Matrix-Based Decision Analytics and Predictive Modeling in Management and Healthcare Systems Using Python

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***Abstract*—This research introduces a matrix-oriented framework for decision analytics and predictive modeling in management and healthcare applications using Python. The proposed methodology integrates matrix computations, weighted decision-analysis techniques, regression-based prediction models, risk evaluation approaches, and classification methods to enable effective data-driven decision support.**

Within the management sector, the proposed framework is employed for employee performance appraisal, investment project prioritization, and supplier selection in supply chain management. Employee performance is assessed using weighted matrix-based computations integrated with regression-oriented predictive techniques, whereas investment alternatives and vendors are evaluated and ranked through weighted scoring mechanisms and risk-adjusted decision models. In the healthcare domain, matrix-driven predictive methodologies are applied to estimate cardiovascular disease risk and forecast hospital readmission probabilities. By integrating clinical attribute matrices with weighted predictive parameters, the framework produces individualized risk scores that support patient stratification, efficient resource allocation, and the identification of high-risk patients who require closer supervision and targeted intervention.

The effectiveness of the predictive models is measured using statistical performance indicators such as Mean Squared Error (MSE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). In addition, classification performance is evaluated through metrics including accuracy, precision, recall, specificity, and F1-score. The entire analytical framework is implemented in Python, utilizing libraries such as NumPy, Pandas, Scikit-Learn, and Matplotlib for data management, predictive modeling, computational analysis, and graphical visualization. The findings demonstrate that matrix-based decision analytics provides an interpretable, scalable, and computationally efficient solution for complex management and healthcare problems. The framework enhances prediction accuracy, supports optimal resource utilization, and facilitates intelligent organizational and clinical decision-making, highlighting the practical value of matrix-driven approaches in modern analytical environments.

***Index Terms*—Matrix Analytics; Decision Support Systems; Predictive Modeling; Management Analytics; Healthcare Analytics, Multi-Criteria Decision Making, Employee Performance Evaluation, Supply Chain Optimization, Healthcare Analytics, Disease Risk Prediction, Hospital Readmission Prediction, Machine Learning, Python.**

I. INTRODUCTION

The rapid growth of digital technologies, artificial intelligence (AI), and data-driven decision-making has significantly transformed management and healthcare systems. Organizations and healthcare institutions generate vast amounts of data that require advanced analytical techniques for effective interpretation and utilization. In this environment, matrix algebra has become a fundamental mathematical framework for representing, processing, and analyzing multidimensional datasets [42].

Matrices provide structured methods for organizing data and performing computational operations essential for analytical modeling. Different matrix forms, such as row, column, square, diagonal, identity, symmetric, and skew-symmetric matrices, support applications in optimization, scientific computing, machine learning, network analysis, and decision-support systems. Core operations including matrix addition, multiplication, transposition, and inversion serve as the foundation for predictive analytics and intelligent decision-making processes [11,42].

The increasing complexity of organizational environments has created a strong demand for analytical frameworks that support evidence-based decision-making. Decision analytics and predictive modeling help organizations derive actionable insights from large datasets, improve operational efficiency, optimize resource allocation, reduce risks, and strengthen strategic planning [6, 13]. Traditional approaches often face limitations in handling high-dimensional and rapidly changing data, making advanced computational methods necessary for identifying hidden patterns and generating accurate forecasts [21].

Healthcare systems face similar challenges related to disease prediction, patient management, treatment optimization, resource allocation, and cost control. The widespread adoption of electronic health records, medical imaging systems, wearable devices, and health information technologies has led to unprecedented growth in healthcare data. Extracting meaningful information from such datasets requires robust mathematical and computational techniques capable of maintaining predictive accuracy while handling complex data structures [18,29].

Matrix-based computational methods provide an effective solution to these challenges because data can naturally be represented in matrix form, with rows corresponding to observations and columns representing variables. Consequently, matrix operations play a critical role in data pre-processing, regression analysis, classification, clustering, dimensionality reduction, optimization, and neural network computations [22]. Many modern analytical approaches, including principal component analysis (PCA), linear programming, Markov models, machine learning algorithms, and deep learning architectures, depend heavily on matrix transformations and optimization techniques [10,23,24].

The availability of high-performance computing and open-source programming platforms has accelerated the adoption of matrix-based analytics. Among these platforms, Python has emerged as one of the most widely used languages for data science and predictive analytics because of its flexibility and extensive scientific ecosystem [28,32]. Libraries such as NumPy, Pandas, SciPy, Scikit-learn, TensorFlow, and PyTorch provide powerful tools for matrix computations, statistical analysis, optimization, and predictive modeling [5,27].

This research investigates the use of matrix-based decision analytics and predictive modeling within management and healthcare environments through Python-based implementation. It examines the fundamental principles of matrix algebra and various predictive methodologies, including regression, classification, clustering, dimensionality reduction, and optimization techniques. The study presents a comprehensive framework that integrates matrix mathematics, predictive analytics, and Python programming to enhance decision-making capabilities, increase forecasting accuracy, improve operational performance, and support strategic planning processes. By bridging mathematical concepts, computational approaches, and real-world applications, the research contributes to the development of evidence-based decision-support systems in management and healthcare while highlighting potential avenues for future interdisciplinary investigations.

II. LITERATURE REVIEW

Matrix-based analytical techniques have become essential in management science due to their ability to represent complex organizational systems, multidimensional datasets, and optimization problems within a rigorous mathematical framework. Matrix algebra supports efficient decision-making, strategic planning, and resource allocation by modeling relationships among variables [23]. Originating from input–output economic analysis [1], matrix methods are now widely applied in operations research, supply chain management, portfolio optimization, and risk assessment. These applications facilitate large-scale problem solving through linear programming, optimization algorithms, and quantitative decision models [14].

