*Proceedings of the 11th World Congress on Mechanical, Chemical, and Material Engineering (MCM'25)*
*Barcelona, Spain - Paris, France - August, 2025*
*Paper No. ICMIE 155*
*DOI: 10.11159/icmie25.155*

# OSH Guardian: An Occupational Health Recommendation System Architecture Based on Worker's Health History and Individual Environmental Monitoring

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***Abstract*** **-** A recommendation system is an application designed to suggest items, content, or services to users based on their preferences or other data. This type of system has the potential to minimize the time and effort involved in the healthcare decision-making process in both clinical and occupational areas. This study presents the architecture of a recommendation system for occupational health and safety. The proposed solution uses both workers' health histories along with data from the Internet of Things monitoring devices that track common agents such as temperature, humidity, illuminance level, noise, dust, ultraviolet radiation, and the presence of flammable gases to assess and predict the likelihood of occupational diseases. The system provides alerts to help organizations make decisions, such as redesigning work processes to minimize workers' exposure to certain agents. The system was tested using exposure data collected in a real work environment.

***Keywords*****:** occupational safety · personalized management · environmental risk assessment · recommendation system · industry 5.0

## 1. Introduction

A recommendation system is an application designed to suggest items, content, or services to users based on their preferences, behaviours, or other data. This type of system is widely used in e-commerce, entertainment, news, and social media platforms. Machine learning algorithms act as the backbone of recommendation systems by enabling them to learn about user interests and find patterns between users or items [1-3].

In the healthcare domain, these systems are called Health Recommender Systems (HRS), designed to assist healthcare professionals with diagnoses and treatments. They also offer patients personalized information based on their health profile to help them monitor and improve their health [4]. HRSs have the potential to minimize the time and effort involved in the healthcare decision-making process in both clinical and occupational domains. However, research on their application in the occupational domain remains limited. In recent years, IoT solutions have begun to use recommendation systems to improve the suggestions by analysing device measurements and/or user behaviour [3-6]. In the field of occupational safety and health IoT devices can collect health parameters and environmental conditions to provide personalized recommendations.

This study presents the architecture of a recommendation system for occupational health and safety. The recommendation system is part of a larger project called OSH Guardian – which is an integrated monitoring system designed for individualized occupational environmental risk assessment and management. The system also includes Internet of Things (IoT) monitoring devices, web applications for employers to conduct worker registration and view exposure data, and a mobile application for workers. The referred monitors measure dust, noise, ultraviolet (UV) radiation, illuminance levels, temperature, and humidity, and check for the presence of flammable gases. The collected data is sent to the server that hosts the recommendation system and the other applications mentioned above. Our integrated monitoring system was previously presented in [7, 8].

The recommendation system uses both workers' health histories and data on exposures collected by the monitoring devices to predict risks and the possibility of the occurrence of occupational diseases. Machine learning-based classifiers are used to determine risk/no risk per sensor and this information is crossed with fixed rules to define recommendations for the organization. The system outputs indicate occupational diseases that can be caused by the monitored agents identified as a risk. The alerts are designed to assist safety and health professionals in making decisions and to help supervisors redesign work processes to minimize a worker's exposure to certain agents.

This paper explains the architecture of the recommendation system and its principles for creating relationships between agents, pre-diagnosed diseases, occupational diseases, and symptoms. The results of the tests conducted using exposure data measured in a real work environment are presented along with the challenges involved in designing this type of system.

## 2. Basic aspects of recommendation systems

A typical recommendation system consists of data collection modules, modelling algorithms to create patterns or relationships, and prediction algorithms to provide recommended items to the user. According to Sun et al. [9], regarding recommendation techniques, the four main categories of recommendation systems are:

• Collaborative Filtering (CF): Uses the ratings/profiles of other users to recommend items. In the healthcare domain, similar health conditions would result in the recommendation of similar treatments.

• Content-Based (CB): Recommends items based on the user's past preferences. In healthcare, this can include historical data on diseases and treatments.

• Knowledge-Based (KB): Recommends items based on knowledge about the items, explicit user preferences, and a set of constraints that describe the dependencies be-tween user preferences and item properties.

• Hybrid: Combines algorithms in different ways to create a more well-rounded recommender.

The typical metrics for evaluating recommendation system’s performance are recall, precision, accuracy, ROC curves, and F-measure [10].

