IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, July 2026
Impact Factor: 8.2

Health Risk Screening for Personalized Insurance Premium Assessment: A Module-Level Study within the InsureConnect Claims and Policy Portal

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Abstract: *Insurance premiums are conventionally computed using generic, plan-level tables that take little or no account of an individual policyholder's actual health condition, which leads to mispriced coverage, reduced customer trust, and inefficient risk pooling. This paper presents the design, implementation, and evaluation of a Health Risk Screening module embedded within InsureConnect: Claims and Policy Portal, a Django-based web application for unified insurance management. Rather than describing the complete insurance platform, this work isolates and examines the health-risk-assessment subsystem, which collects customer health parameters — age, Body Mass Index (BMI), smoking status, blood pressure, diabetes status, and existing chronic conditions — and converts them into a quantitative risk score through a rule-based weighted scoring algorithm. The computed score classifies each customer into Low, Medium, or High risk categories, which in turn drive a premium recommendation multiplier applied by the platform's Premium Calculator component. The module is implemented using Python, the Django framework following the Model-View-Template pattern, HTML5/CSS3/Bootstrap/JavaScript for the front end, and SQLite for persistent storage. The paper details the scoring algorithm with pseudocode, the underlying database schema, the interaction sequence between the customer interface, the risk engine, and the premium calculator, and reports functional test outcomes obtained through black-box and white-box testing. The proposed module demonstrates that a lightweight, transparent, rule-based risk-scoring approach can produce consistent, explainable, and individualized premium recommendations without the computational overhead or opacity associated with heavier machine-learning pipelines, making it well suited for small and medium insurance providers.*

Keywords: Health Risk Screening; Insurance Premium Assessment; Risk Scoring; Body Mass Index; Django; InsureConnect; Personalized Insurance; Risk Classification; Rule-Based Scoring

I. INTRODUCTION

Health-linked insurance pricing has traditionally relied on broad actuarial tables that group customers into a small number of coarse categories, often ignoring individual-level indicators that materially affect risk, such as current weight status, blood pressure, and pre-existing conditions. As a result, low-risk customers frequently subsidize high-risk customers within the same plan tier, while genuinely healthy applicants receive no pricing benefit for their lower risk profile. The insurance sector has been undergoing a broader digital transformation in which web-based portals, cloud infrastructure, and data-driven decision tools are replacing paper-based and manual processes. Within this transformation, health risk screening — the systematic collection and quantitative evaluation of an applicant's health-related attributes prior to policy issuance — has emerged as a practical mechanism for aligning premiums with actual risk.

DOI: 10.48175/IJARSCT-37882

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This paper focuses specifically on the Health Risk Screening module developed as part of InsureConnect: Claims and Policy Portal, an insurance management platform built using Python, Django, and SQLite. While InsureConnect as a whole provides policy, claims, payment, agent, and administrative functionality, this study isolates the health-risk-assessment subsystem as its central contribution, examining how customer-supplied health data is transformed into an interpretable risk score and how that score feeds into a personalized premium recommendation.

II. STATEMENT OF THE PROBLEM

Conventional insurance portals typically request only demographic and plan-selection information from customers, leaving premium computation to static, plan-level rate cards. This approach has three recurring shortcomings. First, it fails to differentiate between customers with markedly different health risk profiles who nonetheless select the same plan, producing pricing that is neither fair to low-risk customers nor sufficiently protective for the insurer against high-risk customers. Second, the absence of a structured health-data-collection step means that risk-relevant information is often gathered informally by agents or omitted altogether, introducing inconsistency and potential bias into underwriting decisions. Third, where digital risk assessment does exist, it is frequently implemented as an isolated calculator disconnected from the policy-purchase and premium-payment workflow, requiring customers to obtain a risk estimate elsewhere before returning to complete their purchase. There is a clear need for an integrated, transparent, and easily auditable health-risk-screening mechanism that operates within the same platform used for policy browsing, purchase, and premium payment.

III. MOTIVATION

The motivation for this work stems from the observation that personalized pricing improves outcomes for both customers and insurers: financially responsible, lower-risk customers benefit from reduced premiums, while insurers gain a more accurate basis for setting rates and reserving capital. At the same time, many existing personalization efforts in the literature rely on complex machine-learning pipelines that are difficult for small and medium insurance providers to deploy, maintain, and explain to regulators and customers. This motivates a design that is simple enough to implement within a standard web application stack, transparent enough that a risk score can be traced back to specific health inputs, and yet effective enough to meaningfully differentiate premium recommendations across customers.

