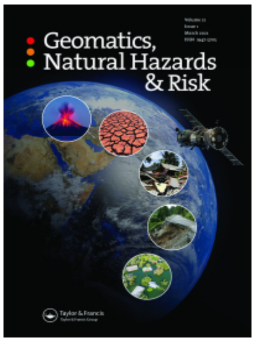

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A correlational research on developing an innovative integrated gas warning system: a case study in ZhongXing, China

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ABSTRACT

Gas explosions and outbursts were the leading types of gas accidents in mining in China with gas concentration exceeding the threshold limit value (TLV) as the leading cause. Current research is focused mainly on using machine learning approaches for avoiding exceeding the TLV of the gas concentration. no published reports were found in the literature of attempts to uncover the correlation between gas data and other data to predict gas concentration. This research aimed to fill this gap and develop an innovative gas warning system for increasing coal mining safety. A mixed qualitative and quantitative research methodology was adopted, including a case study and correlational research. This research found that strong correlations exist between gas, temperature, and wind. It suggests that integrating correlation analysis of data on temperature and wind into gas would improve warning systems' sensitivity and reduce the incidence of explosions and other adverse events. A Unified Modeling Language (UML) model was developed by integrating the Correlation Analysis Theoretical Framework to the existing gas monitoring system for demonstrating an innovative gas warning system. Feasibility verification studies were conducted to verify the proposed method. This informed the development of an Innovative Integrated Gas Warning System which was deployed for user acceptance testing in 2020.

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1. Introduction

China is the world's largest coal producer and has the fourth largest coal reserves. Its coal output remained at similar levels in 2020 as in 2019 to 3,690 MT which accounted for about 46% of global coal production (Hutzler 2020; IEA 2020). Coal mine methane is produced or emitted in association with coal mining activities either from the coal seam itself or from other gassy formations underground, and has always been considered as a danger for underground coal mining as it can create a serious threat to mining safety and productivity due to explosion risk (Karacan et al. 2011, 121). The methane gas is referred to as gas in this paper. Gas explosions and outbursts were the leading types of gas accidents in China with a significant severity compared to other types of coal mine accidents (Wang et al. 2014, 113). Among all the gas disasters, gas concentration exceeding the limit is the leading cause (Zhang et al. 2020, 1). Gas monitoring systems are deployed widely in China's coal mine industry. They are believed to have contributed to a decrease in gas accidents from 414, with the death toll reached 2171 in 2005 to 7, with the death toll reached 30 in 2020 (China Coal Safety 2021). Hazardous accidents are still a problem in underground gassy mines and there is a need for more robust monitoring and early-warning systems for improving coal mining safety (Jo et al. 2019, 183).

Most of the current published research is focused on exploring the methods and framework for avoiding reaching or exceeding the threshold limit value (TLV) of the gas concentration from viewpoints of impacts on geological conditions and coal mining working-face elements. In practice, the existing gas monitoring systems detected mainly real-time data obtained from gas sensors. If the gas data outputs reach or exceed TLV, the gas monitoring system will alert the mine's safety-responsive team. No published papers were found that reported on systems that utilized the collected coal mine data fully; it appears no attempt has been made to uncover the correlation between gas concentration and other data and apply them to predict gas concentration (Zhang et al. 2020, 1, 2).

This research aimed to fill this gap and develop an innovative gas warning system for increasing production safety in the underground coal mining industry. This research proposes that integrating data on different variables into gas would improve warning systems' sensitivity and reduce the incidence of explosions and other adverse events. The mixed qualitative and quantitative research methodology was adopted, including a case study, the boxplot technique, and correlational research. The following sections include the literature review, a case study, data analysis, correlational research and research outcomes, conclusions, limitations, and further research.

2. Literature review

The literature review indicated that most of the current published research focused mainly on analyzing gas data to explore the methods and framework for avoiding exceeding the TLV of the gas concentration from viewpoints of impacts on geographic and coal mining environments. Traditional research focused on analyzing gas data to explore the impacts on geographic and coal mining environments. The current study focused machine learning (ML) models or algorithms (including deep learning) to explore warning models for predicting gas emissions and gas concentrations.

2.1. Related works

Traditional research used the traditional methods and framework from viewpoints of impacts on geographic and coal mining environments. They monitored the risk signals by gas monitoring systems to avoid reaching or exceeding the TLV of the gas concentration. 1 Oct 2019 State Administration of China Coal Safety prevention regulations for Coal and Gas Outburst addressing a limited range of measures, including initial seam gas pressure (P/MPa $\geq$ 0.74), a consistent coefficient ($f \leq 0.5$), and initial rate of methane diffusion ($\triangle p \geq 10$) (China Coal Safety 2019, 3–4). A number of techniques and methods have been used to reduce coal mine risks by monitoring acoustic emission signals, electric radiation, gas emission, and micro-seismic on the physical properties of sound, electricity, magnetism, thermal, and gas (Zhao et al. 2020, 1981).

