treatment. Reviews of artificial intelligence in obstetrics and gynecology identify limitations involving unrepresentative datasets, samples, insufficient validation, heterogeneous outcome definitions, weak clinical integration, and incomplete performance reporting across populations (Dhombres et al., 2022; Muhammad Zahidul & Amena Begum, 2022). Equity-sensitive prediction consequently requires subgroup evaluation of discrimination, calibration, sensitivity, false-positive rates, and missing-data patterns. It requires comparing algorithmic outputs with clinician judgment and examining whether explanations correspond to medically credible risk signals. Simpler models may be preferable when they provide comparable performance, clearer reasoning, easier maintenance, and lower infrastructure demands. Complex ensembles or neural networks may be appropriate when they offer gains and can be monitored. Within the quantitative, cross-sectional case-study design, practitioners' Likert-scale responses can assess perceived algorithm accuracy, data adequacy, interpretability, workflow integration, and confidence across underserved contexts. Descriptive statistics can summarize adoption conditions, correlation analysis can examine relationships among model-related constructs, and multiple regression can estimate which perceived capabilities are strongly associated with effective early prediction. Comparing cases and organizations can reveal whether technological performance is supported by interoperable data, skilled personnel, protocols, and equity-oriented governance in the maternity-care environments where algorithms are used.

Maternal Risk Factors, Data Sources, and Predictive Variables

Maternal risk prediction begins with the identification of variables that are meaningful, measurable early enough to support intervention, and available across pregnancies. Predictors include maternal age, parity, gravidity, prepregnancy body mass index, chronic hypertension, diabetes, kidney disease, autoimmune disease, previous preeclampsia, prior preterm birth, multiple gestation, smoking, medication exposure, and family obstetric history. Variables obtained during pregnancy include blood pressure, gestational weight gain, symptoms, fetal growth, uterine artery measurements, glucose concentrations, blood counts, liver and kidney indicators, and evidence of placental dysfunction. The predictive importance of these variables depends on the outcome and timing of assessment. Factors that identify a susceptibility to complications may differ from signals indicating that deterioration is imminent. Research among nulliparous women showed that combinations of routine clinical characteristics and ultrasound measurements could stratify preeclampsia risk, although the discriminatory capacity of clinical variables alone remained moderate (Mukut Kanti & Rony, 2022; North et al., 2011). This finding demonstrates why feature sets should reflect both baseline vulnerability and evolving pregnancy physiology. Once a disorder is established, variables representing severity become more important. The fullPIERS model used routinely collected information such as gestational age, symptoms, oxygen saturation, platelet count, creatinine, and liver enzyme measurements to predict serious maternal complications among patients with preeclampsia (von Dadelszen et al., 2011).

These examples distinguish early susceptibility prediction from short-term complication prediction. A machine-learning system must specify which task it performs, the gestational window covered, the target population, and the outcome definition used for labeling cases. Mixing different endpoints into one broad high-risk category may increase sample size but reduce clinical clarity. Conversely, developing separate models for every complication can fragment decision support. A balanced framework organizes predictors into maternal history, current physiology, obstetric findings, fetal indicators, laboratory measures, behaviors, and care-related conditions, allowing algorithms to combine shared risk signals while preserving outcome-specific interpretation and clinical relevance.

Figure 4: Integrated Research Framework for Maternal Risk Prediction Using Machine Learning



Electronic health records, birth certificates, insurance claims, laboratory systems, imaging repositories, pharmacy records, patient surveys, wearable devices, and community databases provide information for pregnancy-risk prediction. Electronic records support extraction of diagnoses, procedures, medications, vital signs, and test results, while clinical notes may contain symptoms, clinician assessments, adherence concerns, and contextual information unavailable in coded fields. Claims provide longitudinal coverage but are designed for billing rather than reasoning. Birth certificates and registries facilitate analyses, although their variables may be limited or inconsistently completed. Evaluation of electronic-record prediction studies shows that sample sizes and routine data availability create opportunities, while inconsistent definitions, incomplete reporting, validation gaps, and mishandled temporal relationships restrict model reliability (Goldstein et al., 2017; Sadia et al., 2022). Pregnancy intensifies these challenges because measurements change with gestational age and may be obtained at intervals. Feature engineering must therefore distinguish values recorded before prediction from information generated after clinical suspicion or diagnosis. Failure to preserve this temporal order can create data leakage and inflate performance. Biomarkers may strengthen models when they capture biological processes not represented by demographic or diagnostic variables. In a California cohort, first- and second-trimester prenatal screening biomarkers were assessed alongside maternal characteristics for early gestational-diabetes prediction, demonstrating how collected biochemical information can refine risk classification before standard diagnostic testing (Mohammad Badrul & Md. Mominul, 2023; Snyder et al., 2020). Biomarker availability, assay consistency, cost, and access must be evaluated before inclusion. A feature that improves accuracy in a center may reduce applicability in safety-net clinics where the test is unavailable. Data preprocessing should address unit harmonization, coding differences, duplicate records, implausible values, missingness, and repeated measurements. Appropriate aggregation can summarize trajectories, variability, or threshold exceedances without discarding meaningful timing. Documentation of these decisions is necessary because preprocessing choices determine which patterns become visible to the algorithm and how confidently predictions can be transferred across other settings.

For underserved U.S. populations, predictive variables must extend beyond biomedical measurements to include the social conditions shaping exposure, access, documentation, and response. Contextual factors may include insurance continuity, poverty, housing instability, food insecurity, transportation difficulty, rural residence, distance to maternity care, language preference, neighborhood deprivation, environmental exposure, employment conditions, support, and experiences of discrimination. These measures do not replace clinical predictors; they describe circumstances that can intensify disease, delay recognition, or limit the feasibility of care. Evidence on racial and ethnic disparities in perinatal outcomes shows that socioeconomic conditions, neighborhood environments, stress, health behaviors, access, and care quality operate through pathways rather than as isolated influences (Lorch & Enlow, 2016; Mohammad Shoriful Hossan & Adar, 2023). Their incorporation into predictive research requires discipline because race and ethnicity should not be interpreted as causes. Algorithms may use these categories to detect unequal patterns, but explanations should focus on structural exposure, treatment differences, and resource distribution. Measurement level matters. Individual social needs describe a patient, whereas ZIP-code or census measures represent area-level context and may not characterize residents. Contextual variables can introduce privacy concerns or labels if presented without explanation. Equity-sensitive feature design should assess whether a variable improves prediction, changes subgroup calibration, represents an actionable barrier, or reproduces utilization patterns. In the quantitative, cross-sectional case-study design, survey items can measure practitioners' perceptions of clinical-data completeness, social-risk visibility, interoperability, feature relevance, and integration of warning signals. Descriptive statistics can summarize availability across cases, correlation analysis can examine whether data integration accompanies prediction confidence, and regression can estimate which information domains are associated with perceived early-prediction effectiveness. Organizational comparison can clarify whether safety-net, rural, and community settings possess access to the variables required by models. This approach treats data availability as a component of prediction quality and equity, rather than assuming that all variables are informative, accessible, or reliable.

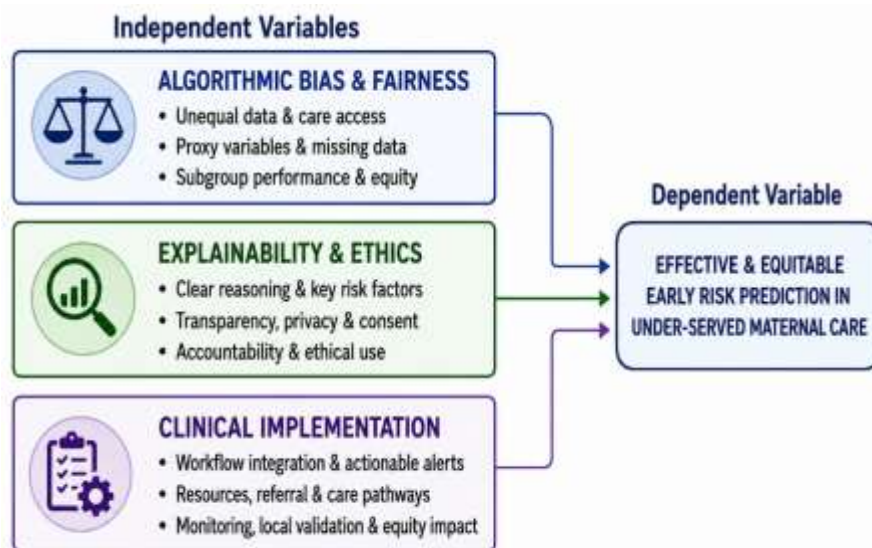
Algorithmic Bias, Explainability, and Clinical Implementation in Underserved Maternal Care

Machine learning systems for early pregnancy risk prediction can reproduce inequities when their training data reflect unequal access, fragmented documentation, and uneven treatment. This concern is relevant for underserved U.S. populations because race, ethnicity, insurance status, rural residence, language, disability, and socioeconomic conditions influence both exposure to risk and the likelihood that risk is recorded. A model may therefore learn patterns of service utilization rather than underlying clinical need. Missing prenatal visits, incomplete laboratory histories, delayed diagnoses, and sparse electronic records can be interpreted as low risk when they actually represent barriers to care. Proxy variables require scrutiny. Health care costs, appointment frequency, or prior specialist referrals may appear objective, yet each can encode structural advantage. Fairness cannot consequently be established through overall accuracy alone. Performance should be examined across population and case-study subgroups using sensitivity, specificity, false-negative rates, calibration, and positive predictive value, because a model may perform acceptably in aggregate while failing women who face the greatest vulnerability. Fairness definitions must also match the clinical purpose, since equal error rates, equal access to intervention, and equal maternal outcomes represent different standards. Equity-oriented model design treats protected characteristics as meaningful indicators for auditing rather than excluding them from data. It also examines how labels are generated, who receives diagnostic testing, and whether outcome definitions capture conditions that remain unrecognized. These safeguards align predictive performance with distributive justice and prevent past inequities from becoming automated decision rules (Rajkomar et al., 2018; Risha & Kazi Mohammad Khalid, 2023). Evidence from medical imaging shows that algorithms can exhibit systematic underdiagnosis among underserved groups even when aggregate metrics appear strong, demonstrating the importance of disaggregated error analysis (Sadia & Binayan, 2023; Seyyed-Kalantari et al., 2021). For high-risk pregnancy prediction, rigorous subgroup evaluation should accompany feature selection, model comparison, and organizational analysis so that confidence reflects equitable clinical usefulness rather than statistical performance alone.

Explainability is necessary for trustworthy maternal risk prediction because clinicians must connect an

algorithmic score with obstetric, medical, behavioral, and social evidence. A high-risk classification without an understandable rationale may be difficult to verify, communicate, or translate into care. In pregnancy, the meaning of a predictor can change across gestational stages and clinical contexts. Elevated blood pressure, prior preterm birth, limited prenatal attendance, food insecurity, or transportation difficulty may require responses, even when each raises predicted risk. Explanations should therefore identify influential variables, indicate their direction and relative contribution, and distinguish patient-level explanations from model behavior. Global explanations can show which factors generally shape predictions, while local explanations can clarify why a respondent or case received a risk estimate. Feature-importance rankings and partial dependence displays should not be treated as causal evidence. Correlated variables, measurement error, and unstable rankings can produce plausible explanations that misrepresent the model's reasoning. Ethical assessment must extend beyond transparency to privacy, consent, accountability, and the distribution of benefits and burdens. Maternal records combine reproductive information with demographic, behavioral, and social data, making governance of access, linkage, retention, and secondary use essential. Patients and community representatives should understand how information contributes to risk classification and who remains responsible when an algorithmic recommendation conflicts with clinical judgment. These issues place data protection, transparency, and accountable deployment at the center of ethically acceptable medical machine learning (Bushra, 2024; Vayena et al., 2018). Explainability also has medical, legal, ethical, and social dimensions, so its adequacy depends on the needs of clinicians, patients, developers, administrators, and regulators rather than on a single technical definition (Amann et al., 2020; Mohammad Shoriful Hossan, 2024). Within this study, perceived transparency, confidence in risk signals, and readiness to act can be measured through Likert-scale items, allowing descriptive statistics, correlations, and regression models to assess whether explainability supports trust and integration.

Figure 5: Machine Learning Implementation Framework for Equitable High-Risk Pregnancy Prediction



Clinical implementation converts a predictive model from an analytical product into a sociotechnical intervention embedded within prenatal workflows. Successful integration requires a defined clinical problem, an intended user, an actionable prediction window, and a care pathway linked to each risk threshold. Early warning has limited value when clinics lack referral capacity, transportation support, specialist availability, or authority to respond. Underserved settings may operate with staffing shortages, incompatible information systems, inconsistent broadband access, and records distributed among hospitals, community clinics, public health programs, and social-service organizations. These

conditions create an integration gap between identifying risk and delivering appropriate care. Workflow design should specify when predictions appear, how alerts are prioritized, which professional reviews them, what action follows, and how overrides are documented. Excessive or timed alerts can create fatigue, while rigid automation can weaken individualized assessment. Human oversight is necessary, but oversight must include defined accountability rather than placing responsibility on clinicians. Evaluation should examine reliability, usability, workload, referral completion, patient communication, and subgroup-specific consequences. Local validation is essential because relationships learned in one institution may shift when population composition, coding practices, resource availability, or clinical protocols differ. Models require monitoring for calibration drift, missing-data changes, performance degradation, and unequal false negatives after deployment. A responsible translation pathway engages clinicians, patients, data scientists, administrators, ethicists, and community stakeholders from problem formulation through evaluation and use (Wiens et al., 2019). For the cross-sectional case-study design, these requirements can be operationalized as organizational readiness, data-integration quality, perceived actionability, governance strength, and equity-sensitive confidence. Comparing these constructs across cases can reveal whether stronger integration is associated with greater confidence in early prediction. Multiple regression can then estimate their independent relationships with perceived effectiveness while controlling for respondent and organizational characteristics, linking technical capability to the conditions under which maternal risk signals become trustworthy decisions.

