Online Safety Risk Management for Underground Mining and Construction Based on IoT and Bayesian Networks

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Abstract –

Management of environmental hazards in underground mining and construction sites has always been a challenging task for project managers and site engineers. Poor ventilation, the production of hazardous gases, dust, and considerable heat and humidity are some of the inherent characteristics of these ecosystems. Most conventional underground risk management methods are static and overly simplistic, making it almost impossible to predict and control these complex hazards. This paper aims to develop an online safety risk management system for underground mining and construction environments that enables dynamic and remote monitoring, analysis, and control of safety risks in underground space. The proposed system benefits from an automated combination of Internet of Things (IoT) wireless sensors as an environmental perception layer and Bayesian networks (BNs) as a powerful risk modelling engine. Using an open-source dataset collected in a real underground coal mine, a proof-of-concept example is presented to demonstrate the applicability of the proposed system. The proposed system will enable real-time and remote monitoring of underground ecosystems and enhance worker safety upon implementation.

Keywords –

Online Safety Risk Management; Internet of Things; Bayesian Networks; Underground Mining and Construction

1 Introduction

Recent years have seen a considerable amount of volatility in the international economy. Aside from political and economic instability, the mining and construction industries are also facing decreasing productivity, skills shortages, and social and environmental concerns [1]. The rapid exhaustion of near-surface coal seams and the growing demand for mineral resources has led underground mining activities to move deeper into the earth to extract coal deposits. Consequently, the environmental condition of mines located at greater depths deteriorates due to poor ventilation and the production of hazardous gases, dust, and a significant amount of heat [2]. Particularly, there are many risks associated with underground coal mining, including high temperatures, high humidity, and the release of destructive gases. Reviews of historical coal mine accidents reveal that, despite technological advancements, major explosions have been ineffectively controlled, and adequate safety measures have failed to be implemented [3, 4]. As these risks are complex in nature, it is often difficult to predict and control them. It is, therefore, imperative to implement innovative solutions, best practices, and additional safety precautions to overcome these challenges and reap substantial economic benefits.

In many regions worldwide, mining and construction companies still use manual methods to assess the risks [5]. On the other hand, the more advanced risk assessment methods are generally offline and static, whereas the risks in underground spaces tend to be dynamic [6]. It has been demonstrated that traditional methods of analysis are insufficient for quantitative evaluation, dynamic control, and uncertainty management [7]. Most studies fail to represent the dynamic nature of coal mining adequately. Additionally, traditional methods cannot examine the non-linear relationships between safety data [8]. Due to the high risks and high costs associated with the experimental analysis of large-scale, complex gas explosions, it is impossible to reproduce the large-scale explosion evolution process through experimental techniques. The Computational Fluid Dynamics (CFD) simulation models are also ineffective since they are computationally intensive and incapable of incorporating dynamic information related to emergency rescues [9]. It is common practice in coal mines to have monitoring, supervision, and dispatching systems well integrated with machinery, devices, and transportation systems. Moreover, systems are designed to monitor natural hazards such as methane concentrations, seismicity, and fires. Even so, the collected data is typically used only for visualization purposes, when deeper analysis could significantly improve many coal mining processes [10].

This paper aims to develop an online safety risk monitoring and management system for underground mining and construction environments that enables real-time, dynamic, and remote monitoring, analysis, and control of safety risks. The study benefits from the powerful risk assessment capabilities of Bayesian Networks (BNs) to represent the probabilistic and complicated nature of safety risks in underground mining and construction environments. The online data streams of the Internet of Things (IoT) sensors provide input to the BNs to enable the real-time monitoring of safety risks.

2 Background Review

This section reviews the state-of-the-art methods and technologies commonly used in the underground environment to manage safety risks.

2.1 Underground Safety Risk Management

Risk analysis methods in underground engineering can be divided into qualitative and quantitative approaches. Among the former are safety testing lists, Delphi's technique, interviews, brainstorming, the comprehensive fuzzy evaluation method, etc. Quantitative approaches include event tree analysis, Fault Tree Analysis (FTA), decision trees, support vector machines, neural networks, etc. [7]. In the mining industry, there has been an increasing interest in risk assessment and management, as evidenced by a significant number of publications and reports focused on these issues. Intensive mining, which results in large-scale production, is associated with numerous risks related to mining operations and the interaction between the mining system and the environment. Therefore, it is particularly important to conduct research on risk analysis, assessment, and management for this sector, especially concerning ecological, social, and economic factors. Risks should not only be evaluated in terms of their professional implications (human factor) but also in terms of their strategic implications (environmental impact) and operational concerns (safety, equipment, and the correctness of the mining process) [11].