This research conducted three rounds of literature reviews to explore the state of research into gas warning systems in underground coal mining. This first-round literature review focused on literature published in Scopus and initially searched 69 papers between 2016 and 2021. The second-round literature reviewed Chinese research publications indexed in China National Knowledge Infrastructure (CNKI 2019). Two hundred and ninety-two articles were initially found. The third-round search was then conducted via China's literature search agency of science and technology (LSAST), which China's Department of Education accredited (LSAST 2020). Two hundred papers and report documents were initially filtered. The searched outcomes clearly showed that China's scholars conducted most research in the field of coal mining. After reviewing the abstract, all publications written in Chinese were eliminated. Twenty-three related articles were reviewed, including Ma and Zhu (2016), Fan et al. (2017), Ma and Dai (2017), Zhang et al. (2017), Ślęzak et al. (2018), Viswasmayee et al. (2018), Xia et al. (2018), Gu et al. (2019), Jo et al. (2019), Song et al. (2019), Xie et al. (2019), Sun and Li (2020), Tutak and Brodny (2019), Wang et al. (2019), Wang et al. (2020), Wu et al. (2020), Liu et al. (2020), Zhang et al. (2020), Zhang et al. (2020a), Zhao et al. (2020), Lu et al. (2021), You et al. (2021), and Zhang et al. (2021). Among them, fourteen studies focused on temperature, wind, dust, C_2H_2, CO_2, CO, O_2, humidity, and other parameters to predict gas concentrations, including Ma and Zhu (2016), Fan et al. (2017), Zhang et al. (2017), Xia et al. (2018), Jo et al. (2019), Song et al. (2019), Tutak and Brodny (2019), Wang et al. (2019), Sun and Li (2020), Wang et al. (2020), Zhang et al. (2020), Zhang et al. (2020a), Zhao et al. (2020), and Zhang et al. (2021). They will be discussed in the following section 6.2 Discussion.

2.2. Related works machine learning

The literature showed that, ML approaches were used widely to analyze and harness the power of the enormous amount of information (Chan et al. 2020, 375). They were extensively used for complex problems in a variety of fields where existing solutions require a lot of hand-tuning, and for problems which there is no solution at all using a traditional approach (Morocho-Cayamcela et al. 2019, 137185; Arango et al. 2021, 993). ML has also been widely used to explore a vast number and types of predictor variables in terms of prediction ability (Féret et al. 2019, 2, 11; Arango et al. 2021, 993). In the coal mining industry, research mainly focused on the ML algorithms and methods of predicting gas emissions and gas concentrations (Ma and Zhu 2016, 1). However, ML is challenging to develop a more efficient and accurate gas concentration prediction system (Zhang et al. 2020, 10).

Three disadvantages were raised at least for using ML methods for predicting gas missions and gas concentrations. The first disadvantage is that the poorly dataset inputs will result in inadequate outputs. ML involves providing data to a computer that can be 'trained' with known or predefined features or objects that allow detection, classification, or pattern recognition in a semi-automated or automated manner (Sagan et al. 2020, 3). ML-based prediction models are highly influenced and related to the training dataset (Féret et al. 2019, 11; Boukerche and Wang 2020, 18). The dataset input quality determines the output quality (Chan et al. 2020, 378). The research highlights the strong influence of the training dataset on machine-learning methods' performances (Féret et al. 2019, 11). Therefore, building ML on low-quality data sources and inadequate training samples will lead to drawing wrong, misleading inferences, and inferior outputs (Sagan et al. 2020, 3; Moghadasi et al. 2021, 881).

Another drawback is that ML-based prediction results could not accurately be interpreted. ML approaches differ from the traditional statistical tools that researchers are trained to apply and interpret based on established reporting standards (e.g., P-value for statistical significance) (Bonanni 2019, 165). ML models can be compared to a black box that takes in inputs to produce outputs with no explanation necessarily of how it produced the outputs and cannot be able to provide better definitions of the problem (Jarrett et al. 2019, 7; Chan et al. 2020, 378). Unexplainable ML models for modeling physical phenomena can lead to inaccurate outputs (Sagan et al. 2020, 3).

One more challenge is the high cost of the computing hardware for improving the efficiency and effectiveness of the ML model. Existing coal mine systems rely too much on a computer center (Zhang et al. 2020, 1). The ML models are consistently implemented on a graphic processing unit (GPU) within the computing hardware, which costs a lot to ensure the models can be trained and run at a relatively high speed (Boukerche and Wang 2020, 18–19).

Due to the above three disadvantages, therefore, this research does not recommend using ML methods to explore the early warning system for a single coal mine. They could not interpret the prediction results. The literature search did not also find existing alarms or warning systems incorporating correlation analysis of gas data and data acquisition from other sensors.

Overall, the up-to-date literature search did not find existing studies on warning systems incorporating correlation analysis of gas data and data acquisition from other sensors. No attempt was made to uncover the correlation between gas concentration and other data and apply them to predict gas concentration (Zhang et al. 2020, 1, 2).

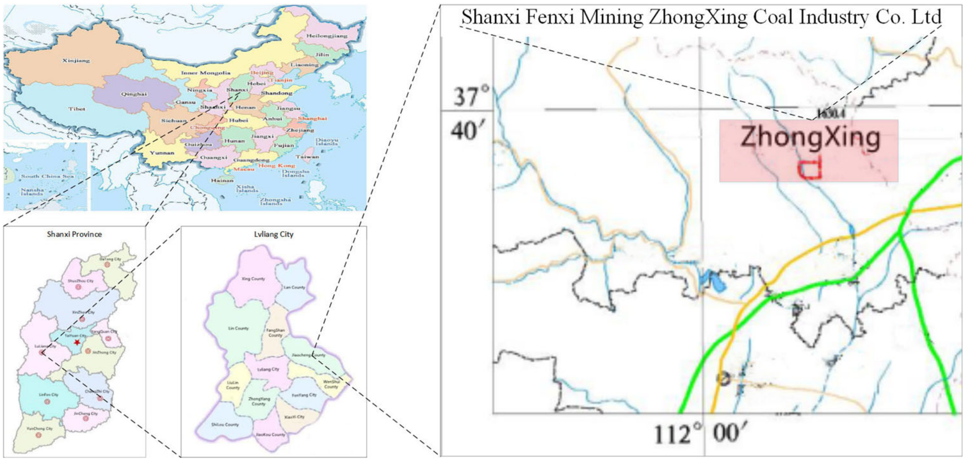

Figure 1. The geographical location of the case study mine in China.