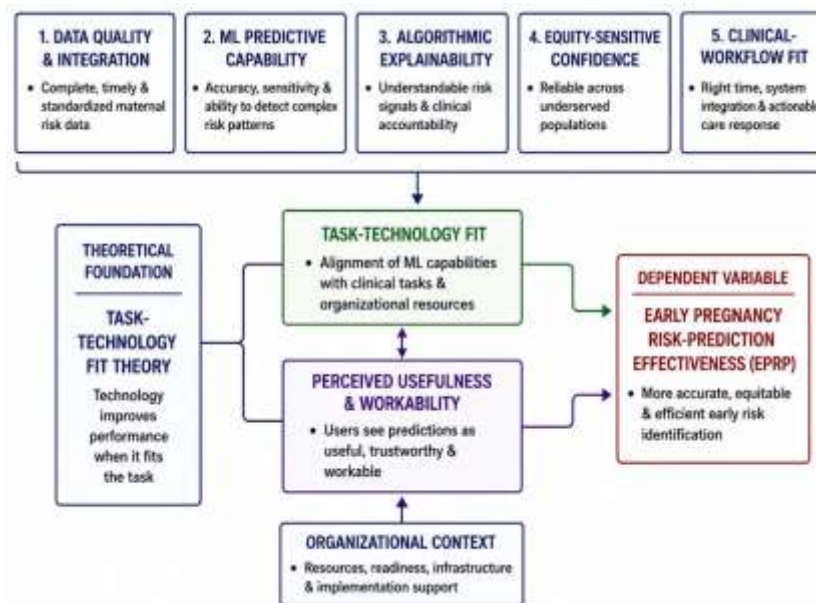
Theoretical Framework: Task-Technology Fit Theory

Task-Technology Fit theory provides the principal theoretical foundation for examining whether machine learning can support early identification of high-risk pregnancy in underserved U.S. populations. The theory proposes that technology contributes to individual or organizational performance when its capabilities correspond with the requirements of the tasks users must complete. In this study, the central task is not simply generating a numerical risk score. It involves combining incomplete maternal histories, clinical measurements, obstetric indicators, behavioral information, and social determinants; recognizing risk early; explaining the prediction; prioritizing appropriate cases; and connecting the result with an actionable care response. The relevant technology characteristics include data-integration capacity, predictive accuracy, sensitivity to rare outcomes, interpretability, interoperability, timeliness, and subgroup reliability. Fit exists when these capabilities help clinicians and organizations perform maternal risk assessment more accurately, consistently, equitably, and efficiently within their actual resource constraints. A technically sophisticated model can consequently have weak task fit when it depends on unavailable variables, produces alerts after the useful intervention window, or requires specialist infrastructure that an underserved clinic does not possess. Research on mobile nursing information systems demonstrates that compatibility between nursing tasks and technological functions is associated with stronger professional performance, supporting the use of fit as a measurable link between technology and clinical work (Hsiao & Chen, 2012; Mst Shurovi, 2024). Task-Technology Fit can also be separated from technology-individual fit and examined alongside organizational readiness, showing that effective use depends on the alignment of system functions, user capabilities, and institutional support (Lin, 2014; Muhammad Zahidul, 2024). Applied to this research, the theory positions clinical-workflow fit as a central explanatory construct while recognizing that data quality, model capability, explainability, equity-sensitive confidence, and organizational readiness jointly determine whether early pregnancy prediction becomes operationally useful. The framework therefore evaluates machine learning as part of a maternal-care system rather than as an isolated algorithm across care settings.

The theoretical model is operationalized through five-point Likert-scale constructs that represent the conditions under which task and technology alignment can improve early maternal risk prediction. Maternal risk-data quality and integration measure whether clinical, obstetric, demographic, behavioral, and social information is sufficiently complete, timely, standardized, and accessible for assessment. Machine-learning predictive capability represents perceived accuracy, consistency, sensitivity, prioritization value, and capacity to recognize complex interactions. Algorithmic explainability measures whether users can understand influential risk signals, evaluate a prediction, communicate its basis, and retain clinical accountability. Equity-sensitive prediction confidence

captures perceived reliability across racial, ethnic, rural, low-income, uninsured, underinsured, and linguistically diverse populations. Clinical-workflow fit measures whether predictions arrive at the correct time, integrate with existing systems, support referral decisions, and correspond with available services. These constructs extend Task-Technology Fit beyond technical compatibility by recognizing that a prediction cannot improve performance unless users consider it useful and workable. Evidence from health information systems indicates that information quality, service quality, system quality, perceived usefulness, and perceived ease of use shape professional acceptance, demonstrating that functional fit and user evaluation operate together (Pai & Huang, 2011; Sadia & Md, 2024). Reviews of technology acceptance in health care similarly show that perceived usefulness and ease of use are important, although their relationships vary across clinical technologies, users, tasks, and organizational environments (Holden & Karsh, 2010; Samia Hossain, 2024). Resource limitations add another layer because facilitating conditions, effort expectancy, social influence, and expected performance can affect whether health professionals adopt digital tools in constrained settings (Azam et al., 2023; Shima Ali et al., 2024). For the proposed cases, these considerations justify measuring respondent characteristics and organizational context as controls. They also support comparisons across clinics and institutions, where identical machine-learning capabilities may generate different levels of perceived effectiveness because workflow demands, data availability, implementation capacity, and patient needs are not uniform across underserved maternal-care settings and population contexts.

Figure 6: Task-Technology Fit Model for Machine Learning-Supported Maternal Risk Assessment



The framework is tested with a multiple linear regression model because the study examines the simultaneous contribution of several Likert-based predictors to perceived early-prediction effectiveness. The proposed study equation is $EPRP_i = \beta_0 + \beta_1 MRDQ_i + \beta_2 MLPC_i + \beta_3 AE_i + \beta_4 ESPC_i + \beta_5 CWF_i + \varepsilon_i$. In this equation, $EPRP_i$ denotes early pregnancy risk-prediction effectiveness for respondent i ; $MRDQ_i$ denotes maternal risk-data quality and integration; $MLPC_i$ denotes machine-learning predictive capability; AE_i denotes algorithmic explainability; $ESPC_i$ denotes equity-sensitive prediction confidence; and CWF_i denotes clinical-workflow fit. The intercept β_0 represents expected effectiveness when all predictors equal zero, while β_1 through β_5 estimate the unique change in EPRP associated with a one-unit increase in each predictor when the remaining variables are held constant. The residual ε_i represents unobserved influences and random error. Composite scores will be calculated by averaging validated questionnaire items assigned to each construct, preserving the original one-to-five response range. Positive coefficients are expected because stronger data foundations, predictive

capability, explainability, equitable confidence, and workflow alignment should correspond with greater perceived effectiveness. The directional hypotheses are expressed as $H_1: \beta_1 > 0$, $H_2: \beta_2 > 0$, $H_3: \beta_3 > 0$, $H_4: \beta_4 > 0$, $H_5: \beta_5 > 0$, and will be assessed using coefficient estimates, standard errors, t statistics, confidence intervals, and p values. The model's R^2 will indicate the proportion of variation in EPRP jointly explained by the five predictors, while adjusted R^2 will account for model complexity. Standardized coefficients will permit comparison of relative predictor importance, and variance inflation factors will assess multicollinearity. Residual normality, linearity, independence, and homoscedasticity will be examined before interpretation. Case and respondent controls may be added in a hierarchical second model without changing the core theoretical equation. This specification makes Task-Technology Fit empirically testable and aligns the theoretical framework with instrument design, correlation analysis, regression results, hypothesis testing, and organizational comparisons from questionnaire development through final interpretation of the empirical findings.

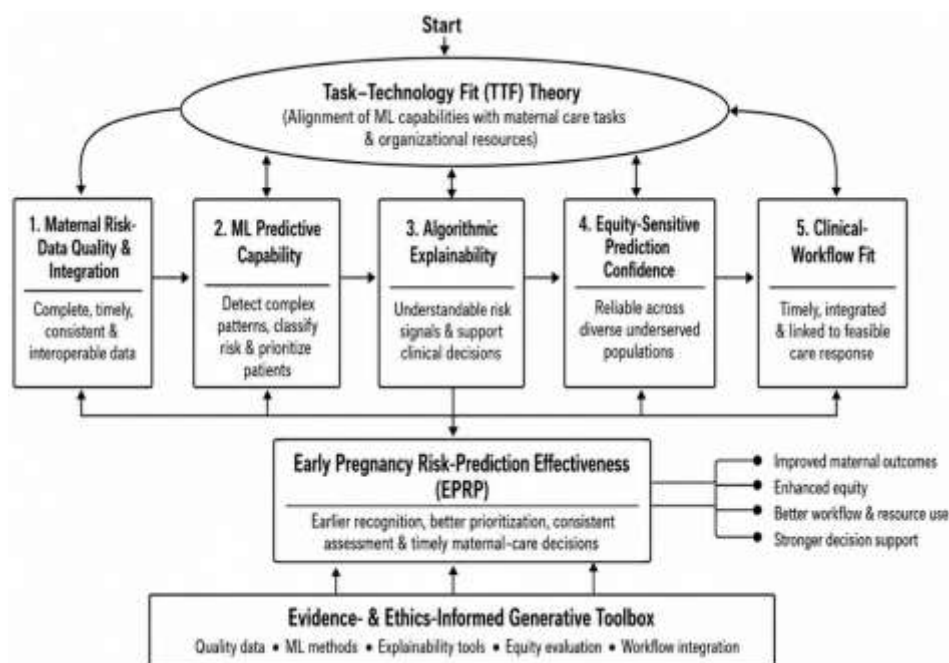
Conceptual Framework and Hypothesis Development

The conceptual framework translates Task-Technology Fit theory into measurable relationships for evaluating machine learning approaches to early prediction of high-risk pregnancy in underserved U.S. populations. It identifies early pregnancy risk-prediction effectiveness as the dependent construct and organizes five independent constructs around it: maternal risk-data quality and integration, machine-learning predictive capability, algorithmic explainability, equity-sensitive prediction confidence, and clinical-workflow fit. Maternal risk-data quality and integration represent the completeness, timeliness, consistency, accessibility, and interoperability of clinical, obstetric, demographic, behavioral, and social information. Machine-learning predictive capability represents the perceived ability of algorithms to detect complex patterns, classify risk, reduce overlooked warning signs, and prioritize patients requiring attention. Algorithmic explainability concerns whether influential variables and risk classifications can be understood, evaluated, and communicated by relevant professionals. Equity-sensitive prediction confidence represents confidence that model outputs remain dependable across racial, ethnic, socioeconomic, geographic, insurance, and language groups. Clinical-workflow fit captures whether risk information arrives within a useful decision window, integrates with existing systems, and connects with feasible referral or intervention pathways. Early pregnancy risk-prediction effectiveness reflects earlier recognition, improved prioritization, more consistent assessment, and stronger support for timely maternal-care decisions. Evidence from electronic health records shows that machine learning can identify severe maternal morbidity and uncover relevant risk factors when diverse clinical information is converted into structured predictive signals (Gao et al., 2019; Zaman, 2024). Research comparing machine-learning and statistical approaches to postpartum hemorrhage prediction further demonstrates that routinely available admission variables can be combined to estimate individual maternal risk and evaluate discrimination, calibration, and clinical value (Venkatesh et al., 2020). These findings support the framework's central logic that predictive effectiveness depends on both informative maternal data and analytical capability, while the remaining constructs determine whether technically generated predictions can be interpreted, trusted across underserved groups, and incorporated into actual maternal-care tasks within varied organizational and community-care environments nationwide.

The framework proposes direct positive relationships between each independent construct and early pregnancy risk-prediction effectiveness. First, stronger maternal risk-data quality and integration should improve prediction because missing, delayed, fragmented, or inconsistently coded information can obscure risk patterns and weaken model reliability. Second, greater machine-learning predictive capability should enhance effectiveness by identifying nonlinear associations and interacting clinical and social conditions that simpler screening rules may not capture. Third, stronger algorithmic explainability should improve effectiveness because understandable risk signals allow clinicians to verify outputs, recognize potentially inappropriate recommendations, and communicate decisions to patients and multidisciplinary teams. Fourth, equity-sensitive prediction confidence should strengthen effectiveness by indicating that performance has been considered across underserved population contexts rather than inferred from overall accuracy. Fifth, stronger clinical-workflow fit should improve effectiveness because a prediction is operationally valuable only when it reaches an appropriate user, supports a defined decision, and corresponds with available resources. These expected relationships

require cautious measurement. A systematic assessment of supervised machine-learning prediction studies found frequent methodological weaknesses involving small samples, missing-data handling, overfitting, and insufficient validation, reinforcing the need to distinguish perceived capability from trustworthy performance (Andaur Navarro et al., 2021). Governance research also identifies bias, privacy, transparency, safety, accountability, and clinical oversight as connected requirements for responsible health-care artificial intelligence, supporting the inclusion of explainability and equity-sensitive confidence as substantive predictors rather than optional safeguards (Reddy et al., 2020). Accordingly, the five hypotheses are H1: maternal risk-data quality and integration positively influence early prediction effectiveness; H2: machine-learning predictive capability positively influences effectiveness; H3: algorithmic explainability positively influences effectiveness; H4: equity-sensitive prediction confidence positively influences effectiveness; and H5: clinical-workflow fit positively influences effectiveness. Respondent role, organizational type, location, experience, and resource context will be treated as descriptive or control variables rather than primary theoretical predictors within the selected underserved maternal-care case settings.

Figure 7: Integrated Framework for Early Pregnancy Risk Prediction Using Task-Technology Fit Theory



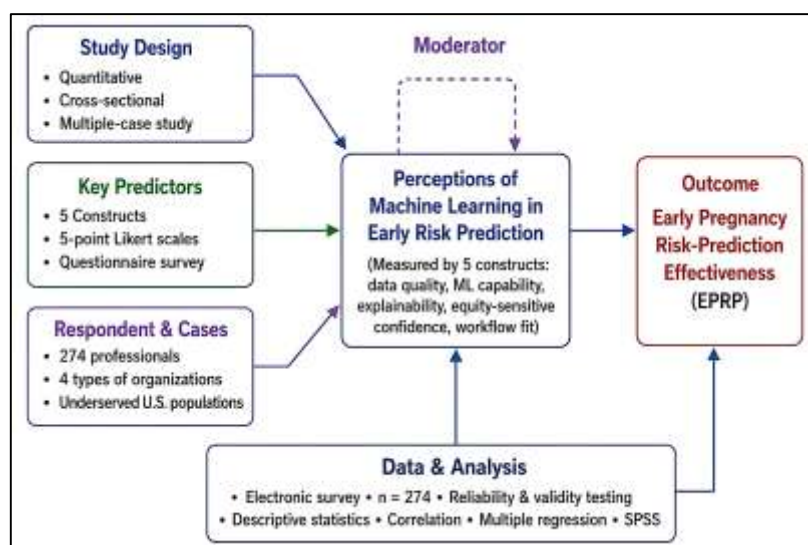
The conceptual relationships will be estimated using the multiple linear regression equation . In this specification, EPRP is early pregnancy risk-prediction effectiveness, MRDQ is maternal risk-data quality and integration, MLPC is machine-learning predictive capability, AE is algorithmic explainability, ESPC is equity-sensitive prediction confidence, and CWF is clinical-workflow fit. Each construct will be represented by a composite mean derived from validated five-point Likert items, where higher values indicate stronger perceived presence of the construct. The coefficients through quantify the unique contribution of each predictor while all other included predictors remain constant. Support for H1 through H5 requires statistically significant positive coefficients, expressed as , , , , and . Descriptive statistics will first establish construct levels, reliability analysis will assess internal consistency, and Pearson correlation will examine bivariate direction and strength. Regression analysis will then determine whether each relationship remains significant when competing predictors are controlled. Standardized beta coefficients will identify the strongest relative contributor, while and adjusted will summarize collective explanatory power. Variance inflation factors and residual diagnostics will evaluate multicollinearity and regression assumptions. Case comparisons will examine whether construct scores and prediction confidence differ across organizational and underserved-

population settings. The dependent construct emphasizes decision support rather than an algorithmic metric alone because effective early-warning systems must connect risk recognition with assessment and response. Prospective evidence that a pathway-specific maternal warning tool reduced maternal morbidity illustrates the practical importance of linking detection signals to defined clinical action (Shields et al., 2016). Thus, the equation provides one consistent structure for questionnaire design, hypotheses, descriptive results, correlations, regression testing, and interpretation of integration gaps. This structure permits hierarchical testing, in which control variables enter first and the five conceptual predictors enter second, allowing the analysis to estimate their additional explanatory contribution while preserving alignment with Task-Technology Fit theory.