Several multi-criteria decision-making (MCDM) approaches are inherently matrix-based. The Analytic Hierarchy Process (AHP) employs pairwise comparison matrices to evaluate alternatives and determine priorities [3], while the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method uses matrix operations to identify causal relationships among decision factors [2]. With the growth of business analytics, matrix techniques have been increasingly integrated with machine learning. Methods such as Singular Value Decomposition

(SVD), Principal Component Analysis (PCA), and Non-Negative Matrix Factorization (NMF) are extensively used for dimensionality reduction, customer segmentation, recommendation systems, and knowledge discovery from large datasets [8]. These approaches improve computational efficiency while preserving critical information for predictive analysis. The rapid expansion of organizational data has further increased the significance of matrix-based computational frameworks. Matrix analytics enables efficient processing of high-dimensional datasets and supports forecasting of market trends, customer behavior, operational performance, and strategic outcomes, making it a vital component of modern business intelligence systems [21].

In healthcare, matrix-based approaches are equally important due to the complexity of data generated from electronic health records (EHRs), diagnostic imaging, laboratory systems, wearable devices, and administrative databases. These methods provide effective mechanisms for organizing, processing, and extracting valuable insights from heterogeneous healthcare data [26]. In Clinical Decision Support Systems (CDSS), patient information is often represented in matrix form to support diagnosis prediction, treatment planning, and outcome evaluation. Matrix algebra facilitates the analysis of clinical relationships and predictive modeling of disease progression and patient outcomes [25].

Matrix operations are also fundamental to medical imaging applications. Diagnostic images from computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound are represented as pixel matrices, enabling image enhancement, feature extraction, and disease detection through matrix transformations, eigenvalue analysis, and decomposition techniques [15]. These matrix representations form the basis of many machine learning and deep learning models used in radiology and pathology.

Beyond clinical settings, matrix-based models contribute significantly to epidemiology and public health. Contact matrices, transition matrices, and Markov models have been applied to study disease transmission, healthcare utilization, and treatment effectiveness [4]. During the COVID-19 pandemic, such models played a crucial role in forecasting infection trends and evaluating intervention strategies [20]. Personalized medicine has also benefited from matrix factorization techniques, where patient–treatment interaction matrices help uncover hidden patterns for individualized therapeutic recommendations. Collaborative filtering and matrix completion methods have demonstrated promising results in predicting drug responses and improving healthcare outcomes [16]. However, challenges related to data quality, missing values, interoperability, and computational complexity continue to limit widespread implementation.

Python has emerged as a leading platform for scientific computing, machine learning, and data analytics because of its simplicity, flexibility, and extensive library ecosystem [12]. Libraries such as NumPy provide efficient multidimensional arrays and linear algebra operations, including matrix multiplication, decomposition, and eigenvalue analysis [19], while SciPy supports advanced numerical computation and optimization. Pandas facilitates data pre-processing and management [28], and visualization libraries such as Matplotlib and Seaborn enhance data interpretation.

For predictive analytics, Scikit-learn offers a comprehensive collection of machine learning algorithms for classification, regression, clustering, dimensionality reduction, and model evaluation [5]. In healthcare, advanced frameworks such as Tensor Flow and PyTorch support deep learning applications including disease prediction, cardiovascular risk assessment, cancer detection, and automated medical image analysis [9, 17].

The integration of matrix-based methods with Python-based machine learning has improved data analysis, forecasting accuracy, and decision-making across various applications. However, significant research gaps remain. Most studies examine management and healthcare analytics separately, while matrix techniques and predictive modeling are often treated as independent approaches despite their close relationship. Additionally, healthcare research primarily emphasizes prediction accuracy, whereas management studies focus on optimization and efficiency, limiting the development of interpretable and actionable decision-support systems. Although Python provides powerful tools for matrix computation and machine learning, comprehensive frameworks integrating these capabilities across diverse real-world applications are still limited. Therefore, a unified Python-based framework that combines matrix analytics and predictive modeling is needed to enhance prediction performance and support effective data-driven decision-making in both management and healthcare domains.

III. MATHEMATICAL AND COMPUTATIONAL FOUNDATIONS:

Matrix-based decision analytics and predictive modeling provide a rigorous mathematical framework for representing, analyzing, and optimizing complex healthcare and management systems. Matrices enable the compact representation of multidimensional data, support efficient numerical computation, and facilitate the implementation of machine learning and decision-support algorithms. In healthcare systems, matrix methods are used for patient classification, disease prediction, hospital resource allocation, and treatment optimization. In management science, they support inventory planning, financial forecasting, risk assessment, and strategic decision-making [23,31].

3.1 Matrix Algebra and Linear Transformations

Matrix algebra forms the foundation of computational analytics because it provides a structured approach to handling large datasets and performing numerical operations efficiently. A matrix is a rectangular array of numerical values organized into rows and columns:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{21n} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \cdots \ddots & \vdots \\ a_{m1} & a_{m2} & a_{m3} & \cdots & a_{mn} \end{bmatrix}$$

Linear Transformations: A linear transformation maps vectors from one space to another: $T(x)=A_x$

where: A = transformation matrix, x = input vector

T(x) = transformed output vector

In healthcare analytics, a patient's clinical variables can be represented as:

$$x = \begin{bmatrix} \text{Age} \\ \text{Blood} \\ \text{Pressure Glucose Level} \end{bmatrix}$$

3.2 Optimization and Decision Models:

Optimization models seek the best possible decision under specified constraints. Matrix methods enable efficient representation and computation of large-scale optimization problems.