2.2 Bayesian Network Applications in Underground Safety

Since their first adoption in the late 1990s, BNs have been extensively used in risk and reliability assessment, accident modelling, diagnostics, and prognostics [6]. Tong et al. [9] developed a BN to study the factors influencing mine gas explosions. The authors used expert knowledge and the Delphi method to determine conditional probabilities. According to the authors, BN offers several advantages, such as multi-scale node variables representing diverse types of influential factors, representing uncertain factors during disaster evolution, and dynamic probability updates. In addition to representing various gas accumulation sources and influences, the proposed model would also incorporate dynamic explosion impacts on ventilation systems and roadways and emergency rescue or intervention measures in the process of successive gas explosions. The BN is generally established by learning the network's structure and the model's parameters based on sufficient data. Nevertheless, collecting enough data in some research fields may be difficult. Expert knowledge can also be used to determine the BN in this case. Despite its ability to structure safety and control knowledge, the proposed method deals with gas explosion accidents passively. It allows the personnel only a minimal time to evacuate the site.

It is also a hot topic in research to learn the structure and relationships in BNs from data. BNs were used by Li et al. [12] to predict rockburst risks in underground spaces. BN was constructed utilizing the Tree augmented Naïve Bayes classifier with five parameters, namely the buried depth of the tunnel, maximum tangential stress of surrounding rock, the uniaxial tensile strength of rock, the uniaxial compressive strength of rock, and elastic energy index. A dataset of rockburst case histories was studied to learn conditional probabilities. The database contained 135 case histories, of which 83 were rockburst cases, and 52 were non-rockburst cases. In addition to the 8-fold cross-validation, the model was also validated with another group of 15 incomplete case histories that were not used during training. The Bayesian approach was utilized by Rusek et al. [13] to create a decision support system for assessing the risk of damage to prefabricated reinforced concrete buildings exposed to the industrial environment of mines that can cause subsidence and tremors. To learn the structure of the BN from data, the authors used two types of score-based methods. The Tabu-search algorithm was used as the first method to search iteratively for potential solutions. Second, a stochastic search algorithm was used based on the global optimization algorithm Simulated Annealing. Analyzes were conducted in R using the catnet and bnlearn packages. The study data was collected from a database of 129 prefabricated reinforced concrete buildings in a copper mining area in Poland. A total of eight damage intensity indices were used to analyze the risk of structural and finishing elements being damaged.

Li et al. [14] used a Fuzzy Bayesian Network (FBN) to analyze the risk factors of ignition in mines. The expert group decision-making method was used to construct risk topological and structural models of ignition sources. Experts were weighted using a FAHP. The technique can be used to calculate the probability of occurrence of potential risk events and the probability distribution of risk factors using causal reasoning, logical reasoning, and sensitivity analysis. Historical data of 215 major gas explosion accidents in China from 2000 to 2017 were studied to characterize possible accidents. Netica software produced by Norsys was used to create the BN. Wu et al. [15] presented a Dynamic Bayesian Network (DBN) to analyze dynamic road surface damage caused by tunnelling over time. In order to construct the DBN and its relationships, the authors consulted standards, technical reports, expert experience, as well as some qualified fault trees. The BN parameters were derived from 786 monitoring records regarding tunnel-induced road surface settlement and its influential variables. This was accomplished by employing the K2 algorithm, a well-known algorithm for BN structure learning. The dynamic nature was determined by expert estimation. In order to demonstrate the feasibility and applicability of the proposed system, a case study was conducted for the Wuhan Yangtze Metro Tunnel in China.

2.3 IoT-Enabled Underground Safety

IoT technology has been applied in a wide array of applications to provide solutions to manufacturing and transportation [16]. In recent years, IoT has also found its way into underground safety applications, helping to improve the safety and efficiency of underground operations. Zhou and Ding [16] proposed an IoT-based hazard energy monitoring system for underground construction sites, which involves identifying hazard energy, collecting data, and analyzing safety barriers. The authors discussed technical, operational, and organizational safety barrier systems and compiled a checklist of hazard energy sources. IoT technologies were employed to gather information about hazardous energy on the underground construction site.

