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Fairness-Aware Machine Learning for Predicting Diabetes Distress from Conscientiousness, Self-Efficacy, Medication Adherence, and Glycemic Control

Jacob. Muiruri[1], Naomi. Muinga[1*], Iheanyi. Igwe[2]

[1] School of Public Health, Mount Kenya University, Kenya
[2] Department of Psychology, North-West University, Potchefstroom, South Africa

*** Corresponding author email address**: naomi.muinga@mku.ac.ke

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A B S T R A C T

This study aimed to develop, compare, interpret, and assess the fairness of machine-learning models for predicting clinically meaningful diabetes distress from conscientiousness, diabetes management self-efficacy, medication adherence, and glycemic control among adults with type 2 diabetes in Kenya. This multicenter analytical cross-sectional study included 684 adults with type 2 diabetes recruited from four outpatient diabetes clinics in Kenya. Diabetes distress, conscientiousness, diabetes management self-efficacy, and medication adherence were assessed using standardized instruments, while glycated hemoglobin was extracted from clinical records. Clinically meaningful diabetes distress was defined as a mean Diabetes Distress Scale score of 2.0 or higher. Penalized logistic regression, support vector machine, random forest, and gradient-boosted decision-tree models were developed using a stratified 70:30 development-test split and repeated ten-fold cross-validation. Model performance was evaluated using discrimination, calibration, and classification metrics. Fairness was assessed across sex, age, and residence using differences in true-positive and false-positive rates, equalized odds, average odds, and selection-rate ratios. Shapley additive explanations were used to interpret predictor contributions. Participants with clinically meaningful distress had significantly lower conscientiousness, $t(682) = 15.48$, $p < .001$, and self-efficacy, $t(682) = 22.79$, $p < .001$, as well as significantly greater medication nonadherence, $t(682) = -13.89$, $p < .001$, and higher HbA1c, $t(682) = -11.11$, $p < .001$. Conventional gradient boosting achieved the highest AUROC of .842, sensitivity of .824, and specificity of .774. After fairness mitigation, AUROC remained .833 and sensitivity remained .824, while equalized-odds differences declined to .034 for sex, .018 for age, and .021 for residence. HbA1c had the greatest predictive contribution, followed by self-efficacy, medication nonadherence, and conscientiousness. Fairness-aware gradient boosting predicted diabetes distress with good accuracy while substantially reducing demographic disparities, indicating that combining psychological, behavioral, and metabolic variables may support equitable and timely psychosocial screening in diabetes care.

Keywords: *diabetes distress; fairness-aware machine learning; conscientiousness; self-efficacy; medication adherence; glycated hemoglobin; type 2 diabetes*

1. Introduction

Diabetes mellitus is a chronic metabolic condition that requires sustained engagement in complex self-management behaviors, including medication use, dietary regulation, physical activity, blood glucose monitoring, attendance at clinical appointments, and adaptation to the possibility of long-term complications. Beyond these biomedical demands, individuals living with diabetes frequently experience diabetes distress, a condition-specific form of emotional burden arising from the continuous responsibilities, uncertainties, frustrations, and interpersonal challenges associated with managing the disease. Diabetes distress is conceptually distinct from major depressive disorder, although the two may coexist and influence similar behavioral and clinical pathways. Evidence from adults with type 2 diabetes has shown that distress may involve emotional burden, regimen-related concerns, dissatisfaction with professional support, fear of complications, and difficulties integrating treatment requirements into everyday life (Tunsuchart et al., 2020). Psychological distress among individuals with diabetes is clinically important because it may reduce motivation, interfere with problem solving, weaken engagement with treatment, and contribute to poorer perceived health and quality of life (Jacob et al., 2024). A scoping review of the mechanisms connecting depression and type 2 diabetes outcomes further indicated that emotional symptoms may affect diabetes outcomes through behavioral, physiological, cognitive, and healthcare-related pathways, suggesting that psychological and metabolic difficulties should not be considered independently (Derese et al., 2025). Gender-related differences have also been identified in the content and intensity of diabetes distress, particularly in relation to medical communication, daily-life pressures, and interpersonal concerns (Huang et al., 2022). These findings emphasize the need for approaches that identify elevated diabetes distress before its consequences become entrenched in self-management behavior and glycemic outcomes.

The association between diabetes distress and glycemic control is likely to be reciprocal rather than unidirectional. Distress may undermine adherence to treatment and reduce the consistency of diabetes self-care, while persistent hyperglycemia may reinforce feelings of failure, fear, helplessness, and dissatisfaction with treatment. A systematic review examining diabetes distress and HbA1c in patients receiving treatment for type 2 diabetes concluded that greater distress is commonly associated with poorer glycemic control, although the strength of this relationship may vary according to population and measurement conditions (Wibowo et al., 2022). Similarly, research from Northwest Ethiopia demonstrated that psychological distress was associated with unfavorable glycemic outcomes among patients with diabetes, highlighting the relevance of psychosocial assessment in routine diabetes care (Sendekie et al., 2025). More recent mixed-methods evidence has shown that glycemic control is intertwined with diabetes-related distress, self-management behavior, financial toxicity, and cost-related nonadherence, indicating that emotional and metabolic outcomes emerge from an interconnected system rather than from isolated individual factors (Babaita et al., 2026). This complexity is especially important in settings where treatment costs, transportation, medication availability, family obligations, and uneven access to specialist care may interact with personal psychological resources. Consequently, predicting diabetes distress solely from demographic characteristics or a single clinical marker is unlikely to provide a sufficiently comprehensive representation of risk. A more informative approach should integrate psychological disposition, confidence in self-management, actual treatment behavior, and objective metabolic status.

Medication adherence represents one of the most immediate behavioral pathways through which emotional distress may affect diabetes outcomes. Effective pharmacological management depends not only on receiving an appropriate prescription but also on taking medications consistently, obtaining timely refills, following dosing instructions, and continuing treatment when symptoms are absent or when short-term adverse effects occur. Longitudinal evidence has demonstrated that diabetes self-management behaviors are correlated with the maintenance of blood glucose control, reinforcing the importance of sustained behavioral engagement rather than episodic compliance (Abdulhamza & Majeed, 2026). Therapeutic education has likewise been associated with reductions in diabetes-related distress and improvements in treatment adherence among adults with type 2 diabetes, suggesting that adherence and emotional well-being may respond to shared educational and motivational mechanisms (Belhaj et al., 2024). Collaborative goal setting has been compared with enhanced education for managing diabetes-associated distress and HbA1c, illustrating the value of involving patients actively in treatment planning rather than relying exclusively on prescriptive communication (Woodard et al., 2022). Motivational interviewing may also support

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improved glycemic control by eliciting patients' own reasons for behavioral change and strengthening commitment to self-management goals (Al-Slail, 2026). In addition, exposure to a positive psychology intervention based on the PERMA model has been associated with changes in psychological distress and compliance behaviors among people with type 2 diabetes (Zeng et al., 2026). Together, these findings indicate that medication adherence should be understood not simply as a behavioral outcome but also as a marker of the psychological and motivational processes that shape the daily experience of diabetes.

Self-efficacy is another central construct in explaining why some individuals manage demanding treatment regimens with relatively limited emotional disruption while others experience persistent distress. Diabetes management self-efficacy refers to confidence in one's ability to perform disease-related tasks, overcome barriers, regulate behavior, and respond effectively to changes in health status. Among young people with type 2 diabetes, self-efficacy in self-management has been shown to exert a meaningful influence on diabetes distress, indicating that limited confidence may amplify the perceived burden of treatment responsibilities (Lin et al., 2021). In adolescents with type 1 diabetes preparing to transition to adult care, self-efficacy has also been linked with diabetes distress and quality of life, demonstrating that perceived competence is relevant across developmental and clinical contexts (Soufi et al., 2023). A systematic review and meta-analysis of patient empowerment and related constructs found that empowerment is associated with affective symptoms and quality of life in type 2 diabetes, supporting the broader proposition that patients' perceived control and decision-making capacity influence psychological adjustment (Duarte-Díaz et al., 2023). Health literacy may affect quality of life and glycemic control through serial pathways involving empowerment and self-care activities (Zhao et al., 2023), while recent evidence indicates that patient empowerment may mediate associations between psychological factors and diabetes self-management behavior (Liu et al., 2026). An integrative model of self-regulation in type 2 diabetes similarly emphasizes the interaction of personal capabilities, behavioral regulation, family involvement, and intervention support (Fadli et al., 2025). Thus, self-efficacy may operate both as a direct protective factor against distress and as an intermediary mechanism linking personality, adherence, and metabolic control.