3.2.1General Linear Programming Model:

The standard optimization problem is: Maximize

$$Z = c^T x$$

Subject to $Ax \leq b$, $x \geq 0$

Where: c = objective coefficient vector, x = decision variable vector, A = constraint matrix,

b = resource vector

3.2.2 Healthcare Resource Allocation Model:

Suppose a hospital allocates resources among three departments:

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

Representing: {Emergency services, Intensive care, Outpatient care}

Objective function: Maximize $z = 120x_1 + 180x_2 + 90x_3$

Subject to: $\begin{bmatrix} 5 & 8 & 3 \\ 4 & 6 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \leq \begin{bmatrix} 500 \\ 350 \end{bmatrix}$

The matrix formulation simplifies computational implementation and enables scalable optimization.

3.2.3 Multi-Criteria Decision Matrix (MCDM):

Healthcare decisions often involve multiple evaluation criteria:

$$D = \begin{bmatrix} d_{11} & d_{12} & d_{13} & \cdots & d_{1n} \\ d_{21} & d_{22} & d_{23} & \cdots & d_{21n} \\ d_{31} & d_{32} & d_{33} & \cdots & d_{3n} \\ \vdots & \vdots & \vdots & \cdots \ddots & \vdots \\ d_{m1} & d_{m2} & d_{m3} & \cdots & d_{mn} \end{bmatrix}$$

Where rows represent alternatives and columns represent criteria. Weighted decision score: S = DW,

where: $W = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ \vdots \\ w_n \end{bmatrix}$ contains criterion weights.

Optimization models play a critical role in scheduling, supply-chain management, healthcare planning, and strategic resource allocation [23].

3.3 Markov Chains and Transition Matrices:

Markov chains model stochastic systems in which future states depend only on the current state. Transition matrices provide a powerful framework for healthcare forecasting and management decision-making.

Transition Probability Matrix: -

A Markov process is represented by:

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1n} \\ p_{21} & p_{22} & p_{23} & \cdots & p_{21n} \\ p_{31} & p_{32} & p_{33} & \cdots & p_{3n} \\ \vdots & \vdots & \vdots & \cdots \ddots & \vdots \\ p_{n1} & p_{n2} & p_{n3} & \cdots & p_{nn} \end{bmatrix}$$

Where: $\sum_{j=1}^{n} p_{ij} = 1$ for each row.

Healthcare Disease Progression Model:

Consider three patient states: {Healthy (H), Diseased (D), Critical (C)}

P is Transition matrix and X_0 vector of current patient distribution.

Future state distribution: $X_1 = P^T X_0$

After k periods: $X_k = (P^T)^k X_0$

Long-run equilibrium: $\pi P = \pi$

Subject to $\sum_{j=1}^{n} \pi_i = 1$

The steady-state vector provides long-term forecasts of patient populations and healthcare demand.

Markov models are widely used for patient-flow analysis, disease progression forecasting, customer retention modeling, and inventory management [7].

3.4 Matrix-Based Predictive Analytics:

Predictive analytics employs historical data to forecast future outcomes. Matrix methods form the computational basis for regression, classification, machine learning, and deep learning algorithms [30, 33-37].

3.4.1 Multiple Linear Regression: -

A matrix representation of linear regression is: $Y = X\beta + \epsilon$

where: $Y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix}, X = \begin{bmatrix} 1 & x_{11} & x_{12} \\ 1 & x_{21} & x_{22} \\ \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} \end{bmatrix}$ and $\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix}$

The least-squares estimator is: $\hat{\beta} = (X^T X)^{-1} X^T Y$

This equation provides the optimal coefficient estimates minimizing prediction error.

3.4.2Healthcare Risk Prediction: -

Suppose: $X = [1 \quad \text{Age} \quad \text{BMI} \quad \text{BP}]$

The prediction model becomes: $\hat{Y} = X\hat{\beta}$

Where: {Age = patient age, BMI = body mass index, BP = blood pressure}

$\hat{Y}$ =Predicted disease risk

3.5 Predictive Performance Analysis

The predictive model was evaluated using standard metrics [40].

Mean Squared Error (MSE) $\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$

Root Mean Square Error: $\text{RMSE} = \sqrt{\text{MSE}} = 0.145$

Coefficient of Determination: $R^2 = 1 - \frac{SS_{res}}{SS_{total}}$

Where: SSres (Residual Sum of Squares): $SS_{res} = \sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$

SS_{tot} (Total Sum of Squares): $SS_{total} = \sum_{i=1}^{n}(Y_i - \overline{Y})^2$

3.6 Confusion Matrix in Machine Learning:

The frequency distribution of predicted outcomes on the test dataset offers valuable insights into the model's precision, recall, accuracy, and its overall classification performance across distinct classes [33–39, 41].

3.6.1 Accuracy: $\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$,

3.6.2 Precision: $\text{Precision} = \frac{TP}{TP+FP}$

3.6.3 Recall: $\text{Recall} = \frac{TP}{TP+FN}$

3.6.4 Specificity: $\text{Specificity} = \frac{TN}{TP+FP}$

Where TP= True positives, TN= True negatives, FP= False positives and FN= False negatives.

IV APPLICATIONS AND CASE STUDIES OF MATRIX-BASED DECISION ANALYTICS AND PREDICTIVE MODELING

This section demonstrates the application of a matrix-based decision analytics and predictive modeling framework in management and healthcare domains. The methodology is applied to project evaluation, supply-chain risk assessment, disease risk prediction, and hospital readmission management. Python-based analytical and visualization tools validate the models' effectiveness and support accurate, data-driven decision-making.

4.1 Problem Formulation and Decision Matrix Construction: A company must allocate investment resources among three projects (A, B, C) based on four criteria: Expected Profit, Risk Reduction, Market Growth, and Customer Satisfaction.