## 3. Recommendation system architecture

The recommendation system is part of the OSH Guardian project, an integrated monitoring system designed for individualized occupational environmental risk assessment and management. The system also includes web applications for organizations, a mobile application for workers, and monitoring devices to measure dust, noise, UV radiation, illuminance, temperature, humidity, and the presence of flammable gas.

The monitoring device is composed of a microcontroller running an embedded application, light-emitting diodes (LEDs) to indicate the detection of high exposures, and low-cost sensors. Measurements are taken every ten minutes for all quantities, except for the concentration of flammable gases, which is checked every minute, because if its volume is dangerous, the worker must leave the building immediately. The monitoring equipment is fully described in our previous studies [7, 8]. During these steps, it was also necessary to build the server with the appropriate applications to process the measurements (IoT software and database), a mobile application backend, and web applications to display exposures, register employees and health profiles, as well as address privacy issues.

In the context of our occupational health and safety recommendation system, the problem is to use both workers' health histories and the data collected by the monitoring devices on exposures to common agents to predict risks and the possibility of occurrence of occupational diseases.

As described earlier in this paper, a recommendation system is knowledge-based if it provides recommendations based on specific user queries. It may ask the user to provide a set of rules for what the results should be. The system then searches its database and returns similar results. Our proposal uses a similar approach, but with pre-fixed rules. The potential users of our system are occupational health professionals and supervisors.

### 3.1. Stages of the integrated monitoring system

The stages of the integrated monitoring system are described below:

1) Employee registration on the system's web interface: the following information must be provided to complete the registration: gender, date of birth, disease history and symptoms, subsidiary, sector, job, job start date, other positions the employee may have at the company (if any), and total time worked in other companies in similar positions. The job must be chosen from a list that contains professional activities related to civil construction and building maintenance. Fourteen jobs were included: air conditioning technician; bricklayer; carpenter; construction cleaning worker; construction general worker; ditcher; drain man; electrician; gardener; gutter installer; painter; plasterer; plumber; and roofer.

2) Continuous data collection with the monitoring devices: The devices send the measurements encrypted to the server running in the cloud.

3) Data storage and processing: The server runs a set of applications to process, display, and analyse data received from the monitoring devices.

4) Recommendation: The system uses both machine learning and pre-fixed rules to generate alerts for the company.

The architecture of the proposed recommendation system is shown in Figure 1.

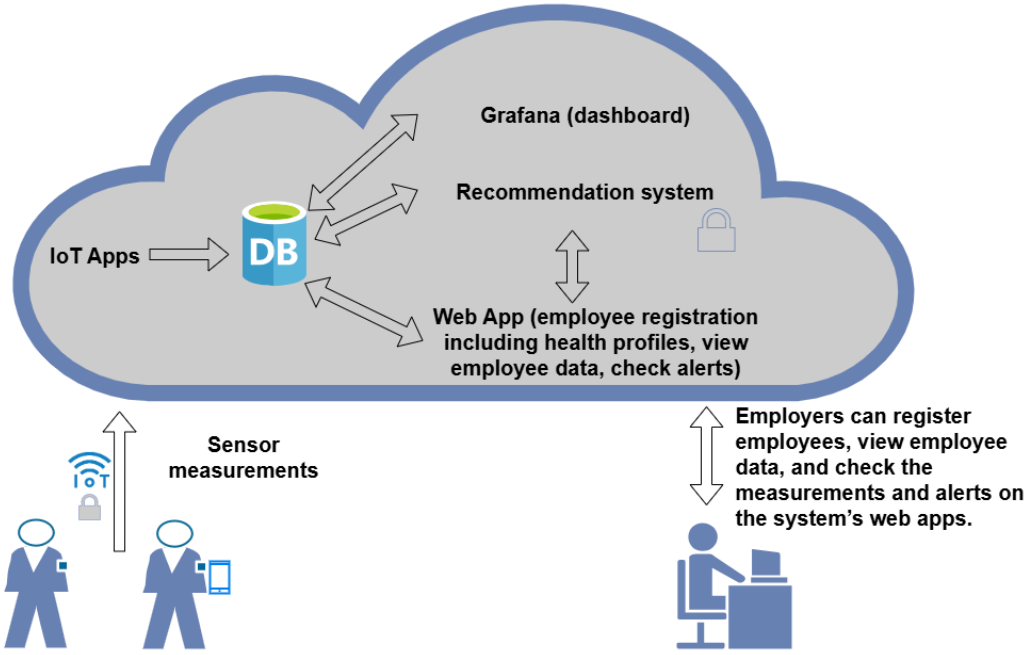


Fig. 1: Architecture of the proposed recommendation system.