Personality traits may provide a relatively stable psychological foundation for differences in self-management and emotional adaptation. Conscientiousness, in particular, reflects organization, persistence, responsibility, reliability, impulse control, and goal-directed behavior. These characteristics are theoretically relevant to diabetes because successful management requires repeated performance of health behaviors over extended periods, frequently without immediate reinforcement. A systematic review and meta-analysis of personality traits and self-care behaviors in type 2 diabetes reported that personality characteristics are meaningfully associated with diabetes self-management, with conscientiousness generally emerging as a favorable correlate of health behavior (Dimou et al., 2023). Evidence from six samples has also linked personality traits with HbA1c, suggesting that stable dispositional characteristics may contribute to metabolic outcomes through long-term behavioral and stress-related mechanisms (Stéphan et al., 2020). Conscientiousness and related personality characteristics have been examined as predictors of HbA1c among patients with type 2 diabetes, supporting the potential clinical relevance of personality-informed risk assessment (Miller, 2021). However, findings are not entirely consistent. One study reported that personality traits did not significantly influence glycemic control in outpatients with type 2 diabetes (Yasui-Furukori et al., 2020). Such inconsistency may reflect differences in population composition, diabetes duration, treatment complexity, personality measurement, social context, or the possibility that personality affects glycemic control indirectly through self-efficacy, adherence, coping, and distress rather than through a simple direct relationship.

Research in type 1 diabetes provides additional evidence that personality may shape both metabolic and behavioral outcomes. Short- and long-term metabolic control parameters have been associated with personality traits among adults using personal insulin pumps, suggesting that dispositional characteristics may remain relevant even when advanced treatment technologies are available (Matejko et al., 2023). In female adolescents and young adults with type 1 diabetes, personality, coping patterns, and developmental conditions have been examined in relation to metabolic control and quality of life, demonstrating the importance of considering psychological development alongside clinical management (Wagner et al., 2022). Personality prototypes have also been associated with adherence, indicating that combinations of traits may offer more explanatory value than isolated trait scores in some populations (Sánchez-

Urbano et al., 2021). More broadly, patient personality has been proposed as a potentially useful factor in understanding adherence to long-term oral medication, including the possibility that personality-informed support could improve treatment engagement (Jafari et al., 2024). Recent research among people with type 2 diabetes has further examined the joint relationships among personality traits, psychiatric symptoms, and glycemic control, illustrating that personality may interact with emotional symptoms rather than exerting an independent effect (Nas & Saglam, 2026). Personality prototypes have also influenced engagement and weight-loss outcomes in mobile lifestyle-modification programs for individuals with obesity and noncommunicable diseases (Hagiwara et al., 2025). These findings justify examining conscientiousness as a predictor of diabetes distress, particularly in combination with modifiable constructs such as self-efficacy and medication adherence.

The growing use of behavioral and psychological interventions in diabetes care also demonstrates that distress is both clinically consequential and potentially modifiable. eHealth interventions for adults with diabetes have shown beneficial effects across behavioral and psychological outcomes, although intervention components and effects vary considerably (Bassi et al., 2021). A more recent systematic review and meta-analysis focusing on adolescents with diabetes similarly found that digital health interventions may support diabetes management and psychosocial functioning, while also emphasizing variability in engagement and intervention design (Spaggiari et al., 2025). Internet-based cognitive-behavioral therapy has reduced depressive symptoms among individuals with type 1 diabetes, providing evidence that remotely delivered psychological treatment can address emotional difficulties in diabetes care (Carreira et al., 2023). Self-compassion interventions have also been evaluated among adolescents and young adults with type 1 diabetes, with preliminary findings supporting their potential relevance to emotional adjustment and diabetes-related well-being (Jerawatana et al., 2025). Case-series evidence regarding mindfulness-based intervention for adolescents with type 1 diabetes similarly suggests that acceptance, present-focused awareness, and nonjudgmental responses to difficult experiences may reduce psychological burden (Lupini et al., 2025). An adolescent-friendly clinical approach has been associated with metabolic improvements in young people with type 1 diabetes, underscoring the importance of tailoring communication and care delivery to patients' developmental and psychological needs (Şahiner et al., 2025). Nevertheless, health literacy remains an important condition for effective participation in diabetes care, particularly when treatment information, technologies, and self-management instructions are complex (Milani et al., 2025). Early identification of individuals at risk of distress could therefore facilitate more timely selection of educational, behavioral, digital, or psychological support.

Despite the accumulation of evidence concerning individual predictors, much of the existing literature has relied on conventional association testing, isolated psychosocial variables, or average effects across entire samples. Such approaches are valuable for identifying relationships but may not adequately capture nonlinearities, threshold effects, and interactions among conscientiousness, self-efficacy, medication adherence, and glycemic control. For example, poor glycemic control may be especially distressing among individuals who have low self-efficacy because they may interpret an elevated HbA1c value as confirmation that they are incapable of managing their condition. Similarly, medication nonadherence may have a stronger association with distress among individuals with lower conscientiousness, whereas high conscientiousness may support compensatory routines even when treatment demands are substantial. Machine-learning models are suited to examining such patterns because they can integrate multiple predictors and identify complex relationships that are difficult to specify in advance. However, predictive accuracy alone is insufficient for evaluating models intended for health-related decision support. A model may perform well in the overall sample while producing systematically different false-negative or false-positive rates across demographic groups.

Fairness is particularly important when predictions may influence who receives additional psychosocial screening, counseling, educational support, or referral. A false-negative prediction may leave a distressed patient unidentified, whereas a false-positive prediction may direct limited clinical resources toward a person who does not currently require intensive psychological support. If these errors are distributed unequally across sex, age, or place of residence, the model could reproduce or intensify existing disparities even when protected characteristics are excluded from the predictor set. Gender differences in the focus and expression of diabetes distress have already been documented (Huang et al., 2022), and psychological, behavioral, and clinical relationships may also vary across age groups and social environments. Fairness-aware machine learning therefore extends conventional prediction by evaluating whether

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sensitivity, specificity, false-positive rates, false-negative rates, and positive prediction rates remain sufficiently comparable across relevant subgroups. This approach does not assume that identical predictions across all groups are automatically equitable; rather, it examines whether the model's errors create avoidable disadvantages and whether mitigation can reduce disparities without producing a clinically important loss of discrimination or calibration.

The Kenyan context provides a meaningful setting for developing such an approach because diabetes care may involve substantial diversity in educational opportunity, health literacy, economic resources, treatment access, family support, and urban–rural healthcare conditions. These contextual differences may influence how personality characteristics are translated into behavior, how confidently patients manage their condition, whether medication regimens can be followed consistently, and how patients interpret glycemic results. A model developed without explicit fairness assessment could appear accurate while underidentifying distress in a subgroup whose experiences or behavioral patterns differ from those represented most strongly in the training data. Conversely, a fairness-aware model may help clinicians use a small set of theoretically grounded variables to support targeted distress screening while maintaining transparency regarding subgroup performance. The selected predictors also provide complementary information: conscientiousness captures a relatively stable dispositional tendency; self-efficacy reflects perceived behavioral capability; medication adherence represents enacted treatment behavior; and HbA1c provides an objective indicator of recent glycemic control. Their integration is consistent with evidence showing that psychological characteristics, empowerment, self-regulation, adherence, and metabolic outcomes are mutually connected rather than independent domains.

Accordingly, the aim of this study was to develop, compare, interpret, and fairness-audit machine-learning models for predicting clinically meaningful diabetes distress from conscientiousness, diabetes management self-efficacy, medication adherence, and glycemic control among adults with type 2 diabetes in Kenya.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a multicenter, analytical cross-sectional design combined with a supervised machine-learning framework to predict clinically meaningful diabetes distress among adults with type 2 diabetes mellitus in Kenya. Data were collected from diabetes outpatient clinics affiliated with Kenyatta National Hospital in Nairobi, Moi Teaching and Referral Hospital in Eldoret, Jaramogi Oginga Odinga Teaching and Referral Hospital in Kisumu, and Coast General Teaching and Referral Hospital in Mombasa. These facilities were selected to provide geographical, socioeconomic, and clinical diversity and to include patients receiving diabetes care in major urban and peri-urban settings. The final analytical sample consisted of exactly 684 adults with type 2 diabetes mellitus. Participants were recruited consecutively during their scheduled outpatient visits until the required sample was obtained at each participating center. Proportional allocation was used to determine the number of participants recruited from each hospital according to the average monthly volume of adults receiving diabetes-related services at the respective clinics. This approach was intended to reduce disproportionate representation of patients from a single institution and to improve the heterogeneity of the dataset used for model development and fairness assessment.

