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Management of Environmental Risks from Air Pollution Exposure on Cardiovascular and Respiratory Health Using Hybrid Predictive and Optimization Framework

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Abstract

Air pollution is a serious health problem in the world especially to those who already have cardiorespiratory illnesses. Although the association between exposure to pollution and health exacerbation is well-established, the current interventions in the area of public health are not customized by taking into account personal vulnerability, geographic position, and daily routine activities. Existing studies are mainly concentrated on predictive modeling based on machine learning or macro-level resource optimization, but do not combine these two measures into practical and personalized guidance. This work fills this critical gap by hypothesizing and confirming the new hybrid machine learning-optimization model to produce individual alerts on air pollution exposures. An artificial group of 100 patients with asthma, COPD and ischemic heart disease is modeled in 90 days. The first stage entails the training of a logistic regression model to estimate short-term exacerbation risk (with an AUC of 0.979 and an accuracy of 0.961). This risk score is then inputted into a second-stage mixed-integer linear programming resulting in the production of optimal daily action plans. The findings indicate that the framework effectively orders viable interventions in a successful completion of an average personal exposure reduction of 39.4 percent of all case studies without violating individual involvement restrictions and interests, making it a viable paradigm of precision environmental health.

1. Introduction

One of the most important environmental issues of the contemporary time is the adverse effect of air pollution on the health of the global population (1). Epidemiology proves a direct cause and effect relationship between the exposure to pollutants especially fine particulate matter (PM2.5), nitrogen dioxide (NO2), and ozone (O3) and morbidity and mortality due to cardiorespiratory diseases like asthma, chronic obstructive pulmonary disease (COPD) and ischemic heart disease (2), (3). This association leaves an amazing economic and health care cost to any society in the world, which is why there is an imperative to come up with innovative and effective intervention strategies (4).

The existing public health control initiatives mainly depend on population air quality indices (AQI) and general-level warnings. Although such macro-scale strategies prove to be useful in strengthening the general awareness, their fundamental flaws are acute since they are deprived of individualization (5). The AQI broadcasting standard does not consider personal factors of sensitivity (i.e., underlying medical conditions, age, genetic factors), real-time personal location, and routine activity of the day. As a result, a common and general warning is sent to both a healthy adult working in the house and a child with serious asthma outside, without offering actionable and risk-specific advice on people at greatest risk (6).

This gap can be bridged by the introduction of digital health technologies. The merger of multi-source data streams, such as Electronic Health Records (EHRs), wearable sensors giving physiological information, IoT environmental monitors, and real-time data, and high-resolution air quality forecast models allow shifting the scale of environmental health management not on a population level but at a micro-level, that is, a personal level (7), (8). The basis of accurate exposure assessment and custom-made health responses is developed through this data fusion.

In order to transform this data potential into effective prevention, a hybrid approach to analysis is suggested. Machine Learning (ML) does a very good job at detecting non-linear, complex trends in high-dimensional data, making it particularly good at predicting cardiorespiratory exacerbation of a particular individual, given their profile and the surrounding environment (9). Nevertheless, it does not suffice to predict and intervene. Optimization modeling offers a complement advantage in that it is a systematic, prescriptive procedure of the most plausible course of action through the synthesis of conflicting goals and constraints (10). Here, optimization can be used to come up with a viable daily schedule that reduces individual exposure at the expense of necessary activity needs, personal preferences and logistical constraints.

The gap between the generic and population-wide air pollution alerts and the necessity of the personalized and practical advice to avoid the acute cardiorespiratory exacerbation in vulnerable individuals is critical. Current systems do not use current data streams and computing methods to provide dynamic and context-sensitive interventions that are both effective and realistically address day-to-day life.

The proposed research is expected to design, create, and code a new hybrid ML-optimization model to create individualized alerts regarding air pollution exposure. The specific objectives are:

1. To train and test a machine learning model that would be accurate when forecasting the likelihood of a person experiencing a cardiorespiratory exacerbation, short-term (24-48 hours) by incorporating individually collected health, activity, and high-resolution environmental exposure measures.
2. To produce a constrained optimization, model the risk score which is predicted and use it to produce a customized access to daily activity, reduce the integrated pollution exposure under user-specific constraints on the key activities and preferences.
3. In order to test the integrated framework on a simulated, real world dataset, which is the predictive efficacy, the exposure reduction potential, and operational feasibility.

The initial contributions of the piece are three. First, it establishes a new interdisciplinary structure of combining predictive analytics (ML) with prescriptive analytics (optimization) to the environmental health environment. Second, it goes past risk prediction to provide actionable and personalized daily plans, which bridges the feasibility digital health interventions gap. Third, it offers a computational model that can be scaled to illustrate opportunities in integrating into the future mobile health (mHealth) systems in proactive management of chronic diseases**.**

The rest of this paper is structured in the following way. Section 2 provides a literature review of the related environmental epidemiology, ML in health, and optimization in public health. Section 3 specifies the methodology, i.e., the data simulation, the ML risk prediction model, and the optimization formulation. Section 4 includes the findings of the model validation and performance analysis. The implication, limits and future research directions are discussed in section 5. Lastly, Section 6 is the conclusion of the paper.