The current gas monitoring systems do not analyze whether other sensors' outputs affect gas data and lack correlational research integrating temperature, wind, and dust into gas variables.

3. Case study

3.1. Current gas monitoring system in the case study mine

This research Case Study mine was Shanxi Fenxi Mining ZhongXing Coal Industry Co. Ltd (ZhongXing) – a large coal mining company in China. ZhongXing was owned wholly by Shanxi Coking Coal Group Co. Ltd, with a designed mining capacity of three million tons per year. Shanxi Coking Coal Group Co. Ltd. was ranked 485th in the 2020 Fortune Global 500 and was the largest coking coal mining company and the largest coking coal supplier in China (SXCC 2020). Other coal mines in China mainly adopted similar systems to the gas monitoring systems deployed in ZhongXing. The research on the Case Study mine may better understand China's current gas monitoring systems. Figure 1 shows the geographical location of the Case Study mine in China.

The existing gas monitoring system in the Case Study mine monitors seven data types obtained from gas sensors, temperature sensors, wind sensors, dust sensors, O2 sensors, CO sensors, and CO2 sensors. Figure 2 shows the current gas monitoring system in The Case Study mine. The current gas monitoring systems focus on detecting real-time data obtained from gas sensors and do not analyze whether other sensors' outputs affect gas data. If gas data are meeting the standard, the data outputs are forwarded to the monitoring system. If the gas data outputs reach and exceeding the TLV, the system will alert the safety-responsive team. Data outputs of temperature, wind, dust, O2, CO, and CO2 are communicated to the monitoring system. These are not included in any risk analysis between the different types of data outputs.

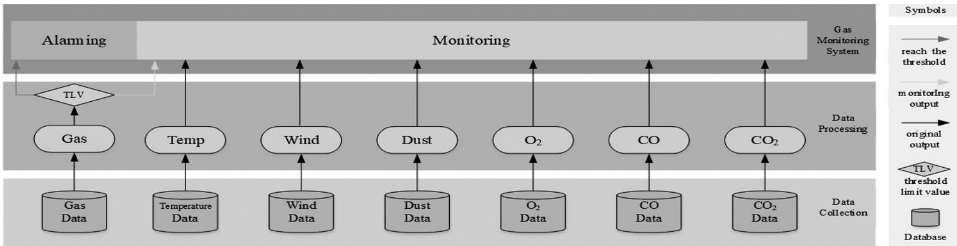

Figure 2. Current gas monitoring system in the case study mine.

Among the seven types of sensors, the data outputs of O2, CO, and CO2 have almost measured no variations and maintained at a constant level from the current gas monitoring system in the Case Study mine. There is no value to be investigated. This research focused on gas, temperature, wind, and dust. Figure 3 shows the location of the sensors installed in the Case Study mine. There are 21 gas sensors (from T1 to T21), 16 temperature sensors (from WD 1 to WD16), 10 wind sensors (from FS1 to FS10), and 2 dust sensors (from FC1 to FC2). The sensors' gas, temperature, wind, and dust codes can be seen in Tables 1–4, respectively.

3.2. Research methodology

The mixed qualitative and quantitative research methodology was adopted in this research, including a case study, boxplot technique, and correlational research. It is critical to eliminate extreme values and outliers before conducting data analysis to real-time data streams. Extreme values and outliers may substantially influence most parametric tests on the statistical analysis, leading to distortion and possibly inaccurate conclusions (Schwertman et al. 2004, 165–166, 173). The boxplot technique is used to eliminate extreme values and outliers. The boxplot technique of exploratory data analysis is better adopted for responding to variation in generalized extreme value distribution shape parameters (Babura et al. 2018, 2). It is well known that outliers, observations that are presumed to come from a different distribution than that for most of the data set (Schwertman et al. 2004, 165). The extensive literature on the subject of outliers attests to its relevance as a significant concern in the statistical analysis of data, which can profoundly influence the statistical analysis and often lead to erroneous conclusions (Schwertman et al. 2004, 165, 166). Boxplot technique is also a simple way commonly employed to identify outliers and has employed a resistant rule for identifying possible outliers in a single batch of the univariate dataset (Schwertman et al. 2004, 166; Babura et al. 2018, 1).

Several statistical significance levels have been accepted for hypothesis testing, including 0.05, 0.01, and 0.001 in social science studies (Wu et al. 2012, 8). P-values of 0.05 are mostly considered acceptable for 'significance' to determine whether or not to reject the null hypothesis (Nahm 2017, 242). However, it is often argued that the p-value only provides information on how incompatible the data are concerning the null hypothesis; Still, it does not give any information on how likely the data would occur under the alternative hypothesis (Shi and Yin 2020, 1). The smaller the significance value, the lower the risk of rejecting the null hypothesis when it is true; this needs to be balanced by the risk of accepting the null hypothesis when it is not

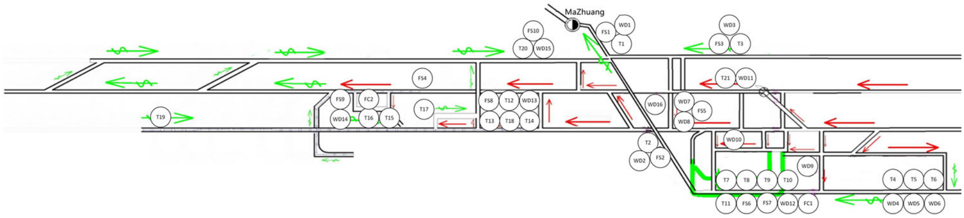

Figure 3. The sensors installed in the case study mine.