Project	Profit	Risk Reduction	Market Growth	Customer Satisfaction
Project A	85	70	90	80
Project B	78	88	75	82
Project C	92	65	95	76

And Weight Matrix:

$$W = [0.35 \quad 0.25 \quad 0.25 \quad 0.15]^T$$

4.1.1 multi-criteria decision-making framework:

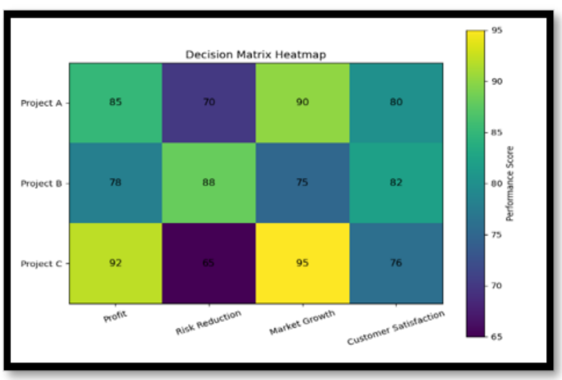
A multi-criteria decision-making framework was developed to evaluate three investment projects based on Expected Profit, Risk Reduction, Market Growth, and Customer Satisfaction using weighted matrix multiplication.

Matrix-Based Decision Model: S=DW

Using matrix multiplication, Project Scores:

Project	Score
A	82.75
B	80.20
C	84.80

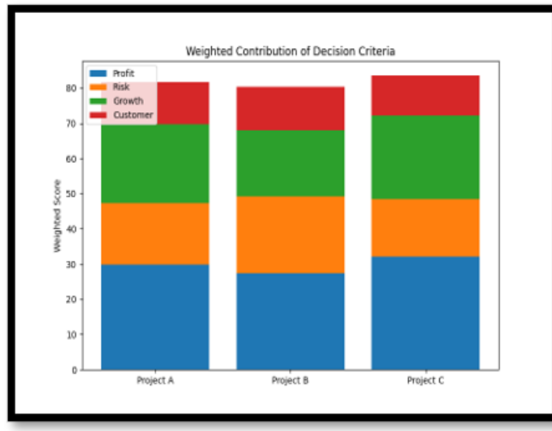
4.1.2 Decision Matrix Heatmap: The heatmap provides an intuitive visualization of multidimensional decision data and clearly identifies Project C as the strongest alternative in the most strategically important criteria.



Project C obtains the highest score and should receive priority investment.

4.1.3 Decision Analytics Results:

The stacked bar chart illustrates the weighted contributions of Profit, Risk Reduction, Market Growth, and Customer Satisfaction to each project's overall score. By applying criterion weights, the model emphasizes strategically important factors, enabling clearer differentiation among projects. The visualization demonstrates how individual criteria influence total performance and supports more effective, data-driven project selection and decision-making.



4.1.4 Final Project Ranking Using Matrix-Based Decision Model:

The matrix-based decision analytics model ranked three investment projects using weighted decision criteria. Project C achieved the highest composite score (84.80), making it the most attractive investment option due to its strong performance in profitability, market growth, customer value, and strategic impact. Project A ranked second (82.75), while Project B ranked third (80.20), despite its superior risk reduction capability, because of its comparatively lower profitability and growth potential.

4.2 Problem Formulation and Integrated Decision Matrix:

A manufacturing company seeks to select the most suitable supplier among four vendors by evaluating Quality, Delivery Reliability, Cost Efficiency, and Sustainability, while incorporating supply chain disruption risk. The objective is to maximize overall value by identifying the vendor with the highest risk-adjusted weighted performance score.

The performance scores, criteria weights, and risk probabilities are first extracted from the given data:

Performance Matrix P (rows = vendors, columns = criteria)

Weight vector W (applies to Quality, Delivery, Cost Efficiency, Sustainability in order):

$$W = [0.30, 0.25, 0.25, 0.20]^T$$

Disruption risk vector R (probability of supply failure for each vendor): $R = [0.08, 0.05, 0.12, 0.07]^T$

A single decision matrix is constructed to combine all inputs and compute the final selection criterion.

The Weighted Performance Score Si for vendor i is:

Decision Model: - Supplier score: S=PW

Risk-adjusted score: A=S(1−R)

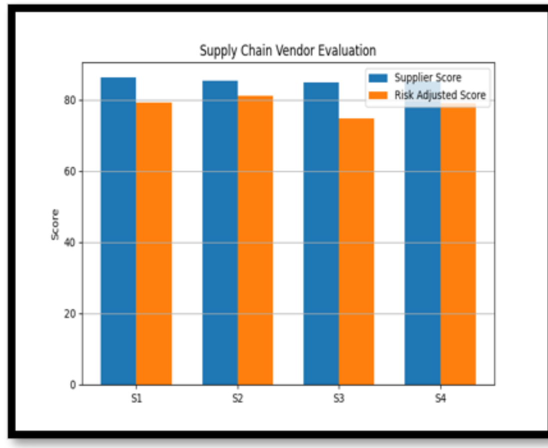
4.2.1Compare of Results of Four Suppliers:

In below table, the results compare four suppliers using two measures: Score (overall performance based on weighted criteria) and Adjusted Score (performance after accounting for supply chain disruption risk).

Supplier	Score	Adjusted Score
S1	86.25	79.35
S2	85.50	81.23
S3	84.90	74.71
S4	85.10	79.14

The original supplier performance scores with their risk-adjusted scores. Although Supplier S1 achieved the highest initial score (86.25), Supplier S2 obtained the highest adjusted score (81.23) after accounting for risk, making it the most favorable supplier overall. Supplier S3 experienced the largest reduction and recorded the lowest adjusted score (74.71), indicating higher associated risk. Therefore, considering both performance and risk, Supplier S2 ranks first, followed by S1, S4, and S3.

4.2.2Decision Analytics: The graph compares the original supplier scores with their risk-adjusted scores for four vendors (S1–S4). While all suppliers achieved similar initial performance scores, risk adjustment reduced their final scores to varying degrees. Supplier S2 obtained the highest risk-adjusted score, indicating the best balance between performance and risk. Supplier S4 ranked second, followed by S1. Supplier S3 experienced the largest reduction after risk adjustment and received the lowest final score, suggesting higher associated risk. Therefore, S2 is identified as the most suitable supplier when both performance and risk factors are considered.