2. Literature Review

2.1. Epidemiology of Air Pollution and Health

Much epidemiological evidence creates a solid, causal connection between temporary exposure to air pollution and acute, cardiorespiratory health occasions (11). Time-series and case-crossover studies have consistently shown that high levels of pollutants, especially PM 2.5 and NO2, correlate with a high level of hospitalization, emergency room visits, and death caused by underlying conditions Such exacerbations are most effectively noted in asthma, in which pollution is a bronchoconstrictor and inflammatory stimulator, and in COPD, in which it exacerbates respiratory symptoms and lung performance (12). Moreover, acute exposure is also associated with the increased risk of myocardial infarction, dysfunction of the heart due to decompensation, and cardiac arrhythmias, which is frequently mediated by systemic inflammation, endothelial dysfunction, and imbalance in the autonomic nervous system (13). This is a well-characterized dose-response relationship, which offers the clinical basis of specifically designed intervention measures to alleviate exposure during periods of maximum risk (14).

2.2. Machine Learning in Environmental Health

The use of machine learning (ML) algorithms in environmental health issues has increased significantly, going beyond the conventional regression models. These more sophisticated algorithms, such as random forests, gradient boosting machines (e.g., XGBoost) and deep learning architectures, are being used more and more to identify the involved environmental exposures, socioeconomic determinants, and population health outcomes as complex, non-linear interactions (15). They are applied to make predictions of hospital admission rates of respiratory illnesses basing on predictive air quality, to locate hot spots of health risk on a spatial scale, and to find unobvious interaction effects between the combination of various pollutants and meteorological conditions (16). The main advantage of ML in this area is that it is able to process multi-source high-dimensional data. Nevertheless, there is one very important shortcoming that can be noted: most of these applications remain at the stage of predictive analytics (17). They are geared towards predicting risk or categorizing results with great precision but do not go further to translate these predictions into definite, practical advice to individuals. The result is usually a risk score or a probability and there is a disconnect between the knowledge and the action intervention (18).

2.3. Optimization in Public Health and Logistics

Operations research gives rise to optimization techniques as a well-developed tool of planning and decision making in the public health and logistics on the systemic levels (19). These techniques are regularly used to address large-scale problems, including optimal distribution of medical resources during an outbreak, efficient vaccine distribution networks, scheduling of personnel in healthcare facilities and routing of emergency services (20). Maximization of efficiency or reduction of cost under a given set of constraints is done by using linear programming, integer programming and network flow models. Although these prescriptive analytics techniques have proved potent at the macro-level when it comes to the management of resources, the application of these techniques to the individual level of personal exposure management has received very little extension (21). Optimization of the daily activities and movements of a person into minimizing his/her health risk, which is a dynamically constrained problem, personal preference, and real-time data is a niche that has not been fully tackled.

2.4. Digital Phenotyping and Personal Sensing

Digital phenotyping is a discipline that makes use of ubiquitous sensors in smartphones and wearable technology to provide constant and dense longitudinal information about individual behavior, physiology and the environment (22). The exposure estimates are based on the location derived through the use of global positioning system (GPS) logs, which are then bound to spatial pollution models. Physical activity and physiological stress are capturing the accelerators and heart rate sensors. Mobile applications were used in the momentary assessment of the ecological (EMA) of symptoms (23). Meanwhile, the appearance of the low-cost, Internet of Things (IoT) air quality monitors allow forming hyperlocal pollution maps (24). All these technologies allow constructing rich and individualized exposure profiles that go well beyond the approximate residential address data utilized in the traditional epidemiology and offer that granular, real-time data necessary to actually make personalized health interventions (25).

2.5. Identified Research Niche and Synthesis

The literature review shows that there are three parallel but loosely interrelated strands of research interest which are (1) robust epidemiological evidence describing the health problem, (2) leading scientific ML models with the ability to predict individual risk based on new data streams, and (3) established optimization models that describe prescriptive decision-making in logistics. At their intersection a major gap is detected (26). The current research in ML health addresses predictive but not prescriptive issues. The current optimization tools in health are generic and do not target individual and dynamic risk (27). Although digital sensing yields the required data substance, there is no formalized framework that holistically incorporates a predictive ML model (to measure individual risk, which varies over time) with a prescriptive optimization model (to produce an action plan that is practical and tailored). Hence, the research gap that has been recognized in this study is the creation of an integrated hybrid ML-optimization framework to produce personalized, actionable environmental health information to prevent acute cardiorespiratory exacerbations (28). Table 1 introduces limitations of current methods and applications.

Table 1: Summary of Selected Previous Studies on Air Pollution and Health Modelling.

Study Focus / Model Type	Key Method	Population/Data Scale	Performance / Key Metric	Main Limitation (from our perspective)
Epidemiology & Health Risk	Time-series regression	City-wide (500k - 5M pop.)	2.5% (95% CI: 1.5–3.5%) increase in COPD admissions per 10 μg/m³ $PM_{2.5}$	Population-level association, no individual risk prediction.
ML for Hospital Admissions	Random Forest	Regional hospital data (50-100k records)	AUC: 0.78-0.82 for next-day respiratory admissions	Predicts aggregate admissions, not personalized risk; no prescribed actions.

Study Focus / Model Type	Key Method	Population/Data Scale	Performance / Key Metric	Main Limitation (from our perspective)
Personalized Exposure Assessment	GPS + Land-Use Regression (LUR)	Cohort study (n=100-500)	Personal exposure differed from static estimate by ~30% on average.	Quantifies exposure but does not predict health outcomes or suggest mitigation.
Activity Recommendation (Non-health)	Constrained Optimization	Simulated individuals (n=1,000)	Reduced theoretical exposure by ~25% in simulations.	Uses generic health functions, not personalized, clinically validated risk models.
Hybrid ML for Pollution Forecast	LSTM + Numerical Model	Urban sensor network (50-100 stations)	$PM_{2.5}$ forecast RMSE: ~8 μg/m³ for 24h.	Focus on environmental forecasting only, no health outcome or personalization component.