### 3.2. Measurement analysis per sensor

In our system machine learning is applied to analyse the readings from different sensors – UV radiation, illuminance level, temperature, humidity, dust, and noise and identify whether the values read represent a risk to the worker's health. The concentration of flammable gases is not considered by the recommendation system, but to alert the worker to leave the building if a dangerous level is detected.

Since it was not possible to find datasets with all the information necessary for training a machine-learning model, a data generator was built for this work using Python programming language. For all the quantities were considered both the ranges that can be read by the monitoring devices, which are dependent on the capabilities of the sensors, and the exposure limits specified in current regulations. Data was generated to represent both normal and risky situations. Classifiers are used to decide the risk/no risk per sensor and this information is matched with the pre-fixed rules to define the recommendations when high exposures are detected. The data generator is fully described in our previous study [8].

The recommendation system has a preventive approach. It should identify in advance conditions that could lead the worker to become sick and not just conditions that do not comply with current regulations. To analyse the sensor

measurements, sixteen machine learning algorithms were evaluated, such as Support Vector Classification (SVC), Decision Tree Classifier, Random Forest Classifier, Gradient Boosting Classifier, Naive Bayes, and K Nearest Neighbour (KNN). The Random Forest model [11] presented a maximum performance for all sensors considering F1-score, precision, recall, AUC, and ROC curves, and was therefore selected to compose the classification solution for this work. The testing of the algorithms is detailed in our previous study [8].

### 3.3. Pre-fixed rules

To create the pre-fixed rules, the appropriate literature was consulted, together with the collaboration of two physicians. The complete set of rules is described in our previous study [7], and a few examples of the rules are shown in Table 1.

Table 1: Examples of relationships between the monitored agents, pre-diagnosed diseases, occupational diseases, and symptoms.

| **Agents** | **Pre-diagnosed Diseases** | **Symptoms** | **Occupational diseases that may be caused by the agents** | **Agents** |
|---|---|---|---|---|
| Dust [12-14] | Asthma<br>Lung cancer<br>Respiratory diseases<br>Previous tuberculosis infection<br>Smoker | Chest pain<br>Cough<br>Dyspnea (shortness of breath)<br>Fever<br>Hemoptysis (blood cough)<br>Weight loss | Pulmonary fibrosis (asbestosis)<br>Lung cancer (due to inhalation of asbestos dust) | Dust [12-14] |
| Heat [15,16] | Diabetes<br>Heart disease<br>Hypertension<br>Hypotension<br>Kidney disease | Chest pain<br>Dyspnea (shortness of breath)<br>Fainting (syncope)<br>Headache<br>Increased thirst<br>Increased urinary volume<br>Weight loss | Dehydration (favours the occurrence of kidney problems)<br>Heart attack<br>Stroke<br>Dryness of the nasal mucosa (favours the emergence of respiratory infections) | Heat [15,16] |

The "Pre-diagnosed Diseases" column consists of pre-existing conditions that are likely to be aggravated if the worker is exposed to the agents. The "Symptoms" column consists of conditions that may be the first signs of an occupational disease caused by the agents. Finally, the "Occupational diseases that may be caused by the agents" column consists of conditions that workers may develop if they are exposed to the agents.

It is important to emphasize that the causes of pre-diagnosed diseases and symptoms reported by workers when they register with the system are irrelevant in the context of the proposed recommendation system. A worker may not know whether the disease was acquired from work-related causes or not, so including this variable would make the relationships more complex. However, it is assumed that a worker with a pre-diagnosed condition, whether or not caused by past

occupational activities, who is frequently exposed to agents known to aggravate such conditions, may have a deterioration in health. Symptoms are relevant because it is assumed that a symptom can be one of the first signs of an occupational disease, even though it may be a temporary condition and not serious. Given the preventive approach of the proposed solution, triggering alerts earlier can be effective, since in a real workplace the employer would have time to change worker assignments, workflows, etc.

In addition, occupational diseases are characterized by a causal link between the damage to the worker's health and work-related exposures, such as physical and/or chemical agents. An employee who is frequently exposed to an agent may or may not develop one or more diseases associated with that agent. However, if the worker is exposed to an agent and becomes ill, a causal relationship can be established. This means that it cannot be concluded that a disease was caused by exposure to specific agents unless the occupational health professional has supporting tests available.