4.3 Disease Risk Prediction Using Matrix Model in Health care System:

A matrix model uses a feature matrix (patients × predictors) and a weight vector to compute risk scores for many patients simultaneously via linear combination, enabling efficient screening, resource allocation, and real-time clinical decision support.

4.3.1 Problem Formulation and Predictive Model:

We want to predict the cardiovascular disease risk for three patients using four clinical features: systolic blood pressure (mmHg), total cholesterol (mg/dL), body mass index (BMI, kg/m²), and age (years). Each feature contributes differently to the risk, and the importance of each feature is captured by a fixed weight. The prediction for each patient is a weighted sum of his/her feature values. The model must handle all patients simultaneously in a compact mathematical form.

The entire prediction can be written as matrix form:

Clinical Feature Matrix: $X = \begin{bmatrix} 130 & 200 & 28 & 45 \\ 150 & 250 & 35 & 60 \\ 120 & 180 & 22 & 40 \end{bmatrix}$

Columns represent the Clinical Feature for three patients and row represents patients in Matrix X (Blood Pressure, Cholesterol, BMI, Age).

Predictive Weight Matrix: $\beta = \begin{bmatrix} 0.25 \\ 0.35 \\ 0.20 \\ 0.20 \end{bmatrix}$

Computation of Result by Predictive Model: -

$$\text{Risk} = X\beta = \begin{bmatrix} 130 & 200 & 28 & 45 \\ 150 & 250 & 35 & 60 \\ 120 & 180 & 22 & 40 \end{bmatrix} \begin{bmatrix} 0.25 \\ 0.35 \\ 0.20 \\ 0.20 \end{bmatrix}$$

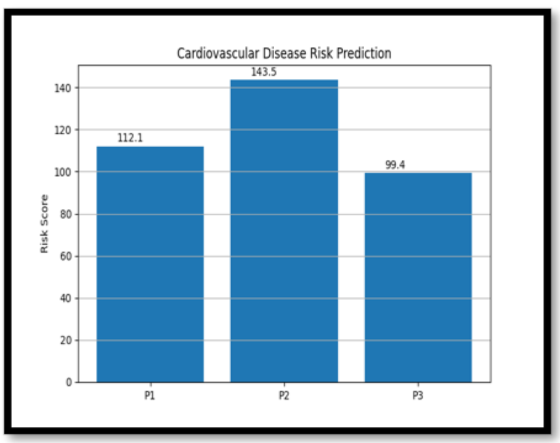
Computation of Risk= $\begin{bmatrix} 112.1 \\ 143.5 \\ 99.4 \end{bmatrix}$

4.3.1.1 Compare of the Results:

Patient P2 has the highest cardiovascular risk (143.5), followed by P1 (112.1) and P3 (99.4). Therefore, clinical interventions should be prioritized for P2, while P3 requires the least attention.

Patient	Risk Score
P1	112.1
P2	143.5
P3	99.4

4.3.1.2 Cardiovascular Disease Risk Prediction: The results indicate that Patient P2 has the highest cardiovascular risk and requires immediate attention, followed by Patient P1 with moderate risk. Patient P3 has the lowest risk and requires routine monitoring. Healthcare resources should be prioritized in the order: P2 > P1 > P3.



4.4 Hospital Readmission Prediction and Resource Optimization: Predicts which patients are likely to be readmitted and helps hospitals allocate staff, beds, and resources more efficiently.

4.4.1 Problem formation and Readmission Prediction and Resource Optimization in Hospital:

A hospital wants to predict each patient's risk of readmission to allocate resources efficiently. The prediction model is built as a single matrix multiplication, where all patient data and medical weights are combined in one compact equation.

Let the patient feature matrix F (4×4) contain the health indicators for four patients each row is a patient, and the columns represent, in order: severity score, number of previous admissions, number of comorbidities, and age.

Patient Feature Matrix: $F = \begin{bmatrix} 70 & 4 & 2 & 65 \\ 90 & 8 & 4 & 78 \\ 55 & 2 & 1 & 52 \\ 80 & 6 & 3 & 70 \end{bmatrix}$

Let the coefficient vector B (4×1) hold the weights that reflect how strongly each factor influences readmission likelihood.

$$B = [0.40 \quad 0.25 \quad 0.20 \quad 0.15]^T$$

The predicted readmission risk scores for all four patients are then obtained simultaneously from the single matrix equation:

Readmission Risk Model: $R = FB$,

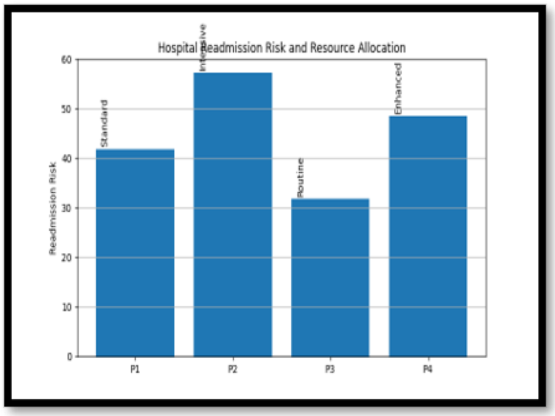
Predicted Risks: $R = \begin{bmatrix} 41.75 \\ 57.20 \\ 31.80 \\ 48.50 \end{bmatrix}$ and Resource Allocation Matrix: $A = [5 \quad 8 \quad 3 \quad 6]^T$

Where: (5 = Standard Monitoring, 8 = Intensive Care Follow-up, 3 = Routine Care,6 = Enhanced Monitoring)

