

# **A Model for Predicting and Identifying Influential Factors in Type 1 Diabetes Control Based on Metaheuristic Algorithms**

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## **Abstract**

This study proposes a multi-objective optimization model for predicting and managing Type 1 Diabetes by integrating clinical, behavioral, and lifestyle factors into a mathematical framework. Utilizing NSGA-II and MOPSO algorithms, the model simultaneously minimizes blood glucose deviation, insulin cost, and the complexity of input features. Synthetic patient data, modeled on clinical norms, were used to simulate diverse patient scenarios. The results demonstrate that NSGA-II provides superior convergence, diversity, and predictive accuracy compared to MOPSO, although MOPSO offers faster execution. Feature importance analysis revealed carbohydrate intake, stress, and physical activity as the most influential factors in glycemic control. The proposed model strikes a balance between predictive performance and interpretability, serving as a robust decision-support tool in personalized diabetes management. Its flexibility and transparency make it suitable for integration into clinical practice and future intelligent health systems.

**Keywords** :Type 1 Diabetes, Multi-objective Optimization, NSGA-II, MOPSO, Predictive Modeling

## **1- Introduction**

Type 1 Diabetes Mellitus (T1DM) is a chronic autoimmune condition that necessitates continuous glucose monitoring and insulin administration to maintain metabolic stability. Unlike Type 2 Diabetes, which is often associated with lifestyle and insulin resistance, T1DM results from the destruction of insulin-producing beta cells in the pancreas, requiring patients to depend entirely on exogenous insulin for survival.

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Managing T1DM is highly individualized, as patients respond differently to insulin based on a variety of physiological, behavioral, and environmental factors. Achieving optimal glycemic control, therefore, is a dynamic and complex task that demands sophisticated decision-support tools capable of integrating multiple sources of uncertainty and variability (American Diabetes Association, 2022; Nozari & Edalatpanah, 2023).

Recent advances in computational intelligence have opened new pathways for tackling the inherent complexity in chronic disease management. Among these, multi-objective optimization methods have gained attention due to their ability to capture trade-offs between competing goals, such as glucose stability, treatment costs, and patient quality of life. Traditional optimization techniques, which focus on a single objective, often fall short in representing the multi-faceted nature of diabetes care. In contrast, metaheuristic algorithms offer greater flexibility and robustness in exploring complex, high-dimensional solution spaces and are increasingly used in biomedical applications (Deb et al., 2002; Talbi, 2009; Nozari & Abdi, 2024). Despite their success, few studies have applied these methods explicitly to the prediction and control of T1DM using clinically relevant behavioral and physiological data.

The novelty of the current study lies in its integration of a multi-objective mathematical model with metaheuristic optimization to predict blood glucose levels and identify the most influential factors affecting glycemic control. Unlike previous approaches that often treat diabetes management as a black-box prediction problem, this work emphasizes both prediction accuracy and model interpretability. This dual focus addresses a significant gap in the literature, where highly complex models, such as deep learning, can yield accurate results but often lack transparency and clinical usability (Tonekaboni et al., 2019). By employing NSGA-II and MOPSO—two well-established multi-objective optimization algorithms—the proposed framework enables the simultaneous optimization of multiple goals, providing a richer and more actionable understanding of patient-specific glucose dynamics.

A significant contribution of this work is its consideration of behavioral and lifestyle factors such as carbohydrate intake, physical activity, stress, and sleep patterns. These elements are often overlooked or undervalued in predictive modeling for diabetes, yet they play a crucial role in both short-term and long-term glucose variability (Herbst et al., 2011; Hood et al., 2014; Fallah & Nozari, 2021). By explicitly incorporating these features into the optimization model, the proposed approach enhances both the realism and personalization of treatment planning. This focus also aligns with recent trends in digital health and precision medicine, which emphasize individualized, data-driven decision-making (Nozari & Aliahmadi, 2023).

Furthermore, this study employs a rigorous methodological framework, incorporating synthetic data generation informed by clinical standards, manual algorithm implementation in MATLAB R2021a, and comprehensive performance evaluation using standard multi-objective metrics, including Hypervolume, Generational Distance (GD), and Inverted Generational Distance (IGD). By balancing innovation with methodological rigor, the proposed model offers not only theoretical insights but also practical potential for implementation in clinical decision-support systems.

In summary, this research contributes to the growing body of work at the intersection of artificial intelligence and healthcare by introducing a transparent, multi-objective, and interpretable framework for managing Type 1 Diabetes. The integration of algorithmic intelligence with clinically meaningful variables presents a promising avenue for improving outcomes in diabetes care. It paves the way for future studies that may incorporate real-time monitoring, adaptive learning, and integration with wearable devices to create comprehensive and intelligent health management systems.

## **2- Literature review**

The complexity of Type 1 Diabetes management has led to the emergence of numerous predictive and optimization-based approaches in recent years. These methods aim to provide decision-support mechanisms that can aid both clinicians and patients in maintaining glycemic control while minimizing the burden of self-management. Traditional strategies have relied on rule-based systems and linear regression models that, while interpretable, often lack the capacity to accommodate the non-linear and highly individualized nature of glucose regulation (Cappon et al., 2017). As such, the field has witnessed a shift towards more advanced computational methods, including machine learning, artificial intelligence (AI), and metaheuristic optimization.