Table 1. Code of gas sensors (from T1 to T21).

No.	Gas sensor name	Code	No.	Gas sensor name	Code
T1	Three mining total wind-back alley T	T010101	T12	Four mining trackway 500 m refuge chambers T	T010301
T2	Three mining auxiliary wind-back alley T	T010102	T13	Four mining trackway air vent T	T010302
T3	Three mining east wing wind-back alley T	T010103	T14	Four mining trackway fan front T	T010303
T4	Three mining emergency shelter Back transition room T	T010104	T15	Four mining trackway working face T	T010304
T5	Three mining emergency shelter front transition room T	T010105	T16	Four mining trackway wind-back alley T	T010305
T6	Three mining emergency refuge survival room T	T010106	T17	Four mining trackway mixing T	T010306
T7	Four mining water bin working face T	T010201	T18	Four mining trackway middle T	T010307
T8	Four mining water bin wind-back alley T	T010202	T19	Four mining trackway downwind side of the rig T	T010308
T9	Four mining water bin air vent T	T010203	T20	Four mining north wing wind-back alley T	T010401
T10	Four mining water bin fan front T	T010204	T21	Four mining belt lanes coal bin T	T010501
T11	Four mining water bin mixing T	T010205			

true (Malhotra et al. 2006, 581). A p-value of 0.01 was often considered highly significant (Benjamin and Berger 2019, 189). This research adopted the value of 0.01 as the cut-off for the significance level to lower the risk of rejecting the null hypothesis.

Correlational research is a research method in which the researcher measures two variables and assesses the statistical relationship (i.e., the correlation) between them with little or no effort to control extraneous variables (Price et al. 2017, 107). This method can be used in any study that does not wish to manipulate the investigated independent variables (Curtis et al. 2016, 21). As a quantitative research method, correlational research results can inform causal inferences and evidence-based practice and then subject them to an experimental study (Thompson et al. 2005, 182, 190). When the correlational research method is adopted, correlation analysis will be undertaken to confirm a strong relationship between the data. It can find comprehensive results to find a linear relationship between linear-dependent variables if it exists; It can give a solid indicator to interpret a strong nonlinear relationship between nonlinear-dependent variables (Al-Rousan et al. 2021, 461) and indicate that two variables are influenced by a common underlying mechanism (Messerli 2012, 1563).

Table 2. Code of temperature sensors (from WD1 to WD16).

No.	Temperature sensor name	Code	No.	Temperature sensor name	Code
WD1	Three mining Total wind-back alley WD	WD010101	WD9	Three mining Infinity rope WD	WD010109
WD2	Three mining auxiliary wind-back alley WD	WD010102	WD10	Three mining substation WD	WD010110
WD3	Three mining East Wing wind-back alley WD	WD010103	WD11	Three mining belt lanes WD	WD010111
WD4	Three mining Emergency Shelter Back Transition Room WD	WD010104	WD12	Four mining water bin wind-back alley WD	WD010201
WD5	Three mining Emergency Shelter Front Transition Room WD	WD010105	WD13	Four mining trackway 500 m Refuge Chambers WD	WD010301
WD6	Three mining Emergency Refuge Survival Room WD	WD010106	WD14	Four mining trackway wind-back alley WD	WD010302
WD7	Three mining trackway winch house WD	WD010107	WD15	Four mining North Wing wind-back alley WD	WD010401
WD8	Three mining waiting room WD	WD010108	WD16	Four mining Infinity rope Refuge Chambers WD	WD010501

Table 3. Code of wind sensors (from FS1 to FS10).

No.	Wind sensor name	Code	No.	Wind sensor name	Code
FS1	Three mining Total wind-back alley FS	FS010101	FS6	Four mining water bin air vent FS	FS010201
FS2	Three mining auxiliary wind-back alley FS	FS010102	FS7	Four mining water bin wind-back alley FS	FS010202
FS3	Three mining East Wing wind-back alley FS	FS010103	FS8	Four mining trackway air vent FS	FS010301
FS4	Three mining trackway middle FS	FS010104	FS9	Four mining trackway wind-back alley FS	FS010302
FS5	Three mining West Wing Orbital Lane Belt Lane Duplex Lane FS	FS010105	FS10	Four mining North Wing wind-back alley FS	FS010401

Figure 4 shows the research flowchart processes in this research. They started by designing a proposed research framework based on the current gas monitoring system, including alarming sub-system and monitoring sub-system, collecting data, conducting data analysis and correlation analysis, probing research outcomes, and exploring an innovative integrated gas warning system.

3.3. Research framework

This research aimed to uncover hidden patterns and correlations between gas, temperature, wind, and dust. This research proposed integrating data on temperature, wind, and dust into gas would improve warning systems' sensitivity and reduce the incidence of explosions and other adverse events. Figure 5 shows the proposed research framework comprising the correlation analyses between the gas (from T1 to T21) and gas, gas and temperature (from WD1 to WD16), gas and wind (FS1 to FS10), and gas and dust (FC1 and FC2).