Zhang et al. [17] proposed an Artificial Intelligence Internet of Things (AIoT) system for real-time monitoring of tunnel construction. The authors categorized tunnel information into three groups: tunnel geometric factors, geological parameters, and shield operational parameters. A database of 12 parameters was created, including the above parameters, and measured settlement data. IoT sensors were used to capture real-time shield data parameters. Geometric and geological parameters were determined prior to tunnel construction. Random Forest models were employed to predict operational parameters for successive rings and the resulting settlement with high accuracy.

Dey et al. [18] proposed a hybrid CNN-LSTM model to improve the safety and productivity of underground coal mines using IoT-enabled sensors. In this study, IoT sensors installed in the underground mine transmitted data wirelessly to the control room on the ground. The CNN-LSTM model extracted spatial and temporal features from mine data to predict the miner's health quality index (MHQI) for working faces and gas concentration levels in goaf areas. The predicted results were displayed in the control room using the graphical user interface developed for the digital mine software. The proposed prediction model achieved an accuracy of 89.2% for MHQI and 99.3% for methane prediction.

3 Methodology

Figure 1 provides an overview of the proposed research framework. There are three interrelated parts to the framework. The first part is associated with the physical underground mining and construction environment. Here, a network of IoT sensors will be deployed according to a predesigned layout to collect data about environmental factors, such as wind speed, temperature, atmospheric pressure, and methane concentration. The measurements will be transferred to data storage for later use in the data pre-processing module. The time-series data will be cleaned and labelled according to the requirements of the BN inputs. A BN will be created that considers the cascading causes and effects of safety accidents in the underground environment. Real-time IoT measurements will then be fed into the BN. Once the BN is activated, the probability distribution of accidents and their consequences will be immediately updated. Different parts of the proposed framework are explained in the following sections.

3.1 Environmental Perception

In the first module of the proposed framework, IoT sensors are used to collect real-time environmental data on underground space. Different types of sensors are utilized for measuring gas concentration levels, wind speed, air pressure, temperature, and humidity. Among the existing gases in underground mines that can potentially increase the risk of safety accidents, such as explosions, are methane and oxygen. These sensors must be installed in various locations within the underground space according to an appropriate deployment strategy to provide a comprehensive view of the environmental status. The working face, ventilation systems, and tunnels are among the critical locations that may require continuous environmental monitoring in underground environments. The data collection interval can differ from seconds to hours based on the type of potential hazard being investigated, the specific environmental factors being monitored, regulatory requirements, the type of underground environment, and the nature of the environment. It must be carefully planned in the deployment strategy. The collected data must then be