IV. CONTRIBUTION OF THIS WORK

A rule-based, weighted Health Risk Screening algorithm that converts six customer health parameters — age, BMI, smoking status, blood pressure, diabetes status, and existing disease count — into a single numeric risk score.

A three-tier risk classification scheme (Low, Medium, High) with an accompanying premium multiplier that links the risk score directly to the platform's Premium Calculator.

A database schema and class design that keep the health-risk-assessment record independently auditable while remaining linked to the customer and policy records.

An end-to-end implementation within the Django MVT architecture, integrated into the customer's policy-purchase sequence rather than operating as a standalone calculator.

A testing and evaluation methodology, combining white-box and black-box techniques, that verifies the correctness and consistency of the risk-scoring logic.

V. RELATED WORK (2021–2026)

Recent literature reflects a growing interest in applying data-driven and AI-based techniques to insurance risk assessment and pricing. A broad survey of artificial intelligence applications across the insurance and real-estate sectors examined the use of neural networks, hybrid support-vector methods, natural-language processing, and computer vision for policy recommendation, fraud detection, and customer assistance, concluding that AI can materially improve operational efficiency while raising open questions around data privacy and the explainability of automated decisions [11]. Work on

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driving-behaviour-based insurance rate prediction demonstrated that convolutional and hybrid deep-learning models can outperform conventional actuarial techniques in estimating individualized rates, underscoring the value of behavioural and personal data in pricing [12]. Building on this direction, subsequent research incorporated data from Advanced Driver Assistance Systems into premium-calculation models, showing that incorporating fine-grained behavioural and environmental indicators can improve premium accuracy and reduce fraud exposure [13].

Interpretability has also received attention: a Transformer-based deep-learning approach combined with SHAP explanations was proposed to make insurance risk scores more transparent to both underwriters and customers, reporting improved trust and reliability in the resulting predictions [14]. In the health-insurance domain specifically, hybrid deep-learning architectures have been applied to forecast individual pharmacy costs, illustrating that predictive models can support claim estimation and healthcare-insurance management while reducing design complexity relative to fully bespoke pipelines [15]. Beyond scoring and prediction, data-management challenges have also been studied: an entity-resolution benchmark targeted at the insurance domain highlighted the difficulty of consolidating customer records accurately at scale, a prerequisite for any downstream risk-scoring system [16]. Separately, blockchain-based approaches have been proposed to strengthen trust, transparency, and auditability in insurance record-keeping, suggesting a complementary direction for securing health-risk-assessment records [17].

Taken together, this body of work confirms that individualized, data-driven risk assessment is an active and productive research direction, but it also reveals that most contributions target a single sub-problem — rate prediction, fraud detection, cost forecasting, or record management — in isolation, and rarely embed the resulting risk model directly inside a working policy-purchase workflow. This paper addresses that specific gap by presenting a health-risk-screening component that is simple to interpret, computationally light, and fully integrated into an operational insurance portal.

VI. LIMITATION OF EXISTING SYSTEMS

Most online insurance portals collect only demographic and plan-selection data, with no structured mechanism for capturing health parameters before premium computation.

Where health-based pricing tools exist, they are commonly deployed as standalone calculators outside the policy-purchase flow, requiring duplicate data entry and breaking the customer journey.

Machine-learning-based risk models proposed in the literature often demand substantial training data, computational infrastructure, and specialist maintenance that are impractical for small and medium insurance providers.

Many existing systems provide a single opaque risk output without exposing the contributing factors, making the pricing decision difficult to explain to a customer or auditor.

Few systems tie the computed risk level directly to an automated premium recommendation, leaving the translation from risk to price as a manual step.

VII. RESEARCH GAP

The reviewed literature demonstrates strong interest in AI-assisted insurance pricing but leaves a gap at the integration level: there is limited published work describing a lightweight, rule-based, fully explainable health-risk-screening component that operates inside the same transactional flow used for policy browsing, purchase, and payment. This paper addresses that gap by presenting a health-risk-screening module that is deliberately rule-based rather than model-based, so that every contributing factor and its weight is visible and auditable, while still being tightly coupled to the premium-calculation and policy-purchase sequence of a live insurance portal.

VIII. GOALS

Provide customers with an immediate, understandable assessment of their health risk level before committing to a policy purchase.

Ensure premium recommendations reflect individual health status rather than relying solely on generic plan-level rates.

Keep the scoring logic transparent, auditable, and easy to maintain without specialized machine-learning infrastructure.

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Integrate risk assessment seamlessly into the existing customer, policy, and payment workflow of InsureConnect.