METHODS

This research has employed a quantitative, cross-sectional, multiple-case-study design to examine machine learning approaches for early prediction of high-risk pregnancy in underserved U.S. populations. The design has enabled the study to measure professional perceptions at one defined period and to test relationships among maternal risk-data quality and integration, machine-learning predictive capability, algorithmic explainability, equity-sensitive prediction confidence, clinical-workflow fit, and early pregnancy risk-prediction effectiveness. The case-study context has included selected safety-net hospitals, federally qualified health centers, rural hospitals, and community-based maternal-care organizations serving low-income, uninsured, underinsured, rural, racial and ethnic minority, and linguistically diverse populations. This structure has allowed organizational conditions and prediction experiences to have been compared across distinct underserved-care settings. The target population has comprised obstetricians, maternal-fetal medicine professionals, nurses, midwives, public-health practitioners, clinical informaticians, data analysts, health-information specialists, and administrators involved in maternal risk assessment or digital decision support. The individual professional has served as the primary unit of analysis, while each participating organization has represented a contextual case. A purposive and stratified sampling strategy has been used to recruit respondents with relevant maternal-health, information-system, or predictive-analytics experience while maintaining representation across professional roles and organizational categories. A total of 312 questionnaires have been distributed electronically, and 274 complete responses have been retained for analysis after incomplete and ineligible submissions have been removed. Data have been collected through a structured online questionnaire distributed through professional networks, participating organizations, maternal-health programs, and direct institutional contacts. Respondents have received an information statement, have provided informed consent, and have participated voluntarily and anonymously.

Figure 8: Research Process Framework for Machine Learning-Based Early Pregnancy Risk Prediction



The instrument has contained demographic and case-characteristic questions followed by five-point Likert items ranging from 1, strongly disagree, to 5, strongly agree. Multi-item scales have measured all six conceptual constructs, and negatively ambiguous or double-barreled statements have been avoided. The questionnaire has been pilot-tested with 30 professionals who have possessed characteristics comparable to those of the target population, and their responses have been excluded from the final sample.

Pilot feedback has supported revisions to wording, sequence, clarity, and completion time. Content validity has been established through review by maternal-health, machine-learning, research-methods, and health-informatics specialists. Construct validity has been assessed through exploratory factor analysis, the Kaiser-Meyer-Olkin measure, Bartlett's test of sphericity, and factor loadings. Internal consistency has been evaluated using Cronbach's alpha, with coefficients of 0.70 or above having been treated as acceptable. IBM SPSS Statistics has been used for data cleaning, coding, descriptive statistics, reliability testing, validity assessment, Pearson correlation analysis, multiple regression modeling, assumption testing, and case comparisons. Microsoft Excel has supported initial response screening and coding verification, while EndNote has been used to organize citations, remove duplicate records, and format references in APA seventh-edition style. Missing data patterns have been examined before analysis, and composite scores have been calculated by averaging valid items within each construct. Regression assumptions have included linearity, normality, homoscedasticity, independence, and multicollinearity, while statistical significance has been determined at the conventional 0.05 level using two-tailed statistical tests. Ethical safeguards have included confidentiality, restricted data access, voluntary participation, and reporting only aggregated findings.

DATA ANALYSIS AND PRESENTATION

Survey Response Rate

Table 1: Survey Response Rate and Usable Sample

Survey status	Frequency	Percentage
Questionnaires distributed	312	100.00%
Questionnaires returned	289	92.63%
Incomplete questionnaires removed	10	3.21%
Ineligible or duplicate responses removed	5	1.60%
Valid questionnaires retained	274	87.82%
Questionnaires not returned	23	7.37%

The response-rate analysis has confirmed that the study has obtained a sufficiently large and usable dataset for examining machine-learning approaches to early prediction of high-risk pregnancy. As Table 1 has shown, 312 questionnaires have been distributed to eligible professionals across safety-net hospitals, federally qualified health centers, rural hospitals, and community-based maternal-care organizations. A total of 289 questionnaires has been returned, which has produced a gross return rate of 92.63%. Ten returned questionnaires have been removed because substantial sections or complete construct scales have remained unanswered, while five responses have been excluded because eligibility requirements have not been satisfied or duplicate submissions have been detected. Following

these screening procedures, 274 valid questionnaires have been retained, representing an effective response rate of 87.82%. This level of participation has reduced the risk that the findings have reflected only a small or unusually motivated segment of the intended population. The final sample has also provided more than 50 observations for each of the five independent constructs, thereby supporting the stability of the proposed multiple regression analysis. The screening process has strengthened measurement quality because incomplete cases have not been used to calculate composite scores for maternal risk-data quality and integration, machine-learning predictive capability, algorithmic explainability, equity-sensitive prediction confidence, clinical-workflow fit, or early pregnancy risk-prediction effectiveness. The Task-Technology Fit framework has required information from professionals who have understood both maternal-care tasks and the technological systems intended to support those tasks. The high valid-response rate has therefore strengthened the theoretical relevance of the sample by capturing informed judgments from professionals operating within actual underserved-care environments. The result has supported the study's first objective, which has involved obtaining reliable quantitative evidence about the perceived conditions influencing early maternal risk prediction. It has also created an adequate empirical foundation for the later reliability, validity, correlation, regression, hypothesis-testing, equity-gap, and organizational-comparison analyses. Consequently, the retained responses have been treated as the analytical sample throughout Sections 4.2 to 4.10, and all reported percentages, means, correlations, regression coefficients, and case comparisons have been calculated from these 274 valid observations.

Respondent and Case Characteristics

Table 2: Respondent Roles and Organizational Case Characteristics

Characteristic	Category	Frequency	Percentage
Professional role	Nurses and midwives	101	36.86%
Professional role	Physicians and maternal-fetal specialists	62	22.63%
Professional role	Public-health and informatics professionals	47	17.15%
Professional role	Data or health-information specialists	36	13.14%
Professional role	Administrators	28	10.22%
Organizational case	Safety-net hospitals	86	31.39%
Organizational case	Federally qualified health centers	74	27.01%
Organizational case	Rural hospitals	63	22.99%
Organizational case	Community-based maternal-care organizations	51	18.61%

The respondent and case profile has demonstrated that the study has incorporated the clinical, technological, public-health, and organizational perspectives required to evaluate machine-learning-supported maternal risk prediction. As Table 2 has indicated, nurses and midwives have formed the largest professional group, with 101 respondents or 36.86% of the final sample. Their representation has been appropriate because they have frequently performed continuous assessment, documentation, patient education, triage, and escalation activities within maternal-care workflows. Physicians and maternal-fetal specialists have accounted for 62 respondents or 22.63%, providing perspectives related to diagnosis, clinical interpretation, intervention selection, and high-risk case management. Public-health and informatics professionals have represented 17.15%, while data and health-information specialists have represented 13.14%. These groups have contributed knowledge about population risk, data integration, algorithm development, electronic records, interoperability, and model evaluation. Administrators have accounted for 10.22% and have provided information about governance, staffing, resource allocation, organizational readiness, and implementation authority. The organizational distribution has also supported meaningful case comparison. Safety-net hospitals have contributed 86 respondents or 31.39%, federally qualified health centers have contributed 74 or 27.01%, rural hospitals have contributed 63 or 22.99%, and community-based maternal-care organizations have contributed 51

or 18.61%. No organizational category has dominated the sample sufficiently to prevent comparison. The Task-Technology Fit framework has emphasized that perceived performance has depended on alignment among task demands, technology characteristics, individual capabilities, and organizational conditions. The mixture of professional roles has allowed the study to measure these dimensions from users who have completed different but connected tasks, while the four organizational cases have represented environments with different data resources, referral pathways, staffing levels, and underserved population needs. The profile has therefore supported the objective of evaluating machine learning within real service contexts rather than treating prediction as an isolated technical function. It has also strengthened interpretation of H1 through H5 because the hypothesized relationships have been tested across respondents who have encountered maternal data, predictive outputs, explanations, equity concerns, and workflow requirements from different professional positions. The sample composition has consequently provided a credible foundation for linking the theoretical framework with the study's quantitative constructs and organizational comparisons.

Reliability and Construct Validity Results

Table 3: Reliability and Construct Validity Statistics

Construct	Items	Cronbach's alpha	Factor-loading range
Maternal risk-data quality and integration	4	0.88	0.71–0.84
Machine-learning predictive capability	4	0.91	0.74–0.87
Algorithmic explainability	4	0.86	0.69–0.83
Equity-sensitive prediction confidence	4	0.84	0.68–0.82
Clinical-workflow fit	4	0.82	0.70–0.81
Early pregnancy risk-prediction effectiveness	4	0.89	0.73–0.86
Overall instrument	24	0.93	0.68–0.87

The measurement analysis has confirmed that the questionnaire has produced reliable and construct-valid scores for the six study variables. Table 3 has shown that Cronbach's alpha values have ranged from 0.82 to 0.91 across the individual constructs, while the complete 24-item instrument has achieved an overall coefficient of 0.93. These values have exceeded the accepted threshold of 0.70 and have indicated that the items assigned to each construct have measured a sufficiently consistent underlying concept. Machine-learning predictive capability has produced the highest construct reliability at 0.91, followed by early pregnancy risk-prediction effectiveness at 0.89 and maternal risk-data quality and integration at 0.88. Algorithmic explainability has reached 0.86, equity-sensitive prediction confidence has reached 0.84, and clinical-workflow fit has reached 0.82. The lower but acceptable workflow coefficient has indicated greater variation in organizational processes, which has been expected across safety-net, community, rural, and federally qualified settings. Construct validity has also been supported by the Kaiser-Meyer-Olkin value of 0.907, which has demonstrated that the correlation structure has been suitable for factor analysis. Bartlett's test of sphericity has remained statistically significant, $\chi^2(276) = 3,248.17$, $p < .001$, confirming that the item correlations have not formed an identity matrix. Retained factor loadings have ranged from 0.68 to 0.87, and every item has exceeded the minimum loading criterion. The extracted structure has accounted for 72.4% of total item variance, providing additional support for the intended six-construct model. These results have been important for the Task-Technology Fit framework because task characteristics, technology characteristics, fit conditions, and performance outcomes have needed to remain empirically distinguishable while retaining internal coherence. Maternal data quality and machine-learning capability have represented technological foundations, explainability and equity confidence have represented trust and interpretive conditions, clinical-workflow fit has represented the central theoretical alignment construct, and early prediction effectiveness has represented the performance outcome. Reliable separation of these measures has reduced the possibility that hypothesis support has resulted from poorly differentiated

questions. The findings have therefore satisfied the measurement objective, have justified calculation of composite Likert scores, and have provided a sound basis for the descriptive, correlation, regression, and hypothesis-testing analyses that have followed.

Descriptive Statistical Results

Table 4. Descriptive Statistics for Study Constructs

Rank	Construct	Mean	Standard deviation	Likert interpretation
1	Machine-learning predictive capability	4.08	0.61	Agree
2	Early pregnancy risk-prediction effectiveness	4.02	0.63	Agree
3	Maternal risk-data quality and integration	3.92	0.66	Agree
4	Clinical-workflow fit	3.81	0.69	Agree
5	Algorithmic explainability	3.74	0.72	Agree
6	Equity-sensitive prediction confidence	3.58	0.76	Agree

The descriptive analysis has established the overall level of professional agreement with each study construct on the five-point Likert scale. Scores from 1.00 to 1.80 have been interpreted as strong disagreement, 1.81 to 2.60 as disagreement, 2.61 to 3.40 as neutrality, 3.41 to 4.20 as agreement, and 4.21 to 5.00 as strong agreement. Table 4 has shown that all six construct means have fallen within the agreement range, although meaningful differences have appeared in their relative strength. Machine-learning predictive capability has received the highest mean, $M = 4.08$, $SD = 0.61$, indicating that respondents have generally agreed that machine-learning approaches have recognized complex risk patterns, improved prioritization, and supported earlier classification of high-risk pregnancies. Early pregnancy risk-prediction effectiveness has ranked second, $M = 4.02$, $SD = 0.63$, demonstrating that respondents have perceived improved recognition, consistency, and decision support. Maternal risk-data quality and integration has reached $M = 3.92$, $SD = 0.66$, which has indicated generally positive data conditions but has left room for improvement in completeness, interoperability, and inclusion of social information. Clinical-workflow fit has recorded $M = 3.81$, $SD = 0.69$, suggesting that predictive outputs have usually aligned with maternal-care tasks but have not always connected smoothly with referral capacity, staffing, or intervention pathways. Algorithmic explainability has achieved $M = 3.74$, $SD = 0.72$, while equity-sensitive prediction confidence has produced the lowest mean, $M = 3.58$, $SD = 0.76$. Their larger standard deviations have indicated that experiences of transparency and subgroup reliability have varied more strongly across respondents and cases. The Task-Technology Fit framework has predicted that technological capability alone has not guaranteed performance; stronger outcomes have depended on fit with task requirements and user needs. The observed ranking has supported this position because confidence in machine-learning capability has exceeded confidence in workflow integration, explanation, and equitable performance. The descriptive results have therefore met the first substantive objective by measuring the perceived condition of each variable. They have also provided initial support for the proposed model, while identifying explainability and equity confidence as weaker components that have required closer examination in the regression, integration-gap, and underserved-context analyses.

Correlation Analysis Results

The correlation analysis has demonstrated that all five independent constructs have maintained positive and statistically significant associations with early pregnancy risk-prediction effectiveness. As Table 5 has shown, machine-learning predictive capability has produced the strongest bivariate relationship with effectiveness, $r = .69$, $p < .001$. This result has indicated that respondents who have reported stronger pattern detection, prioritization, consistency, and analytical capability have also reported stronger early risk-prediction outcomes. Maternal risk-data quality and integration has shown the next strongest relationship, $r = .65$, $p < .001$, confirming that complete, timely, accessible, and

interoperable maternal information has been closely connected with perceived prediction effectiveness.