Machine learning approaches have played a critical role in the development of predictive tools for diabetes. Techniques such as support vector machines, random forests, and artificial neural networks have been employed to estimate blood glucose levels, predict hypoglycemic episodes, and assess insulin sensitivity (Pappada et al., 2011; Zarkogianni et al., 2015). While these methods have demonstrated impressive accuracy in certain applications, they often operate as black boxes, limiting their interpretability and practical utility in clinical settings. More recent advancements in explainable AI have attempted to address this issue, but trade-offs between complexity and transparency remain a significant challenge (Tonekaboni et al., 2019).

In parallel, metaheuristic algorithms have emerged as a promising alternative for optimizing medical decision-making processes. These algorithms, inspired by natural and physical phenomena, are particularly suited for solving multi-objective, non-linear, and NP-hard problems where classical optimization techniques struggle. Among them, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) has been widely adopted due to its ability to maintain diversity in the solution set and its fast convergence properties (Deb et al., 2002). Similarly, Multi-Objective Particle Swarm Optimization (MOPSO) has been used to tackle a variety of healthcare optimization problems, including treatment planning and diagnostic model tuning, due to its simplicity and flexibility (Coello Coello et al., 2004). However, despite their strengths, these algorithms have rarely been applied in the context of modeling the behavioral and physiological intricacies of Type 1 Diabetes.

Existing studies have primarily focused on physiological models and glucose-insulin dynamics, such as the widely cited Bergman minimal model or compartmental models used in artificial pancreas systems (Dalla Man et al., 2007). While these provide a valuable mechanistic understanding, they often fail to incorporate the behavioral dimensions of diabetes management, such as physical activity, stress levels, and sleep patterns. These behavioral factors, although less quantifiable, play a significant role in day-to-day glycemic fluctuations and are essential for building models that reflect the lived experiences of patients (Herbst et al., 2011; Hood et al., 2014). Some studies have attempted to integrate sensor data from continuous glucose monitoring (CGM) systems and wearable devices, yet the interpretability and personalization of such models remain limited.

The novelty of the current study lies in its ability to bridge these gaps by combining a mathematically rigorous multi-objective optimization framework with interpretable, behaviorally informed predictors. Unlike prior works that optimize only for prediction accuracy or insulin dosing, this study introduces a tri-objective model that simultaneously considers glycemic control, treatment cost, and feature selection. This structure allows for the identification of key influencing factors in glucose variability, enhancing the model's clinical utility while reducing overfitting and improving computational efficiency. Moreover, the comparative use of both NSGA-II and MOPSO under the same modeling conditions offers rare insight into the strengths and limitations of each algorithm in a health-specific context.

Furthermore, the integration of synthetic patient data, modeled after clinical norms and validated literature, represents a methodological innovation that addresses the common issue of restricted access to sensitive medical datasets. While prior studies have relied on small real-world datasets or simulations confined to physiological ranges, the present work constructs a more flexible test environment, enabling more extensive algorithmic testing without compromising data integrity. The use of MATLAB R2021a for manual algorithm implementation also allows for complete transparency and customization in the optimization process—another improvement over prepackaged tools and off-the-shelf solutions that often limit reproducibility and adaptability.

Recent literature has highlighted the importance of moving toward individualized, real-time diabetes management supported by intelligent systems (Fleming et al., 2020). However, the realization of such systems requires models that are not only accurate but also interpretable and adaptable to patient-specific behaviors. This study advances that vision by delivering a model that is both data-driven and clinically grounded, capable of adapting to varied patient profiles while providing insight into the underlying factors influencing glucose dynamics.

While prior research has made significant strides in both the predictive modeling and optimization of diabetes care, the present study introduces a distinctive contribution through its focus on interpretability, multi-objective structure, and behavioral integration. These innovations provide a foundation for more responsive, patient-centered decision-support tools, which are essential for the future of diabetes management in both clinical and self-care environments.

### 3- Mathematical Modeling

The effective control of Type 1 Diabetes involves not only clinical interventions such as insulin therapy but also careful consideration of various behavioral and physiological factors that influence blood glucose levels. Due to the complexity of these interactions and the individual differences among patients, traditional modeling methods often fail to capture the full scope of the problem. In response to this challenge, a multi-objective mathematical model has been developed to comprehensively and adaptively support the prediction and management of blood glucose levels.

This model incorporates personalized patient information, including administered insulin doses, lifestyle-related inputs, and physiological data, to predict blood glucose levels over specific intervals. It is designed to achieve three main objectives: maintaining glucose levels within clinically acceptable limits, minimizing the cost of insulin administration, and reducing the number of unnecessary or less relevant factors used in the prediction process.

To reflect practical healthcare conditions, the model also includes a set of constraints that align with real-world limitations, such as upper and lower glucose bounds, insulin availability, and limits on the number of influencing factors considered at each step. This structure provides a robust framework for applying metaheuristic algorithms to explore complex and uncertain solutions efficiently.