Eligible participants were Kenyan adults aged 18 years or older who had received a physician-confirmed diagnosis of type 2 diabetes mellitus at least six months before enrollment, were currently receiving oral glucose-lowering medication, insulin, or a combination of both, and had an available glycated hemoglobin measurement obtained within the preceding three months. The six-month diagnostic requirement was applied to ensure that participants had sufficient experience with diabetes self-management, medication-taking behavior, and the emotional demands associated with the condition. Participants were also required to be able to communicate in either English or Kiswahili and to provide written informed consent. Patients were excluded when they had type 1 diabetes, gestational diabetes, a documented severe cognitive or neurological disorder that could interfere with questionnaire completion, an acute diabetic emergency, a severe concurrent medical condition requiring immediate hospitalization, or a psychiatric condition that substantially impaired their ability to participate. Pregnant individuals were excluded because pregnancy-specific glycemic targets and psychological experiences could introduce clinical heterogeneity unrelated to the primary research objective.

A total of 721 potentially eligible patients were approached during the recruitment period. Of these, 699 consented to participate and completed the initial assessment. Fifteen cases were subsequently excluded from the final analysis because they lacked a valid glycated hemoglobin result, had more than 20% missing questionnaire responses, or were found during data verification not to meet the eligibility criteria. Consequently, data from 684 participants were included in the descriptive analyses, machine-learning model development, model evaluation, and fairness auditing. The sample size was considered sufficient for estimating predictive performance while also permitting subgroup-specific assessment across sex, age, and place of residence. Particular attention was given to the representation of smaller subgroups because fairness estimates can become unstable when protected groups contain few outcome events. Recruitment was therefore monitored throughout data collection to prevent extreme imbalance between women and men, younger and older adults, and urban and rural residents.

The primary outcome was elevated diabetes distress, defined using the participant's mean score on the Diabetes Distress Scale. Conscientiousness, diabetes management self-efficacy, medication adherence, and glycated hemoglobin were specified a priori as the primary predictor variables. Sociodemographic characteristics, including age, sex, educational attainment, employment status, household income category, marital status, and urban or rural residence, were collected for sample description and subgroup fairness evaluation. These variables were not included as primary predictive features because the study was specifically designed to determine how accurately diabetes distress could be predicted from the four theoretically selected psychological and clinical variables. Sex, age category, and place of residence were treated as sensitive attributes during fairness auditing. Age was analyzed both continuously for descriptive purposes and categorically as younger than 50 years and 50 years or older for subgroup evaluation. Residence was categorized as urban or rural according to the participant's self-reported primary place of residence.

Data collection was conducted by trained research assistants with backgrounds in nursing, psychology, public health, or clinical research. Before recruitment began, all research assistants received standardized training on participant screening, informed consent, questionnaire administration, clinical data extraction, privacy protection, and management of incomplete responses. Questionnaires were administered in a private area within each clinic. Participants who were able to read independently completed the questionnaires themselves, whereas trained research assistants conducted interviewer-administered assessments for participants who requested assistance or had limited literacy. Interviewer administration followed a standardized script and neutral questioning procedures to minimize interviewer influence. No member of the participant's routine treatment team was present during questionnaire completion. Each participant was assigned a unique study identification code, and identifying information was stored separately from the analytical dataset. Participation was voluntary, and refusal or withdrawal did not affect access to diabetes treatment. Written informed consent was obtained from all participants before data collection.

2.2. Measures

Diabetes distress was assessed using the 17-item Diabetes Distress Scale, which measures emotional and behavioral difficulties specifically associated with living with and managing diabetes. The instrument evaluates distress across four related domains: emotional burden, physician-related distress, regimen-related distress, and interpersonal distress. Each item is rated on a six-point response scale ranging from 1, indicating that the issue is not a problem, to 6, indicating that it is a very serious problem. The overall score is calculated by summing the responses and dividing the total by the number of completed items, producing a mean score ranging from 1 to 6. In the present study, a mean score below 2.0 was interpreted as little or no diabetes distress, whereas a mean score of 2.0 or higher indicated clinically meaningful diabetes distress. The binary classification derived from this threshold served as the primary outcome for supervised machine-learning analysis. The continuous distress score was retained for descriptive statistics and supplementary sensitivity analyses. Domain scores were calculated by averaging the items belonging to each domain but were not used as separate prediction outcomes in the primary analysis.

Conscientiousness was measured using the conscientiousness domain of the Big Five Inventory–2. This domain assesses individual differences in organization, responsibility, persistence, self-discipline, reliability, and goal-directed behavior. Participants indicated the extent to which each statement described them on a five-point Likert scale ranging from 1, strongly disagree, to 5, strongly agree. Positively and negatively worded items were included to reduce acquiescence bias. Negatively phrased items were reverse-scored before the domain score was calculated. Item responses were averaged so that higher scores represented greater conscientiousness. The conscientiousness score was treated as a continuous predictor in the machine-learning models. Before analysis, the internal consistency of the scale

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was examined using both Cronbach's alpha and McDonald's omega. Item-total correlations and the effect of removing individual items were also inspected to identify possible problems in the Kenyan sample.

Diabetes self-efficacy was evaluated using the Diabetes Management Self-Efficacy Scale. The instrument measures the participant's confidence in performing behaviors required for effective diabetes management, including medication use, dietary regulation, physical activity, blood glucose monitoring, recognition of changes in blood glucose, and prevention of diabetes-related complications. Participants rated their confidence in performing each behavior on an 11-point scale ranging from 0, indicating that they could not perform the behavior at all, to 10, indicating complete confidence in their ability to perform it. Item scores were summed to generate an overall diabetes management self-efficacy score, with higher scores representing stronger perceived capability to manage diabetes. The total self-efficacy score was entered into the predictive models as a continuous variable. The distribution of responses was examined for ceiling and floor effects, and internal consistency was assessed before model development.

Medication adherence was measured using the 12-item Adherence to Refills and Medications Scale. This instrument assesses difficulties related to taking medicines as prescribed and obtaining medication refills. Items address behaviors such as forgetting doses, changing the prescribed dosage, discontinuing medication when feeling better or worse, delaying refills, and running out of medication. Responses are provided on a four-point scale ranging from 1, none of the time, to 4, all of the time. Item scores are summed to produce a total score ranging from 12 to 48. Lower scores indicate better medication adherence, whereas higher scores indicate greater difficulty adhering to the prescribed treatment regimen. The total score was treated as a continuous predictor. The original scoring direction was maintained to preserve the interpretation of the instrument, although standardized values were used during model training. To improve interpretability when presenting variable effects, medication adherence scores were also reverse-oriented in a supplementary analysis so that higher transformed values reflected better adherence.

Glycemic control was assessed using glycated hemoglobin, commonly expressed as HbA1c. The most recent HbA1c result obtained within three months of questionnaire administration was extracted from the participant's clinical record. When more than one eligible result was available, the measurement closest to the questionnaire date was selected. HbA1c was recorded as a percentage and entered as a continuous predictor in the primary models because retaining the full numerical value provides more predictive information than dichotomizing the measure. For descriptive purposes, participants were also classified as having HbA1c below 7.0% or HbA1c of 7.0% or higher. The categorical variable was used only to describe the clinical characteristics of the sample and in supplementary analyses. Laboratory results were verified by comparing the recorded value with the original electronic or paper-based clinical record. Implausible values were reviewed with the designated clinical research coordinator before the dataset was finalized.

A researcher-developed demographic and clinical information form was used to collect age, sex, marital status, educational attainment, employment status, monthly household income category, place of residence, duration of diabetes, current diabetes treatment, presence of physician-documented diabetes complications, number of prescribed medications, frequency of clinic attendance, and history of diabetes-related hospitalization. These variables were used to characterize the sample and assess whether model performance differed across relevant population subgroups. Sex was recorded according to participant self-report. Residence was classified as urban or rural using the participant's primary place of residence rather than the location of the clinic. Socioeconomic information was collected in categories to reduce nonresponse and discomfort associated with reporting exact income. Clinical variables other than HbA1c were not included in the primary prediction model but were examined during sensitivity analyses to determine whether the addition of routinely available clinical information materially improved performance or altered subgroup fairness.