When focusing on the correlation analyses of gas and gas, the dependent variable is gas. The independent variables are other gases. For example, when T1 was the dependent variable, other 20 gases (from T2 to T21) would be independent variables.

Table 4. Code of dust sensors.

No.	Dust sensor name	Code
FC1	Four mining water bin working face FC	FC010201
FC2	Four mining trackway wind-back alley FC	FC010301

A correlation analysis would examine whether T1 was affected by the changes from T2 to T21. When focusing on the correlation analyses of gas and temperature, gas and wind, or gas and dust, the dependent variable is gas. The independent variables are temperature, wind, or dust. The correlation analysis would examine whether gas data was affected by the changes from sixteen temperature sensors, two wind sensors, or two dust sensors.

3.4. Data collection

The research data was collected from the gas monitoring system installed in Mine No.4 North in the Case Study mine. Data collection occurred at an interval of 15 seconds. 65,535 data points were initially obtained from each sensor between 00:00:00 am on 25 September 2020, and 20:48:00 am on 16 October 2020. 3,211,215 data points in total were obtained from 49 sensors, including gas sensors (21), temperature sensors (16), wind sensors (10), and dust sensors (2).

4. Data analysis

Data pre-processing was conducted first. Reliability and exploratory factor analyses were then undertaken separately between gas and gas, gas and temperature, gas and wind, and gas and dust. The correlation analysis was performed between the results of the above data analysis. IBM® SPSS® Statistics version 26 was used for data analysis.

4.1. Data pre-processing

The raw data gathered in most industrial processes usually comes with many other quality issues such as out-of-range values, outliers, noises, errors in measurement, missing values, etc. (Moghadasi et al. 2021, 881). Data pre-processing is a necessary procedure before conducting data analysis to real-time data streams. It consists of transforming the data values of a specific dataset, aiming to optimize the information acquisition and process; at the same time, there is a massive contrast between the maximum and minimum values of the dataset, so normalizing the data minimizes the complexity of the algorithm for its corresponding processing (Larriva-Novo et al. 2021, 6). Data pre-processing will focus on the raw data and cover three data cleaning procedures, including eliminating extreme values, eliminating outliers, and standardizing data.

Extreme data values (also called extreme values in this paper) were considered the out-of-range values in this research. The extreme values can lead to substantially biased inference and cannot be omitted (Barlow et al. 2020, 765). Other data quality issues such as noises, errors in measurement, missing values, etc., will be solved by

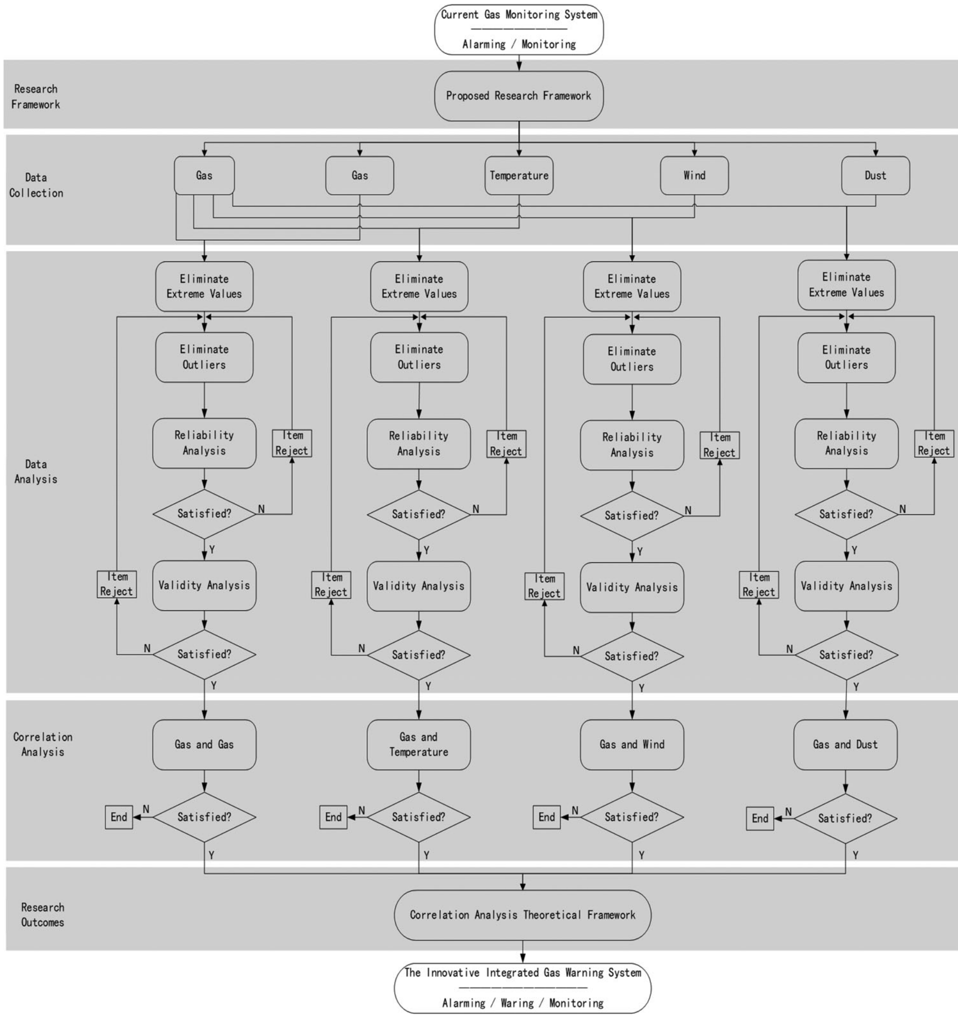

Figure 4. Research flowchart.