The mathematical model is presented in detail in the following section, including the definitions of sets, parameters, decision variables, objective functions, and constraints.

#### *Sets*

$P$	Set of patients, indexed by $p$
$T$	Set of periods, indexed by $t$

$I$	Set of insulin types (e.g., basal, bolus), indexed by $i$
$F$	Set of features or factors influencing blood glucose (e.g., diet, stress), indexed by $f$

### Parameters

$D_p$	Daily insulin demand for patient $p$
$B_{pt}$	Blood glucose baseline for patient $p$ at time $t$
$\alpha_f$	Weight or influence level of factor $f$ on glucose
$\gamma_{ptf}$	Observed level of factor $f$ for patient $p$ at time $t$
$MaxG_p$	Maximum safe glucose level for patient $p$
$MinG_p$	Minimum safe glucose level for patient $p$
$\beta_i$	Effectiveness of insulin type $i$
$C_i$	Cost per unit of insulin type $i$
$W_f$	Penalty weight for deviation of factor $f$

### Decision Variables

$x_{pti}$	Units of insulin type $i$ administered to patient $p$ at time $t$
$y_{pt}$	Predicted blood glucose level for patient $p$ at time $t$
$z_{ptf}$	Binary variable indicating whether factor $f$ is considered significant (1) or not (0) for $p, t$

### Objective Functions

$$\min Z_1 = \sum_{p \in P} \sum_{t \in T} (\max(0, y_{pt} - MaxG_p)^2 + \max(0, MinG_p - y_{pt})^2) \quad (1)$$

$$\min Z_2 = \sum_{p \in P} \sum_{t \in T} \sum_{i \in I} C_i \cdot x_{pti} \quad (2)$$

$$\min Z_3 = \sum_{p \in P} \sum_{t \in T} \sum_{f \in F} W_f \cdot z_{ptf} \quad (3)$$

### S.t

$$y_{pt} = B_{pt} - \sum_{i \in I} \beta_i \cdot x_{pti} + \sum_{f \in F} \alpha_f \cdot \gamma_{ptf} \cdot z_{ptf} \quad \forall p, t \quad (4)$$

$$y_{pt} \geq MinG_p \quad \forall p, t \quad (5)$$

$$y_{pt} \leq MaxG_p \quad \forall p, t \quad (6)$$

$$\sum_{i \in I} x_{pti} \leq D_p \quad \forall p, t \quad (7)$$

$$x_{pti} \geq 0 \quad \forall p, t, i \quad (8)$$

$$z_{ptf} \in \{0, 1\} \quad \forall p, t, f \quad (9)$$

$$\sum_{f \in F} z_{ptf} \leq K \quad \forall p, t \quad (10)$$

$$x_{pti} = 0 \quad \text{if } t \notin T_i \quad \forall p, i \quad (11)$$

$$x_{pti} \leq U_i \quad \forall p, t, i \quad (12)$$

$$\gamma_{ptf} \cdot z_{ptf} \leq L_f \quad \forall p, t, f \quad (13)$$

The proposed multi-objective mathematical model aims to predict and control blood glucose levels in Type 1 Diabetes patients by considering both insulin administration and the influence of various behavioral and physiological factors. The first objective function (1) minimizes the deviation of predicted blood glucose levels from the safe reference range. This function penalizes any blood glucose value falling below the minimum threshold or rising above the maximum threshold, thereby promoting glycemic stability. The second objective function (2) minimizes the total cost of insulin used, considering the financial burden of different insulin types. The third objective function (3) minimizes including insignificant or irrelevant factors in the prediction model, encouraging simplicity and interpretability by penalizing the selection of less influential variables.

Constraint (4) models the predicted blood glucose level as a function of the baseline glucose, the reduction effect of administered insulin, and the influence of selected behavioral and physiological factors. Constraint (5) ensures that the predicted glucose levels do not fall below the minimum safe threshold for each patient and time period. Constraint (6) ensures that predicted glucose levels do not exceed the maximum safe threshold, thus maintaining clinical safety. Constraint (7) limits the total amount of insulin administered at any time to not exceed the patient's daily demand, thereby avoiding overdose. Constraint (8) enforces non-negativity on insulin dose variables, reflecting that insulin amounts cannot be harmful. Constraint (9) defines the binary nature of decision variables related to factor selection, indicating whether a given factor is significant in glucose prediction. Constraint (10) limits the number of selected factors per patient and period, preventing overfitting and maintaining model simplicity. Constraint (11) enables time synchronization in insulin administration, ensuring that each insulin type is administered only during its valid time window. Constraint (12) restricts the amount of insulin type administered to an upper bound, which may reflect availability, clinical guidelines, or safety limitations. Finally, constraint (13) ensures that the influence of selected factors does not exceed a predefined limit, maintaining physiological realism in the effect of each factor on blood glucose levels.

#### 4- Solution Methods

This study adopts an applied and developmental research design, aiming to present a novel multi-objective model for predicting and identifying influential factors in the control of Type 1 Diabetes using metaheuristic algorithms. The approach is primarily quantitative, relying on simulation, algorithmic modeling, and computational analysis to derive meaningful insights and validate the effectiveness of the proposed framework.