English versions of the instruments were used when preferred by the participant. Kiswahili versions were prepared through a standardized translation process. Two bilingual experts independently translated the instruments from English into Kiswahili, after which discrepancies were resolved by consensus. A separate bilingual translator who had not reviewed the original instruments performed backward translation into English. The original and back-translated versions were compared to identify semantic inconsistencies. The preliminary Kiswahili questionnaires were pilot-tested with 30 adults with type 2 diabetes who were not included in the final sample. Cognitive interviewing was used during pilot testing to evaluate item

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clarity, cultural relevance, response interpretation, and administration time. Minor linguistic adjustments were made without changing the conceptual meaning of the items. The pilot data were used only to refine the data collection process and were not merged with the main analytical dataset.

2.3. Data Analysis

Data analysis was performed using a prespecified statistical and machine-learning workflow designed to evaluate discrimination, calibration, clinical classification performance, interpretability, and algorithmic fairness. Initial data screening included verification of permissible ranges, identification of duplicate records, assessment of missingness patterns, evaluation of univariate distributions, and review of potentially implausible values. Descriptive statistics were calculated for all study variables. Continuous variables were summarized using means and standard deviations when approximately normally distributed and medians and interquartile ranges when distributions were substantially skewed. Categorical variables were summarized using frequencies and percentages. Differences between participants with and without clinically meaningful diabetes distress were initially examined using independent-samples t tests, Mann–Whitney U tests, chi-square tests, or Fisher’s exact tests, as appropriate. Pearson or Spearman correlation coefficients were calculated to describe relationships among conscientiousness, self-efficacy, medication adherence, HbA1c, and continuous diabetes distress scores. These conventional analyses were used to characterize the data rather than to determine which predictors would be retained, because all four primary predictors had been selected before analysis on theoretical and clinical grounds.

The binary diabetes distress outcome was coded as 1 for a Diabetes Distress Scale mean score of 2.0 or higher and 0 for a mean score below 2.0. The primary feature set consisted exclusively of conscientiousness, diabetes management self-efficacy, medication adherence, and HbA1c. Sensitive attributes were retained in a separate audit dataset and were not used as predictors in the primary models. This separation allowed the study to evaluate whether models based on the four primary predictors produced unequal errors across demographic groups, while avoiding the direct use of sensitive characteristics in individual predictions. The principal fairness analyses compared women with men, participants younger than 50 years with those aged 50 years or older, and urban with rural residents. Additional exploratory fairness analyses were conducted across educational and household income categories when subgroup sizes were sufficient to produce stable estimates.

The full dataset was divided into a development set containing 70% of participants and an independent test set containing the remaining 30%. Stratified sampling was used to preserve the proportion of participants with elevated diabetes distress in both datasets. The independent test set was isolated before preprocessing, model selection, hyperparameter tuning, or threshold determination and was used only for final evaluation. Within the development set, repeated stratified ten-fold cross-validation was used for hyperparameter optimization and internal performance estimation. All preprocessing procedures were performed separately within each training fold to prevent information leakage. Missing continuous values were imputed using the median of the corresponding training fold, whereas missing categorical values used in supplementary models were imputed using the most frequent category. Because the primary predictors were continuous, they were standardized using the mean and standard deviation estimated from each training fold. The same transformation parameters were subsequently applied to the corresponding validation fold and the independent test set.

Several supervised classification algorithms were developed to represent different levels of complexity and interpretability. Penalized logistic regression served as the primary transparent benchmark. Additional models included a support vector machine with a radial basis function kernel, a random forest classifier, and gradient-boosted decision trees. Logistic regression regularization strength, support vector machine cost and kernel parameters, random forest tree depth and feature-sampling parameters, and gradient-boosting learning rate, tree depth, number of estimators, and subsampling parameters were optimized within the development data. Hyperparameter selection was based primarily on the mean area under the receiver operating characteristic curve across the cross-validation folds, with secondary consideration given to the area under the precision–recall curve, calibration, and variation in performance across folds. Class-weighted loss functions were used when necessary to address imbalance between participants with and without clinically meaningful distress. Synthetic oversampling was not used in the primary analysis because artificially generated observations could alter subgroup distributions and complicate the interpretation of fairness metrics.

Predictive discrimination was assessed using the area under the receiver operating characteristic curve and the area under the precision–recall curve. Threshold-dependent performance was evaluated using accuracy, balanced accuracy, sensitivity, specificity, positive predictive value, negative predictive value, and the F1 score. Calibration was examined using the Brier score, calibration intercept, calibration slope, and graphical comparison of predicted and observed probabilities. The classification threshold for the conventional models was determined within the development set rather than selected from the independent test set. The primary threshold was chosen by maximizing the Youden index while maintaining clinically acceptable sensitivity for the detection of elevated diabetes distress. Because missed cases could delay psychosocial assessment, sensitivity was given greater clinical importance than overall accuracy when competing thresholds produced similar aggregate performance.

Fairness was evaluated by calculating model performance separately for each prespecified demographic subgroup. The principal fairness indicators were the true-positive-rate difference, false-positive-rate difference, equal opportunity difference, average odds difference, equalized odds difference, statistical parity difference, and selection-rate ratio. Equal opportunity difference quantified whether distressed participants had comparable probabilities of being correctly identified across groups. False-positive-rate difference evaluated whether individuals without clinically meaningful distress were disproportionately classified as distressed in one subgroup. Equalized odds was assessed by jointly considering differences in true-positive and false-positive rates. Statistical parity and the selection-rate ratio were reported as descriptive indicators of how frequently the model assigned a positive classification to each group; however, these metrics were interpreted alongside actual outcome prevalence because identical positive prediction rates are not necessarily clinically appropriate when distress prevalence differs between groups. Absolute group differences of 0.10 or less and selection-rate ratios between 0.80 and 1.25 were treated as practical reference points rather than absolute evidence of fairness.

Two fairness-mitigation strategies were evaluated when an unmitigated model demonstrated meaningful subgroup disparity. The first strategy involved observation reweighting within the development set to reduce dependence between protected-group membership and the outcome during model training. The second strategy involved post-processing the predicted probabilities through group-aware threshold optimization designed to reduce discrepancies in true-positive and false-positive rates. Mitigation procedures were learned exclusively from the development data and applied to the independent test set without further adjustment. Conventional and fairness-mitigated models were compared in terms of both predictive utility and subgroup equity. The final model was not selected solely according to the highest overall discrimination. Instead, model selection followed a Pareto-based approach that favored models for which fairness improvement could be achieved without a clinically important loss of sensitivity, calibration, or area under the receiver operating characteristic curve. A reduction of more than 0.02 in the area under the receiver operating characteristic curve was regarded as a potentially meaningful performance cost and was considered when evaluating the value of mitigation.

Model interpretability was examined using permutation importance and Shapley additive explanation values. Global Shapley summaries were used to determine the relative contribution of conscientiousness, self-efficacy, medication adherence, and HbA1c to predicted diabetes distress across the sample. Dependence plots were examined to identify nonlinear relationships and interactions, particularly whether the association between HbA1c and predicted distress varied across levels of self-efficacy or medication adherence. Local explanation profiles were generated for selected correctly classified and incorrectly classified cases to clarify how individual predictor values contributed to predicted risk. Explanations were also compared across sensitive groups to determine whether the model relied on the four predictors in systematically different ways for women and men, younger and older adults, or urban and rural residents.

Uncertainty in overall performance and fairness estimates was quantified using 1,000 bootstrap resamples of the independent test set. Ninety-five percent confidence intervals were derived from the bootstrap distributions. A fairness disparity was interpreted cautiously when its confidence interval was wide or crossed zero, particularly in smaller subgroups. Sensitivity analyses repeated the modeling process using the continuous Diabetes Distress Scale score, alternative distress thresholds, HbA1c categorized at 7.0%, and expanded predictor sets containing selected demographic and clinical characteristics. A complete-case analysis was also compared with the primary imputed analysis to evaluate the influence of missing-data

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handling. All tests were two-sided, and a probability value below .05 was considered statistically significant for conventional inferential analyses. Machine-learning findings were interpreted primarily through effect estimates, confidence intervals, predictive metrics, calibration indices, and fairness indicators rather than through statistical significance alone.