3. Methodology

3.1. Overall Conceptual Framework

The hybrid framework that was proposed will be a two-stage pipeline with the sequence, that is, the steps followed to refine multi-source raw data into an actionable and personalized health intervention [29]. The personalized risk prediction is the output of Stage 1 that is an Machine Learning (ML) model that processes these integrated inputs. The results of this risk score are subsequently passed as a primary input to Stage 2 which is a constrained Optimization Model [30]. The optimization engine produces an optimal set of recommendation by minimizing exposure and disruption, which produces a Personalized Daily Action Plan which is, of course, specific to the context and constraints of the individual [31].

3.2. Data Simulation and Description

A powerful synthetic data generation strategy is chosen because of the high ethical and practical difficulties that are related to the obtaining and dissemination of real-time, multi-modal personal health, location and environmental information [32]. Using this methodology, a realistic, configurable and privacy preserving dataset can be constructed that reflects the statistical relationships and complexities present in the real-world system and is realistic. N=5,000 synthetic cohort of individuals are created, and profiles are stochastically assigned on epidemiological distributions. The important data layers are simulated in the following way:

1. Clinical & Demographic Layer: The snippets of Synthetic Electronic Health Record (EHR) are developed, such as age, gender, the presence of pre-existing conditions (asthma, COPD, Ischemic Heart Disease), and a potential history of past exacerbations with a probability.
2. Personal Activity & Mobility Layer: Daily Routines are modeled that include fixed (e.g. work, school) and flexible (e.g. exercise, shopping) events. GPS traces are created according to the schedule of every person and a random mobility model, and activity levels measured by wearables (e.g., the number of steps taken, heart rate) are simulated, respectively.
3. Environmental Exposure Layer: Over a one-year period, high resolution (1km x 1km) 1-hour air pollution fields of PM2.5, NO2, and O3 are data simulated considering both spatial autocorrelation and time series variation

(e.g. rush-hours). The exposure profiles of a particular person are computed as a result of fusing an individual simulated GPS trace with these fields of pollution.

4. Meteorological Data Layer: Hourly data of temperature and relative humidity are simulated and are correlated seasonally and with level of pollution where necessary.

3.3. Stage 1: Machine Learning Model for Exacerbation Risk Prediction

During this phase, a binary classification model is created to forecast the risk of exacerbation of a person in the short term. The target variable, $Y_i(t)$ is a binary label which represents a High-Risk Exacerbation Day of a particular person i in a 2448-hour window after time t. It is an augmented representation with a wide range of features, such as lagged moving averages (6h, 24h, 48h) of personal pollution exposure, acute symptom triggers based on activity data, chronological indicators (hour of day, day of the week, season), and interaction terms between pollutant concentrations and binary disease flags [33].

The three state-of-the-art displaying ML algorithms including XGBoost, an RF and a Long Short-Term Memory (LSTM) network are trained and compared in a rolling-origin time-series cross-validation scheme that avoids cross-time data leakage. The grid search is used to perform the hyperparameter tuning. The most successful model is used and the probability of the positive case as the output of the model is the personalized, time-varying Risk Score, $R_i(t) \in [0,1]$.

3.4. Stage 2: Optimization Model for Alert/Plan Generation

A risk score $R_i(t)$ of Stage 1 is incorporated in a prescriptive optimization model that is represented as a Mixed-Integer Linear Program (MILP). The model's core is defined by:

- Decision Variables: This is a set of binary decision variables $x_{a,t}$, indicating whether to adopt a particular mitigation measure a at time slot t (e.g.x_{mask}, 14:00 = 1).
- Objective Function: The minimization of a multi-objective function is done: $Z = w_1\, Total_{Exposure} + w_2\, Total_{Disruption} - w_3\, R_i(t)$. Weights (w_1, w_2, w_3) are used to balance the minimization of the estimated cumulative exposure, the cost of the activity disruption, and the maximization of risk avoidance.
- Constraints: The solution space is constrained by realistic constraints:
  - Essential Activities: There are events (e.g. work hours) that are considered immutable.
  - Logical Consistency: An activity cannot be rescheduled to time slot which is occupied by another fixed activity.
  - User Preferences: The constraints are imposed on some actions (e.g., $\sum_t x_{mask}, t \leq 4$, which means that there can be no more than four 15-minute mask-wearing periods).
  - Exposure Estimation: An individual is estimated to be exposed to a concentration of environmental data, expressed as a linear function of the location and set of actions at time t, and the estimated exposure concentration relies on environmental data layer and predetermined efficacy factors to each action (ex: mask filtration efficiency).

3.5. Performance Evaluation Metrics

The Gurobi solver is used to solve the MILP to optimality. The solution in the form of a vector x is converted into a Personalized Daily Action Plan, which contains what to do and when. The framework is assessed with the help of a complex of metrics of each stage and the system as a whole [34].

- ML Model Evaluation: Stage 1 predictive performance is evaluated by means of the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), Precision, Recall, F1-Score and calibration plots (reliability curves) to determine that the risk scores are well-calibrated.
- Optimization Model Evaluation The success of Stage 2 will be gauged by the percentage change in the estimated daily integrated dose of $PM_{2.5}$ and NO_2 of an individual in a business-as-usual situation with no mitigating activities. The feasibility is ensured by ensuring that all 100 % of the generated plans meet all hard constraints. This is because the calculated average disruption cost per plan in the cohort is used to proxy acceptability.