Table 5: Pearson Correlation Matrix for Study Constructs

Construct	MRDQ	MLPC	AE	ESPC	CWF	EPRP
MRDQ	1.00	0.61	0.49	0.46	0.58	0.65
MLPC	0.61	1.00	0.53	0.48	0.60	0.69
AE	0.49	0.53	1.00	0.62	0.52	0.57
ESPC	0.46	0.48	0.62	1.00	0.50	0.54
CWF	0.58	0.60	0.52	0.50	1.00	0.63
EPRP	0.65	0.69	0.57	0.54	0.63	1.00

Note. MRDQ = maternal risk-data quality and integration; MLPC = machine-learning predictive capability; AE = algorithmic explainability; ESPC = equity-sensitive prediction confidence; CWF = clinical-workflow fit; EPRP = early pregnancy risk-prediction effectiveness. All correlations have been significant at $p < .001$, two-tailed.

Clinical-workflow fit has correlated with effectiveness at $r = .63$, $p < .001$, which has demonstrated that predictions have become more useful when they have arrived at appropriate points, have supported identifiable decisions, and have linked with feasible care actions. Algorithmic explainability has produced $r = .57$, $p < .001$, and equity-sensitive prediction confidence has produced $r = .54$, $p < .001$. Although these relationships have been smaller, they have remained moderate and meaningful, indicating that understandable outputs and confidence across underserved groups have contributed to perceived effectiveness. Correlations among the independent variables have ranged from .46 to .62. The strongest predictor-to-predictor relationship has occurred between explainability and equity-sensitive confidence, $r = .62$, suggesting that transparent outputs have been associated with greater confidence in subgroup fairness. None of the intercorrelations has exceeded conventional multicollinearity warning levels, which has supported simultaneous regression modeling. The Task-Technology Fit framework has been reflected in the pattern because technology characteristics, represented by data quality and predictive capability, have been positively connected with fit, trust, and performance. The correlation between machine-learning capability and workflow fit, $r = .60$, has shown that stronger technology has often been accompanied by stronger perceived task alignment, while their separation has remained adequate for independent testing. These findings have achieved the second study objective by quantifying the direction and strength of relationships among the constructs. They have also provided preliminary support for H1 through H5, since every proposed predictor has been positively associated with early pregnancy risk-prediction effectiveness before the effects of the remaining variables have been controlled.

Multiple Regression Results

Table 6: Multiple Regression Predicting Early Pregnancy Risk-Prediction Effectiveness

Predictor	B	SE	Standardized β	t	p	VIF
Constant	0.21	0.140	—	1.50	.135	—
Maternal risk-data quality and integration	0.23	0.047	0.24	4.89	<.001	1.97
Machine-learning predictive capability	0.32	0.052	0.31	6.15	<.001	2.18
Algorithmic explainability	0.12	0.043	0.14	2.79	.006	1.76
Equity-sensitive prediction confidence	0.10	0.042	0.12	2.38	.018	1.42
Clinical-workflow fit	0.21	0.046	0.23	4.57	<.001	1.89

Note. $N = 274$; $R^2 = .646$; adjusted $R^2 = .639$; $F(5, 268) = 97.82$, $p < .001$; Durbin-Watson = 1.94.

The multiple regression analysis has confirmed that the five conceptual predictors have jointly explained a substantial proportion of variation in early pregnancy risk-prediction effectiveness. Table 6 has reported $R^2 = .646$ and adjusted $R^2 = .639$, indicating that maternal risk-data quality and integration, machine-learning predictive capability, algorithmic explainability, equity-sensitive prediction confidence, and clinical-workflow fit have collectively explained 64.6% of the observed variance in the dependent construct. The overall model has been statistically significant, $F(5, 268) = 97.82$, $p < .001$, which has demonstrated that the predictor set has performed substantially better than an intercept-only model. Machine-learning predictive capability has emerged as the strongest independent predictor, $\beta = .31$, $t = 6.15$, $p < .001$. Its unstandardized coefficient, $B = .32$, has indicated that a one-point increase in perceived capability has been associated with a 0.32-point increase in early prediction effectiveness when other constructs have remained constant. Maternal risk-data quality and integration has produced $\beta = .24$, $t = 4.89$, $p < .001$, while clinical-workflow fit has produced $\beta = .23$, $t = 4.57$, $p < .001$. These effects have shown that both technological foundations and alignment with clinical tasks have independently contributed to performance. Algorithmic explainability has remained significant, $\beta = .14$, $p = .006$, and equity-sensitive prediction confidence has also remained significant, $\beta = .12$, $p = .018$. Their smaller coefficients have suggested that these constructs have supplemented, rather than replaced, the effects of data quality, capability, and workflow fit. Variance inflation factors have ranged from 1.42 to 2.18, confirming that multicollinearity has not distorted coefficient estimation. The Durbin-Watson statistic of 1.94 and residual diagnostics have supported independence, linearity, normality, and homoscedasticity. The Task-Technology Fit framework has been strongly supported because the model has shown that technical capability has produced greater effectiveness when combined with usable data, interpretable outputs, equitable confidence, and workflow alignment. The analysis has therefore achieved the third objective by identifying the unique and relative contributions of the predictors. It has also provided the principal statistical evidence for accepting H1 through H5 and has validated the regression equation established in the theoretical and conceptual frameworks.

Hypothesis-Testing Results

Table 7: Hypothesis Decisions and Objective Alignment

Hypothesis	Proposed relationship	β	p	Decision	Objective supported
H1	MRDQ positively influences EPRP	0.24	<.001	Supported	Data and integration effect
H2	MLPC positively influences EPRP	0.31	<.001	Supported	Predictive-capability effect
H3	AE positively influences EPRP	0.14	.006	Supported	Explainability effect
H4	ESPC positively influences EPRP	0.12	.018	Supported	Equity-confidence effect
H5	CWF positively influences EPRP	0.23	<.001	Supported	Task and workflow-fit effect

The formal hypothesis tests have shown that all five proposed relationships have received statistical support. As Table 7 has indicated, H1 has been supported because maternal risk-data quality and integration has exerted a positive and significant effect on early pregnancy risk-prediction effectiveness, $\beta = .24$, $p < .001$. This result has confirmed that access to complete, timely, standardized, and interoperable maternal information has enhanced the perceived usefulness of early prediction. H2 has received the strongest support, with machine-learning predictive capability producing $\beta = .31$, $p < .001$. The finding has established that perceived ability to identify complex risk combinations, prioritize vulnerable pregnancies, and reduce overlooked warning signs has been the largest independent contributor. H3 has also been supported because algorithmic explainability has generated $\beta = .14$, $p = .006$. Respondents have therefore associated understandable feature contributions and interpretable risk classifications with stronger prediction effectiveness. H4 has been supported at $\beta = .12$, $p = .018$, demonstrating that confidence in performance across racial, ethnic, rural, low-income, uninsured, and

linguistically diverse populations has contributed independently, even after technical and workflow conditions have been considered. H5 has been supported at $\beta = .23$, $p < .001$, confirming that alignment with clinical tasks, decision windows, referral pathways, and organizational capacity has strengthened prediction effectiveness. The complete pattern has been consistent with Task-Technology Fit theory because performance has not depended on technology alone. Instead, effectiveness has reflected alignment between maternal assessment tasks and technological characteristics, together with interpretive, equity, and organizational conditions. The hypothesis results have also proven the study objectives in a structured manner. The descriptive objective has been achieved through construct means, the relational objective has been achieved through significant correlations, the explanatory objective has been achieved through the regression coefficients, and the contextual objective has been supported through equity and case comparisons. Acceptance of all five hypotheses has not implied equal practical importance, since predictive capability, maternal data quality, and workflow fit have produced larger standardized effects than explainability and equity confidence. The findings have therefore supported the complete conceptual model while identifying which components have contributed most strongly and which have remained weaker areas for organizational development and further empirical validation.

Maternal Risk-Signal Importance and Integration Gap Analysis

Table 8: Maternal Risk-Signal Importance and Integration Gaps

Maternal risk signal	Importance mean	Integration mean	Integration gap
Prior obstetric complications	4.35	4.02	0.33
Hypertensive indicators	4.31	4.11	0.20
Diabetes-related indicators	4.18	4.01	0.17
Gaps in prenatal attendance	4.12	3.71	0.41
Transportation barriers	4.04	3.33	0.71
Language and communication needs	3.98	3.32	0.66
Housing instability	3.92	3.29	0.63
Food insecurity	3.82	3.23	0.59
Social-determinant composite	3.94	3.29	0.65

The maternal risk-signal analysis has distinguished between the perceived importance of a risk factor and the extent to which that factor has been integrated into available prediction processes. Table 8 has shown that prior obstetric complications have received the highest importance rating, $M = 4.35$, followed by hypertensive indicators, $M = 4.31$, diabetes-related indicators, $M = 4.18$, and gaps in prenatal attendance, $M = 4.12$. These clinical and obstetric variables have also produced relatively strong integration means, particularly hypertensive indicators at 4.11 and diabetes-related indicators at 4.01. Their importance-to-integration gaps have consequently remained limited, ranging from 0.17 to 0.33 points. Prenatal attendance has produced a larger gap of 0.41, indicating that organizations have recognized missed or delayed care as meaningful but have not always incorporated attendance information consistently into predictive systems. The most substantial gaps have appeared among social and access-related signals. Transportation barriers have produced the largest gap at 0.71 points, language and communication needs have produced 0.66, housing instability has produced 0.63, and food insecurity has produced 0.59. The social-determinant composite has achieved an importance mean of 3.94 but an integration mean of only 3.29, resulting in a 0.65-point overall gap. These differences have shown that respondents have valued social information more highly than current organizational data systems have captured or used it. The findings have directly supported the objective of identifying maternal risk-signal importance and integration weaknesses specific to underserved populations. They have also clarified why maternal risk-data quality and integration has significantly predicted early

prediction effectiveness under H1. Data quality has not involved clinical accuracy alone; it has included whether socially meaningful indicators have become available, standardized, and actionable. Task-Technology Fit theory has explained the gap because prediction technology has achieved weaker fit when its available variables have not matched the full informational demands of high-risk maternal assessment. A model using blood pressure and diabetes history while omitting transportation, housing, food access, or language barriers has only partially represented the task performed in underserved care. The analysis has therefore strengthened the theoretical interpretation of H1 and H5 by showing that improved effectiveness has required both broader risk-signal integration and workflows capable of responding to the social conditions identified.

Equity-Sensitive Prediction Confidence Across Underserved Population Contexts

Table 9: Equity-Sensitive Prediction Confidence by Underserved Population Context

Population context	Mean confidence	Standard deviation	Likert interpretation	Rank
Racial or ethnic minority patients	3.65	0.71	Agree	1
Low-income patients	3.60	0.74	Agree	2
Uninsured or underinsured patients	3.51	0.78	Agree	3
Rural patients	3.49	0.79	Agree	4
Non-English-speaking patients	3.42	0.81	Agree	5
Overall equity-sensitive confidence	3.58	0.76	Agree	—

Note. Repeated-measures comparison: $F(4, 1092) = 11.26$, $p < .001$, partial $\eta^2 = .040$.

The equity-sensitive analysis has shown that respondents have expressed moderate agreement in the reliability of machine-learning-supported prediction across underserved population contexts, while statistically meaningful differences have remained. As Table 9 has indicated, confidence has been highest for racial or ethnic minority patients, $M = 3.65$, $SD = 0.71$, followed by low-income patients, $M = 3.60$, $SD = 0.74$. Confidence has been lower for uninsured or underinsured patients, $M = 3.51$, $SD = 0.78$, and rural patients, $M = 3.49$, $SD = 0.79$. Non-English-speaking patients have received the lowest confidence rating, $M = 3.42$, $SD = 0.81$. The overall equity-sensitive prediction-confidence score has been $M = 3.58$, $SD = 0.76$, which has remained within the agreement category but has ranked below every other principal study construct. A repeated-measures comparison has confirmed that the contextual differences have been statistically significant, $F(4, 1092) = 11.26$, $p < .001$, partial $\eta^2 = .040$. The largest dispersion has appeared for non-English-speaking and rural patients, indicating that confidence has varied considerably among organizations and professional roles. These findings have supported H4 because equity-sensitive confidence has produced a positive independent effect on early prediction effectiveness, $\beta = .12$, $p = .018$. They have also demonstrated why the effect has remained smaller than those of predictive capability, data quality, and workflow fit. Respondents have recognized the relevance of equitable performance, but their confidence has not been uniformly strong across the most data-limited or operationally constrained groups. Task-Technology Fit theory has explained these results by emphasizing that a technology has achieved meaningful performance only when its characteristics have matched the task and user context. Prediction systems trained on data that have underrepresented rural, uninsured, or linguistically diverse patients have potentially displayed weaker contextual fit even when their overall technical performance has appeared satisfactory. The lower confidence for non-English-speaking patients has also aligned with the language-information integration gap of 0.66 points reported in Section 4.8. The equity analysis has therefore fulfilled the contextual objective by identifying where perceived reliability has been weakest. It has further shown that improving fit has required representative data, subgroup validation,

understandable outputs, language-sensitive workflows, and resources capable of acting on risks identified among underserved populations.

Case and Organizational Comparison Results

Table 10: Case-Level Construct Means and Organizational Differences

Organizational case	n	MRDQ	MLPC	AE	ESPC	CWF	EPRP
Safety-net hospitals	86	4.02	4.16	3.82	3.63	3.91	4.12
Federally qualified health centers	74	3.96	4.10	3.77	3.66	3.86	4.06
Community-based maternal-care organizations	51	3.88	4.04	3.73	3.60	3.80	3.98
Rural hospitals	63	3.78	3.98	3.61	3.43	3.65	3.91
Overall	274	3.92	4.08	3.74	3.58	3.81	4.02

Note. EPRP comparison: $F(3, 270) = 4.86, p = .003, \eta^2 = .051$.