updating better hardware devices such as sensors in the gas monitoring system and adopting more effective data collection algorithms. They will not be mainly discussed in this research. Anomaly data were mainly observed as the outliers presumed to come from a different distribution than those for most of the dataset (Schwertman et al. 2004, 165). Outliers come from the other distribution than that for most of the datasets, may have substantial influence in most parametric tests, which can profoundly influence the statistical analysis and often lead to distortion and possibly inaccurate and erroneous conclusions (Schwertman et al. 2004, 165–166, 173). Anomaly data will be considered as outliers in this research. The most common methods for standardizing data include z-score normalization, min-max standardization, and distance to target normalization, and raking ranking normalization) (Larriva-Novo et al. 2021, 2; Luana et al. 2021, 3). Z-score normalization method will be used in this research. The reason is that a data standardization based on the scaling of variables using the z-score algorithm may increase the outcomes' precision

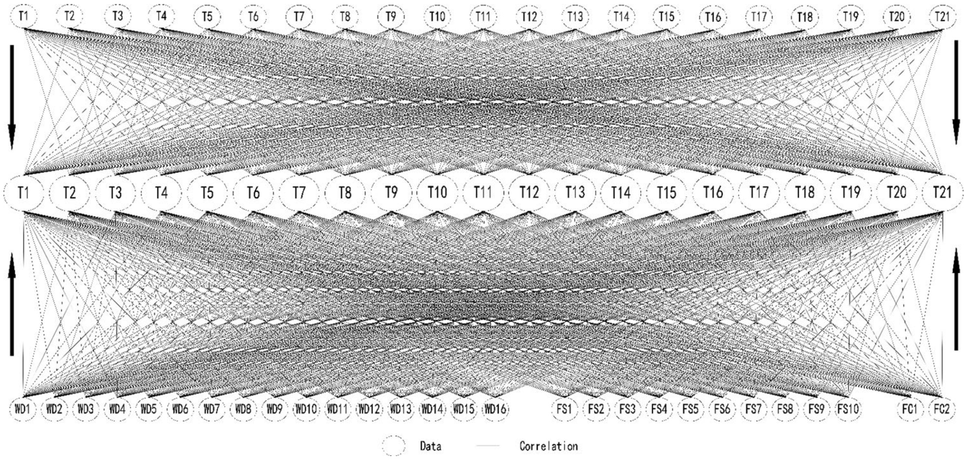

Figure 5. Proposed research framework.

comparing other techniques (Larriva-Novo et al. 2021, 12). Therefore, before conducting data analysis for the real-time datasets, the boxplot technique of exploratory data analysis was used to eliminate extreme values and outliers. Data standardization was then followed as data were collected from the different sensors with a variety of measurements.

After data pre-processing, 9,430 data points for each sensor and 462,070 in total were finally forwarded into the reliability and exploratory factor analysis procedures. The time series of the dataset outputs of all sensors can be seen in Appendices 1–4 (Supplementary material).

4.2. Data analysis between gas and gas

The reliability and exploratory factor analyses were conducted between 21 items (T1 to T21). As a result, three correlational groups were found and satisfactorily met the standards of the reliability and exploratory factor analyses (Table 5). All values of Cronbach's Alpha (0.869, 0.919, and 0.955) were considered to have very good reliability (above 0.8). In the exploratory factor analysis test, all values of Kaiser-Meyer-Olkin (KMO) (0.839, 0.889, and 0.932) were considered a perfect measure (greater than 0.8). Bartlett's test of sphericity was 0.000 ($p < 0.001$). All average communality measures were adequate (greater than 0.6); all anti-image Correlations values were more significant than 0.5.

4.3. Data analysis between gas and temperature

The reliability exploratory factor analyses were conducted between gas and temperature, including 21 gas items (T1 to T21) and 16 temperature items (WD1 to WD16). As a result, sixteen correlational groups were identified and satisfactorily met the standards of the reliability and exploratory factor analyses (Table 6). All values of Cronbach's Alpha were considered to have very good reliability (above 0.8). All KMO values were considered a perfect measure (greater than 0.7) except T12 and WD13.

Table 5. The reliability and exploratory factor analyses between gas and gas.

No.	Gas sensors	Gas sensors	Cronbach's Alpha	KMO	Average communality	Anti-image correlations
1	T1,T2,T3,T4,T5,T6,T7,T8,T9,T10,T11, T14,T16,T17,T18,T20,T21	T1,T2,T3,T4,T5,T6,T7, T8,T9,T10,T11,T14, T16,T17,T18,T20,T21	0.869	0.839	0.65	>0.5
2	T1,T2,T3,T4,T5,T6,T8,T9,T11,T12,T14, T15,T16,T17,T18,T19,T20,T21	T12,T15,T19	0.919	0.889	0.741	>0.5
3	T1,T2,T7,T8,T9,T11,T12,T13,T16,T17, T19,T20	T13	0.955	0.932	0.677	>0.5

Bartlett's test of sphericity was 0.000 ($p < 0.001$). All average communality values were good (greater than 0.6), and Anti-image Correlations were more significant than 0.5.

The correlation group between T12 and WD13 also met the standards of data analysis. Cronbach's Alpha was considered to have outstanding reliability (0.973). Bartlett's test of sphericity was 0.000 ($p < 0.001$). The average communality was great (0.974). Anti-image Correlation was more significant than 0.5.