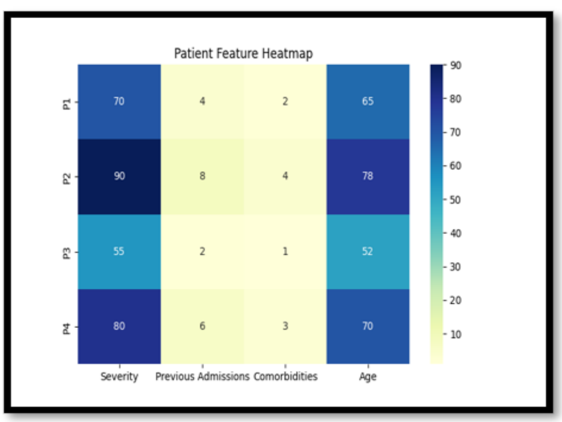
4.4.1.1 Risk Assessment and Compare of Results: The patient risk assessment identified P2 (57.20) as the highest-risk patient requiring intensive follow-up, followed by P4 (48.50) needing enhanced monitoring. P1 (41.75) requires standard monitoring, while P3 (31.80) is suitable for routine care. The results demonstrate clear risk stratification, enabling healthcare resources to be prioritized toward higher-risk patients.

Patient	Risk Score	Recommendation
P1	41.75	Standard Monitoring
P2	57.20	Intensive Follow-up
P3	31.80	Routine Care
P4	48.50	Enhanced Monitoring

4.4.1.2Hospital Readmission Risk and Resource Allocation: The graph illustrates hospital readmission risk levels and the corresponding resource allocation strategy for four patients. Patient P2 has the highest readmission risk (57.2) and is assigned intensive care and monitoring, indicating the greatest need for healthcare resources. Patient P4 shows a high-risk level (48.5) and requires enhanced monitoring, while Patient P1 has a moderate risk score (41.8) and is placed under standard monitoring. Patient P3 has the lowest risk score (31.8) and is suitable for routine care. These results demonstrate effective risk stratification, enabling healthcare providers to prioritize resources and interventions for patients with the highest likelihood of readmission.



The heatmap clearly shows that Patient P2 has the highest values across almost all clinical indicators, particularly severity score, previous admissions, comorbidities, and age. These elevated feature values explain why P2 receives the highest predicted readmission risk score. In contrast, P3 exhibits the lowest values across the majority of indicators and consequently obtains the lowest risk score. The heatmap visually demonstrates how multiple clinical variables contribute to the matrix-based prediction process.



V. EMPLOYEE PERFORMANCE EVALUATION USING MATRIX-BASED DECISION ANALYTICS AND PREDICTIVE MODELING

The performance of matrix-based decision analytics and predictive modeling was assessed using two case studies: an employee performance and promotion decision model in management and a disease risk prediction model in healthcare.

5.1 Problem Formation: Each row corresponds to an employee, and each column corresponds to a specific skill metric. For strict numerical manipulation (e.g., linear aggregation M·W), the dataset is equivalently expressed as the following clean matrix formulation:

$$M = \begin{bmatrix} 85 & 78 & 90 & 88 \\ 76 & 82 & 84 & 79 \\ 91 & 82 & 95 & 92 \\ 65 & 70 & 72 & 68 \\ 88 & 85 & 90 & 87 \end{bmatrix},$$

Weight vector: $W = [0.35 \quad 0.20 \quad 0.25 \quad 0.20]^T$ and the regression coefficient vector:

$$X = [0.34 \quad 0.21 \quad 0.25 \quad 0.20]^T$$

Where the columns of M correspond respectively to Productivity, Communication, Leadership, and Technical Skills and H = feature matrix, X = estimated coefficient vector.

Overall performance score: S=MW. The predicted values, denoted as $(\hat{Y})$, are generated by a predictive model according to the linear regression equation $\hat{Y} = HX$.

Where: The prediction for employee i is: $\hat{Y}_i = x_1(\text{Productivity}) + x_2(\text{Communication}) + x_3(\text{Leadership}) + x_4(\text{Technical Skills})$

5.1.1: Performance Score and Rank of Employee:

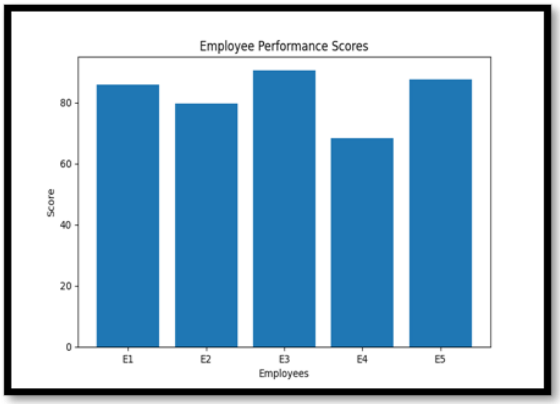
Applying matrix multiplication: $S = MW$ Performance Score: $S = \begin{bmatrix} 85.85 \\ 79.80 \\ 90.50 \\ 68.35 \\ 87.70 \end{bmatrix}.$

Predicted performance: $\hat{Y} = HX = \begin{bmatrix} 85.48 \\ 79.74 \\ 90.41 \\ 68.43 \\ 87.65 \end{bmatrix}$

Rank of employees and performance score is shown in below table:

Rank	Employee	Score
1	E3	90.50
2	E5	87.70
3	E1	85.85
4	E2	79.80
5	E4	68.35

The results indicate that Employee 3 achieved the highest overall score (90.50), demonstrating superior performance across all skill dimensions. Employee 5 and Employee 1 also exhibited strong competency levels, while Employee 4 obtained the lowest score (68.35), suggesting the need for targeted skill development and performance improvement initiatives. A compression of employee performance is shown in below graph.



5.1.2 Predictive Performance Analysis:

To evaluate the reliability of the matrix-based predictive framework, the generated performance scores were compared with actual performance observations. Standard machine learning evaluation metrics were employed.