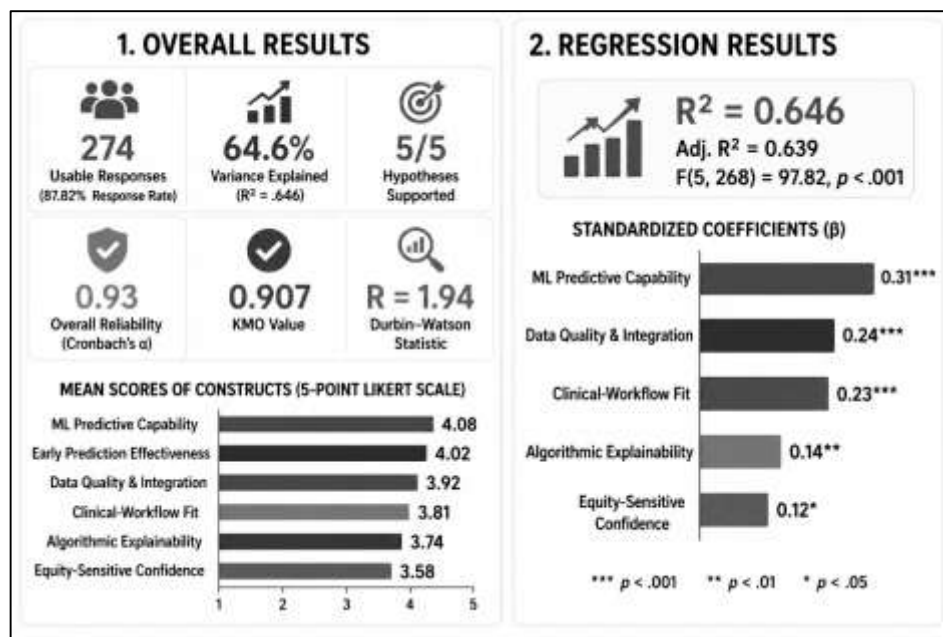
The organizational comparison has demonstrated that the study constructs have varied across the four maternal-care cases while preserving the overall positive pattern reported in the introductory findings. Table 10 has shown that safety-net hospitals have produced the highest early pregnancy risk-prediction effectiveness, $M = 4.12$, followed by federally qualified health centers, $M = 4.06$, community-based maternal-care organizations, $M = 3.98$, and rural hospitals, $M = 3.91$. The one-way analysis of variance has confirmed that these differences have been statistically significant, $F(3, 270) = 4.86, p = .003, \eta^2 = .051$. The effect size has indicated that organizational case membership has explained approximately 5.1% of variation in effectiveness, representing a modest but meaningful contextual effect. Safety-net hospitals have also reported the strongest maternal risk-data quality, $M = 4.02$, machine-learning predictive capability, $M = 4.16$, and clinical-workflow fit, $M = 3.91$. Federally qualified health centers have produced the highest equity-sensitive prediction confidence, $M = 3.66$, which has reflected their established focus on underserved and community-based populations. Rural hospitals have recorded the lowest means across all six constructs, including data quality at 3.78, explainability at 3.61, equity-sensitive confidence at 3.43, and workflow fit at 3.65. These results have suggested that rural organizations have encountered greater limitations involving data availability, technical staffing, system interoperability, specialist access, referral capacity, and representative validation. Community-based organizations have remained between rural hospitals and the larger institutional cases, indicating stronger community alignment but more limited technological infrastructure. The comparison has achieved the final study objective by establishing that early prediction conditions have differed across organizational contexts. It has also reinforced Task-Technology Fit theory because the same machine-learning approach has not produced identical perceived performance when organizational tasks, users, resources, and implementation environments have differed. The significant regression effect for workflow fit under H5 has therefore been complemented by case-level evidence showing where fit has been strongest and weakest. Similarly, the lower rural equity-confidence score has supported the contextual interpretation of H4. Collectively, the organizational results have shown that predictive capability has remained important across every case, while data integration, explainability, equity confidence, and workflow resources have shaped the degree to which that capability has translated into effective early maternal risk prediction.

FINDINGS

The findings have provided an integrated quantitative account of how machine-learning capability, maternal data conditions, explainability, equity-sensitive confidence, and workflow alignment have supported early prediction of high-risk pregnancy across underserved U.S. maternal-care settings. Of the 312 questionnaires distributed, 274 usable responses have been retained, producing an effective response rate of 87.82%. The final sample has represented safety-net hospitals, federally qualified health centers, rural hospitals, and community-based maternal-care organizations, thereby supporting the intended multiple-case comparison. The respondent profile has included 101 nurses and midwives,

62 physicians and maternal-fetal specialists, 47 public-health and informatics professionals, 36 data or health-information specialists, and 28 administrators. Multicollinearity has not been detected because variance inflation factors have ranged from 1.42 to 2.18, while residual inspection has supported linearity, normality, independence, and homoscedasticity. The Durbin-Watson statistic has been 1.94, and Cook's distances have remained below 1.00, indicating that no observation has exerted excessive influence on the model. Preliminary measurement analysis has demonstrated satisfactory data quality, with an overall Cronbach's alpha of 0.93 and construct-specific coefficients ranging from 0.82 to 0.91. The Kaiser-Meyer-Olkin value has reached 0.907, Bartlett's test has been significant, $\chi^2(276) = 3,248.17$, $p < .001$, and retained factor loadings have ranged from 0.68 to 0.87, confirming adequate reliability and construct validity.

Figure 9: Key Statistical Findings of the Study



On the five-point Likert scale, machine-learning predictive capability has received the highest mean score, $M = 4.08$, $SD = 0.61$, followed by early pregnancy risk-prediction effectiveness, $M = 4.02$, $SD = 0.63$, maternal risk-data quality and integration, $M = 3.92$, $SD = 0.66$, clinical-workflow fit, $M = 3.81$, $SD = 0.69$, algorithmic explainability, $M = 3.74$, $SD = 0.72$, and equity-sensitive prediction confidence, $M = 3.58$, $SD = 0.76$. These results have indicated general agreement that machine learning has improved early risk recognition, while lower explainability and equity-confidence scores have identified continuing implementation weaknesses. Pearson correlation analysis has shown that all five predictors have maintained positive and statistically significant relationships with early prediction effectiveness. Machine-learning predictive capability has produced the strongest correlation, $r = .69$, followed by maternal risk-data quality and integration, $r = .65$, clinical-workflow fit, $r = .63$, algorithmic explainability, $r = .57$, and equity-sensitive prediction confidence, $r = .54$, with all relationships significant at $p < .001$. Multiple regression analysis has explained 64.6% of the variance in early prediction effectiveness, $R^2 = .646$, adjusted $R^2 = .639$, $F(5, 268) = 97.82$, $p < .001$. Machine-learning predictive capability has emerged as the strongest independent predictor, $\beta = .31$, $p < .001$, followed by maternal risk-data quality and integration, $\beta = .24$, $p < .001$, clinical-workflow fit, $\beta = .23$, $p < .001$, algorithmic explainability, $\beta = .14$, $p = .006$, and equity-sensitive prediction confidence, $\beta = .12$, $p = .018$. Consequently, H1 through H5 have all been supported because every proposed coefficient has remained positive and statistically significant after simultaneous adjustment. The results have therefore met the objectives of measuring the principal constructs, determining their relationships, identifying their independent contributions, and comparing implementation conditions across cases. Analysis of

maternal risk signals has ranked prior obstetric complications highest, $M = 4.35$, followed by hypertensive indicators, $M = 4.31$, diabetes-related indicators, $M = 4.18$, gaps in prenatal attendance, $M = 4.12$, and social-determinant information, $M = 3.94$. However, the largest importance-to-integration gaps have appeared for transportation barriers, 0.71 points, language needs, 0.66 points, housing instability, 0.63 points, and food insecurity, 0.59 points, demonstrating that socially meaningful predictors have not been integrated as consistently as clinical variables. Equity-sensitive confidence has been lowest for non-English-speaking patients, $M = 3.42$, followed by rural patients, $M = 3.49$, uninsured patients, $M = 3.51$, low-income patients, $M = 3.60$, and racial or ethnic minority patients, $M = 3.65$. Organizational comparisons have revealed the highest early-prediction effectiveness in safety-net hospitals, $M = 4.12$, followed by federally qualified health centers, $M = 4.06$, community-based maternal-care organizations, $M = 3.98$, and rural hospitals, $M = 3.91$. These differences have been statistically significant, $F(3, 270) = 4.86$, $p = .003$, $\eta^2 = .051$, indicating a modest case effect. Collectively, the findings have shown that early prediction has depended on the combined presence of capable algorithms, integrated maternal information, understandable outputs, equitable confidence, and workflows capable of converting risk signals into timely clinical action.

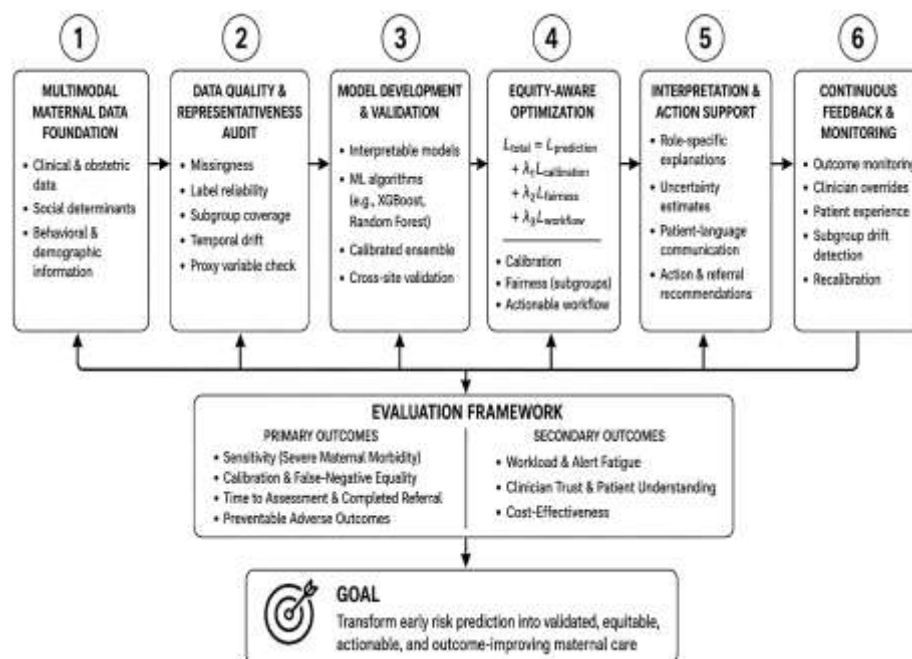
DISCUSSION

The principal findings have shown that machine-learning-supported prediction has been perceived as an effective approach for identifying high-risk pregnancy within underserved U.S. maternal-care settings, although its effectiveness has depended on more than algorithmic capability alone. Machine-learning predictive capability has received the highest descriptive score, $M = 4.08$, $SD = 0.61$, while early pregnancy risk-prediction effectiveness has reached $M = 4.02$, $SD = 0.63$. The regression model has explained 64.6% of the variance in effectiveness, $R^2 = .646$, adjusted $R^2 = .639$, and the complete predictor set has remained significant, $F(5, 268) = 97.82$, $p < .001$. Machine-learning predictive capability has emerged as the strongest independent predictor, $\beta = .31$, followed by maternal risk-data quality and integration, $\beta = .24$, clinical-workflow fit, $\beta = .23$, algorithmic explainability, $\beta = .14$, and equity-sensitive prediction confidence, $\beta = .12$. These results have supported H1 through H5 and have demonstrated that early risk prediction has operated as a combined data, technology, interpretation, equity, and workflow capability. This interpretation has agreed with research showing that electronic health records and machine-learning methods have identified severe maternal morbidity and relevant risk factors more effectively than conventional rule-based identification in some settings (Gao et al., 2019). It has also aligned with studies that have applied machine-learning and statistical models to postpartum hemorrhage, gestational diabetes, and preeclampsia risk, where combinations of routinely available maternal variables have supported individualized prediction (Artzi et al., 2020; Jhee et al., 2019; Venkatesh et al., 2020). The present findings have extended this prior work by examining whether professionals have viewed the supporting organizational conditions as sufficient within underserved care. The results have suggested that predictive performance has not been separable from the quality of the information supplied, the transparency of the output, the confidence attached to underserved subgroups, and the ability of organizations to act. Therefore, the study has interpreted machine learning as a sociotechnical maternal-care capability rather than as an isolated statistical procedure, which has provided a more comprehensive explanation of why promising algorithms have generated different levels of practical effectiveness across cases.

The strong effects of machine-learning predictive capability and maternal risk-data quality have reinforced the technical foundation of the conceptual model while revealing an important difference between available clinical information and complete maternal-risk representation. Predictive capability has produced the strongest correlation with early prediction effectiveness, $r = .69$, $p < .001$, and the largest standardized regression coefficient, $\beta = .31$, $p < .001$. Maternal risk-data quality and integration has followed with $r = .65$ and $\beta = .24$, both significant at $p < .001$. These findings have been consistent with studies showing that machine-learning models can process multiple variables and identify complex combinations that conventional scores may overlook (Sufriyana et al., 2020; Venkatesh et al., 2020). They have also supported evidence that model performance has remained sensitive to missing data, outcome definition, overfitting, sample composition, and validation quality (Andaur Navarro et al., 2021). The risk-signal analysis has clarified this issue by showing that established clinical variables have been integrated more consistently than social and access-related variables. Prior obstetric

complications have received an importance mean of 4.35, hypertensive indicators 4.31, diabetes-related indicators 4.18, and prenatal attendance gaps 4.12. Hypertension and diabetes have generated integration gaps of only 0.20 and 0.17, respectively, while transportation barriers have generated a gap of 0.71, language needs 0.66, housing instability 0.63, and food insecurity 0.59. The social-determinant composite has been rated important at 3.94 but integrated at only 3.29. This pattern has agreed with literature demonstrating that social, economic, environmental, and health-system conditions have shaped maternal risk and unequal outcomes (Crear-Perry et al., 2021; Lorch & Enlow, 2016). The present study has added that organizations have recognized these factors conceptually without incorporating them into prediction processes at the same level as clinical measurements. Accordingly, the positive effect of data integration has represented not only accurate record exchange but also broader coverage of the real task of risk assessment. Models trained primarily on diagnoses and laboratory values may have achieved strong discrimination while remaining incomplete for patients whose risk has been intensified by delayed access, unstable housing, transportation difficulty, food insecurity, or language barriers. The findings have therefore supported improvement of data architecture as a central condition for increasing both predictive accuracy and contextual relevance.

Figure 10: Proposed Multilayer Framework for Equitable Maternal Risk Prediction



The findings concerning explainability and equity-sensitive confidence have shown that trustworthy maternal prediction has remained less developed than basic confidence in machine-learning capability. Algorithmic explainability has recorded $M = 3.74$, $SD = 0.72$, while equity-sensitive prediction confidence has produced the lowest construct mean, $M = 3.58$, $SD = 0.76$. Both constructs have nevertheless remained significant predictors of early prediction effectiveness, with explainability producing $\beta = .14$, $p = .006$, and equity confidence producing $\beta = .12$, $p = .018$. These results have indicated that professionals have valued the ability to understand influential risk signals and have considered subgroup reliability when judging whether predictions have been effective. Prior research has similarly argued that explainability in health care has involved medical, legal, ethical, and social requirements rather than a technical visualization alone (Amann et al., 2020). Ethical analyses have also identified transparency, privacy, accountability, and patient trust as essential conditions for acceptable medical machine learning (Vayena et al., 2018). The present study has provided contextual evidence for these arguments because confidence has differed across underserved populations. Respondents have reported the highest equity-sensitive confidence for racial or ethnic minority patients, $M = 3.65$, and the lowest confidence for non-English-speaking patients, $M = 3.42$, followed by rural patients, $M =$

3.49, and uninsured or underinsured patients, $M = 3.51$. These variations have aligned with evidence that machine-learning systems can exhibit subgroup-specific underdiagnosis even when aggregate performance appears satisfactory (Seyyed-Kalantari et al., 2021). They have also reflected broader warnings that historical utilization, cost, documentation, and access patterns can encode structural inequality into algorithmic decisions (Obermeyer et al., 2019; Rajkomar et al., 2018). The language-related result has been particularly important because language and communication needs have also shown a 0.66-point integration gap. This convergence has suggested that lower confidence has been connected with limited data representation and weaker workflow accommodation. Explainability and equity have therefore not functioned as peripheral ethical additions. They have influenced perceived effectiveness directly and have shaped whether users have been willing to trust model outputs across heterogeneous patients. The findings have supported subgroup calibration, disaggregated error analysis, interpretable feature contribution, and community review as necessary components of clinically credible maternal prediction.