## 4. Tests

The real-world tests were conducted at a construction and maintenance company in Porto Alegre, Brazil. The tests ran for 6 days from 9 am to 6 pm. During the tests, six devices were placed near the workers, but they were not directly used or handled by the workers to avoid discomfort, interference with work routines, and privacy concerns. A civil construction and maintenance workplace was selected to conduct the experiments because this type of workplace is widely known to be hazardous, with the possibility of high exposure to all the monitored agents.

To protect privacy, no confidential employee information, such as personal and health profile data, was provided. The company representative provided only general information about the composition of the team, such as the proportion of men and women, age group, jobs, and time with the company. There were 20 workers and they were all between the ages of 20 and 50, including both men (70%) and women (30%), who had been with the company between 2 to 15 years. The workers involved had the following jobs: air conditioning technicians, bricklayers, carpenters, construction cleaning workers, construction general workers, drain men, electricians, gardeners, painters, and roofers. Based on this general information, two fictitious employee health profiles with very common diseases were created to enable analysis of the potential impact of the recommendation system in a real-world application. These profiles were registered in the web application and they are shown in Table 2.

Table 2. Employee health profiles.

| Device / Worker | Gender | Age | Years with the company | Pre-diagnosed diseases | Symptoms |
|---|---|---|---|---|---|
| 6001 - Bricklayer 1 | M | 44 | 10 | Asthma | None |
| 6006 - Painter 1 | M | 37 | 4 | Previous allergic diseases and reactions<br>Heart disease | Dyspnea (shortness of breath) |

The tests were conducted only on clear days between December 09, 2024, and December 28, 2024, to avoid damaging the devices, which were placed outdoors near the workstations. Days with intermittent transmission due to connectivity issues were excluded from the analysis.

## 5. Results

The devices monitored all the above-mentioned quantities. Unit 6001 was placed near a group of workers performing maintenance on the pavement in the sun. The unit remained in the shade of a tree or under an umbrella. The test period was from December 09 to December 14 for this group of workers due to the activity that was performed. During the testing, the

weather was sunny every day and temperatures were above 30 degrees on most days. Figure 2 shows the exposure data for the monitoring device 6001. The graphs were generated using the Grafana tool [17].

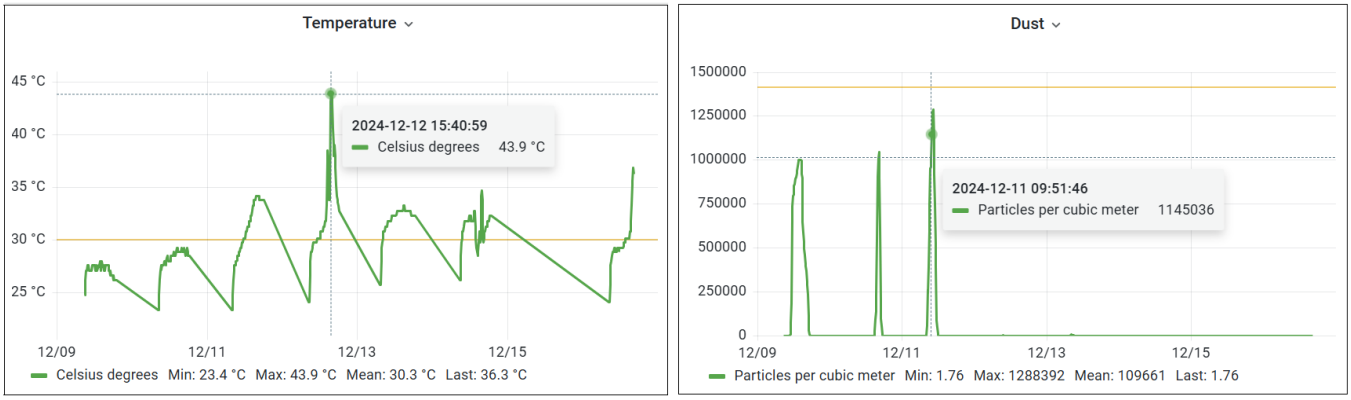


Fig. 2. Temperature and dust exposure graphs for bricklayer 1.