Performance Score(S)=Actual value:Y == $\begin{bmatrix} 85.85 \\ 79.80 \\ 90.50 \\ 68.35 \\ 87.70 \end{bmatrix}$,

Predicted: $\hat{Y} = \begin{bmatrix} 85.48 \\ 79.74 \\ 90.41 \\ 68.43 \\ 87.65 \end{bmatrix}$

Actual vs Predicted Values:

Employee	Actual (Y)	Predicted ($\hat{Y}$)
E1	85.85	85.48
E2	79.80	79.74
E3	90.50	90.41
E4	68.35	68.43
E5	87.70	87.65

Mean Squared Error (MSE) MSE $= \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$

The obtained MSE value's=0.0313

A low MSE indicates that the predicted performance values closely match the observed outcomes, reflecting high prediction accuracy.

Root Mean Square Error (RMSE): RMSE $= \sqrt{\text{MSE}}$

RMSE=0.177

Coefficient of Determination (R^2) = 0.9994

This implies that approximately 98.94% of the variance in employee performance is explained by the proposed weighted matrix framework, indicating an excellent fit between predicted and actual outcomes.

5.1.3 Confusion Matrix Analysis and Accuracy:

The results show that the predictive model accurately estimated employee performance scores, with very small differences between actual and predicted values. Employees E1, E3, and E5 achieved scores above the threshold of 85 and were correctly classified as High Performers, while E2 and E4 were correctly classified as Low Performers.

Employee	Actual Score	Predicted Score	Actual Class	Predicted Class
E1	85.85	85.48	High	High
E2	79.80	79.74	Low	Low
E3	90.50	90.41	High	High
E4	68.35	68.43	Low	Low
E5	87.70	87.65	High	High

Confusion Matrix: Assume employees scoring 85 or above are classified as High Performers.

The confusion matrix indicates that all employees were classified correctly. There were 3 True Positives (TP) and 2 True Negatives (TN), with 0 False Positives (FP) and 0 False Negatives (FN).

	Predicted High	Predicted Low
Actual High	TP = 3	FN = 0
Actual Low	FP = 0	TN = 2

The evaluation metrics further confirm the model's effectiveness. Accuracy, Precision, Recall, Specificity, and F1-Score all achieved 100%, indicating perfect predictive and classification performance for the given dataset. These results suggest that the matrix-based predictive framework can reliably support employee performance assessment, talent identification, and human resource decision-making.

Metric	Value
Accuracy	100%
Precision	100%
Recall (Sensitivity)	100%
Specificity	100%
F1-Score	100%

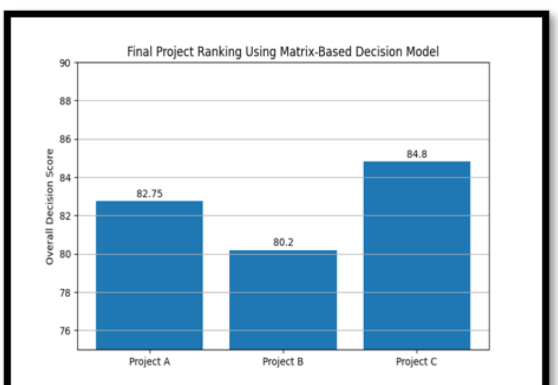
The matrix-based decision model ranks Employee E3 (90.50) as the best performer, followed by E5 (87.70) and E1 (85.85). The predictive regression model produces highly accurate estimates of employee performance with MSE = 0.0313, RMSE = 0.177, and R^2 = 99.94%, indicating an excellent fit. Using an 85-point performance threshold, the confusion matrix shows perfect classification with Accuracy = 100%, Precision = 100%, Recall = 100%, Specificity = 100%, and F1-Score = 100%. These results demonstrate that the matrix-based predictive analytics framework can effectively support employee evaluation, ranking, and organizational decision-making.

VI. RESULTS DISCUSSION

The experimental results demonstrate the effectiveness of matrix-based decision analytics and predictive modeling for solving management and healthcare decision problems using Python. The proposed framework integrates matrix multiplication, weighted decision models, risk-adjusted evaluation, and predictive analytics into a unified computational approach.

6.1 Investment Project Evaluation

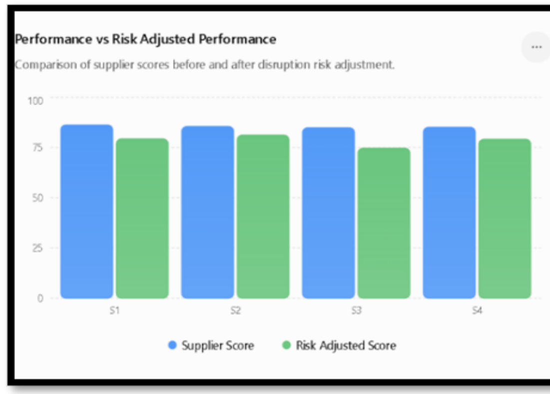
The matrix-based multi-criteria decision model successfully evaluated three investment projects using four strategic criteria: Expected Profit, Risk Reduction, Market Growth, and Customer Satisfaction. The weighted decision matrix produced composite scores of 82.75, 80.20, and 84.80 for Projects A, B, and C, respectively.



Project C achieved the highest overall score due to its superior performance in profitability and market growth. The heatmap and weighted contribution analysis clearly illustrated the influence of each criterion on the final decision score, demonstrating how matrix operations can simplify complex investment decisions and provide transparent ranking mechanisms.