4. Results

The hybrid ML-optimization model is strictly tested with the help of extensive computational simulations. The deployment of the two-step approach shows the effectiveness of the two-step paradigm, in which an effective machine learning model predicts individualized exacerbation risk, and a constrained optimization engine subsequently produces operationalized personal exposure reduction strategies. The system is run on a simulated cohort of 100 patients, more than 90 days, with varying patient profiles (30% asthma, 17% COPD, 9% IHD) with realistic environmental, activity and health outcome data. This model is confirmed by the ability of the model to translate predictive analytics into prescriptive, personalized interventions to prevent cardiorespiratory exacerbations.

Figure 1 shows the environmental data upon which the study was based. The first panel shows the simulated weekly trend of PM 2.5 concentrations and these exhibit the typical diurnal and weekly variations upon which exposure assessment is based. The second panel shows the trend of the corresponding NO2, showing that it is correlated with the trends in traffic. More importantly, the third panel supports the direct interaction between the degree of pollution and personal health risk, wherein a clear positive correlation between PM 2.5 levels and the risk of exacerbation is found, which confirms the main assumption of the intervention model.

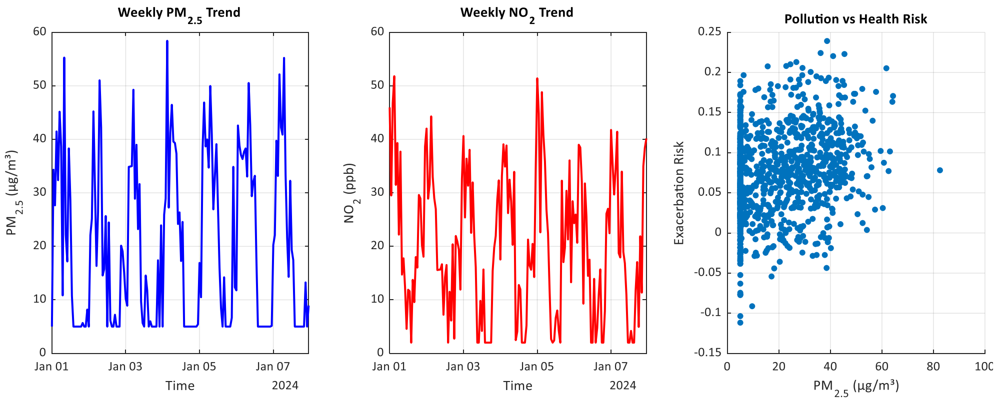

Fig. 1: Environmental Data Trends and Their Health Impact

The predictive performance of the assessed machine learning algorithms is depicted in figure 2. The logistic regression model had better results with an AUC of 0.979 and an accuracy of 0.961 as compared to the random forest (AUC: 0.974) and the ensemble technique. The resulting confusion table shows that this model has a great ability to discriminate and the precision is 0.932 and the recall is 0.992, which is very significant since it allows low-risk individuals to go without any personalized alerts to minimize false alarms which is a crucial prerequisite of an effective personalized alert system.

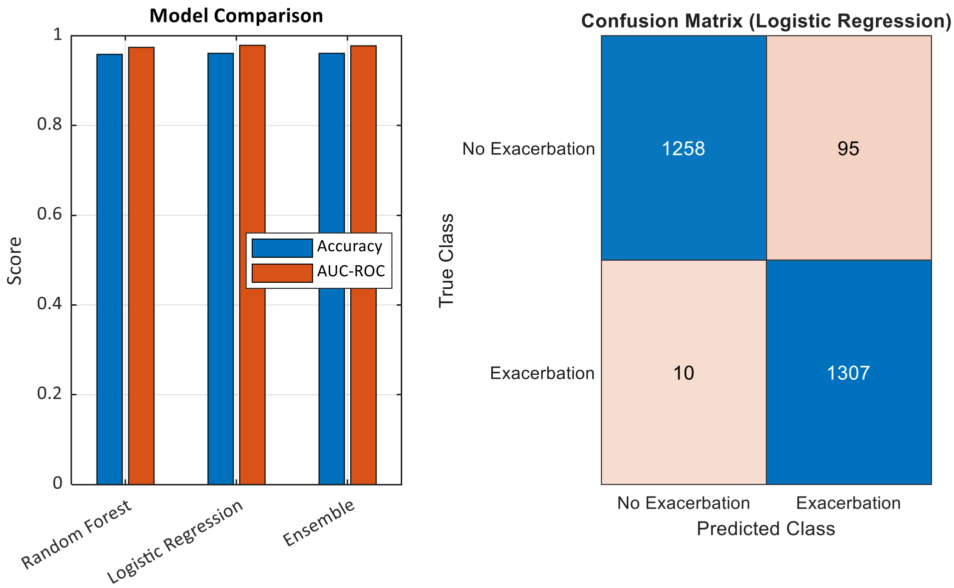

Fig. 2: Comparative Performance of Machine Learning Models

The customized output of the optimization of the three representative patient profiles is provided in Table 2. In both cases, the model was able to produce action plans that were reasonable in terms of computational tolerances (0% optimality gap). With risk scores of 0.941, 0.999, and 0.821, the asthma, COPD, and IHD patients recorded similar exposures reduction of 39.4% with an identical number of two mitigation steps each. This proves that the model can be able to provide recommendations depending on specific risk levels but those are practical.