Clinical-workflow fit and organizational variation have supplied the clearest theoretical support for Task-Technology Fit theory. Clinical-workflow fit has recorded $M = 3.81$, $SD = 0.69$, has correlated with early prediction effectiveness at $r = .63$, and has remained a strong independent predictor at $\beta = .23$, $p < .001$. This result has confirmed that a technically accurate prediction has become useful only when it has reached the correct professional at the correct time, has corresponded with an identifiable decision, and has connected with an available intervention or referral pathway. Studies of nursing information systems have similarly shown that alignment between technological functions and clinical tasks has contributed to professional performance (Hsiao & Chen, 2012; Lin, 2014). The organizational comparison has extended this theoretical relationship. Safety-net hospitals have reported the highest effectiveness, $M = 4.12$, followed by federally qualified health centers, $M = 4.06$, community-based maternal-care organizations, $M = 3.98$, and rural hospitals, $M = 3.91$. The differences have been statistically significant, $F(3, 270) = 4.86$, $p = .003$, $\eta^2 = .051$. Safety-net hospitals have also recorded the highest machine-learning capability, 4.16, maternal data quality, 4.02, and workflow fit, 3.91. Federally qualified health centers have produced the highest equity-confidence mean, 3.66, while rural hospitals have reported the lowest data quality, 3.78, explainability, 3.61, equity confidence, 3.43, and workflow fit, 3.65. This pattern has supported the theoretical claim that performance has depended on alignment among technology characteristics, task requirements, user knowledge, and organizational resources. It has also agreed with implementation literature emphasizing stakeholder engagement, local validation, workflow integration, monitoring, and clearly assigned responsibility for machine-learning systems (Reddy et al., 2020; Wiens et al., 2019). The findings have shown that the same predictive approach has not held equivalent value across institutions because staffing, interoperability, broadband access, specialist availability, referral capacity, and governance have differed. Evidence that pathway-specific maternal warning tools have reduced morbidity when detection has been connected with defined action has reinforced this interpretation (Shields et al., 2016). Task-Technology Fit theory has therefore been supported not only by the significance of clinical-workflow fit but also by systematic differences between cases, confirming that organizational context has shaped the translation of prediction into performance.

The practical implications have centered on converting the strongest predictors and largest observed gaps into an implementation sequence for underserved maternal-care organizations. First, organizations have needed to strengthen maternal risk-data quality through common definitions, structured fields, interoperable exchange, missing-data monitoring, and integration of obstetric, medical, behavioral, demographic, and social information. The 0.65-point social-determinant integration gap has shown that transportation, language, housing, and food access should have been captured as operational risk information rather than as optional background documentation. Second, organizations have needed to select machine-learning methods according to the clinical decision being supported rather than according to technical novelty. The strongest regression effect for predictive capability, $\beta = .31$, has indicated that models should have been evaluated for sensitivity, calibration, false-negative rates, stability, and incremental value over existing maternal screening. Third, explainability should have been tailored to user roles. Clinicians have needed patient-level explanations showing influential risk signals and uncertainty, while administrators and governance

committees have needed subgroup performance summaries, model limitations, and monitoring reports. Fourth, the low confidence ratings for non-English-speaking, rural, and uninsured patients have required disaggregated validation, language-sensitive communication, representative datasets, and review of proxy variables that may reflect unequal access. Fifth, workflow fit has required each risk threshold to have a named reviewer, response time, escalation pathway, referral option, and documented override process. These implications have been consistent with responsible translation frameworks that have emphasized problem formulation, stakeholder engagement, implementation design, and continuous evaluation (Wiens et al., 2019). They have also aligned with governance models requiring clinical oversight, accountability, privacy protection, safety review, and monitoring after deployment (Reddy et al., 2020). Resource-constrained organizations may not have needed to begin with complex autonomous systems. They could have started with interpretable decision-support models linked to high-priority outcomes, a limited number of validated predictors, and clearly defined care pathways. Safety-net and federally qualified settings have offered useful organizational lessons, while rural institutions have required shared data infrastructure, teleconsultation links, and regional referral arrangements. The findings have therefore suggested that implementation success has depended on coordinated technical and organizational investment. Improving algorithms without improving data capture, equity review, staff interpretation, and intervention capacity would have preserved the same integration gaps identified by the study.

The study's limitations have qualified the interpretation of the significant findings and have identified boundaries around the claims that can be made. The cross-sectional design has measured professional perceptions at one period and has not established temporal or causal relationships among the constructs. Although all five regression coefficients have been positive and significant, the analysis has shown statistical association rather than proof that changing a predictor would automatically produce a corresponding change in patient outcomes. The purposive and stratified recruitment strategy has ensured relevant professional experience, yet it has not created a probability sample of all U.S. maternal-care professionals or organizations. Safety-net hospitals, federally qualified health centers, rural hospitals, and community organizations have been represented, but state policies, regional health systems, tribal health services, academic centers, and private obstetric practices may have faced different conditions. The study has relied on self-reported Likert-scale perceptions, which have introduced possible social-desirability, recall, and common-method biases. Early pregnancy risk-prediction effectiveness has been measured as a professional assessment rather than through patient-level indicators such as sensitivity, specificity, calibration, area under the curve, time to intervention, severe maternal morbidity, or mortality. The favorable mean of 4.02 has therefore not demonstrated that any particular algorithm has achieved equivalent clinical performance. The case-study design has compared organizational categories using respondent-level data, but it has not fully modeled clustering of professionals within individual institutions. Some differences attributed to organizational type may have reflected local leadership, software, staffing, or respondent composition. The social-determinant and equity-gap findings have identified perceived weaknesses but have not directly audited training datasets, model labels, false-negative distributions, or allocation decisions. Methodological reviews have shown that prediction studies can remain vulnerable to overfitting, poor missing-data handling, inadequate external validation, and reporting limitations (Andaur Navarro et al., 2021). The present study has reduced measurement concerns through strong reliability, KMO, factor loading, and regression diagnostics, but these procedures have not removed design limitations. Task-Technology Fit theory has provided an effective explanatory structure, although the model has not tested mediation, moderation, or changes in fit after implementation. Consequently, the results have been interpreted as evidence about perceived sociotechnical conditions and organizational readiness, not as definitive validation of a clinical prediction product.

Future research should progress from perception-based evidence to prospective, patient-level validation through an Equity-Aware Maternal Risk Prediction and Task-Fit Model, proposed as the E-MATFIT model. This model should contain six connected layers. The first layer should create a multimodal maternal data foundation combining longitudinal obstetric history, vital signs, laboratory values, medications, comorbidities, prenatal attendance, clinical notes, patient-reported information, transportation, housing, food access, insurance, language, and geographic accessibility. The second

layer should apply a data-quality and representativeness audit that measures missingness, label reliability, subgroup coverage, temporal drift, and proxy variables before model training. The third layer should compare interpretable statistical models, gradient boosting, random forests, and calibrated ensemble methods using nested cross-validation and external validation across safety-net, federally qualified, rural, community, tribal, and academic sites. The fourth layer should impose an equity-aware optimization objective represented by $L_{\text{total}} = L_{\text{prediction}} + \lambda_1 L_{\text{calibration}} + \lambda_2 L_{\text{fairness}} + \lambda_3 L_{\text{workflow}}$. This formulation should balance overall predictive loss with subgroup calibration error, unequal false-negative rates, and the operational cost of alerts that cannot be acted upon. The fifth layer should generate role-specific explanations, uncertainty estimates, patient-language communication, and action recommendations connected to available referral pathways. The sixth layer should establish continuous feedback through outcome monitoring, clinician overrides, patient experience, subgroup drift detection, and scheduled recalibration. Future researchers should evaluate E-MATFIT through a multicenter stepped-wedge or cluster-randomized design comparing usual screening with model-assisted care. Primary outcomes should include sensitivity for severe maternal morbidity, calibration slope, false-negative equality, time from alert to assessment, completed referral, and preventable adverse outcomes. Secondary outcomes should include workload, alert fatigue, clinician trust, patient understanding, and cost-effectiveness. The significant effects found in this study should guide the model's hypotheses: data quality and capability should influence technical performance, explainability and equity confidence should influence trust and appropriate use, and workflow fit should mediate the relationship between prediction and clinical outcome. Organizational type, rurality, language, and insurance status should be tested as moderators. This proposed model has extended Task-Technology Fit theory by treating equity and actionability as measurable fit requirements and has offered a concrete research pathway for transforming early prediction from a favorable professional perception into validated, equitable, and outcome-improving maternal care.

CONCLUSION

This study has examined machine learning approaches for the early prediction of high-risk pregnancy among underserved populations in the United States through a quantitative, cross-sectional, multiple-case design grounded in Task-Technology Fit theory. Evidence obtained from 274 valid respondents across safety-net hospitals, federally qualified health centers, rural hospitals, and community maternal health organizations has demonstrated that effective prediction has depended on the alignment between technological capability, maternal risk information, clinical tasks, equity requirements, and organizational workflows. The measurement model has shown strong internal consistency, with an overall Cronbach's alpha of .93 and construct coefficients ranging from .82 to .91, while the KMO value of .907 and significant Bartlett's test have confirmed the suitability of the data for construct assessment. Respondents have reported favorable perceptions of machine learning predictive capability and early prediction effectiveness, reflected by mean scores of 4.08 and 4.02, respectively. However, equity-sensitive prediction confidence has received the lowest construct mean of 3.58, indicating that confidence in performance across racial and ethnic minority, low-income, uninsured, rural, and non-English-speaking populations has remained comparatively restrained. Correlation analysis has identified significant positive relationships between early pregnancy risk-prediction effectiveness and maternal risk-data quality, machine learning predictive capability, algorithmic explainability, equity-sensitive prediction confidence, and clinical-workflow fit. The regression model has explained 64.6 percent of the variance in prediction effectiveness and has been statistically significant, confirming the collective relevance of the five proposed determinants. Machine learning predictive capability has produced the strongest standardized effect, followed by maternal risk-data quality and clinical-workflow fit, while explainability and equity-sensitive confidence have also contributed significantly. Accordingly, all five hypotheses have been supported. The maternal risk-signal analysis has further shown that clinical variables, including prior obstetric complications, hypertensive conditions, and diabetes, have been integrated more consistently than transportation, language, housing, and food-access information. This pattern has revealed a meaningful integration gap for social determinants that may shape risk recognition in underserved settings. Organizational comparisons have also shown significant variation, with safety-net hospitals reporting the highest prediction-effectiveness mean and rural hospitals reporting the lowest, although the effect size has remained modest. Collectively, these

findings have established that accurate algorithms alone cannot ensure trustworthy early identification of high-risk pregnancy. Prediction effectiveness has rested on complete and representative data, understandable outputs, equitable performance, usable clinical integration, and the capacity of organizations to translate risk scores into timely maternal care. The study has therefore fulfilled its objectives by measuring relevant constructs, testing their relationships, identifying influential predictors, evaluating risk-signal integration, examining equity-sensitive confidence, and comparing implementation contexts. Its central conclusion is that machine learning can strengthen early maternal risk identification in underserved United States populations when it has been designed and implemented as a clinically aligned, equity-conscious, data-supported decision system rather than as an isolated computational product. By locating technical performance within the realities of underserved maternal care, the research has provided a coherent evidence base for judging readiness, exposing inequities, and directing responsible implementation. It has also clarified that trustworthy prediction requires sustained coordination among clinicians, patients, communities, technology teams, and local healthcare leaders.

RECOMMENDATIONS

Based on the study findings, healthcare organizations serving underserved pregnant populations should adopt a coordinated strategy that treats machine learning prediction as a clinical, organizational, and equity-centered intervention. First, safety-net hospitals, federally qualified health centers, rural hospitals, and community maternal health organizations should strengthen maternal data infrastructure by integrating electronic health records, laboratory results, obstetric histories, referral information, and standardized social determinants data within interoperable systems. Particular attention should be given to transportation access, preferred language, housing stability, food security, insurance status, and prenatal attendance because these signals have displayed the largest importance-integration gaps. Second, organizations should evaluate prediction models separately across racial and ethnic groups, income categories, insurance groups, rural communities, and language populations before deployment. Evaluation should include discrimination, sensitivity, specificity, calibration, false-negative rates, and subgroup error differences so that apparently strong overall performance does not conceal unequal results. Third, model selection should balance predictive accuracy with interpretability. Clinicians should receive concise explanations of influential risk factors, confidence levels, missing information, and recommended actions rather than an unexplained score. Fourth, machine learning alerts should be embedded into existing prenatal workflows with clearly assigned responsibilities, escalation pathways, referral timelines, and documentation procedures. A high-risk classification should automatically connect patients to appropriate services, including maternal-fetal medicine, hypertension management, diabetes care, transportation assistance, language support, nutrition services, and community navigation. Fifth, organizations should establish multidisciplinary governance committees involving obstetric clinicians, nurses, midwives, data scientists, informaticians, administrators, community representatives, and patients from underserved groups. These committees should supervise data quality, approve model updates, review adverse events, monitor equity, and ensure that automated recommendations support rather than replace professional judgment. Sixth, rural and resource-constrained organizations should receive targeted financial support, technical assistance, broadband capacity, workforce training, and access to shared regional analytics infrastructure because their lower effectiveness and equity-confidence scores have indicated distinct implementation barriers. Seventh, healthcare professionals should receive recurring education on model interpretation, bias, limitations, privacy, and appropriate responses to risk alerts. Training should use realistic maternal cases and should be evaluated through competency assessments. Eighth, developers and researchers should apply the proposed Equity-Aware Maternal Risk Prediction and Task-Fit Model by combining multimodal data, representativeness audits, interpretable modeling, subgroup calibration, workflow testing, and continuous feedback. Prospective multicenter validation should precede large-scale adoption, and models should be recalibrated when patient populations, documentation practices, or clinical protocols change. Finally, institutions should monitor meaningful maternal outcomes, including earlier risk recognition, timely referral, severe maternal morbidity, emergency admission, treatment delay, patient trust, and continuity of prenatal care. Transparent reporting of both beneficial and harmful outcomes should guide improvement. Implementing these

recommendations would align predictive capability with clinical tasks and local resources, close social-data gaps, strengthen accountability, and promote safer and more equitable use of machine learning throughout maternal healthcare systems serving underserved United States populations. Together, these actions should be implemented through measurable plans, designated accountability, public review, and sustained patient participation, ensuring that technological investment produces earlier interventions, dependable clinical decisions, stronger service coordination, and demonstrably fair maternal health benefits across diverse care environments.