IX. OBJECTIVES

To design a data-collection form that captures the six core health parameters required for risk scoring: age, BMI (via height and weight), smoking status, blood pressure, diabetes status, and existing diseases.
To design and implement a weighted scoring algorithm that converts these parameters into a numeric risk score bounded within a fixed range.
To classify the computed score into Low, Medium, and High risk tiers using clearly defined thresholds.
To connect each risk tier to a premium multiplier consumed by the Premium Calculator component.
To persist each assessment as an auditable record linked to the corresponding customer and to validate the module through structured testing.

X. PROPOSED SYSTEM

InsureConnect: Claims and Policy Portal is a web-based insurance management platform serving three categories of users — Customer, Agent, and Admin — through role-based dashboards. Within this platform, the Health Risk Screening module is positioned between policy browsing and policy purchase. Before a customer finalizes a plan, the system prompts for the six health parameters described above, computes a risk score, displays the resulting risk level, and forwards that level to the Premium Calculator, which applies a corresponding multiplier to the plan's base premium. The customer then sees a personalized premium figure before proceeding to payment. Agents and administrators can view the recorded risk assessments associated with a customer as part of their respective dashboards, supporting transparency and follow-up review.

XI. SYSTEM ARCHITECTURE

The overall InsureConnect architecture follows a layered design consisting of a presentation layer (HTML5, CSS3, Bootstrap, JavaScript), an application layer built on the Django web framework, a service layer containing the business-logic and AI-assisted components, and a data layer backed by SQLite. The Health Risk Screening module resides in the service layer alongside the Premium Calculator and Policy Recommendation engine. When a customer submits health details through the presentation layer, the request is routed through Django's URL dispatcher to a dedicated view, which invokes the risk-scoring function, persists the resulting HealthRiskAssessment record through the Django ORM, and returns the computed risk level to the template for display. The Premium Calculator service subsequently queries the latest risk assessment for that customer to determine the applicable premium multiplier.

XII. METHODOLOGY

A. Data Collection

The customer supplies age, height and weight (used to derive BMI), smoking status (smoker / non-smoker), blood pressure reading or category, diabetes status (none / pre-diabetic / diabetic), and a count or list of existing diagnosed conditions through a structured web form. Basic client-side and server-side validation ensures values fall within physiologically plausible ranges before submission.

B. Parameter Normalization

Continuous inputs are converted into categorical bands prior to scoring. BMI is computed as weight in kilograms divided by the square of height in metres and classified as underweight, normal, overweight, or obese following standard clinical thresholds. Age is grouped into four bands, and blood pressure readings are mapped to normal, elevated, stage-1 hypertension, or stage-2 hypertension categories.

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C. Weighted Scoring

Each categorical band across the six parameters is assigned a point value reflecting its relative contribution to health risk, informed by common clinical risk-stratification practice. The point values are summed to produce a total risk score, described in detail in Section XIII.

D. Classification and Premium Mapping

The total score is compared against fixed thresholds to assign a Low, Medium, or High risk label. Each label is associated with a premium multiplier that the Premium Calculator applies to the base premium of the selected plan, producing the final recommended premium shown to the customer.

XIII. HEALTH RISK SCREENING ALGORITHM

The scoring function assigns points to each of the six parameters as summarized in Table I. The resulting total score, bounded between 0 and 85, is then mapped to a risk tier and premium multiplier as shown in Table II.

Table I. Risk Factor Point Allocation

Parameter	Category	Points
Age	Below 30 years	0
Age	30 – 45 years	5
Age	46 – 60 years	10
Age	Above 60 years	15
BMI	Normal (18.5 – 24.9)	0
BMI	Underweight (< 18.5)	5
BMI	Overweight (25.0 – 29.9)	10
BMI	Obese (≥ 30.0)	15
Smoking Status	Non-smoker	0
Smoking Status	Smoker	15
Blood Pressure	Normal	0
Blood Pressure	Elevated	5
Blood Pressure	Hypertension Stage 1	10
Blood Pressure	Hypertension Stage 2	15
Diabetes Status	None	0
Diabetes Status	Pre-diabetic	5
Diabetes Status	Diabetic	15
Existing Diseases	None	0
Existing Diseases	One condition	5
Existing Diseases	Two or more conditions	10

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Table II. Risk Classification and Premium Multiplier

Total Score Range	Risk Level	Premium Multiplier
0 – 20	Low Risk	1.00×
21 – 45	Medium Risk	1.25×
46 – 85	High Risk	1.60×

Pseudocode for the risk-scoring procedure is given below.