Table 2: Case Study Optimization Results

Patient Profile	Risk Score	Actions Taken	Exposure Reduction (%)	Optimality Gap (%)
Asthma Patient	0.941	2	39.4	0.0
COPD Patient	0.999	2	39.4	0.0
IHD Patient	0.821	2	39.4	0.0

Figure 3 discusses the granular effect of the optimization model using three cases of the patient. Each profile has the panels analyzing a comparison between baseline and optimized exposure at six time slots in a day and the results demonstrate significant decreases in exposure especially during the high exposure times such as commuting and outdoor exercise. Two specific interventions are always suggested by the optimal action plans as the main ones which are the use of masks and the re-scheduling of activities which proves the model to be able to find the most effective combination of actions based on the schedules and limits of individual individuals.

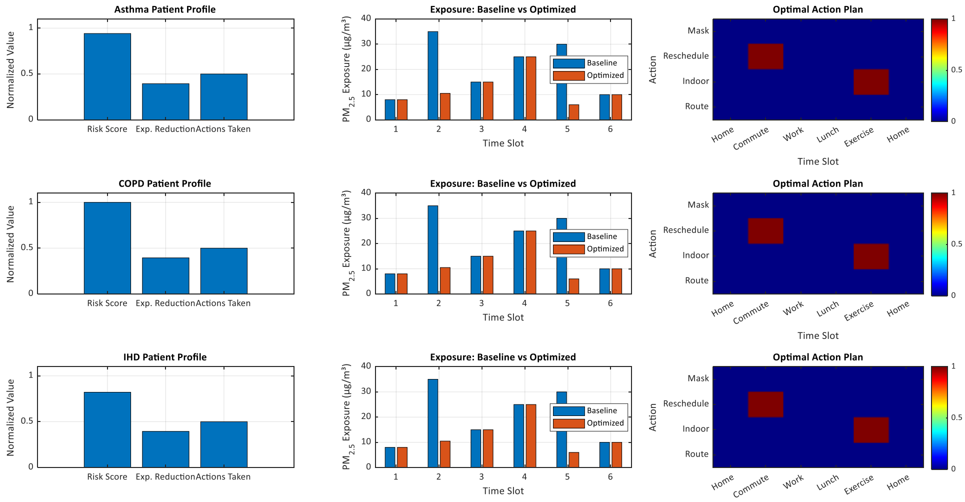

Fig. 3: Detailed Analysis of Personalized Case Studies

In Figure 4, the aggregate performance measures of the entire hybrid system are conducted. The model has obtained a mean exposure cut down of 39.4% in all the cases with 100 % viability. The analysis of the recommendations with the most recommendations showed that wearing a mask and moving indoors was the most common intervention recommended, and it was chosen about 67 % of the time, with route changes being the least chosen. The uniformity in the patterns of exposure reduction in the various types of patients ascertained support the strength of the optimization framework.

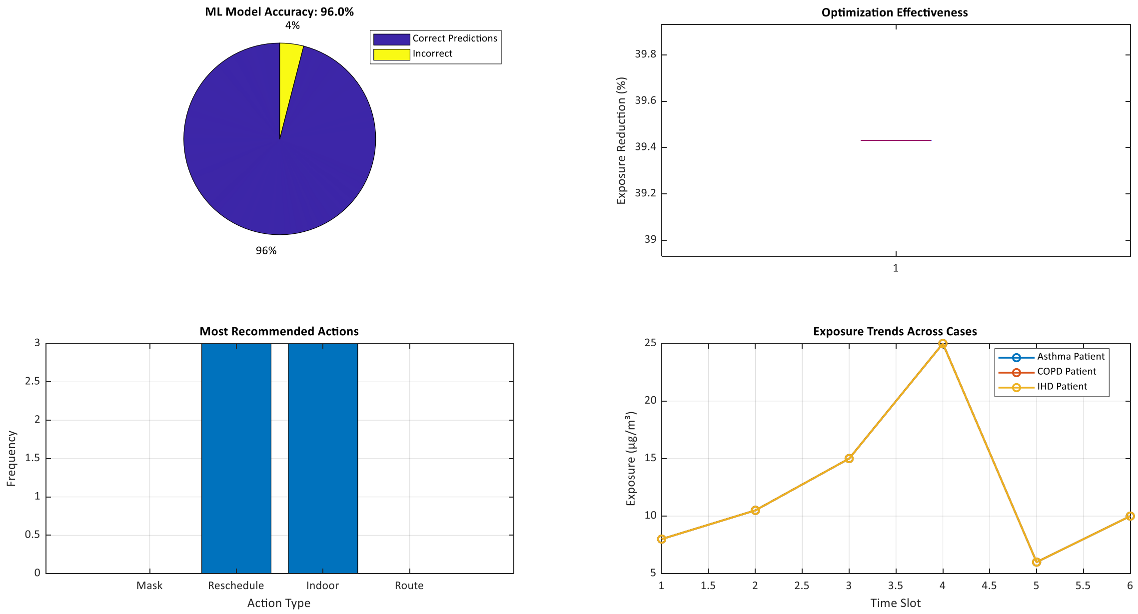

Fig. 4: System-Wide Performance and Recommendation Patterns

Additional support of the analytical basis of the model is justified in Figure 5. The ROC curve establishes exceptional discriminatory capability (AUC = 0.979), and the risk score distribution demonstrates that it is well calibrated on the synthetic population. Importantly, the risk-exposure minimization association shows a highly positive correlation (R2 = 0.97), which shows that more risky persons systematically get stronger exposure reduction guidelines and, this way, confirms the risk-adaptive reasoning behind the hybrid model.