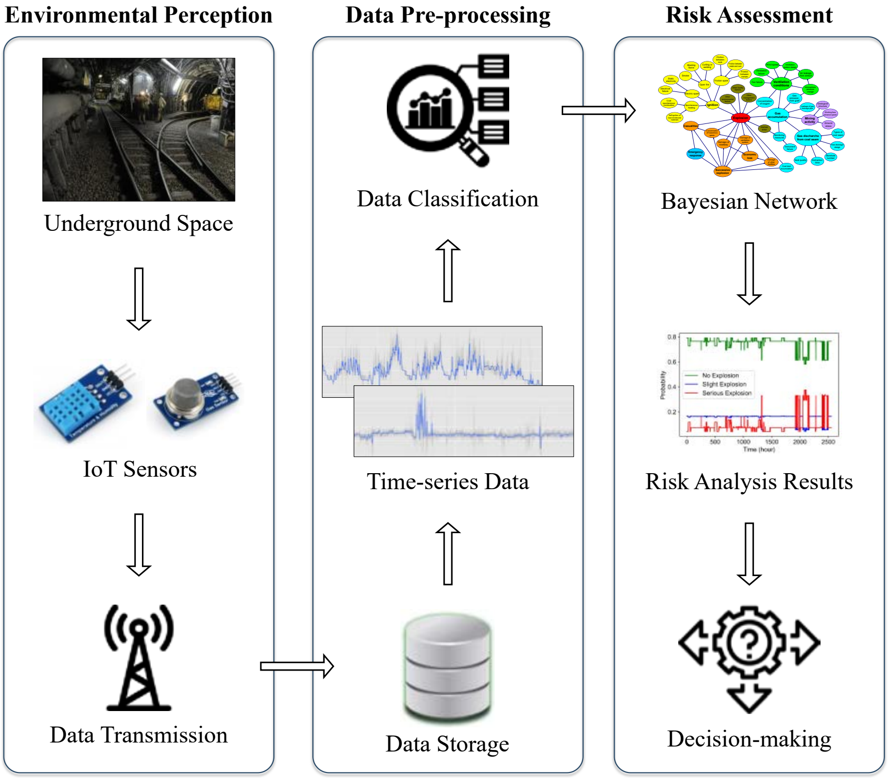

Figure 1. Proposed online safety risk management framework.

transmitted to data storage for later use in the following modules of the proposed framework. Based on industry standards and common practices, Wi-Fi is the most commonly used technology for data transmission in coal mining applications, followed by LTE and 5G [19]. Therefore, these wireless technologies should be considered when selecting data transmission tools.

3.2 Data Pre-processing

The raw data collected from the IoT sensors are in the form of numerical time-series data. In contrast, the input data to the BN must typically be in the form of categorical data. Therefore, a data cleaning and classification process on the raw data is necessary to prepare them for the risk assessment module. If the sensors are installed and calibrated correctly, the possibility of generating flawed data would be minimal. Any missing data or outliers should be cleaned in the pre-processing module. Next, the clean data must be classified and labelled according to the requirements of the Bayesian network. In this step, safety experts must define appropriate thresholds for categorising the data. For example, when the gas concentration in coal mines exceeds the one per cent limit, the mining operation will be subject to potential interruptions, and panic might be inflicted on the workers [20]. As a result, the one per cent limit can be defined as the threshold for classifying the gas concentration level as serious in coal mines. Concentration values below this threshold will be labeled as slight concentration, while values exceeding this threshold will be classified as serious discharge. These discrete categories will then be utilized as evidence in the BN model to update the risk of other nodes within the network. This logic can also be applied to the raw environmental data generated by the other types of sensors.

3.3 Risk Assessment

The BN is used in the proposed framework as a robust risk assessment tool. BNs are directed acyclic graphs that represent probabilistic relationships among variables. A BN consists of nodes representing random variables. A causal relationship is indicated by an arrow connecting two nodes, while the absence of an arrow indicates conditional independence between two variables. BN modelling begins with identifying the network structure to analyze the conditional independence and dependency relationships between the input variables. Following the definition of the BN structure, it is necessary to describe the intensity of the relationship, that is, the conditional probability of one variable given another. Assuming that a BN has n nodes, the joint probability of the BN's random variables would be defined as:

$$P(U) = P(X_1, \dots, X_n) = \prod_{i=1}^{n} P(X_i | \pi(X_i)) \qquad (1)$$

Where X_i denotes the ith random variable, and $\pi(X_i)$ represents the set of parent nodes of X_i.

In the case of discrete variables, Conditional Probability Tables (CPTs) can be used, which determine how likely it is that the "end node" will be in one of its possible states if the "origin node" will be in one of its possible states as well. A BN has the additional feature of being updated as new evidence is acquired, a process referred to as belief updating [12]. Regarding safety and disaster risk management, each node in the BN can represent one of the causes or consequences of the accident [21]. A similar definition was taken in this framework for identifying the structure of the BN.

After developing the BN, the real-time data pre-processed in the previous module are fed into it as new evidence. The BN then initiates the belief updating process to calculate the new probability of the accident node, along with the probabilities of all its causes and consequences. The result will be an online and real-time risk assessment chart for the critical nodes, which can be used to assist the decision-makers and safety managers in foreseeing the occurrence of any safety accidents, tracing the most likely causes of the accident, and taking preventive measures to control the accident and its consequences. In the next section, a case study is conducted to illustrate the details of implementing the different steps of the proposed framework.

4 Case Study

A proof-of-concept example of a case coal mine in Poland was taken to illustrate the applicability of the proposed methodology. The following sections explain the different parts of the method implementation for the proof-of-concept example.