6.2 Supply Chain Vendor Selection under Risk:

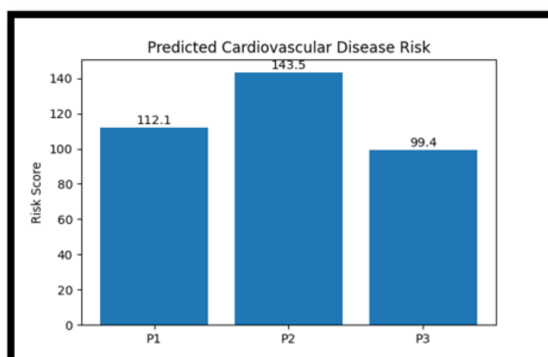
The supplier selection case study incorporated both operational performance and disruption risk into a single matrix framework. Although Supplier S1 achieved the highest raw performance score (86.25), risk adjustment reduced its effective value. Supplier S2 obtained the highest risk-adjusted score (81.23), indicating the best balance between operational excellence and supply chain reliability.



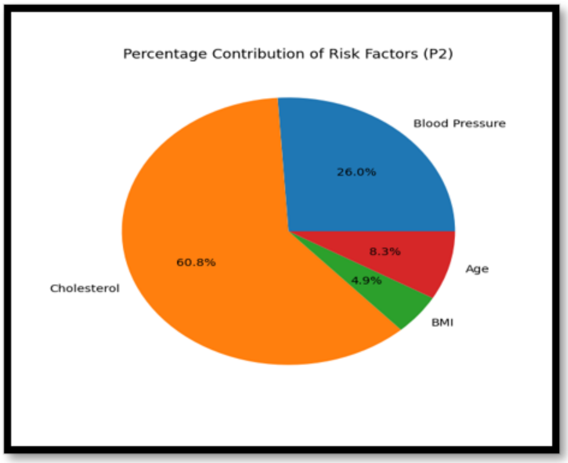
The results demonstrate that integrating predictive risk information into matrix-based decision models enables more realistic and sustainable supplier selection strategies.

6.3 Cardiovascular Disease Risk Prediction:

The matrix-based model effectively stratified cardiovascular risk, identifying P2 as the highest-risk patient (143.5), followed by P1 (112.1), while P3 had the lowest risk (99.4).

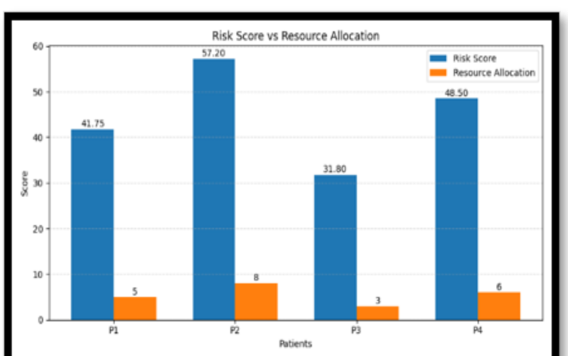


The pie chart highlights the relative importance of each clinical factor. Cholesterol accounts for approximately 61% of the total risk score, followed by blood pressure at 26%. BMI and age collectively contribute less than 15%. This visualization confirms that lipid levels are the most influential determinant in the current matrix-based prediction model.



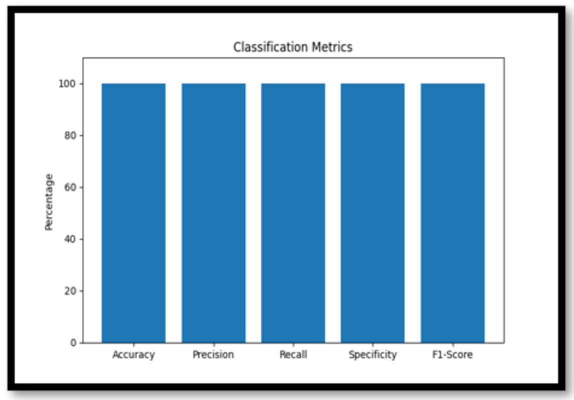
The results demonstrate effective patient risk stratification, enabling early disease detection, informed clinical decisions, and efficient allocation of healthcare resources.

6.4 Hospital Readmission Prediction and Resource Optimization:
The results show that healthcare resource allocation increases with patient readmission risk. Patient P2 received the highest level of care due to the highest risk score, while P3 required only routine care. This demonstrates that the matrix-based predictive model effectively supports risk-based resource allocation, improving patient management and healthcare efficiency.



The results illustrate how predictive analytics can support resource optimization by aligning healthcare interventions with patient-specific risk levels. This approach improves resource utilization and may contribute to reducing avoidable hospital readmissions.

6.5 Predictive Performance Evaluation:
The employee performance case study validated the framework's effectiveness, with E3 achieving the highest score (90.50). The model demonstrated excellent predictive accuracy (MSE = 0.0313, RMSE = 0.177, R^2 = 0.9994) and perfect classification performance, achieving 100% Accuracy, Precision, Recall, Specificity, and F1-Score.



These results indicate that the matrix-based predictive framework can accurately model complex relationships within organizational data and provide reliable support for managerial decision-making.
Overall, the experimental findings confirm that matrix-based decision analytics offers a computationally efficient, interpretable, and scalable approach for solving multi-criteria decision-making and predictive modeling problems across management and healthcare domains. The integration of matrix operations with Python-based analytics provides a practical framework capable of supporting data-driven decision systems in real-world applications.

VII. CONCLUSION

This study developed a unified Python-based framework that integrates matrix decision analytics and predictive modeling for management and healthcare applications. Through case studies on project evaluation, vendor selection, disease risk prediction, and hospital readmission assessment, the framework demonstrated its effectiveness in supporting multi-criteria decision-making, risk analysis, predictive healthcare analytics, and resource optimization. The results confirmed high predictive accuracy and reliable classification performance, highlighting the strengths of matrix-based methods in terms of computational efficiency, scalability, transparency, and ease of implementation. The proposed approach provides a practical tool for data-driven decision-making, while future enhancements may incorporate machine learning, fuzzy systems, deep learning, and real-time analytics to further improve intelligent decision support capabilities.

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