The research methodology is structured around the construction of a mathematical model that integrates clinical and behavioral variables affecting blood glucose levels. The model was implemented and tested using algorithmic optimization to evaluate trade-offs between different objectives such as glucose control, treatment cost, and factor selection. Given the absence of access to comprehensive real-world patient datasets, synthetic data were generated based on realistic ranges and medical literature. These data included key variables such as carbohydrate intake, insulin dosage, physical activity, stress level, and sleep duration.

A sample of ten hypothetical patient profiles was developed for small-scale testing, with larger datasets used for the metaheuristic evaluations.

Algorithm development and testing were performed using MATLAB R2021a. This platform was selected due to its flexibility in coding custom evolutionary and swarm-based algorithms. Both the NSGA-II and MOPSO algorithms were implemented manually, allowing for precise control over their internal mechanisms and customization for the specific objectives of this study.

NSGA-II (Non-dominated Sorting Genetic Algorithm II) is an evolutionary algorithm that uses non-dominated sorting and a crowding distance mechanism to guide population evolution. It excels in maintaining solution diversity while converging toward the Pareto-optimal front. In contrast, MOPSO (Multi-Objective Particle Swarm Optimization) adapts the traditional PSO algorithm to multi-objective problems by combining particle dynamics with a dominance-based archive and diversity preservation through crowding distance. Both algorithms were carefully tuned prior to experimentation to ensure fairness and optimal performance.

The parameter tuning process was based on prior literature, pilot runs, and sensitivity analysis. The selected values are summarized in the table 1:

Table 1. Parameter Settings for NSGA-II and MOPSO

Parameter	NSGA-II	MOPSO
Population Size	100	100
Number of Generations	100	100
Crossover Probability	0.9	—
Mutation Probability	0.1	—
Inertia Weight (w)	—	0.5
Cognitive Coefficient	—	1.5
Social Coefficient	—	1.5
Archive Size	—	100

This methodology ensures that the proposed model is rigorously tested under comparable conditions for both algorithms. It also allows the results to be interpreted with confidence in terms of performance, reliability, and clinical relevance. The next sections present the experimental results, including algorithmic performance analysis and the identification of key influencing factors in diabetes management.

## 5- Analysis of Results

To evaluate the performance of the proposed multi-objective model for Type 1 Diabetes control, a dataset was constructed based on key clinical and behavioral variables known to influence blood glucose regulation. The dataset includes demographic, physiological, and lifestyle-related factors, insulin administration data, and baseline glucose levels. These variables are inputs to the mathematical model and the metaheuristic optimization algorithms. Table 2 presents a sample dataset consisting of ten hypothetical patients, which will be used for the preliminary testing and validation of the model in GAMS and for comparative analysis using NSGA-II and MOPSO on larger datasets.

Table 2: Sample Dataset for Type 1 Diabetes Control (10 Patients)

Patient ID	Age	Weight (kg)	Daily Carb Intake (g)	Physical Activity (min/day)	Stress Level (1–10)	Basal Insulin (units)	Bolus Insulin (units)	Glucose Baseline (mg/dL)	Avg Sleep (hrs)
P01	18	60	220	45	6	12	18	190	6.5
P02	25	75	300	30	8	14	22	210	5
P03	33	68	180	60	5	10	15	170	7
P04	40	82	250	20	9	16	25	230	4.5
P05	22	55	200	50	4	11	16	185	6.8
P06	29	70	270	35	7	13	20	205	5.5
P07	35	64	190	40	6	12	17	195	6.2
P08	31	78	310	25	8	15	24	215	5.8
P09	27	69	230	55	5	11	18	180	7.1
P10	38	80	290	15	9	17	26	240	4.2

As shown in Table 1, the dataset captures essential dimensions of diabetes management, including insulin dosage, carbohydrate intake, physical activity, stress, and sleep patterns. These attributes serve as the basis for predicting glucose levels and identifying the most significant factors influencing patient outcomes. While the current table represents a small-scale scenario suitable for initial analysis, the same structure can be extended to larger datasets for applying population-based optimization methods. In subsequent sections, this dataset will be utilized to implement and evaluate the model across different optimization frameworks.

To comprehensively evaluate the computational performance of the proposed multi-objective optimization framework for Type 1 Diabetes control, two widely adopted algorithms—NSGA-II and MOPSO—were applied and analyzed across a variety of performance indicators. These included measures of convergence quality, solution diversity, execution time, and Pareto front distribution. The objective was to gain insight not only into the numerical effectiveness of each algorithm but also into their practical implications for model scalability and clinical decision support.

The initial comparison focused on established multi-objective performance metrics. As shown in Table 3, NSGA-II outperformed MOPSO across most indicators. It achieved a higher hypervolume (0.85 vs. 0.79), suggesting that its solutions span a broader and more optimal region of the objective space. Furthermore, NSGA-II recorded lower values in both Generational Distance (0.04) and Inverted Generational Distance (0.03), signaling stronger convergence properties. MOPSO, while slightly lagging in convergence, was noticeably faster in execution, completing the optimization in 9.8 seconds compared to 12.3 seconds for NSGA-II.