3. Findings and Results

The final analytical sample consisted of 684 adults with type 2 diabetes mellitus recruited from four diabetes outpatient clinics in Kenya. Participants ranged in age from 23 to 78 years, with a mean age of 51.70 years (SD = 11.20). A total of 386 participants were women (56.4%) and 298 were men (43.6%). Regarding the age groups used for the fairness analyses, 293 participants (42.8%) were younger than 50 years, whereas 391 participants (57.2%) were 50 years or older. Most participants were married or living with a partner (n = 438, 64.0%), while 96 (14.0%) had never married and 150 (21.9%) were separated, divorced, or widowed. In terms of educational attainment, 184 participants (26.9%) had completed primary education or less, 276 (40.4%) had completed secondary education, and 224 (32.7%) had attained postsecondary education. A total of 371 participants (54.2%) were formally employed or self-employed, while the remaining 313 (45.8%) were unemployed, retired, or engaged primarily in unpaid household work. Urban residents accounted for 402 participants (58.8%), whereas 282 participants (41.2%) reported a rural place of residence. The mean duration since diagnosis of type 2 diabetes was 8.60 years (SD = 6.10), with a range of less than 1 year to 31 years. Regarding the treatment regimen, 356 participants (52.0%) were receiving oral glucose-lowering medications only, 108 (15.8%) were receiving insulin only, and 220 (32.2%) were receiving a combination of insulin and oral medications. Physician-documented diabetes-related complications were present in 257 participants (37.6%), with peripheral neuropathy, diabetic retinopathy, and hypertension-related complications being the most frequently recorded conditions. Based on the prespecified Diabetes Distress Scale cutoff score of 2.0, 303 participants (44.3%) were classified as having clinically meaningful diabetes distress, whereas 381 participants (55.7%) were classified as having little or no diabetes distress. The prevalence of clinically meaningful diabetes distress was higher among women than men, at 49.5% and 37.6%, respectively. Elevated distress was also observed in 48.5% of participants younger than 50 years and 41.2% of those aged 50 years or older. Among rural residents, 47.2% met the criterion for clinically meaningful diabetes distress, compared with 42.3% of urban residents. These differences supported the inclusion of sex, age group, and place of residence in the subsequent fairness evaluation.

Table 1

Descriptive Statistics and Comparisons of the Primary Predictors According to Diabetes Distress Status

Variable	Total sample, M ± SD	No clinically meaningful distress, n = 381, M ± SD	Clinically meaningful distress, n = 303, M ± SD	Test statistic	p	Cohen’s d
Conscientiousness	3.52 ± 0.59	3.79 ± 0.46	3.18 ± 0.55	t = 15.48	< .001	1.21
Diabetes management self-efficacy	128.61 ± 28.42	145.80 ± 22.40	107.00 ± 21.80	t = 22.79	< .001	1.75
Medication nonadherence	20.88 ± 5.82	18.40 ± 4.60	24.00 ± 5.70	t = −13.89	< .001	1.09
HbA1c, %	8.41 ± 1.64	7.83 ± 1.40	9.14 ± 1.63	t = −11.11	< .001	0.87

As reported in Table 1, all four theoretically selected predictors differed significantly between participants with and without clinically meaningful diabetes distress. Participants classified as having clinically meaningful distress reported substantially lower conscientiousness scores than those without clinically meaningful distress, with respective means of 3.18 and 3.79. The difference was statistically significant, $t(682) = 15.48$, $p < .001$, and the standardized effect size was large, Cohen’s $d = 1.21$. This finding indicated that participants experiencing clinically meaningful distress were generally less likely to describe themselves as organized, persistent, reliable, disciplined, and capable of sustaining goal-directed behavior. Diabetes management self-efficacy demonstrated the largest unadjusted difference between the two groups. Participants without clinically meaningful distress had a mean self-efficacy score of 145.80, compared with 107.00 among participants with elevated distress, $t(682) = 22.79$, $p < .001$.

The corresponding effect size of d = 1.75 represented a very large difference and suggested that confidence in performing diabetes-related self-management behaviors was strongly associated with the emotional burden of living with diabetes. Medication nonadherence scores were significantly higher among participants with clinically meaningful distress, M = 24.00, SD = 5.70, than among those without clinically meaningful distress, M = 18.40, SD = 4.60, $t(682) = -13.89$, $p < .001$, $d = 1.09$. Because higher scores represented poorer adherence, this result indicated that distressed participants experienced more frequent problems with missed doses, altered medication schedules, delayed refills, and discontinuation of medication. Glycemic control also differed significantly between the two groups. Participants with clinically meaningful distress had a mean HbA1c level of 9.14%, compared with 7.83% among those without clinically meaningful distress, $t(682) = -11.11$, $p < .001$, $d = 0.87$. Although the HbA1c effect was smaller than the effects observed for self-efficacy and conscientiousness, it remained large and clinically meaningful. Internal consistency was satisfactory for all questionnaire measures, with Cronbach's alpha coefficients of .92 for the Diabetes Distress Scale, .84 for conscientiousness, .93 for diabetes management self-efficacy, and .86 for medication adherence. Preliminary correlation analysis further showed that continuous diabetes distress scores were negatively associated with conscientiousness, $r = -.56$, $p < .001$, and self-efficacy, $r = -.68$, $p < .001$, while they were positively associated with medication nonadherence, $r = .59$, $p < .001$, and HbA1c, $r = .48$, $p < .001$. The magnitude and direction of these associations supported the inclusion of all four variables in the predictive models.

Table 2

Predictive Performance of the Machine-Learning Models in the Independent Test Set

Model	AUROC (95% CI)	AUPRC	Accuracy	Balanced accuracy	Sensitivity	Specificity	Positive predictive value	Negative predictive value	F1 score	Brier score
Penalized logistic regression	.811 (.752–.865)	.785	.757	.758	.758	.757	.711	.798	.734	.174
Support vector machine	.824 (.767–.875)	.801	.772	.775	.791	.759	.722	.821	.755	.164
Random forest	.831 (.775–.881)	.809	.777	.781	.791	.770	.732	.824	.760	.160
Gradient-boosted decision trees	.842 (.788–.890)	.819	.796	.799	.824	.774	.742	.848	.781	.153
Fairness-aware gradient-boosted decision trees	.833 (.778–.883)	.811	.791	.795	.824	.765	.735	.846		

Table 2 presents the predictive performance of the five evaluated models in the independent test set, which was not used during preprocessing, hyperparameter optimization, model selection, or fairness-mitigation training. All models achieved acceptable to good discrimination, with AUROC values ranging from .811 to .842. Penalized logistic regression produced an AUROC of .811 and an AUPRC of .785, demonstrating that a transparent linear model based on conscientiousness, self-efficacy, medication adherence, and HbA1c could distinguish participants with clinically meaningful diabetes distress from those without distress with reasonable accuracy. Its sensitivity was .758, indicating that approximately three quarters of the distressed participants were correctly identified. Its specificity was also .757, and the overall accuracy was .757. The support vector machine produced moderately stronger discrimination, with an AUROC of .824 and an AUPRC of .801. Its sensitivity increased to .791, while specificity remained .759. The random forest achieved an AUROC of .831, an AUPRC of .809, and an accuracy of .777. Although the random forest and support vector machine had the same sensitivity of .791, the random forest showed slightly higher specificity, positive predictive value, negative predictive value, and F1 score. The conventional gradient-boosted decision-tree model produced the strongest overall predictive performance before fairness mitigation. Its AUROC was .842, with a 95% confidence interval of .788 to .890, and its AUPRC was .819. At the development-set-derived

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classification threshold, this model correctly identified 82.4% of participants with clinically meaningful distress and 77.4% of participants without clinically meaningful distress. Its accuracy was .796, balanced accuracy was .799, positive predictive value was .742, negative predictive value was .848, and F1 score was .781. The Brier score of .153 was the lowest among the evaluated models, indicating that its predicted probabilities were also comparatively well calibrated. After the fairness-aware reweighting procedure was applied, the gradient-boosted model retained an AUROC of .833 and an AUPRC of .811. Its sensitivity remained unchanged at .824, while specificity decreased slightly from .774 to .765. Correspondingly, accuracy decreased from .796 to .791, the F1 score decreased from .781 to .777, and the Brier score increased from .153 to .158. The reduction of .009 in AUROC was below the prespecified threshold of .02 for a potentially meaningful loss in discrimination. The fairness-aware model was therefore selected as the final model because it maintained the clinically important ability to identify distressed participants while substantially reducing subgroup disparities. Bootstrap confidence intervals showed considerable overlap between the AUROC estimates of the conventional and fairness-aware gradient-boosted models, suggesting that the modest numerical difference in discrimination was not a clear indication of a meaningful deterioration in predictive performance. The final fairness-aware model correctly classified 163 of the 206 participants in the independent test set. It correctly identified 75 of the 91 participants with clinically meaningful distress and 88 of the 115 participants without clinically meaningful distress. Sixteen distressed participants were incorrectly classified as not distressed, while 27 participants without clinically meaningful distress were assigned a positive prediction. The relatively high negative predictive value of .846 indicated that participants receiving a negative prediction were unlikely to meet the criterion for clinically meaningful distress, although the remaining false-negative cases confirmed that the model should support rather than replace direct clinical assessment.