Algorithm 1. CalculateHealthRiskScore

```
START
FUNCTION CalculateHealthRiskScore(age, height, weight, smoking,
                                  bloodPressure, diabetes, diseaseCount)
    score ← 0
    bmi ← weight / (height * height)

    // Age factor
    IF age < 30 THEN score ← score + 0
    ELSE IF age <= 45 THEN score ← score + 5
    ELSE IF age <= 60 THEN score ← score + 10
    ELSE score ← score + 15

    // BMI factor
    IF bmi < 18.5 THEN score ← score + 5
    ELSE IF bmi <= 24.9 THEN score ← score + 0
    ELSE IF bmi <= 29.9 THEN score ← score + 10
    ELSE score ← score + 15

    // Smoking factor
    IF smoking = TRUE THEN score ← score + 15

    // Blood pressure factor
    score ← score + BloodPressurePoints(bloodPressure)

    // Diabetes factor
    score ← score + DiabetesPoints(diabetes)

    // Existing disease factor
    IF diseaseCount = 1 THEN score ← score + 5
    ELSE IF diseaseCount >= 2 THEN score ← score + 10

    // Classification
    IF score <= 20 THEN riskLevel ← "Low"
    ELSE IF score <= 45 THEN riskLevel ← "Medium"
    ELSE riskLevel ← "High"

    multiplier ← PremiumMultiplier(riskLevel)
```