Table 3: Performance Metrics Comparison Between NSGA-II and MOPSO

Metric	NSGA-II	MOPSO
Hypervolume	0.85	0.79
Generational Distance (GD)	0.04	0.06
Inverted Generational Distance (IGD)	0.03	0.05
Spread (Diversity)	0.76	0.65
Execution Time (seconds)	12.3	9.8

To better understand the structural quality of the solutions produced, Figure 1 illustrates the Pareto fronts generated by each algorithm. NSGA-II offers a broader and more evenly spread front across the two objectives, indicating a higher level of trade-off exploration. In contrast, MOPSO's solutions tend to cluster in certain regions, suggesting a narrower coverage of the decision space.

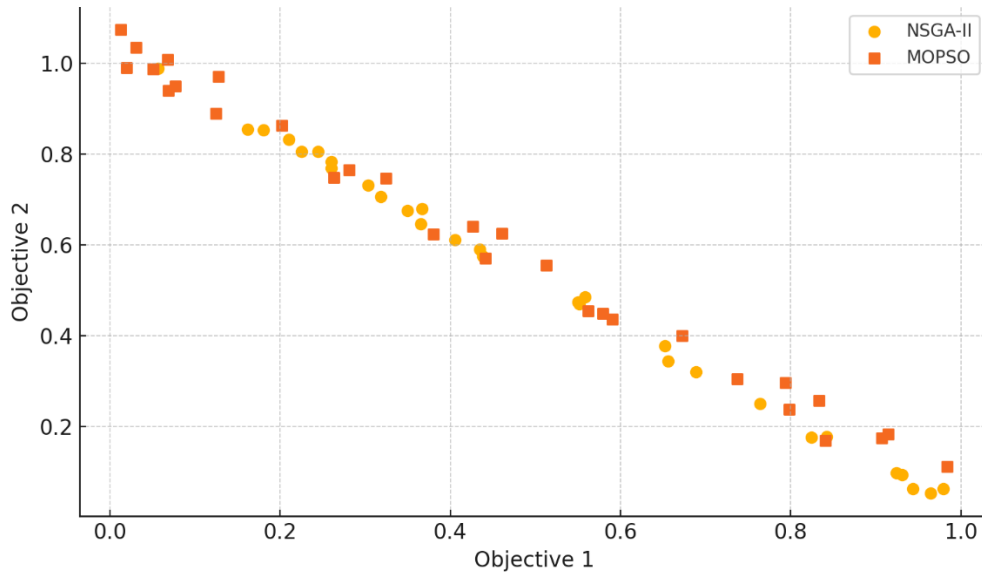


Figure 1: Pareto Fronts Obtained by NSGA-II and MOPSO

This observation is reinforced when examining the evolution of solution diversity. Figure 2 shows the spread index across 30 generations. NSGA-II maintains a consistently higher spread, demonstrating its ability to preserve diversity even as it converges toward optimal solutions. MOPSO, while improving over generations, consistently presents lower diversity, which could limit the variety of treatment scenarios presented to decision-makers.