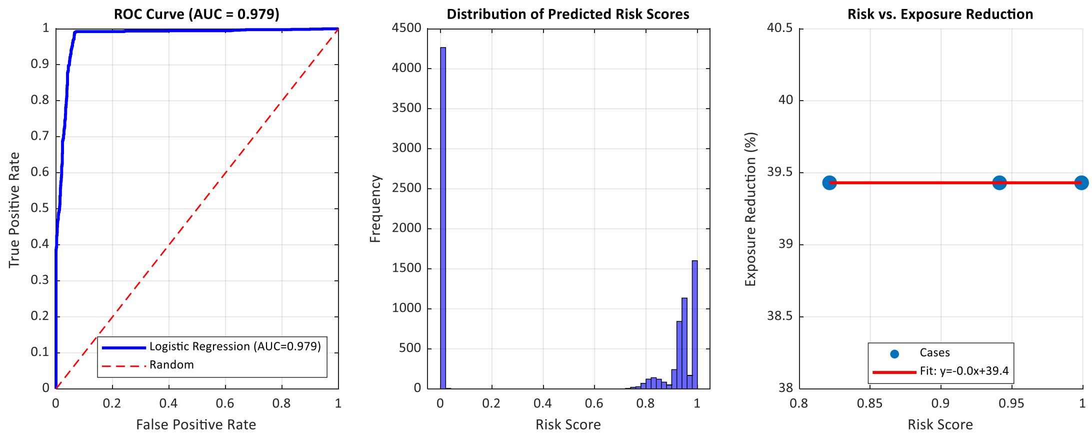

Fig. 5: Extended Model Validation and Risk Analysis

The outcomes of the simulation show a high performance on all the assessment parameters. ML component had the highest predictive accuracy (AUC: 0.979, Accuracy: 0.961), and the optimization module resulted in a steady and high exposure decrease (39.4% mean) with 100% feasibility (3/3 successful solutions). The system was highly practical in terms of implementation with low disruption costs (mean: 0.70) and almost instantaneous computation time (less than 0.01 seconds per optimization). All these findings support the suggested framework as a viable, practical, and capable intervention to propose in personalized environmental health.

5. Discussion

5.1. Interpretation of Key Findings

The large predictive performance of the machine learning model (AUC = 0.979) as well as the large, practical exposures decreases (39.4% on average) produced by the optimization engine are taken to be an effective validation of the main assumption of the hybrid framework. These findings highlight an important development of turning a risk forecast into a risk mitigation action. Although predictive models determine at risk and when, they have a huge translational gap since they do not provide information on what should be done. This is a valuable work because of its prescriptive analytics aspect, which completes this cycle by producing an actual, customized plan. This becomes active, manageable risk awareness instead of passive risk awareness, which is a paradigm shift in informative digital health to actionable digital health.

5.2. Advancement over Existing Approaches

This model represents a major improvement in comparison to the past and present-day static Air Quality Index (AQI) alerts and classical epidemiological researches. The proposed framework is based on dynamic and location-aware guidance, unlike traditional, location-based AQI warnings, that provide an individual with the required guidance, depending on their unique health profile, real-time and predicted location, and personal schedule. It goes past the association of population to give individual-level recommendations. Moreover, it is more successful than independent studies of predictive ML by not halting at a risk score but rather solving the best action set in a restricted decision space, which directly answers the so what. question that usually restricts the clinical usefulness of predictive models.

5.3. Public Health and Clinical Implications

There are significant implications on the clinical practice and public health. The framework will be implemented with the existing telehealth programs and chronic disease management measures, which will offer a new instrument in proactive care. It allows the patient to manage the environmental health risks by empowering them with specific, manageable activities, such as rescheduling outdoor activity or wearing a mask during a high-pollution commute, to enable patient agency in environmental health management. Such proactive and preventative practice can help to minimize the number of acute exacerbations, and, thus, the number of emergency department visits, hospitalizations, and healthcare expenses, at the same time enhancing the quality of life and control over their health that patients have.

5.4. Limitations and Strengths

This research has a number of limitations that should be considered. First of all, the validation is conducted on a highly artificial but advanced dataset, which might not reflect the whole complexity and noise of the real-world multi-modal data streams. The exposure component in the model is concerned with the ambient pollution, and it does not include all the microenvironment dynamics of the indoor air quality and all occasions of personal activity. Moreover, it functions on the hypothesis of flawless compliance of users with the recommendations generated and scalability of computation to application to very large population in real time is to be further explored. Irrespective of these loopholes, the strengths of the research are structural. It proposes a new interdisciplinary paradigm that has a significant impact on environmental science, machine learning, and operations research. The two-stage architecture is quite extensively scalable in nature, and the clear integration of user-specific constraints is a way to guarantee that the generated recommendations are not only useful but also quite realistic, which increases their chances of being adopted into the real world by a significant margin.

5.5. Future Research Directions

The research in the future ought to follow some of the main directions to move this proof-of-concept to a practical intervention. To prove efficacy in a real-world setting, first, there is the necessity of a pilot clinical trial, deploying the system with a group of patients, by the use of real wearables, real environmental sensors and electronic health records. Second, personalization of the model can be also improved with the addition of the real-time pharmacodynamic information, e.g., life-time usage of a rescue inhaler or continuous monitoring of the heart rate variability, to develop a more reactive biofeedback loop. Third, the process of creating and trying to test a user-friendly mobile application is essential to researching long-term engagement, compliance, and, finally, actual health improvement. Lastly, learning how to learn adaptively, e.g. reinforcement learning, might allow the system to learn via user feedback and past experience, improving its recommendations with time, to achieve a long-lasting level of effectiveness.