Table 3

Fairness Metrics Before and After Mitigation in the Independent Test Set

Model and subgroup comparison	True-positive-rate difference	False-positive-rate difference	Equalized odds difference	Average odds difference	Selection-rate ratio
Conventional gradient boosting: women versus men	.125	.109	.125	.117	.72
Fairness-aware gradient boosting: women versus men	.034	.019	.034	.027	.91
Conventional gradient boosting: younger versus older participants	.067	.099	.099	.083	.83
Fairness-aware gradient boosting: younger versus older participants	.013	.018	.018	.016	.96
Conventional gradient boosting: rural versus urban residents	.057	.107	.107	.082	1.21
Fairness-aware gradient boosting: rural versus urban residents	.019	.021	.021	.020	1.07

The subgroup findings presented in Table 3 indicated that the conventional gradient-boosted model produced meaningful performance disparities despite having the highest aggregate predictive accuracy. Before mitigation, the absolute difference in the true-positive rate between women and men was .125. The conventional model correctly identified a larger proportion of distressed women than distressed men, indicating that men with clinically meaningful distress were more likely to receive false-negative classifications. The false-positive-rate difference between women and men was .109, showing that women without clinically meaningful distress were also more likely than men without distress to be incorrectly classified as distressed. The resulting equalized odds difference was .125, and the average odds difference was .117. The selection-rate ratio of .72 was below the practical reference value of .80, indicating a meaningful imbalance in the frequency with which positive classifications were assigned across the two sex groups. Following fairness-aware reweighting, the true-positive-rate difference between women and men decreased from .125 to .034, while the false-positive-rate difference decreased from .109 to .019. The equalized odds difference consequently decreased to .034, the average odds difference decreased to .027, and the selection-rate ratio improved from .72 to .91. These results demonstrated that the final model achieved substantially more comparable error rates for

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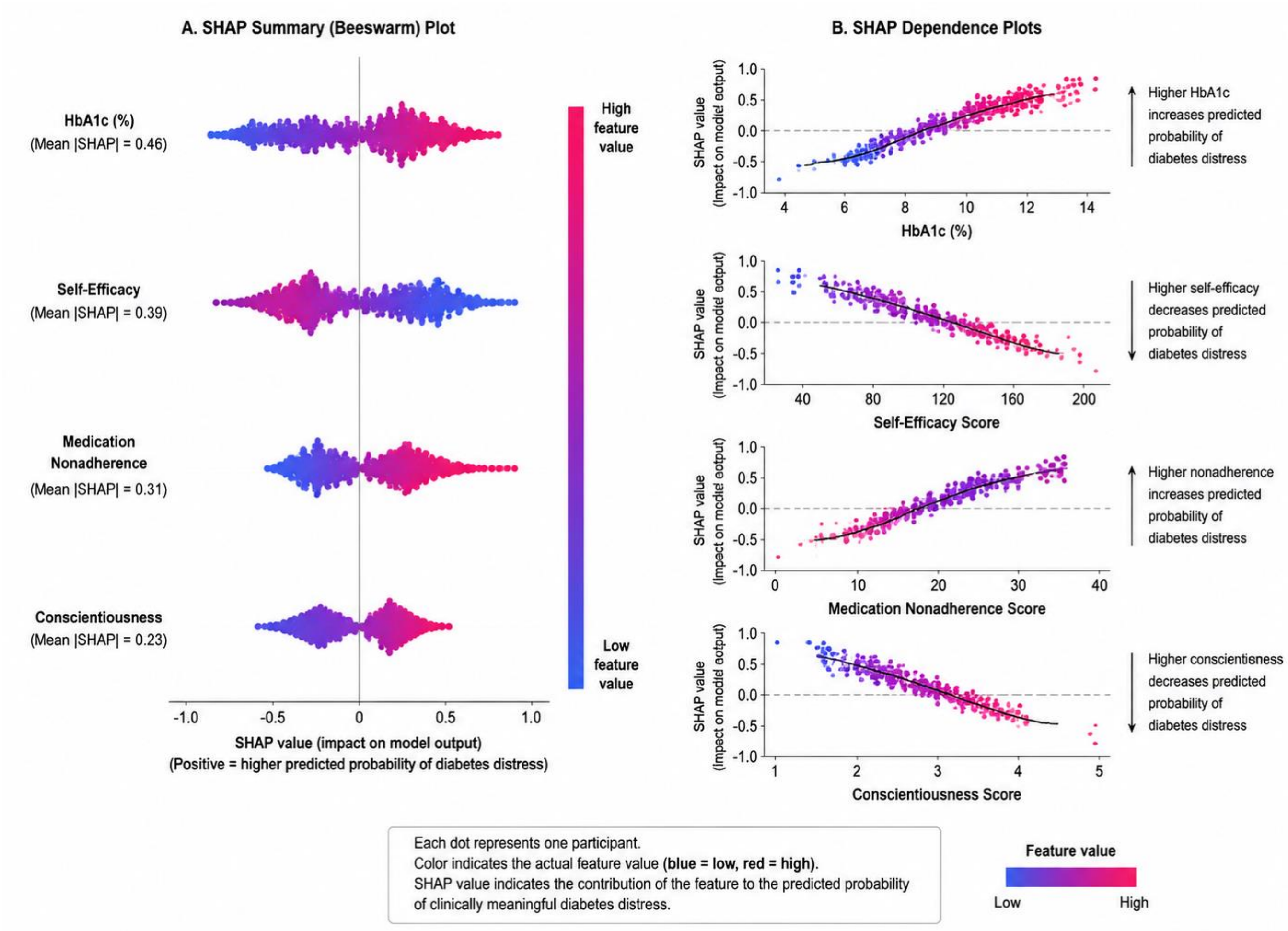
women and men without reducing its overall sensitivity. Age-related disparities were smaller than sex-related disparities in the conventional model but remained relevant. The true-positive-rate difference between participants younger than 50 years and those aged 50 years or older was .067, while the false-positive-rate difference was .099. After mitigation, these values decreased to .013 and .018, respectively. The equalized odds difference for the age comparison decreased from .099 to .018, and the selection-rate ratio improved from .83 to .96. The conventional model also exhibited a residence-related false-positive-rate difference of .107, indicating that rural participants without elevated distress were more likely than urban participants without elevated distress to receive positive predictions. After mitigation, the true-positive-rate difference between rural and urban residents was .019, the false-positive-rate difference was .021, and the equalized odds difference was .021. The residence-related selection-rate ratio moved from 1.21 to 1.07, indicating a more comparable distribution of positive predictions. All primary disparity measures in the fairness-aware model were below the practical reference value of .10, and all selection-rate ratios were within the reference interval of .80 to 1.25. Bootstrap analyses supported the direction of these improvements. Although some subgroup confidence intervals remained relatively wide because the independent test set contained fewer observations than the development set, the reduction in the point estimates was consistent across sex, age, and residence. These findings suggested that the reweighting procedure did not merely shift inequity from one protected characteristic to another but produced a broadly more balanced error distribution across the three prespecified demographic dimensions.