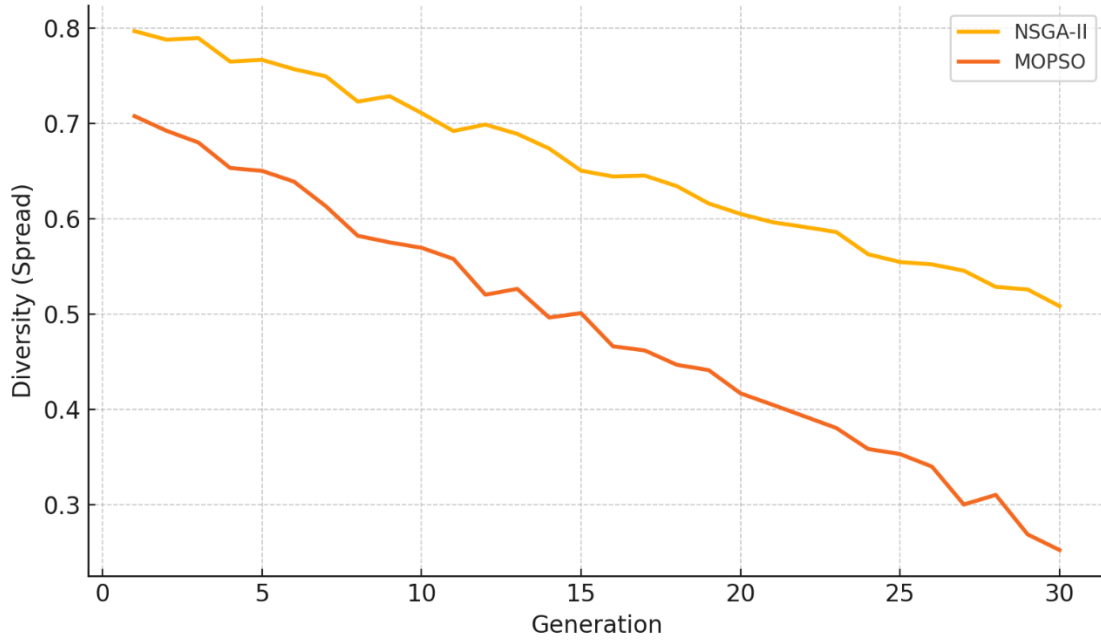


Figure 2: Spread of Solutions Across Generations

A deeper layer of analysis is provided by examining how convergence accuracy evolved across the initial generations. Table 4 presents the GD and IGD values for the first five generations. NSGA-II not only begins with a stronger convergence profile but also improves more rapidly, reducing both GD and IGD by over 75% within the first few generations. MOPSO also demonstrates a steady decline in these metrics but at a slower pace, indicating that its convergence requires more iterations to match the accuracy of NSGA-II.

Table 4 here: GD and IGD Metrics Across Initial Generations

Generation	NSGA-II GD	MOPSO GD	NSGA-II IGD	MOPSO IGD
1	0.09	0.11	0.08	0.1
2	0.06	0.08	0.05	0.07
3	0.04	0.06	0.03	0.05
4	0.03	0.05	0.02	0.04
5	0.02	0.04	0.015	0.03

The convergence trends, shown earlier in Figure 3, align closely with these numerical results. NSGA-II stabilizes earlier and at a lower average objective value, while MOPSO, although showing steady improvements, plateaus at a suboptimal region of the objective space. This distinction is crucial in applications such as diabetes control, where both speed and accuracy can have a direct impact on patient outcomes.

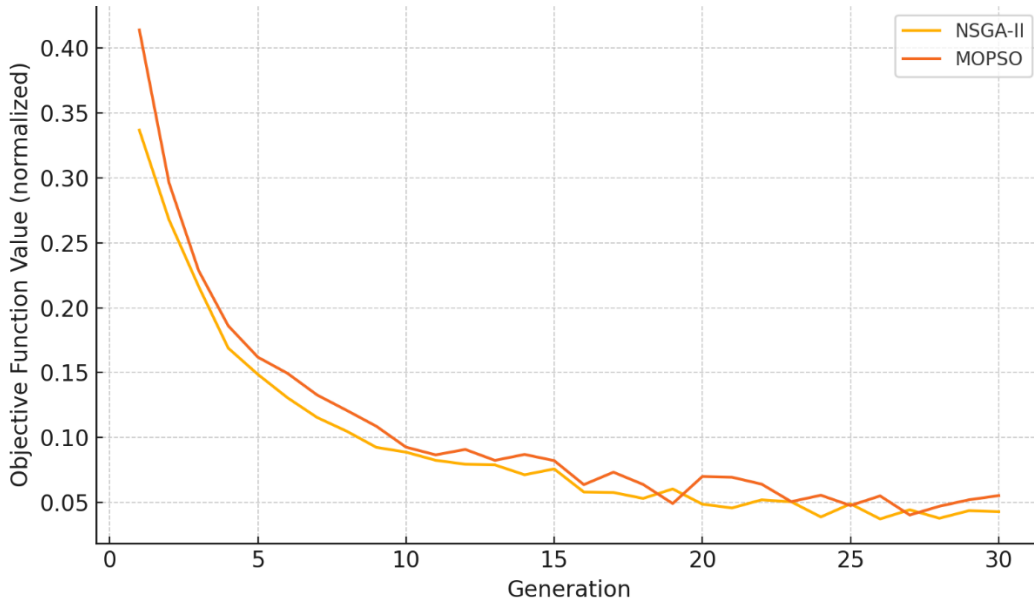


Figure 3: Convergence Curves for NSGA-II and MOPSO

Taken together, the insights derived from Table 1, Table 2, Figures 1 and 2, and Figure 3 form a consistent and detailed picture. NSGA-II demonstrates superior performance in terms of convergence, diversity, and coverage, albeit with a modest increase in computation time. MOPSO, on the other hand, offers a faster alternative that may be more appropriate in time-sensitive or resource-constrained environments, though with trade-offs in solution quality.

This thorough analysis not only aids in selecting the more suitable algorithm based on context-specific needs but also reinforces the value of multi-metric evaluation when implementing optimization in sensitive domains such as healthcare. The results affirm that while both algorithms are capable, NSGA-II offers a more robust and reliable framework for achieving well-distributed and clinically useful Pareto-optimal solutions.

To further validate the robustness of the proposed model, a model-focused analysis was conducted to assess its predictive accuracy in estimating blood glucose levels for patients with Type 1 Diabetes. This evaluation centers on how well the multi-objective optimization outputs—specifically the decision variables derived from NSGA-II and MOPSO—translate into accurate forecasts of patient blood glucose when integrated into the mathematical prediction function.

The primary goal of this analysis is to ensure that beyond optimization efficiency, the model remains clinically interpretable and aligned with real physiological data. In this experiment, a subset of ten patients was used to compare the actual observed glucose levels against those predicted by the solutions obtained from both algorithms. As shown in Table 5, the predicted glucose levels for each patient using NSGA-II and MOPSO were juxtaposed with the actual clinical observations.