As illustrated in Figure 2, high temperatures and high exposure to dust were recorded for employee "Bricklayer 1". The higher temperature was 43,9 ˚C and the higher volume of particles per cubic meter was 1,288,392, with an average of 109,661. According to the rules of the recommendation system, which are more restrictive than the current standards, the desirable values of temperature are under 30 ˚C and 1,000,000 particles/m$^3$. The high levels of dust were detected due to the activities of removing pieces of the concrete from the pavement using a crusher and a hammer. In addition, high levels of exposure to UV radiation were detected, with a total SED of 66,3. The maximum value for a day should be 1,3 SED. The proposed system, by adopting a preventive approach, considers that daily values of 0,5 SED should already generate alerts, given the seriousness of the illnesses that can be caused by excessive exposure to the sun. On several occasions, during the tests, the noise level exceeded 84 dB, and low relative humidity (under 50% and even under 40%) also occurred. No significant variations in illuminance were recorded because the device remained stationary.

Unit 6006 was placed in the shade most of the time, near a group of workers who were painting a wall. The test period was from December 16 to December 28 for this group of workers due to the activity being performed. During the test, it was sunny every day and the temperature was above 30 degrees on most of the days. According to the measurements obtained from the monitoring device, the higher temperature was 36,9 ˚C. Relative humidity under 50% was registered, but not most of the time. The other quantities were mostly normal. Table 3 summarizes the recommendations made by the system.

Table 3. Recommendations.

| **Device / Worker** | **Pre-diagnosed diseases** | **Symptoms** | **Agents with high exposures** | **Diseases that may be caused due to exposures** |
|---|---|---|---|---|
| 6001 - Bricklayer 1 | Asthma | None | Dust<br>Heat<br>Low humidity<br>Noise<br>UV | Pulmonary fibrosis, lung cancer, dehydration, heart attack, stroke, dryness of the nasal mucosa, worsening of respiratory diseases, hearing loss, hypertension, skin lesions, burns, skin cancer, photosensitization, |

| | | | | |
|---|---|---|---|---|
| | | | | erythema, acute inflammatory eye reactions, increased risk of cataracts, suppression of the immune system |
| 6006 - Painter 1 | Previous allergic diseases and reactions Heart disease | Dyspnea (shortness of breath) | Heat Low humidity | Dehydration, heart attack, stroke, dryness of the nasal mucosa, worsening of respiratory diseases |

## 6. Discussion

During the tests with the OSH Guardian complete monitoring system in a real working environment, the very high levels of dust, temperature, noise, and UV radiation measured for the group of workers who were close to the 6001-device stood out. Low levels of relative humidity were also recorded. The workers were maintaining a pavement in the sun. On the other hand, the workers near to the 6006-device were exposed to high temperatures, up to 36,9 degrees Celsius, while the other quantities were normal when they were painting a wall, mostly in the shade. It was highlighted that groups of workers performing activities at the same site may have very different exposure levels to the same agents, which underscores the need for further investigation into potential health risks.

In terms of the main challenges faced in establishing the architecture of the recommendation system, the following should be highlighted:

1) Given the large number of health conditions that may result from and/or be aggravated by the exposures, it is difficult to select items to establish relevant relationships between agents, health profiles, and occupational diseases.

2) A person who is often exposed to an agent may or may not develop a disease associated with that agent. This means that alerts should always be preventive. In a commercial application, the ability to set preferences and filters regarding the number of alerts or intensity should be necessary, especially when dealing with a large number of workers.

3) It was not possible to find on the Internet datasets all the information necessary to train the machine learning models to analyse the readings from the sensors, so it was needed to build a data generator.

4) It was also not possible to find a dataset with information on health profiles, exposures, and occupational diseases. This type of dataset could be used to include in the recommendation system the analysis of past events in similar scenarios.

## 7. Conclusion

This paper presents the architecture of a recommendation system for occupational health and safety, using both workers' health profiles and data collected by IoT devices. The system was tested in a real workplace in the construction and maintenance industry. The tests revealed very high exposures of a group of workers to dust, temperature, noise, and UV radiation, emphasizing the relevance of this type of individualized environmental risk monitoring and management. In the design of the recommendation system, due to the large number of possibilities, the selection of items to build relevant relationships between agents, health profiles and occupational diseases is a very complex task. Together with this problem, the lack of datasets with common measurements and diagnosed occupational diseases is a relevant challenge for the design of occupational health recommendation systems.

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