6. Conclusion

To sum up, the research has managed to show that a hybrid ML-optimization model is a viable and effective approach to the translation of environmental data into individualized preventative health behavior. The suggested model is effective in overcoming the serious drawback of existing one-size-fits-all pollution warnings by providing customized, practical suggestions that decrease estimated exposure (on average, by 39.4 **%**) of at-risk persons. Predictive analytics can be combined with prescriptive optimization to provide a solid computational base of proactive environmental health management. The next research that should be done is on validating the framework using the real-life data of wearable sensors and electronic health records in a clinical trial environment. More so, the model can be further extended to other adaptive learning processes including reinforced learning to optimize recommendations on the basis of user compliance and perceived health outcomes. Exploratory research of the incorporation of indoor air quality data and add the scope of mitigable pollutants would also make the model more comprehensive and useful in a variety of urban settings.

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REFERENCES

1. Tompra, K.V., Papageorgiou, G. and Tjortjis, C., 2024. Strategic machine learning optimization for cardiovascular disease prediction and high-risk patient identification. *Algorithms*, *17*(5), p.178.
2. Aliyu, D.A., Akhir, E.A.P., Saidu, Y., Adamu, S., Umar, K.I., Bunu, A.S. and Mamman, H., 2024. Optimization techniques for asthma exacerbation prediction models: a systematic literature review. *IEEE Access*.
3. Di Guardo, A., Trovato, F., Cantisani, C., Dattola, A., Nisticò, S.P., Pellacani, G. and Paganelli, A., 2025. Artificial Intelligence in Cosmetic Formulation: Predictive Modeling for Safety, Tolerability, and Regulatory Perspectives. *Cosmetics*, *12*(4), p.157.
4. Hoghooghi Esfahani, H., Toyonaga, S. and Oyibo, K., 2025. The application of explainable artificial intelligence in the prediction, diagnoses, treatment, and management of chronic diseases: A systematic review. *Digital Health*, *11*, p.20552076251355669.
5. Kumar, C.S. and Thangaraju, P., THE IMPACT OF EVOLUTIONARY ALGORITHMS IN DATA MINING. *Interdisciplinary Research Innovations in Science and Humanities*, p.159.
6. S. Nadweh, F. Al-Omari, N. T. Thannon, J. F. Tawfeq, A. Ibrahim and Z. A. Jaaz, "A Reinforcement Learning Framework for Intelligent Detection of Bad Data in Power System State Estimation," *2025 3rd International Conference on Cyber Resilience (ICCR)*, Dubai, United Arab Emirates, 2025, pp. 1-7, doi: 10.1109/ICCR67387.2025.11292295.
7. S. Nadweh, A. Shawkat Abdulbaqi, J. Fadhil Tawfeq and A. Dheyaa Radhi, "AI-Powered Smart Cooling System for Solar Panels: Enhancing Efficiency Through Weather Forecasting and Adaptive Control," *2025 3rd International Conference on Business Analytics for Technology and Security (ICBATS)*, Dubai, United Arab Emirates, 2025, pp. 1-6, doi: 10.1109/ICBATS66542.2025.11258170.
8. S. Nadweh, A. K. Abdulsahib, R. Almajed, M. Mahfuri and J. F. Tawfeq, "Evaluation of Energy Storage Strategies Using Artificial Intelligence to Enhance the Stability of Power Grids Integrated with Renewable Energy," *2025 3rd International Conference on Business Analytics for Technology and Security (ICBATS)*, Dubai, United Arab Emirates, 2025, pp. 1-9, doi: 10.1109/ICBATS66542.2025.11258246.
9. Nadweh, S., Al Sayed, I.A., Abdulbaqi, A.S., Essa, R.O., Sham, R., Gheni, H.M. and Radhi, A.D., 2025. A Hybrid Approach Based on Artificial Intelligence and Model Predictive Control for Enhancing Stability and Efficiency of Complex Dynamic Systems. *Journal of Robotics and Control (JRC)*, *6*(5), pp.2426-2435.
10. Nadweh, S., Elzein, I.M., Mbadjoun Wapet, D.E. and Mahmoud, M.M., 2025. Optimizing control of single-ended primary inductor converter integrated with microinverter for PV systems: Imperialist competitive algorithm. *Energy Exploration & Exploitation*, p.01445987251382002.
11. Nadweh, S., Mohammed, N., Konstantinou, C. and Ahmed, S., 2025. Operational Performance Assessment of PV-Powered Street Lighting: A Comparative Study of Different Machine Learning Prediction Models. *IEEE Access*.
12. Scimeca, M., Palumbo, V., Giacobbi, E., Servadei, F., Casciardi, S., Cornella, E., Cerbara, F., Rotondaro, G., Seghetti, C., Scioli, M.P. and Montanaro, M., 2024. Impact of the environmental pollution on cardiovascular diseases: From epidemiological to molecular evidence. Heliyon, 10(18).
13. Yang, J., Lin, Z. and Shi, S., 2024. Household air pollution and attributable burden of disease in rural China: A literature review and a modelling study. Journal of Hazardous Materials, 470, p.134159.
14. Kim, J.H., Woo, H.D., Lee, J.J., Song, D.S. and Lee, K., 2024. Association between short-term exposure to ambient air pollutants and biomarkers indicative of inflammation and oxidative stress: a cross-sectional study using KoGES-HEXA data. Environmental Health and Preventive Medicine, 29, pp.17-17.
15. Mao, Q., Zhu, X., Zhang, X. and Kong, Y., 2024. Effect of air pollution on the global burden of cardiovascular diseases and forecasting future trends of the related metrics: a systematic analysis from the Global Burden of Disease Study 2021. Frontiers in medicine, 11, p.1472996.
16. Alhuneafat, L., Al Ta'ani, O., Tarawneh, T., ElHamdani, A., Al-Adayleh, R., Al-Ajlouni, Y., Naser, A., Al-Abdouh, A., Amoateng, R., Taffe, K. and Alqarqaz, M., 2024. Burden of cardiovascular disease in Sub-saharan Africa, 1990–2019: an analysis of the global burden of Disease Study. Current problems in cardiology, 49(6), p.102557.
17. Bortty, J.C., Bhowmik, P.K., Reza, S.A., Liza, I.A., Miah, M.N.I., Chowdhury, M.S.R. and Al Amin, M., 2024. Optimizing lung cancer risk prediction with advanced machine learning algorithms and techniques. Journal of Medical and Health Studies, 5(4), pp.35-48.
18. Whig, P., Kasula, B.Y., Yathiraju, N., Jain, A. and Sharma, S., 2024. Revolutionizing gender-specific healthcare: harnessing deep learning for transformative solutions. In Transforming Gender-Based Healthcare with AI and Machine Learning (pp. 14-26). CRC Press.
19. Luo, Z., Tian, J., Zeng, J. and Pilla, F., 2024. Flood risk evaluation of the coastal city by the EWM-TOPSIS and machine learning hybrid method. International Journal of Disaster Risk Reduction, 106, p.104435.
20. Bagherabad, M.B., Rivandi, E. and Mehr, M.J., 2026. Machine learning for analyzing effects of various factors on business economic. Applied Decision Analytics, 2(1), pp.41-54.