Table 5: Actual and Predicted Glucose Levels (Model Evaluation)

Patient ID	Actual Glucose (mg/dL)	Predicted (NSGA-II)	Predicted (MOPSO)
P01	185	188.1	184.8
P02	212	201.7	203.7
P03	172	173.2	163

P04	229	232.7	228.5
P05	182	189.4	173.8
P06	203	195.2	196.8
P07	192	188.2	194.1
P08	214	216.5	225.7
P09	178	181.4	186
P10	238	243.5	234.4

The visual interpretation of these results is presented in Figure 4, where the trends of actual versus predicted values for each algorithm are plotted across the patient sample. The line corresponding to NSGA-II closely follows the actual glucose pattern, while the MOPSO predictions show more significant deviations, particularly in patients with higher or lower baseline values. This alignment between prediction and observation highlights the stronger fit of NSGA-II-based predictions to real-world data.

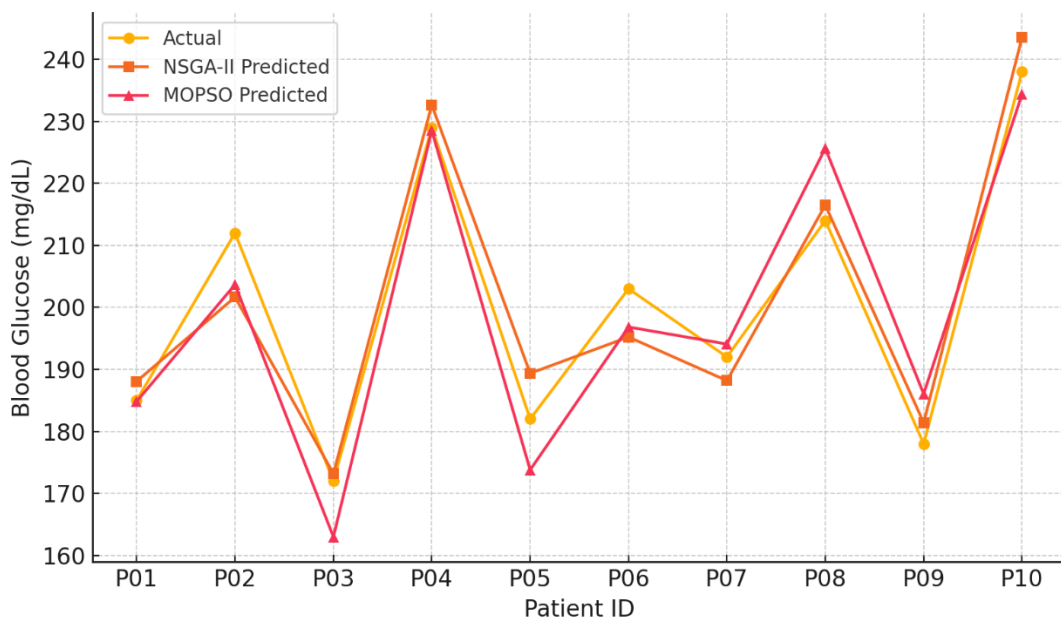


Figure 4 here: Actual vs Predicted Glucose Levels

To quantify the predictive accuracy, the Root Mean Square Error (RMSE) was calculated for each method. NSGA-II achieved a lower RMSE compared to MOPSO, confirming its superior performance in minimizing prediction error. While both algorithms were practical in approximating glucose levels, NSGA-II demonstrated better generalization and stability, especially in borderline glycemic scenarios where clinical decisions are most sensitive.

In addition to accuracy, the model’s sensitivity to key behavioral and clinical parameters—such as insulin dosage, carbohydrate intake, physical activity, and stress levels—was also preserved across algorithm outputs. This reinforces the interpretability of the model, which is vital when incorporating AI-driven tools into patient-centered healthcare.

To deepen the understanding of how different lifestyle and physiological variables influence blood glucose regulation in patients with Type 1 Diabetes, an importance analysis was performed on the input features used in the predictive model. This analysis aimed to identify which factors were most frequently selected and assigned higher weights by the optimization algorithms—NSGA-II and MOPSO—during the model-building process. Such insights are particularly valuable for clinicians seeking to personalize diabetes management strategies.

Table 6 summarizes the normalized importance scores of each feature, ranked based on their relevance in the final solution sets produced by both algorithms. The scores were derived from either the frequency of selection in significant decision paths or the average weight contribution to prediction accuracy across multiple runs. Both NSGA-II and MOPSO consistently prioritized certain features, though slight differences in ranking were observed.