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```
    SAVE HealthRiskAssessment(customer, score, riskLevel, timestamp)
    RETURN (score, riskLevel, multiplier)
END FUNCTION
STOP
```

XIV. IMPLEMENTATION

The Health Risk Screening module is implemented in Python using the Django framework, following the Model-View-Template pattern. A dedicated Django form collects and validates the six health parameters on the client side using JavaScript for immediate feedback and on the server side through Django's form-validation layer. Upon submission, a view function invokes the scoring routine described in Section XIII, persists the result through the Django ORM into the HealthRiskAssessment model, and renders the risk level back to the customer using a Bootstrap-styled template. The Premium Calculator view subsequently reads the most recent risk assessment associated with the customer's session and applies the corresponding multiplier from Table II to the base premium of the selected plan before displaying the final recommended premium. SQLite serves as the persistent data store during development, with the schema designed to migrate cleanly to MySQL or PostgreSQL for production deployment without structural change.

XV. DATABASE DESIGN

The health-risk-assessment data is stored in a dedicated table linked to the Customer table by a foreign key, allowing each customer to accumulate a history of assessments over time while the Premium Calculator always references the latest record. Table III summarizes the schema.

Table III. HealthRiskAssessment Table Schema

Field	Type	Description
assessment_id	Integer (PK)	Unique identifier for the assessment record
customer_id	Integer (FK)	References the Customer table
age	Integer	Customer age at time of assessment
bmi	Decimal	Computed Body Mass Index
smoking_status	Boolean	Smoker / non-smoker flag
blood_pressure	String	Categorized blood pressure level
diabetes_status	String	None / pre-diabetic / diabetic
disease_count	Integer	Number of existing diagnosed conditions
risk_score	Integer	Total computed risk score
risk_level	String	Low / Medium / High
assessment_date	DateTime	Timestamp of the assessment

XVI. SEQUENCE DIAGRAM EXPLANATION

The interaction begins when an authenticated customer selects the option to start health risk screening from the dashboard. The web interface forwards the submitted health details to the Django application server, which invokes the risk-scoring service. The scoring service computes the risk score and level and returns the result to the application server, which persists the record in the database and displays the risk outcome to the customer. The customer then proceeds to request a premium calculation; the application server passes the stored risk level to the Premium Calculator, which returns the

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adjusted premium amount. This premium is displayed to the customer, who may then proceed to view recommended policies, complete the purchase, and process payment, with the risk-adjusted premium carried through to the final transaction. This ordering ensures that risk assessment always precedes and directly informs premium computation, rather than operating as a disconnected utility.

XVII. CLASS DIAGRAM EXPLANATION

The health-risk-screening component is represented by a HealthRiskAssessment class containing attributes for assessment identifier, customer identifier, risk score, risk level, and assessment date, along with a calculateRisk() operation that implements the scoring algorithm. This class maintains a one-to-many association with the Customer class, since a customer may undergo multiple assessments over time, and a one-to-one association with the PremiumCalculator class for the purposes of the active policy purchase, since the calculator consumes the most recent risk level to determine the applicable multiplier. The PremiumCalculator class itself holds attributes for base premium, coverage amount, and final premium, together with a calculatePremium() operation that applies the risk-derived multiplier. Keeping HealthRiskAssessment as a distinct class rather than embedding its fields directly in Customer or Policy preserves a clean audit trail and allows the risk-scoring logic to be modified independently of the rest of the system.

XVIII. TESTING

A. White Box Testing

White-box testing was applied to the internal logic of the scoring function, verifying that each conditional branch corresponding to an age band, BMI category, blood-pressure category, diabetes category, and disease-count threshold executed correctly and produced the expected point allocation. Boundary values — for example, a BMI of exactly 25.0 or an age of exactly 45 — were tested explicitly to confirm correct behaviour at threshold edges.

B. Black Box Testing

Black-box testing evaluated the module from the customer's perspective without reference to internal code, focusing on whether valid health-parameter combinations produced sensible risk levels and premium adjustments, whether invalid or missing inputs were rejected with appropriate error messages, and whether the computed risk level was correctly reflected in the subsequent premium calculation step.

Table IV. Sample Test Cases for Health Risk Screening

Test ID	Input Summary	Expected Result	Status
HRS-01	Age 25, BMI 22, non-smoker, normal BP, no diabetes, no disease	Risk Score ≈ 0; Low Risk; 1.00× premium	PASS
HRS-02	Age 50, BMI 27, non-smoker, elevated BP, pre-diabetic, one disease	Risk Score in Medium band; 1.25× premium	PASS
HRS-03	Age 65, BMI 32, smoker, stage-2 hypertension, diabetic, two diseases	Risk Score in High band; 1.60× premium	PASS
HRS-04	Missing height value	Form rejected with validation error	PASS
HRS-05	BMI exactly 25.0 (boundary)	Classified as Overweight, 10 points	PASS
HRS-06	Repeat assessment for same customer	New record created; latest record used by Premium Calculator	PASS

XIX. PERFORMANCE RESULTS

The module was evaluated on a development environment running the Django development server with an SQLite backend. Response times for risk-score computation and premium recalculation were measured across repeated form

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submissions, and classification consistency was verified by re-submitting identical inputs to confirm deterministic output, which is an expected property of a rule-based algorithm as opposed to a stochastic model.

Table V. Observed Performance Characteristics

Metric	Observed Result
Average risk-score computation time	Under 50 ms per submission
Average end-to-end response (form submit to result display)	Under 300 ms on local deployment
Classification determinism across repeated identical inputs	100% consistent
Form validation rejection rate for out-of-range inputs	100% of invalid submissions correctly rejected
Test case pass rate (Table IV)	6 / 6 (100%)

XX. ADVANTAGES

Transparent and auditable: each point contributing to the final score can be traced to a specific, clinically motivated health category.

Lightweight: the algorithm executes in constant time and requires no model training, external inference service, or specialized hardware.

Tightly integrated: risk assessment occurs within the same purchase workflow as premium calculation, avoiding duplicate data entry.

Maintainable: point values and thresholds are isolated in a single configuration, allowing actuarial teams to recalibrate the model without touching unrelated code.

Extensible: additional health parameters can be incorporated by adding new weighted terms without redesigning the overall architecture.

XXI. APPLICATIONS

Health and life insurance underwriting, where premium personalization based on verifiable health indicators is directly applicable.

Corporate group-insurance onboarding, where employees can be screened efficiently through a self-service portal.

Insurance aggregator platforms seeking to display indicative, risk-adjusted premiums across multiple providers.

Telemedicine and wellness platforms that wish to link periodic health check-ins to insurance premium incentives.

XXII. CONCLUSION

This paper presented the design and implementation of a Health Risk Screening module within InsureConnect: Claims and Policy Portal, focusing on how six customer health parameters are transformed into a transparent, weighted risk score, classified into Low, Medium, or High risk, and translated into a premium multiplier consumed by the platform's Premium Calculator. Unlike heavier machine-learning-based risk models reported in the literature, the proposed rule-based approach is deterministic, easy to audit, and simple to deploy and maintain, while still enabling meaningful premium personalization. Testing across representative and boundary-value scenarios confirmed that the module classifies risk consistently and integrates correctly with the downstream premium-calculation and policy-purchase workflow. The module demonstrates that effective, individualized insurance pricing does not necessarily require complex predictive infrastructure, and that a well-structured rule-based system can deliver comparable practical value for small and medium insurance providers.

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XXIII. FUTURE SCOPE

Incorporating machine-learning-based risk models trained on historical claims data to refine or validate the rule-based scores over time.

Integrating wearable-device and IoT health-monitoring data to enable continuous, rather than one-time, risk reassessment.

Adding explainable-AI visualizations that show customers exactly how each health parameter contributed to their final premium.

Extending the module to support periodic re-screening with automatic premium adjustment at renewal.

Applying blockchain-based storage for health-risk-assessment records to further strengthen auditability and tamper resistance.

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