4.1 Open-source Methane Dataset

This study simulated live streams of IoT data using an open-source dataset from a coal mine in Poland. The data were collected from 28 different sensors located at various locations within the case coal mine between 2 March 2014 and 16 June 2014. A total of 9,199,930 samples are included in this dataset. The measurements are taken at intervals of one second. The dataset contains no missing values. Kozielski et al. [22] first published the dataset, but it was previously used by Ślęzak et al. [10] to train a forecasting model to predict near-future methane concentration levels in coal mines. Table 1 describes the characteristics of the sensors and the other features used to collect the open-source dataset.

4.2 Bayesian Network of Methane Explosion Accidents

A preliminary BN was developed for methane explosion accidents in underground coal mines as part of the case implementation. The network has eight categories of nodes: methane accumulation, ignition, mining properties, ventilation, accidents, consequences, mitigation measures, and human error. In Figure 2, each category is represented by a different color. A review of relevant literature was conducted to determine the structure of the network and the probability of each root node. The conditional probabilities of intermediate nodes were estimated using reasonable assumptions and an analysis of the general relationship discussed in the literature. BNs were developed using BayesFusion's GeNIe Modeler [23].

Table 1. Characteristics of sensors used for collecting the open-source methane dataset.

Category	Sensor/Feature	Number of Sensors/Features
Climatic condition	Anemometer	3
	Temperature	2
	Humidity	2
	Barometer	2
	Methane meter	7
	High-concentration methane meter	1
The activity of the longwall shearer	Pressure difference on the methane drainage flange	1
	The pressure inside the methane drainage pipeline	1
	The temperature inside the pipeline	1
	Methane delivery	1
	Current meter	5
	Driving direction	1
	Cutter loader speed	1

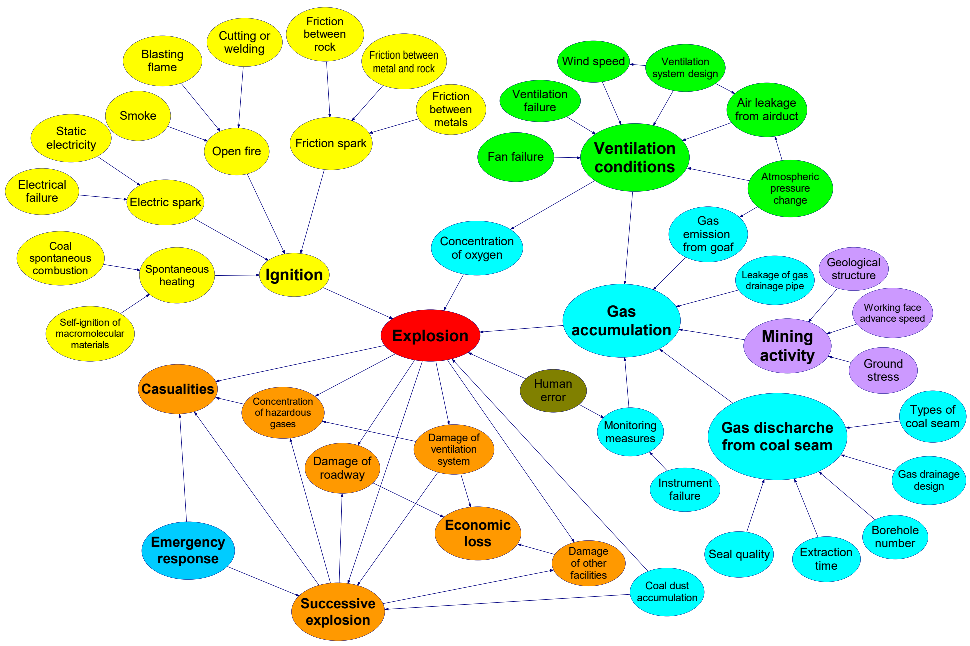

Figure 2. Bayesian network of methane explosion accidents in underground coal mines.

4.3 Live Risk Monitoring System

In the third part of the case study, a simple algorithm was developed to link IoT data streams to the Bayesian network. It was accomplished by using the Python wrapper for the SMILE Engine. The SMILE library is a set of C++ classes that manage the Genie Modeler from different software [24] via an Application Programming Interface (API). In the first step, the size of the dataset was reduced by taking the average of measurements every 600 seconds as the representative of each ten minutes. This resulted in 15,334 samples, each representing ten minutes rather than 9 million samples, each representing one second. For this purpose, an algorithm was developed using the Pandas package in Python [25]. Afterwards, a separate algorithm was designed to incorporate the pieces of evidence into the preliminary BN and calculate the evolution of the explosion risk. This was achieved using the SMILE wrapper in Python.