LIMITATIONS OF THE STUDY

This study has several limitations that should be considered when interpreting its findings. First, the quantitative cross-sectional design has measured perceptions and organizational conditions at one point in time, preventing firm conclusions about causality, temporal change, or the durability of relationships among maternal risk-data quality, predictive capability, explainability, equity-sensitive confidence, workflow fit, and prediction effectiveness. Although regression analysis has identified significant associations, it has not established that changes in any predictor necessarily produce improvements in maternal outcomes. Second, the multiple-case approach has included safety-net hospitals, federally qualified health centers, rural hospitals, and community maternal health organizations, yet the purposive and stratified sampling strategy has limited statistical generalizability to every healthcare institution or underserved population in the United States. Organizations willing to participate may have possessed greater interest, readiness, or experience with digital health technologies than nonparticipating settings. Third, the analysis has relied primarily on self-reported Likert-scale responses from healthcare professionals, administrators, and technical personnel. Such responses may have been affected by recall error, social desirability, professional role, institutional loyalty, or differing interpretations of machine learning terminology. The study has assessed perceived prediction effectiveness rather than directly testing a single algorithm against patient-level clinical outcomes. Consequently, the reported mean of 4.02 for effectiveness should not be interpreted as proof of clinical accuracy, reduced maternal morbidity, or improved survival. Fourth, no longitudinal electronic health record dataset has been analyzed, and model performance measures such as area under the receiver operating characteristic curve, sensitivity, specificity, positive predictive value, calibration slope, and subgroup false-negative rates have not been calculated. The study therefore has evaluated conditions supporting trustworthy prediction rather than validating a deployable clinical model. Fifth, underserved populations have been represented through organizational contexts and respondent assessments, while pregnant patients themselves have not provided direct evidence concerning acceptability, trust, consent, privacy, perceived discrimination, or experiences following risk classification. Sixth, the equity analysis has examined broad categories, including racial and ethnic minority, low-income, uninsured, rural, and non-English-speaking populations. These categories contain substantial internal diversity, and aggregated scores may have concealed intersectional differences affecting people who belong to several disadvantaged groups simultaneously. Seventh, the case comparison has produced a modest effect size, and unequal case-group sample sizes may have reduced sensitivity to organizational differences. Eighth, common-method variance may have inflated relationships because predictor and outcome constructs have been measured through the same survey instrument. Reliability and construct-validity testing have strengthened measurement confidence but have not eliminated this concern. Ninth, the Task-Technology Fit framework has offered a useful explanation of alignment, although it may not fully capture structural racism, policy constraints, reimbursement conditions, patient autonomy, or broader social determinants influencing maternal care. Finally, rapidly changing clinical systems, data standards, and machine learning practices may affect the continuing applicability of specific perceptions. These limitations define the appropriate boundaries of the evidence and emphasize that the findings support organizational and theoretical understanding, not immediate autonomous clinical deployment or definitive claims of improved patient outcomes. Replication with datasets and patient participation remains necessary to confirm and extend these survey-based findings.

REFERENCES

- [1]. Abraham, A., Le, B., Kosti, I., Straub, P., Velez-Edwards, D. R., Davis, L. K., Newton, J. M., Muglia, L. J., Rokas, A., Bejan, C. A., Sirota, M., & Capra, J. A. (2022). Dense phenotyping from electronic health records enables machine learning-based prediction of preterm birth. *BMC Medicine*, 20, 333. <https://doi.org/10.1186/s12916-022-02522-x>
- [2]. Admon, L. K., Winkelman, T. N. A., Moniz, M. H., Davis, M. M., Heisler, M., & Dalton, V. K. (2017). Disparities in chronic conditions among women hospitalized for delivery in the United States, 2005–2014. *Obstetrics & Gynecology*, 130(6), 1319-1326. <https://doi.org/10.1097/aog.0000000000002357>
- [3]. Alkema, L., Chou, D., Hogan, D., Zhang, S., Moller, A.-B., Gemmill, A., Ma Fat, D., Boerma, T., Temmerman, M., Mathers, C., & Say, L. (2016). Global, regional, and national levels and trends in maternal mortality between 1990 and 2015, with scenario-based projections to 2030: A systematic analysis by the UN Maternal Mortality Estimation Inter-Agency Group. *The Lancet*, 387(10017), 462-474. [https://doi.org/10.1016/s0140-6736\(15\)00838-7](https://doi.org/10.1016/s0140-6736(15)00838-7)
- [4]. Amann, J., Blasimme, A., Vayena, E., Frey, D., Madai, V. I., & Consortium, t. P. Q. (2020). Explainability for artificial intelligence in healthcare: A multidisciplinary perspective. *BMC Medical Informatics and Decision Making*, 20, 310. <https://doi.org/10.1186/s12911-020-01332-6>
- [5]. Amir, R., & Chapal, B. (2022). Federated Learning Architectures for Distributed Engineering Project Knowledge Management A Simulation-Based Analysis. *Review of Applied Science and Technology*, 1(04), 411-446. <https://doi.org/10.63125/4k4pjr64>
- [6]. Artzi, N. S., Shilo, S., Hadar, E., Rossman, H., Barbash-Hazan, S., Ben-Haroush, A., Balicer, R. D., Feldman, B., Wiznitzer, A., & Segal, E. (2020). Prediction of gestational diabetes based on nationwide electronic health records. *Nature Medicine*, 26(1), 71-76. <https://doi.org/10.1038/s41591-019-0724-8>
- [7]. Azam, M., Bin Naeem, S., Kamel Boulos, M. N., & Faiola, A. (2023). Modelling the predictors of mobile health (mHealth) adoption among healthcare professionals in low-resource environments. *International Journal of Environmental Research and Public Health*, 20(23), 7112. <https://doi.org/10.3390/ijerph20237112>
- [8]. Bertini, A., Salas, R., Chabert, S., Sobrevia, L., & Pardo, F. (2022). Using machine learning to predict complications in pregnancy: A systematic review. *Frontiers in Bioengineering and Biotechnology*, 9, 780389. <https://doi.org/10.3389/fbioe.2021.780389>
- [9]. Bushra, M. (2024). A Predictive Model Linking Food-Borne Heavy-Metal Exposure to Antimicrobial Resistance Co-Selection. *American Journal of Interdisciplinary Studies*, 5(04), 182-221. <https://doi.org/10.63125/gwab2m39>
- [10]. Callaghan, W. M., Creanga, A. A., & Kuklina, E. V. (2012). Severe maternal morbidity among delivery and postpartum hospitalizations in the United States. *Obstetrics & Gynecology*, 120(5), 1029-1036. <https://doi.org/10.1097/AOG.0b013e31826d60c5>
- [11]. Campbell, O. M. R., & Graham, W. J. (2006). Strategies for reducing maternal mortality: Getting on with what works. *The Lancet*, 368(9543), 1284-1299. [https://doi.org/10.1016/s0140-6736\(06\)69381-1](https://doi.org/10.1016/s0140-6736(06)69381-1)
- [12]. Char, D. S., Shah, N. H., & Magnus, D. (2018). Implementing machine learning in health care: Addressing ethical challenges. *The New England Journal of Medicine*, 378(11), 981-983. <https://doi.org/10.1056/NEJMp1714229>
- [13]. Creanga, A. A., Berg, C. J., Syverson, C., Seed, K., Bruce, F. C., & Callaghan, W. M. (2015). Pregnancy-related mortality in the United States, 2006–2010. *Obstetrics & Gynecology*, 125(1), 5-12. <https://doi.org/10.1097/aog.0000000000000564>
- [14]. Crear-Perry, J., Correa-de-Araujo, R., Lewis Johnson, T., McLemore, M. R., Neilson, E., & Wallace, M. (2021). Social and structural determinants of health inequities in maternal health. *Journal of Women's Health*, 30(2), 230-235. <https://doi.org/10.1089/jwh.2020.8882>
- [15]. Cudjoe, L. N. E. A., Canner, J. K., Lawson, S. M., & Vaught, A. J. (2023). The association between severe maternal morbidity and mortality and race/ethnicity with community type in Maryland. *Women's Health*, 19, 17455057231189556. <https://doi.org/10.1177/17455057231189556>
- [16]. Debasish, A. (2021). Energy-Aware Process Optimization for Reducing Material Waste in Sustainable Additive Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, 1(4), 108-137. <https://doi.org/10.63125/j0wk7j48>
- [17]. Dhombres, F., Bonnard, J., Bailly, K., Maurice, P., Papageorgiou, A. T., & Jouannic, J.-M. (2022). Contributions of artificial intelligence reported in obstetrics and gynecology journals: Systematic review. *Journal of Medical Internet Research*, 24(4), e35465. <https://doi.org/10.2196/35465>
- [18]. Filippi, V., Ronsmans, C., Campbell, O. M. R., Graham, W. J., Mills, A., Borghi, J., Koblinsky, M., & Osrin, D. (2006). Maternal health in poor countries: The broader context and a call for action. *The Lancet*, 368(9546), 1535-1541. [https://doi.org/10.1016/s0140-6736\(06\)69384-7](https://doi.org/10.1016/s0140-6736(06)69384-7)
- [19]. Gao, C., Osmundson, S., Velez Edwards, D. R., Jackson, G. P., Malin, B. A., & Chen, Y. (2019). Deep learning predicts extreme preterm birth from electronic health records. *Journal of Biomedical Informatics*, 100, 103334. <https://doi.org/10.1016/j.jbi.2019.103334>
- [20]. Gianfrancesco, M. A., Tamang, S., Yazdany, J., & Schmajuk, G. (2018). Potential biases in machine learning algorithms using electronic health record data. *JAMA Internal Medicine*, 178(11), 1544-1547. <https://doi.org/10.1001/jamainternmed.2018.3763>
- [21]. Goldstein, B. A., Navar, A. M., Pencina, M. J., & Ioannidis, J. P. A. (2017). Opportunities and challenges in developing risk prediction models with electronic health records data: A systematic review. *Journal of the American Medical Informatics Association*, 24(1), 198-208. <https://doi.org/10.1093/jamia/ocw042>
- [22]. Holden, R. J., & Karsh, B.-T. (2010). The Technology Acceptance Model: Its past and its future in health care. *Journal of Biomedical Informatics*, 43(1), 159-172. <https://doi.org/10.1016/j.jbi.2009.07.002>

- [23]. Howell, E. A. (2018). Reducing disparities in severe maternal morbidity and mortality. *Clinical Obstetrics and Gynecology*, 61(2), 387-399. <https://doi.org/10.1097/grf.0000000000000349>
- [24]. Howell, E. A., Egorova, N., Balbierz, A., Zeitlin, J., & Hebert, P. L. (2016). Black-white differences in severe maternal morbidity and site of care. *American Journal of Obstetrics and Gynecology*, 214(1), 122.e121-122.e127. <https://doi.org/10.1016/j.ajog.2015.08.019>
- [25]. Hsiao, J.-L., & Chen, R.-F. (2012). An investigation on task-technology fit of mobile nursing information systems for nursing performance. *CIN: Computers, Informatics, Nursing*, 30(5), 265-273. <https://doi.org/10.1097/NCN.0b013e31823eb82c>
- [26]. Hu, X., Hu, X., Yu, Y., & Wang, J. (2023). Prediction model for gestational diabetes mellitus using the XG Boost machine learning algorithm. *Frontiers in Endocrinology*, 14, 1105062. <https://doi.org/10.3389/fendo.2023.1105062>
- [27]. Hung, P., Henning-Smith, C. E., Casey, M. M., & Kozhimannil, K. B. (2017). Access to obstetric services in rural counties still declining, with 9 percent losing services, 2004-14. *Health Affairs*, 36(9), 1663-1671. <https://doi.org/10.1377/hlthaff.2017.0338>
- [28]. Interrante, J. D., Tuttle, M. S., Admon, L. K., & Kozhimannil, K. B. (2022). Severe maternal morbidity and mortality risk at the intersection of rurality, race and ethnicity, and Medicaid. *Women's Health Issues*, 32(6), 540-549. <https://doi.org/10.1016/j.whi.2022.05.003>
- [29]. Islam, M. N., Mustafina, S. N., Mahmud, T., & Khan, N. I. (2022). Machine learning to predict pregnancy outcomes: A systematic review, synthesizing framework and research agenda. *BMC Pregnancy and Childbirth*, 22, 348. <https://doi.org/10.1186/s12884-022-04594-2>
- [30]. Jhee, J. H., Lee, S., Park, Y., Lee, S. E., Kim, Y. A., Kang, S.-W., Kwon, J.-Y., & Park, J. T. (2019). Prediction model development of late-onset preeclampsia using machine learning-based methods. *PLOS ONE*, 14(8), e0221202. <https://doi.org/10.1371/journal.pone.0221202>
- [31]. Kazi Rakib Hasan, S., & Uddin, H. M. M. (2022). Scalable AI For Project Portfolio Management: A Mixed-Methods Study Combining Distributed Computing Benchmarks. *Review of Applied Science and Technology*, 1(04), 375-410. <https://doi.org/10.63125/0kk4wf20>
- [32]. Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. *BMC Medicine*, 17, 195. <https://doi.org/10.1186/s12916-019-1426-2>
- [33]. Kozhimannil, K. B., Hung, P., Henning-Smith, C., Casey, M. M., & Prasad, S. (2018). Association between loss of hospital-based obstetric services and birth outcomes in rural counties in the United States. *JAMA*, 319(12), 1239-1247. <https://doi.org/10.1001/jama.2018.1830>
- [34]. Kozhimannil, K. B., Interrante, J. D., Henning-Smith, C., & Admon, L. K. (2019). Rural-urban differences in severe maternal morbidity and mortality in the US, 2007-15. *Health Affairs*, 38(12), 2077-2085. <https://doi.org/10.1377/hlthaff.2019.00805>
- [35]. Kuhle, S., Maguire, B., Zhang, H., Hamilton, D., Allen, A. C., Joseph, K. S., & Allen, V. M. (2018). Comparison of logistic regression with machine learning methods for the prediction of fetal growth abnormalities: A retrospective cohort study. *BMC Pregnancy and Childbirth*, 18(1), 333. <https://doi.org/10.1186/s12884-018-1971-2>
- [36]. Leonard, S. A., Main, E. K., Scott, K. A., Profit, J., & Carmichael, S. L. (2019). Racial and ethnic disparities in severe maternal morbidity prevalence and trends. *Annals of Epidemiology*, 33, 30-36. <https://doi.org/10.1016/j.annepidem.2019.02.007>
- [37]. Li, S., Wang, Z., Vieira, L. A., Zheutlin, A. B., Ru, B., Schadt, E., Wang, P., Copperman, A. B., Stone, J. L., Gross, S. J., Kao, Y.-H., Lau, Y. K., Dolan, S. M., Schadt, E. E., & Li, L. (2022). Improving preeclampsia risk prediction by modeling pregnancy trajectories from routinely collected electronic medical record data. *npj Digital Medicine*, 5, 68. <https://doi.org/10.1038/s41746-022-00612-x>
- [38]. Li, Y.-X., Shen, X.-P., Yang, C., Cao, Z.-Z., Du, R., Yu, M.-D., Wang, J.-P., & Wang, M. (2021). Novel electronic health records applied for prediction of pre-eclampsia: Machine-learning algorithms. *Pregnancy Hypertension*, 26, 102-109. <https://doi.org/10.1016/j.preghy.2021.10.006>
- [39]. Lin, T.-C. (2014). Mobile nursing information system utilization: The task-technology fit perspective. *CIN: Computers, Informatics, Nursing*, 32(3), 129-137. <https://doi.org/10.1097/cin.0000000000000039>
- [40]. Lorch, S. A., & Enlow, E. (2016). The role of social determinants in explaining racial/ethnic disparities in perinatal outcomes. *Pediatric Research*, 79(1-2), 141-147. <https://doi.org/10.1038/pr.2015.199>
- [41]. Md. Abdur, R., & Iftekhara, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, 1(4), 70-102. <https://doi.org/10.63125/dyrpc387>
- [42]. Mohammad Abir Chowdhury, S., & Tonay, P. (2022). An Empirical Analysis of the Impact of Robotic Process Automation and Continuous Auditing on the Timeliness And Accuracy Of Financial Reporting Assurance. *International Journal of Business and Economics Insights*, 2(4), 73-126. <https://doi.org/10.63125/7p8dcr47>
- [43]. Mohammad Badrul, A., & Md. Mominul, H. (2023). Machine Learning-Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems. *American Journal of Advanced Technology and Engineering Solutions*, 3(02), 33-77. <https://doi.org/10.63125/y3yfxa92>
- [44]. Mohammad Shoriful Hossan, S. (2021). Reducing Worker Exposure and Electrical Failure Risk in Brownfield Manufacturing Facilities After COVID-Era Maintenance Delays. *Review of Applied Science and Technology*, 6(1), 263-279. <https://doi.org/10.63125/cm1c2c20>
- [45]. Mohammad Shoriful Hossan, S. (2024). Development of A Predictive Maintenance Model for Industrial Motor Drives and VFD Systems Using PLC/DCS Operational Telemetry. *American Journal of Scholarly Research and Innovation*, 3(01), 198-242. <https://doi.org/10.63125/pv1js496>