4.4. Data analysis between gas and wind

The reliability and exploratory factor analyses were conducted between gas and wind, including 21 gas items (T1 to T21) and 10 temperature items (FS1 to FS10). As a result, eight correlational groups were justified and satisfactorily met the standards of the reliability and exploratory factor analyses (see Table 7). All values of Cronbach's Alpha were considered to have fair or reasonable reliability (above 0.65). All KMO values were supposed to be acceptable measures (greater than 0.624). Bartlett's test of sphericity was 0.000 ($p < 0.001$). All average communality values were good (greater than 0.6), and Anti-image Correlations were more significant than 0.5.

4.5. Data analysis between gas and dust

During the data analysis for 23 items, including gas sensors (21), and dust sensors (2), all items were rejected due to dissatisfaction with the reliability analysis. No further investigation was conducted between gas and dust.

5. Correlation analysis and research outcomes

5.1. Correlation coefficient

Correlation analyses were then undertaken to confirm a strong relationship between gas and gas, gas and temperature, and gas and wind. The correlation's strength may be quantified and determined by the value of the correlation coefficient (Baranyai et al. 2021, 5) and analyzed using Pearson's correlation coefficient (r) (called correlation coefficient in this research) as a measure used to describe the linear association between two random variables (Chung et al. 2020, 7; Saccenti et al. 2020, 1; Sukawutthiya et al. 2021, 2). The correlation coefficient was the most commonly used correlation function to find the degree of the relationship between linear variables of

Table 6. The reliability and exploratory factor analyses between gas and temperature.

No.	Gas sensors	Temperature sensor	Cronbach's Alpha	KMO	Average communality	Anti-image correlations
1	T1,T2,T4,T5,T6,T7,T8,T14,T15,T16,T17,T18,T19,T20	WD1	0.94	0.909	0.725	>0.5
2	T1,T2,T4,T5,T6,T7,T8,T14,T15,T16,T17,T18,T19,T20	WD2	0.947	0.913	0.74	>0.5
3	T1,T2,T6,T14,T15,T16,T17,T18,T19,T20,T21	WD3	0.917	0.864	0.701	>0.5
4	T1,T2,T4,T5,T6,T7,T8,T9,T10,T11,T14,T16,T17,T18,T20,T21	WD4	0.875	0.84	0.699	>0.5
5	T1,T2,T3,T4,T5,T6,T7,T9,T12,T16,T18,T21	WD5	0.899	0.829	0.669	>0.5
6	T1,T2,T4,T5,T6,T7,T8,T9,T10,T11,T14,T16,T17,T18,T20,T21	WD6	0.874	0.838	0.697	>0.5
7	T1,T2,T4,T6,T12,T14,T15,T16,T17,T18,T19,T20,T21	WD7	0.89	0.822	0.649	>0.5
8	T1,T2,T4,T5,T6,T7,T8,T9,T10,T11,T14,T16,T17,T18,T20,T21	WD8	0.872	0.844	0.634	>0.5
9	T1,T2,T3,T6,T14,T15,T16,T17,T18,T19,T20,T21	WD9	0.914	0.852	0.697	>0.5
10	T1,T2,T4,T5,T6,T7,T8,T9,T10,T11,T14,T16,T17,T18,T20,T21	WD10	0.877	0.847	0.692	>0.5
11	T1,T2,T3,T4,T5,T6,T7,T8,T9,T10,T11,T14,T16,T17,T18,T20,T21	WD11	0.873	0.84	0.609	>0.5
12	T1,T2,T3,T4,T5,T6,T7,T8,T9,T10,T11,T14,T16,T17,T18,T20,T21	WD12	0.872	0.834	0.662	>0.5
13	T12	WD13	0.973	0.5	0.974	>0.5
14	T7,T8,T9,T11,T12,T16,T17,T19,T20,T21	WD14	0.795	0.745	0.606	>0.5
15	T1,T2,T3,T4,T5,T6,T7,T8,T9,T10,T11,T14,T16,T17,T18,T20,T21	WD15	0.875	0.842	0.613	>0.5
16	T1,T2,T3,T4,T5,T6,T9,T11,T12,T14,T15,T16,T17,T18,T19,T20,T21	WD16	0.907	0.852	0.746	>0.5

interest is given in terms of the correlation coefficient, and a value approaching unity indicates a robust linear relationship and vice versa (Al-Rousan et al. 2021, 285, 460; Asri et al. 2018, 288; Souza et al. 2021, 611).

Thus, the correlation coefficient was used to evaluate and measure the correlation between two pairs of input and output variables. The correlation coefficient's magnitude indicates that the strength of the relationship depends on how the coefficient is close to −1 or 1, which is the range of the correlation coefficient (Al-Rousan et al. 2021, 460). But there is no standard classification to the correlation coefficient scales. Figure 6 briefly listed the correlation coefficient scales classified in Q1 publications in January 2021. This research defined six scales to classify the degree and magnitude of correlation as great (between ± 0.9 and ± 1), very good (between ± 0.75 and ± 0.89), good (between ± 0.5 and ± 0.74), fair (between ± 0.3 and ± 0.49), poor (between ± 0.0 and < ± 0.29), and no correlation (zero) (see Figure 6). Correlations value with ±0.3 or above indicates the existence of a correlation between two variables.