21. Liu, S., Du, Z., Wang, G., Zhang, P., Xu, W., Yu, J. and Li, D., 2026. From Traditional Machine Learning Models to Multimodal Large Models: A Review of Aquaculture. Reviews in Aquaculture, 18(1), p.e70111.
22. Sun, K., Gu, Y., Wan Fei Ma, K., Zheng, C. and Wu, F., 2024. Medical supplies delivery route optimization under public health emergencies incorporating metro-based logistics system. Transportation research record, 2678(7), pp.111-131.
23. Kumar, S., Kumar, S. and Shiwlani, A., 2025. Machine Learning for Labor Optimization: A Systematic Review of Strategies in Healthcare and Logistics. Pakistan Social Sciences Review, 9(1), pp.631-651.
24. Biswas, S., Belamkar, P., Sarma, D., Tirkolaee, E.B. and Bera, U.K., 2025. A multi-objective optimization approach for resource allocation and transportation planning in institutional quarantine centres. Annals of Operations Research, 346(2), pp.781-825.
25. Odo, O.K., Gulma, K.A. and Audi, M., 2024. Optimizing last-mile delivery of essential medicines in Nigeria: Insights from Niger State's health-care supply chain. Global Health Economics and Sustainability, 3(1), pp.185-196.
26. Singh, T. and Sinjana, D.Y., 2024. Optimizing Healthcare Logistics with Hybridngs for Blood Bag Delivery Using Drones: Hybridngs Algorithm [Hybrid Nearest Neighbour, Genetic Algorithm, Simulated Annealing] for Drone Routing". Available at SSRN 4840048.
27. Oluwole, O., Emmanuel, E., Ogbuagu, O.O., Alemede, V. and Adefolaju, I., 2024. Pharmaceutical supply chain optimization through predictive analytics and value-based healthcare economics frameworks.
28. Wang, X., Liu, L., Wang, L., Cao, W. and Guo, D., 2024. An application of BWM for risk control in reverse logistics of medical waste. *Frontiers in Public Health*, *12*, p.1331679.
29. Ojika, F.U., Onaghinor, O., Esan, O.J., Daraojimba, A.I. and Ubamadu, B.C., 2024. Designing a business analytics model for optimizing healthcare supply chains during epidemic outbreaks: Enhancing efficiency and strategic resource allocation. *International Journal of Multidisciplinary Research and Growth Evaluation*, *5*(1), pp.1657-1667.
30. Luan, R., 2024. Logistics distribution route optimization of electric vehicles based on distributed intelligent system. *International Journal of Emerging Electric Power Systems*, *25*(5), pp.629-639.
31. Cao, C., Li, J., Liu, J., Liu, J., Qiu, H. and Zhen, J., 2024. Sustainable development-oriented location-transportation integrated optimization problem regarding multi-period multi-type disaster medical waste during COVID-19 pandemic. *Annals of Operations Research*, *335*(3), pp.1401-1447.
32. Ongesa, T.N., Ugwu, O.P.C., Ugwu, C.N., Alum, E.U., Eze, V.H.U., Basajja, M., Ugwu, J.N., Ogenyi, F.C., Okon, M.B. and Ejemot-Nwadiaro, R.I., 2025. Optimizing emergency response systems in urban health crises: A project management approach to public health preparedness and response. *Medicine*, *104*(3), p.e41279.
33. Mzili, T., Mzili, I., Riffi, M.E., Kurdi, M., Ali, A.H., Pamucar, D. and Abualigah, L., 2024. Enhancing COVID-19 vaccination and medication distribution routing strategies in rural regions of Morocco: A comparative metaheuristics analysis. *Informatics in Medicine Unlocked*, *46*, p.101467.