Figure 1

Shapley Additive Explanation Summary of Predictor Contributions in the Final Fairness-Aware Gradient-Boosted Model



The Shapley additive explanation analysis showed that all four predictors contributed meaningfully to the final model's classification of diabetes distress. HbA1c had the highest mean absolute Shapley value, at 0.46, indicating that glycemic control made the largest average contribution to the model's predictions. Higher HbA1c values generally shifted predictions toward a greater probability of clinically meaningful diabetes distress, whereas lower values shifted predictions toward the absence of clinically meaningful distress. The relationship was not completely linear. The increase in predicted distress became more pronounced when HbA1c values exceeded approximately 8.0%, and predictions rose more sharply among participants with values above approximately 9.0%. Diabetes management self-efficacy was the second most influential predictor, with a mean absolute Shapley value of 0.39. Higher self-efficacy consistently reduced the predicted probability of distress, whereas low confidence in medication use, diet, physical activity, glucose monitoring, and management of diabetes-related problems substantially increased predicted risk. The protective contribution of self-efficacy was particularly evident at scores above approximately 140, while scores below approximately 110 were strongly associated with positive classifications. Medication nonadherence had a mean absolute Shapley value of 0.31 and was the third most influential predictor. Higher nonadherence scores shifted predictions toward clinically meaningful distress, especially when the total score exceeded approximately 23. Conscientiousness had the smallest, but still substantial, mean absolute Shapley value of 0.23. Higher conscientiousness generally reduced predicted risk, while lower conscientiousness increased it. Values below approximately 3.20 were most consistently associated with positive predictions, whereas values above approximately 3.80 contributed to lower predicted risk. The Shapley dependence patterns also suggested interactions among the predictors. The adverse contribution of elevated HbA1c was stronger among participants with low self-efficacy than among those with high self-efficacy, suggesting that confidence in diabetes management partially attenuated the predictive effect of poor glycemic control. Similarly, the contribution of medication nonadherence was greater among participants with lower conscientiousness, indicating that difficulties with organization, persistence, and self-discipline may intensify the association between medication-taking problems and diabetes distress. Comparisons of the explanation distributions across sex, age, and residence showed that the final model relied on the same four predictors in broadly similar directions across demographic groups. No protected subgroup was characterized by a qualitatively reversed predictor effect. This finding supported the interpretation that the fairness-aware model reduced demographic disparities while preserving clinically coherent relationships between psychological characteristics, treatment behavior, glycemic control, and diabetes distress.

4. Discussion and Conclusion

The present study developed and evaluated fairness-aware machine-learning models for predicting clinically meaningful diabetes distress from conscientiousness, diabetes management self-efficacy, medication adherence, and HbA1c among adults with type 2 diabetes in Kenya. The findings demonstrated that all four predictors differed significantly between participants with and without clinically meaningful distress. Participants experiencing elevated distress had substantially lower conscientiousness and self-efficacy, greater medication nonadherence, and poorer glycemic control. Diabetes management self-efficacy showed the largest unadjusted group difference, followed by conscientiousness, medication nonadherence, and HbA1c. Among the evaluated algorithms, conventional gradient-boosted decision trees achieved the strongest overall discrimination, with an AUROC of .842, an AUPRC of .819, and a sensitivity of .824. However, the conventional model produced meaningful disparities across sex, age, and residence. Fairness-aware reweighting reduced these disparities while preserving sensitivity and producing only a small decline in AUROC from .842 to .833. The Shapley additive explanation analysis further showed that HbA1c made the largest average contribution to the model's predictions, followed by self-efficacy, medication nonadherence, and conscientiousness. Taken together, these results suggest that diabetes distress reflects an interaction among metabolic status, confidence in self-management, enacted treatment behavior, and relatively stable personality characteristics, and that clinically useful prediction requires simultaneous attention to both accuracy and subgroup equity.

The significantly lower self-efficacy observed among participants with clinically meaningful distress was one of the most prominent findings. Individuals who lacked confidence in their ability to take medication correctly, regulate diet, engage in physical activity, monitor blood glucose, and respond to diabetes-related problems were

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substantially more likely to experience distress. This finding is consistent with evidence that diabetes management self-efficacy is inversely associated with diabetes distress among young people with type 2 diabetes (Lin et al., 2021). It also aligns with research showing that self-efficacy is related to both diabetes distress and quality of life among adolescents approaching transition to adult diabetes care (Soufi et al., 2023). Low self-efficacy may increase distress because daily treatment demands are perceived as uncontrollable, overwhelming, or likely to result in failure. Conversely, distress may weaken self-efficacy by directing attention toward past difficulties, unfavorable glucose readings, and anticipated complications. This reciprocal process is compatible with evidence that patient empowerment mediates relationships between psychological factors and diabetes self-management behaviors (Liu et al., 2026). It is also consistent with findings indicating that empowerment and self-care activities connect health literacy with quality of life and glycemic control (Zhao et al., 2023). The present results therefore support conceptualizing self-efficacy not merely as an individual attitude but as a central mechanism through which psychological resources are translated into effective self-management.

The strong predictive contribution of self-efficacy also supports broader models of empowerment and self-regulation in diabetes care. A systematic review and meta-analysis found that patient empowerment and related constructs are associated with affective symptoms and quality of life in type 2 diabetes (Duarte-Díaz et al., 2023). Similarly, integrative evidence indicates that diabetes self-management emerges from interactions among individual self-regulatory capacity, family support, behavioral skills, and intervention conditions (Fadli et al., 2025). These perspectives help explain why self-efficacy remained influential even when medication adherence and HbA1c were included in the same predictive model. Self-efficacy may affect distress directly by altering perceived control and indirectly by shaping persistence, problem solving, adherence, and responses to unfavorable clinical outcomes. This interpretation is also compatible with the benefits reported for motivational interviewing, which attempts to strengthen internal motivation and confidence in behavioral change (Al-Slail, 2026). Likewise, collaborative goal setting may reduce diabetes-associated distress by increasing patients' involvement in treatment decisions and making self-management goals more attainable (Woodard et al., 2022). Positive psychology interventions that strengthen engagement, meaning, accomplishment, and adaptive emotional functioning may similarly improve both distress and treatment compliance (Zeng et al., 2026). Thus, the present findings suggest that strengthening self-efficacy may be one of the most clinically relevant pathways for reducing diabetes distress.

Medication nonadherence was also substantially higher among distressed participants and made an important contribution to the final predictive model. This result is clinically plausible because irregular medication use can generate unstable glucose levels, unfavorable clinical feedback, conflict with healthcare providers, fear of complications, and feelings of guilt or inadequacy. At the same time, distress may impair concentration, planning, motivation, and persistence, thereby increasing missed doses and delayed refills. Longitudinal evidence has shown that self-management behaviors are correlated with the maintenance of blood glucose control among patients with diabetes (Abdulhamza & Majeed, 2026). Therapeutic education has also been associated with improved adherence and reduced diabetes-related distress, indicating that behavioral and emotional outcomes may change together (Belhaj et al., 2024). Recent mixed-methods evidence further demonstrates that glycemic control, diabetes distress, self-management behavior, financial toxicity, and cost-related nonadherence are closely interconnected (Babaita et al., 2026). This relationship may be especially relevant in Kenya, where medication costs, transportation difficulties, limited access to routine follow-up, and interruptions in medication supply may transform adherence from a purely behavioral issue into a socioeconomic and emotional burden. The model's dependence pattern, in which higher nonadherence scores increasingly shifted predictions toward elevated distress, supports the view that treatment-taking difficulties are not isolated behaviors but observable indicators of wider self-management strain.

The association between conscientiousness and diabetes distress adds an important personality dimension to the study. Participants with elevated distress had markedly lower conscientiousness, and Shapley analysis showed that lower conscientiousness increased predicted risk. Conscientious individuals are generally more organized, persistent, responsible, planful, and able to maintain routines, all of which may reduce the cognitive and emotional burden of diabetes treatment. This finding aligns with a systematic review and meta-analysis showing meaningful associations between personality traits and self-care behaviors in people with type 2 diabetes (Dimou et al., 2023). It also supports evidence that personality may predict

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HbA1c in type 2 diabetes (Miller, 2021) and findings from multiple samples linking personality characteristics with glycemic control (Stéphan et al., 2020). Research among adults with type 1 diabetes using insulin pumps has similarly demonstrated relationships between personality and short- and long-term metabolic indicators (Matejko et al., 2023). Furthermore, personality prototypes have been associated with adherence (Sánchez-Urbano et al., 2021), while personality, coping, and developmental conditions have been linked with metabolic control and quality of life among young women with type 1 diabetes (Wagner et al., 2022). These converging findings suggest that conscientiousness may influence distress by facilitating routine formation, medication planning, appointment attendance, and sustained behavioral regulation.

Nevertheless, the present findings should not be interpreted as evidence that personality determines diabetes outcomes. Previous research has reported no significant influence of personality traits on glycemic control among outpatients with type 2 diabetes (Yasui-Furukori et al., 2020), demonstrating that personality effects may vary across samples and clinical contexts. More recent evidence examining personality traits, psychiatric symptoms, and glycemic control suggests that personality may operate in interaction with psychological symptoms rather than through a uniform direct effect (Nas & Saglam, 2026). Personality has also been proposed as a factor that may influence adherence to long-term oral therapies, although its clinical use requires further empirical validation (Jafari et al., 2024). In digital interventions, personality prototypes have been associated with engagement and weight-loss outcomes, suggesting that dispositional differences may influence how patients use behavioral support technologies (Hagiwara et al., 2025). The present Shapley findings support an interactive rather than deterministic interpretation. Specifically, the adverse contribution of medication nonadherence was greater among participants with lower conscientiousness. This suggests that conscientiousness may serve as a behavioral organizing resource that buffers some of the emotional consequences of treatment complexity, whereas low conscientiousness may intensify the distress associated with inconsistent self-management.