In this case study, the values of only two sensors were selected as an example to update the BN in real time. The first selected sensor was one of the most critical methane meter sensors installed close to the longwall. This sensor's values were used as evidence to update the Gas discharge from the coal seam node (see Figure 2). The methane concentration levels above one per cent were considered serious gas discharge, and the levels below this threshold were labelled as slight gas discharge [20]. The other selected sensor was the closest anemometer to the longwall, which was used to update the ventilation conditions through the wind speed node (see Figure 2). Here, the values above 0.3 m/s were considered adequate wind speed, between 0.15 m/s and 0.3 m/s were considered ordinary, and those below 0.15 m/s were regarded as inadequate wind speed. Figure 3 displays the evolution of the explosion risk at each interval.

Reviewing the open-source dataset, the wind speed in the case coal mine was consistently adequate, but the gas concentration reached above the one per cent limit during the data collection. As seen in Figure 3, the effect of this phenomenon was reflected in the evolution diagram of the explosion risk. Generally, it can be stated that, in the data collection period, the case coal mine was a safe environment in terms of the methane explosion. Other researchers can conduct a similar analysis to assess the safety risks in underground space.

5 Conclusions

An online underground safety risk assessment framework was proposed in this paper. The framework benefits from the mutual benefits of IoT sensors to generate real-time environmental data and BNs, as a robust risk assessment engine. A case study was conducted on an open-source dataset of methane concentration in an underground coal mine in Poland. The results indicate that the proposed framework is capable of assisting safety managers in underground mines to monitor the risks of safety accidents on a real-time basis and take appropriate measures as necessary.

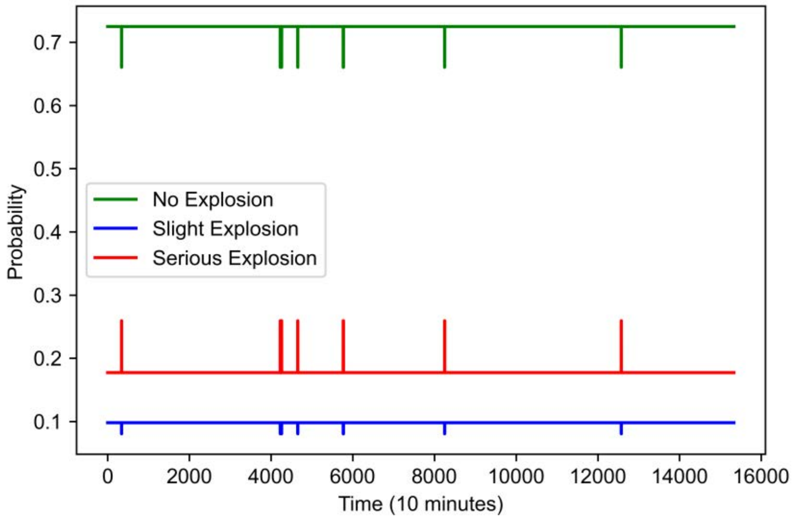

Figure 3. The explosion risk evolution diagram.

The proposed framework yields two important deliverables that can contribute to the field of safety in underground environments. Firstly, developing a Bayesian network enables the capture and retention of tacit knowledge within the underground environment from safety experts. Due to its implicit nature, this knowledge is often difficult to transfer to others, but it can be effectively captured and applied to improve safety practices in underground mining and construction by means of the developed BN. Second, implementing the framework will lead to the development of an online system that allows for real-time monitoring and assessment of safety risks in underground environments. Through this system, safety measures can be continuously evaluated and improved, as well as potential risks can be identified and addressed before they escalate into more serious incidents.

One of the limitations of the current study is that the structure and the conditional probabilities of the developed BN were derived based on the data and information available in the literature. Future studies can use historical data, expert knowledge, or a combination of these two to create a more accurate BN. Further research can also explore the use of additional sensors to provide a more comprehensive understanding of the framework and generate more accurate results.

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