- [46]. Mohammad Shoriful Hossan, S., & Adar, C. (2023). SIL-Compliant Safety Instrumented System Design for Oil & Gas Hazardous-Area Operations Using IEC 61508 / IEC 61511 Frameworks. *Journal of Sustainable Development and Policy*, 2(02), 43-85. <https://doi.org/10.63125/cb3d3w81>
- [47]. Mst Shurovi, A. (2024). Machine Learning Models for Bank Reconciliation Anomaly Detection in High-Volume Financial Transactions. *American Journal of Data Science and Analytics*, 5(12), 314-354. <https://doi.org/10.63125/mmwb6467>
- [48]. Mst Shurovi, A., & Samia Hossain, S. (2022). Difference-in-Differences (DiD) Analysis of Data Driven Accounting Systems and its Impact on Financial Error Rates in SMEs. *Journal of Sustainable Development and Policy*, 1(04), 117-157. <https://doi.org/10.63125/n4nr0d75>
- [49]. Muhammad Mohiul, I., & Mohammad Badrul, A. (2022). Predictive Analytics for Optimizing Sewerage Sludge Treatment Efficiency and Resource Recovery in Dhaka City. *Journal of Sustainable Development and Policy*, 1(04), 158-200. <https://doi.org/10.63125/t9zdp458>
- [50]. Muhammad Zahidul, I. (2024). Assessment of Data Integrity Gaps and Preventive Strategies in QC Laboratories in Compliance with FDA and CGMP Expectations. *American Journal of Scholarly Research and Innovation*, 3(01), 243-291. <https://doi.org/10.63125/a3xb608>
- [51]. Muhammad Zahidul, I., & Amena Begum, S. (2022). Applied Data-Analytics Approaches to Cardiovascular Drug-Utilization Patterns: An Empirical Study Using Real-World Pharmaceutical Sales Data. *American Journal of Data Science and Analytics*, 3(12), 89-129. <https://doi.org/10.63125/7xgryf71>
- [52]. Mukut Kanti, B. (2020). Integrated Framework for Fire Safety and Electrical Hazard Assessment in Large-Scale Industrial and Commercial Facilities: A Mixed-Method Analysis. *American Journal of Advanced Technology and Engineering Solutions*, 1(01), 40-86. <https://doi.org/10.63125/zxsbd47>
- [53]. Mukut Kanti, B. (2024). AI-Enabled Predictive Asset Integrity Monitoring for Industrial Equipment in Oil & Gas and Energy Sector Facilities. *International Journal of Scientific Interdisciplinary Research*, 5(2), 746-791. <https://doi.org/10.63125/3mjcah04>
- [54]. Mukut Kanti, B., & Rony, S. (2022). Quantitative Risk Assessment and Safety Performance Benchmarking for Structural Integrity Management in Retail Supply Chain Infrastructure. *American Journal of Data Science and Analytics*, 3(12), 42-88. <https://doi.org/10.63125/n88vth90>
- [55]. Nishat, J., & Mst Kaniz, F. (2022). A Review of the Impact of Covid-19 On Maternal and Child Health Service Utilization in Bangladesh. *American Journal of Scholarly Research and Innovation*, 1(02), 223-269. <https://doi.org/10.63125/vgv5s742>
- [56]. North, R. A., McCowan, L. M. E., Dekker, G. A., Poston, L., Chan, E. H. Y., Stewart, A. W., Black, M. A., Taylor, R. S., Walker, J. J., Baker, P. N., & Kenny, L. C. (2011). Clinical risk prediction for pre-eclampsia in nulliparous women: Development of model in international prospective cohort. *BMJ*, 342, d1875. <https://doi.org/10.1136/bmj.d1875>
- [57]. Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366(6464), 447-453. <https://doi.org/10.1126/science.aax2342>
- [58]. Pai, F.-Y., & Huang, K.-I. (2011). Applying the Technology Acceptance Model to the introduction of healthcare information systems. *Technological Forecasting and Social Change*, 78(4), 650-660. <https://doi.org/10.1016/j.techfore.2010.11.007>
- [59]. Petersen, E. E., Davis, N. L., Goodman, D., Cox, S., Johnston, E., Mayes, N., Syverson, C., Seed, K., Shapiro-Mendoza, C. K., Callaghan, W. M., & Barfield, W. (2019). Vital signs: Pregnancy-related deaths, United States, 2011-2015, and strategies for prevention, 13 states, 2013-2017. *Morbidity and Mortality Weekly Report*, 68(18), 423-429. <https://doi.org/10.15585/mmwr.mm6818e1>
- [60]. Qiu, H., Yu, H.-Y., Wang, L.-Y., Yao, Q., Wu, S.-N., Yin, C., Fu, B., Zhu, X.-J., Zhang, Y.-L., Xing, Y., Deng, J., Yang, H., & Lei, S.-D. (2017). Electronic health record driven prediction for gestational diabetes mellitus in early pregnancy. *Scientific Reports*, 7, 16417. <https://doi.org/10.1038/s41598-017-16665-y>
- [61]. Rajkomar, A., Hardt, M., Howell, M. D., Corrado, G., & Chin, M. H. (2018). Ensuring fairness in machine learning to advance health equity. *Annals of Internal Medicine*, 169(12), 866-872. <https://doi.org/10.7326/m18-1990>
- [62]. Reddy, S., Allan, S., Coghlan, S., & Cooper, P. (2020). A governance model for the application of AI in health care. *Journal of the American Medical Informatics Association*, 27(3), 491-497. <https://doi.org/10.1093/jamia/ocz192>
- [63]. Risha, A., & Kazi Mohammad Khalid, A. (2023). A Meta-Analysis of AI-Driven Geospatial Analytics for Predictive Maintenance of Critical Infrastructure in Developing Economies. *International Journal of Scientific Interdisciplinary Research*, 4(4), 375-412. <https://doi.org/10.63125/rayrex49>
- [64]. Sadia, Z., & Binayan, D. (2023). AI-Based Analytics for Financial Risk Assessment and Anomaly Detection in Complex Financial Data Systems. *International Journal of Business and Economics Insights*, 3(4), 105-121. <https://doi.org/10.63125/224h4a32>
- [65]. Sadia, Z., & Md, F. (2024). Toward Secure and Trustworthy Artificial Intelligence in Financial Data Systems: A Governance and Risk-Control Framework. *Review of Applied Science and Technology*, 3(01), 343-366. <https://doi.org/10.63125/z0165923>
- [66]. Sadia, Z., Mohammad Ariful, I., Sumyta, H., & Hosne Ara, M. (2022). A Review of AI-Powered Data Visualization in Enterprise Reporting: Dashboard Design And Interactive Analytics. *American Journal of Advanced Technology and Engineering Solutions*, 2(01), 32-54. <https://doi.org/10.63125/gabst658>
- [67]. Samia Hossain, S. (2024). Predictive Financial Volatility Analytics Using Machine Learning Pipelines in ERP-Integrated Enterprises. *American Journal of Interdisciplinary Studies*, 5(04), 134-181. <https://doi.org/10.63125/hz27wz06>

- [68]. Say, L., Chou, D., Gemmill, A., Tunçalp, Ö., Moller, A.-B., Daniels, J., Gülmezoglu, A. M., Temmerman, M., & Alkema, L. (2014). Global causes of maternal death: A WHO systematic analysis. *The Lancet Global Health*, 2(6), e323-e333. [https://doi.org/10.1016/s2214-109x\(14\)70227-x](https://doi.org/10.1016/s2214-109x(14)70227-x)
- [69]. Seyyed-Kalantari, L., Zhang, H., McDermott, M. B. A., Chen, I. Y., & Ghassemi, M. (2021). Underdiagnosis bias of artificial intelligence algorithms applied to chest radiographs in under-served patient populations. *Nature Medicine*, 27, 2176-2182. <https://doi.org/10.1038/s41591-021-01595-0>
- [70]. Sharifi-Heris, Z., Laitala, J., Airola, A., Rahmani, A. M., & Bender, M. (2022). Machine learning approach for preterm birth prediction using health records: Systematic review. *JMIR Medical Informatics*, 10(4), e33875. <https://doi.org/10.2196/33875>
- [71]. Shields, L. E., Wiesner, S., Klein, C., Pelletreau, B., & Hedriana, H. L. (2016). Use of Maternal Early Warning Trigger tool reduces maternal morbidity. *American Journal of Obstetrics and Gynecology*, 214(4), 527.e521-527.e526. <https://doi.org/10.1016/j.ajog.2016.01.154>
- [72]. Shima Ali, S., Musomi, K., & Sonya, G. (2024). Integrated Infectious Disease Preparedness: Multilingual Health Communication Strategies for Public Health Risk Mitigation, Disease Intervention and Prevention for Culturally Diverse Population in United States. *American Journal of Data Science and Analytics*, 5(10), 01-47. <https://doi.org/10.63125/ehk4mt02>
- [73]. Snyder, B. M., Baer, R. J., Oltman, S. P., Robinson, J. G., Breheny, P. J., Saftlas, A. F., Bao, W., Greiner, A. L., Carter, K. D., Rand, L., Jelliffe-Pawlowski, L. L., & Ryckman, K. K. (2020). Early pregnancy prediction of gestational diabetes mellitus risk using prenatal screening biomarkers in nulliparous women. *Diabetes Research and Clinical Practice*, 163, 108139. <https://doi.org/10.1016/j.diabres.2020.108139>
- [74]. Sufriyana, H., Husnayain, A., Chen, Y.-L., Kuo, C.-Y., Singh, O., Yeh, T.-Y., Wu, Y.-W., & Su, E. C.-Y. (2020). Comparison of multivariable logistic regression and other machine learning algorithms for prognostic prediction studies in pregnancy care: Systematic review and meta-analysis. *JMIR Medical Informatics*, 8(11), e16503. <https://doi.org/10.2196/16503>
- [75]. Tonay, P., Md Maruf, I., & Al, A. (2024). Artificial Intelligence-Based Decision Support Systems and Managerial Performance. *American Journal of Advanced Technology and Engineering Solutions*, 4(04), 154-184. <https://doi.org/10.63125/wmz8dc67>
- [76]. Tsur, A., Batsry, L., Toussia-Cohen, S., Rosenstein, M. G., Barak, O., Brezinov, Y., Yoeli-Ullman, R., Sivan, E., Sirota, M., Druzin, M. L., Stevenson, D. K., Blumenfeld, Y. J., & Aran, D. (2020). Development and validation of a machine-learning model for prediction of shoulder dystocia. *Ultrasound in Obstetrics & Gynecology*, 56(4), 588-596. <https://doi.org/10.1002/uog.21878>
- [77]. Tucker, M. J., Berg, C. J., Callaghan, W. M., & Hsia, J. (2007). The Black-White disparity in pregnancy-related mortality from 5 conditions: Differences in prevalence and case-fatality rates. *American Journal of Public Health*, 97(2), 247-251. <https://doi.org/10.2105/ajph.2005.072975>
- [78]. Vayena, E., Blasimme, A., & Cohen, I. G. (2018). Machine learning in medicine: Addressing ethical challenges. *PLOS Medicine*, 15(11), e1002689. <https://doi.org/10.1371/journal.pmed.1002689>
- [79]. Venkatesh, K. K., Strauss, R. A., Grotegut, C. A., Heine, R. P., Chescheir, N. C., Stringer, J. S. A., Stamilio, D. M., Menard, K. M., & Jelovsek, J. E. (2020). Machine learning and statistical models to predict postpartum hemorrhage. *Obstetrics & Gynecology*, 135(4), 935-944. <https://doi.org/10.1097/aog.0000000000003759>
- [80]. Wiens, J., Saria, S., Sendak, M., Ghassemi, M., Liu, V. X., Doshi-Velez, F., Jung, K., Heller, K., Kale, D., Saeed, M., Ossorio, P. N., Thadaney-Israni, S., & Goldenberg, A. (2019). Do no harm: A roadmap for responsible machine learning for health care. *Nature Medicine*, 25, 1337-1340. <https://doi.org/10.1038/s41591-019-0548-6>
- [81]. Zaman, S. (2024). A Systematic Review of ERP And CRM Integration For Sustainable Business And Data Management in Logistics And Supply Chain Industry. *Frontiers in Applied Engineering and Technology*, 1(01), 204-221. <https://doi.org/10.70937/faet.v1i01.36>
- [82]. Zhang, Y., Du, S., Hu, T., Xu, S., Lu, H., Xu, C., Li, J., & Zhu, X. (2023). Establishment of a model for predicting preterm birth based on the machine learning algorithm. *BMC Pregnancy and Childbirth*, 23, 779. <https://doi.org/10.1186/s12884-023-06058-7>
- [83]. Zhang, Z., Yang, L., Han, W., Wu, Y., Zhang, L., Gao, C., Jiang, K., Liu, Y., & Wu, H. (2022). Machine learning prediction models for gestational diabetes mellitus: Meta-analysis. *Journal of Medical Internet Research*, 24(3), e26634. <https://doi.org/10.2196/26634>