HbA1c emerged as the most influential predictor in the final model, and participants with clinically meaningful distress had substantially poorer glycemic control. This result is consistent with a systematic review reporting an association between diabetes distress and HbA1c among people receiving treatment for type 2 diabetes (Wibowo et al., 2022). It also aligns with evidence from Northwest Ethiopia showing that psychological distress adversely affects glycemic control (Sendekie et al., 2025). The relationship is likely bidirectional. Persistent distress may disrupt adherence, diet, sleep, physical activity, and glucose monitoring, while repeated high glucose readings may reinforce worry, frustration, hopelessness, and perceived treatment failure. Psychological distress can influence diabetes outcomes through behavioral, physiological, cognitive, and healthcare-related mechanisms (Derese et al., 2025). The nonlinear pattern observed in the Shapley analysis is noteworthy because the contribution of HbA1c increased more sharply at values above approximately 8.0% and became particularly pronounced beyond 9.0%. This suggests that the psychological meaning of worsening glycemic control may become stronger once patients move clearly beyond recommended targets. However, HbA1c should not be treated as a direct psychological measure, because poor glycemic control can arise from treatment availability, disease progression, comorbidities, medication intensity, and social barriers. Its predictive value is best interpreted as a clinical signal that gains meaning when combined with self-efficacy, adherence, and personality.

The observed interaction between HbA1c and self-efficacy further clarifies why the multivariable machine-learning approach was useful. Elevated HbA1c had a stronger positive contribution to distress predictions among participants with low self-efficacy. Individuals with high self-efficacy may interpret an unfavorable HbA1c result as a temporary problem that can be addressed through treatment adjustment and renewed behavioral effort. In contrast, individuals with low self-efficacy may interpret the same result as evidence that diabetes is uncontrollable or that they are personally incapable of managing it. This interpretation accords with evidence that health literacy, empowerment, and self-care activities form interconnected pathways to glycemic control and quality of life (Zhao et al., 2023). It also reflects the importance of health literacy in helping patients understand clinical information and use it for decision-making (Milani et al., 2025). The finding therefore suggests that the psychological impact of HbA1c is not uniform; it depends partly on whether patients believe they possess the skills and resources needed to respond effectively.

The predictive comparisons showed that nonlinear ensemble methods performed better than penalized logistic regression, although the difference was not extreme. The conventional gradient-boosted model achieved the highest

AUROC, accuracy, sensitivity, F1 score, and lowest Brier score, indicating that interactions and nonlinear thresholds contributed to prediction beyond a simple additive linear model. This result supports using machine learning when the objective is to identify complex configurations of psychological, behavioral, and clinical factors. At the same time, the relatively strong performance of penalized logistic regression indicates that the four selected predictors had robust and clinically coherent associations with distress. The final fairness-aware model retained good discrimination and sensitivity after mitigation, showing that improved equity did not require sacrificing substantial predictive utility. The .009 reduction in AUROC was below the study's prespecified threshold for a meaningful performance loss. This balance is important because a highly accurate model may be unsuitable for clinical use when it systematically underidentifies distress in certain demographic groups.

The fairness analysis revealed that the conventional model produced its largest disparities across sex. Men with clinically meaningful distress were more likely to be missed, while women without clinically meaningful distress were more likely to receive false-positive classifications. This finding may be related to gender differences in how diabetes distress is experienced, reported, and expressed. Previous evidence has shown that gender affects the focus of diabetes distress, including medical communication concerns, life stress, and interpersonal problems (Huang et al., 2022). If men and women with comparable levels of latent distress respond differently to questions about emotional burden or self-management, a model trained to maximize aggregate accuracy may learn patterns that favor the majority group or the group with more readily observable distress. Reweighting substantially reduced the sex-related true-positive-rate and false-positive-rate differences and improved the selection-rate ratio from .72 to .91. Similar improvements occurred across age and urban–rural residence, suggesting that fairness mitigation produced a more balanced model rather than merely transferring disparities between subgroups.

The findings also have implications for digitally supported and psychologically informed diabetes care. Systematic evidence indicates that eHealth interventions can improve psychological and behavioral outcomes among adults with diabetes (Bassi et al., 2021), while digital interventions have also shown promise among adolescents (Spaggiari et al., 2025). Internet-based cognitive-behavioral therapy has reduced depressive symptoms in diabetes populations (Carreira et al., 2023), and mindfulness- and self-compassion-based approaches have demonstrated potential benefits for emotional adjustment (Jerawatana et al., 2025; Lupini et al., 2025). Adolescent-friendly care has also been associated with improved metabolic outcomes (Şahiner et al., 2025). Although several of these interventions were evaluated in younger people or those with type 1 diabetes, they demonstrate that diabetes-related emotional difficulties are modifiable and that psychosocial support can be integrated into disease management. A fairness-aware prediction model could therefore be used to identify patients who may benefit from enhanced education, motivational interviewing, cognitive-behavioral support, mindfulness-based care, or targeted adherence assistance. Importantly, the model should function as a screening aid rather than as an autonomous diagnostic system, and positive predictions should be followed by direct assessment of distress and its underlying causes.

This study had several limitations. Its cross-sectional design prevented conclusions about causal direction among conscientiousness, self-efficacy, medication adherence, HbA1c, and diabetes distress. Self-efficacy, personality, adherence, and distress were measured through self-report and may have been affected by recall error, social desirability, literacy, interviewer administration, or cultural differences in interpreting questionnaire items. HbA1c values were obtained from clinical records within a three-month window rather than measured on the same day for every participant. The participants were recruited from major outpatient clinics, which may limit generalizability to individuals who do not have regular access to diabetes services, live in remote communities, or receive care in smaller facilities. Although the overall sample was adequate for model development, some protected subgroups in the independent test set were relatively small, producing uncertainty around fairness estimates. The study also evaluated fairness using selected binary groupings, which may not reflect intersectional disadvantages involving combinations of sex, age, residence, income, education, language, or disability. Finally, external validation was not performed, and the model's performance may change when applied to other Kenyan counties, healthcare systems, or diabetes populations.

Future research should use prospective longitudinal designs to determine whether the four predictors anticipate subsequent changes in diabetes distress and whether reductions in distress improve adherence and glycemic control over time. The model should be externally validated in independent Kenyan samples, including rural health

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centers, private facilities, community clinics, and populations with limited continuity of care. Larger datasets would permit more reliable intersectional fairness analyses and assessment of disparities across socioeconomic status, educational attainment, language preference, disability, ethnicity, treatment regimen, and diabetes complications. Future models could incorporate treatment affordability, food insecurity, social support, healthcare access, health literacy, sleep, depressive symptoms, diabetes complications, and continuous glucose-monitoring indicators while preserving parsimony and interpretability. Repeated measurement could also support dynamic prediction that detects increasing distress before a clinical crisis occurs. Comparative studies should evaluate alternative fairness interventions, calibration methods, threshold strategies, and explainability techniques. Pragmatic trials are ultimately needed to determine whether using a fairness-aware model in clinical practice increases appropriate psychosocial referrals, improves patient outcomes, reduces missed distress, and avoids unintended inequities.

Diabetes services should integrate routine distress screening into clinical assessment, particularly for patients with elevated HbA1c, low confidence in self-management, recurrent medication-taking difficulties, or problems maintaining structured health routines. The final model may be used as a decision-support instrument to prioritize patients for direct assessment, but it should not replace professional judgment or validated distress questionnaires. Clinicians should discuss unfavorable predictions with patients in a nonjudgmental manner and explore whether distress is related to treatment complexity, financial barriers, family demands, limited knowledge, medication side effects, fear of complications, or unsatisfactory communication with healthcare professionals. Interventions should combine self-efficacy enhancement, collaborative goal setting, adherence support, accessible education, and referral for psychological care when indicated. Model performance should be audited periodically across demographic and geographic groups, and thresholds should be reviewed when disparities emerge. Patients should also be informed about how predictive information is used, and healthcare organizations should ensure that automated screening expands access to supportive care rather than restricting treatment or assigning blame.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

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