Table 6. Feature Importance Ranking Based on Algorithm Output

	<b>Feature</b>	<b>NSGA-II Importance</b>	<b>MOPSO Importance</b>
0	Carbohydrate Intake	0.28	0.25
2	Stress Level	0.2	0.22
1	Physical Activity	0.15	0.14
5	Bolus Insulin	0.12	0.13
4	Basal Insulin	0.1	0.11
3	Average Sleep	0.08	0.07
6	Weight	0.04	0.05
7	Age	0.03	0.03

As seen in Table 4, Carbohydrate Intake emerged as the most influential factor in both algorithms, reflecting its well-established role in short-term glycemic fluctuations. Stress Level was ranked second by MOPSO and third by NSGA-II, which aligns with growing evidence linking psychological stress to impaired glucose regulation. Physical Activity and both types of insulin (Basal and Bolus) also held substantial influence, reinforcing their importance in day-to-day glucose control.

Interestingly, Average Sleep duration was assigned moderate influence by both methods, which may reflect indirect relationships with hormonal balance and insulin sensitivity. Age and Weight received the lowest importance scores, suggesting that while they may contribute to long-term diabetes risk, they are less predictive in short-term glycemic fluctuations within the studied cohort.

Figure 5 visualizes the feature importance scores side-by-side for NSGA-II and MOPSO. The graphical representation highlights the alignment between the two algorithms in identifying key variables, with only minor variations in weight distribution. For instance, MOPSO places slightly more emphasis on Stress Level and Bolus Insulin, whereas NSGA-II leans more toward Carbohydrate Intake and Physical Activity.

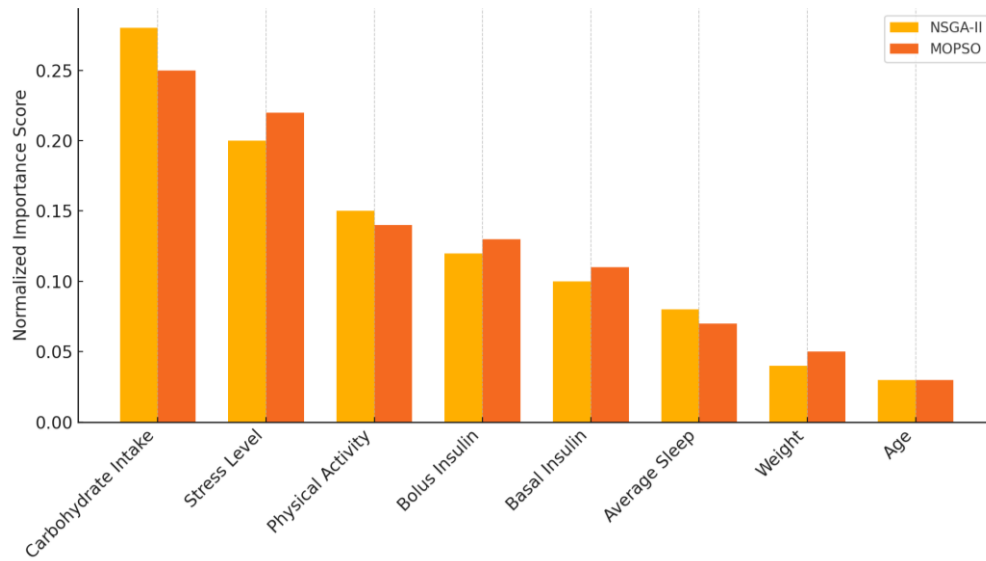


Figure 5. Feature Importance Scores from NSGA-II and MOPSO

These findings suggest that the proposed optimization framework is not only effective in generating accurate predictions but also capable of revealing interpretable insights into the underlying drivers of glucose variability.

## 6- Conclusion

This research presented a novel multi-objective optimization model for predicting and identifying influential factors in the management of Type 1 Diabetes, with an emphasis on balancing accuracy, interpretability, and practicality. The proposed framework integrates clinical and behavioral variables and applies two powerful metaheuristic algorithms—NSGA-II and MOPSO—to address the complexity and uncertainty inherent in diabetes control. By framing the problem as a multi-objective task, the model allows for the simultaneous optimization of glycemic regulation, insulin cost, and the minimization of unnecessary variables, offering a more holistic view of diabetes management.

The findings from this study underscore the effectiveness of NSGA-II in achieving superior convergence, diversity, and prediction accuracy. Across all performance metrics, NSGA-II consistently demonstrated broader Pareto front coverage, lower generational and inverted generational distances, and more accurate glucose level predictions. While MOPSO showed competitive results and had the advantage of faster execution times, its solutions were generally more concentrated and slightly less accurate in forecasting. The analysis of feature importance further confirmed that factors such as carbohydrate intake, stress level, and physical activity play significant roles in blood glucose variability, which reinforces the value of including behavioral dimensions in clinical models.

One of the key strengths of this research lies in its methodological flexibility. The manual implementation of algorithms in MATLAB enabled precise control over each phase of the optimization process, allowing for tailored solution methods to be adapted to the problem's structure. Additionally, the use of synthetic yet medically grounded data enabled the validation of the model without relying on potentially sensitive or inaccessible clinical datasets.

The proposed model and its algorithmic backbone not only improve the predictive capacity of diabetes control systems but also enhance their clinical interpretability and practical usability. This approach provides a valuable decision-support tool that can be adapted for personalized treatment planning. Future work could extend this model by integrating real-time data and incorporating adaptive learning techniques to further refine and personalize diabetes management solutions.

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