5.2. Correlation analysis studies

The relations of 420 variables were tested to any existing correlations between gas data and other gas data. The result indicates there are existing 163 significant correlations. They include 2 correlations as great (between 0.9 and 1), 6 as very good (between 0.75 and 0.89), 57 as good (between 0.5 and 0.74), and 98 as fair (between 0.3 and 0.49) (see Table 8). 168 correlations were as poor (between 0 and 0.29). 89 items did not have any correlation. Table 9 presented a correlation value with ±0.3 or above, indicating a correlation between two variables. The results of significant

Table 7. The reliability and exploratory factor analyses between gas and wind.

No.	Gas sensors	Wind sensor	Cronbach's Alpha	KMO	Average communality	Anti-image correlations
1	T1,T16,T17,T19	FS3	0.712	0.685	0.673	>0.5
2	T1,T2,T12	FS4	0.895	0.824	0.761	>0.5
3	T2,T9,T13	FS5	0.868	0.751	0.717	>0.5
4	T1,T2,T3,T4,T5,T6,T7,T9,T11,T12, T16,T18,T21	FS6	0.893	0.862	0.71	>0.5
5	T1,T2,T3,T5,T7,T8,T9,T11,T12,T14, T15,T17,T19,T20,T21	FS7	0.889	0.865	0.685	>0.5
6	T1,T2,T3,T4,T5,T6,T7,T8,T9,T10,T11, T14,T15,T19,T20	FS8	0.929	0.901	0.74	>0.5
7	T1,T2,T4,T5,T6,T7,T8,T9,T11,T12,T15, T16,T17,T18,T20,T21	FS9	0.89	0.846	0.68	>0.5
8	T3,T10,T12,T13,T14,T17,T20	FS10	0.65	0.624	0.62	>0.5

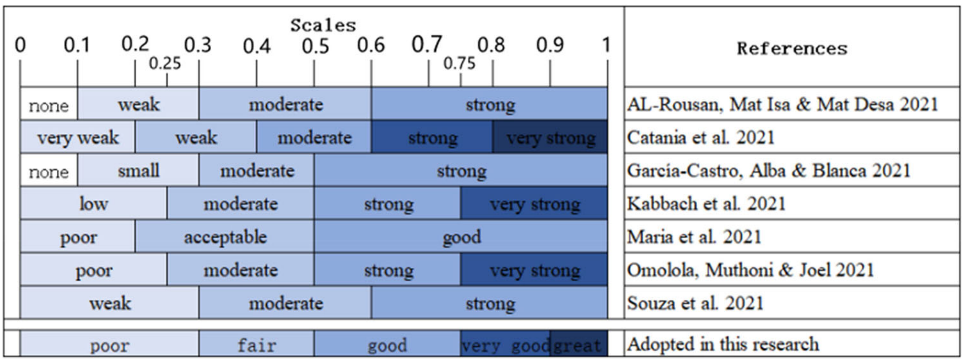

Figure 6. The classifications of the correlation coefficient scales in Q1 publications in Jan 2021.

correlations between gas and gas were then demonstrated in Figure 7. The lines' size expressed the correlations of great, very good, good, fair, and poor between variables.

The second correlation analysis was followed to test any existing correlations between gas data and temperature data. The relations of 336 variables were tested. The result indicates there are existing 130 significant correlations. They include one correlation as great, 5 as very good, 49 as good, and 75 as fair (see Table 10). Ninety correlations were as poor. 116 items did not have any correlation. Table 11 presented a correlation value with ±0.3 or above, indicating a correlation between two variables. The results of significant correlations between gas and temperature were then demonstrated in Figure 8.

The third correlation analysis was finally conducted to test any existing correlations between gas data and wind data. The relations of 210 variables were tested. 35 significant correlations existed, including 16 as good and 19 as fair (see Table 12). Forty correlations were as poor. 135 items did not have any correlation. Table 13 presented a correlation value with ±0.3 or above, indicating a correlation between two variables. The results of significant correlations between gas and wind were then demonstrated in Figure 9.

5.3. Research outcomes

As the research outcome of the Proposed Research Framework (see Figure 5), the Correlation Analysis Theoretical Framework (see Figure 10) was then explored based on

Table 8. Correlation analysis between gas and gas.

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20	T21
T1		.971**	.425**	.084**	.056**	.144**	−.058**	−.032*	.298**	.123**	.190**			.228**		.526**	.370**	.498**		.365**	.195**
T2	.971**		.376**	0.013	−0.015	.081**	−.139**	−.101**	.262**	.077**	.142**			.168**		.534**	.341**	.496**		.286**	.148**
T3	.425**	.376**		.204**	.221**	.214**	−.062**	.074**	−0.023	.091**	0.009			.106**		.334**	.292**	.223**		.222**	.231**
T4	.084**	0.013	.204**		.708**	.816**	.552**	.410**	.238**	.218**	.285**			.425**		0.024	.194**	.159**		.429**	.589**
T5	.056**	−0.015	.221**	.708**		.662**	.563**	.499**	.220**	.284**	.318**			.432**		.028*	.217**	.123**		.377**	.528**
T6	.144**	.081**	.214**	.816**	.662**		.507**	.357**	.255**	.211**	.290**			.413**		.066**	.182**	.230**		.402**	.632**
T7	−.058**	−.139**	−.062**	.552**	.563**	.507**		.761**	.461**	.281**	.553**			.388**		−.140**	.125**	−.062**		.397**	.328**
T8	−.032*	−.101**	.074**	.410**	.499**	.357**	.761**		.455**	.306**	.602**			.321**		.025*	.276**	−0.021		.410**	.243**
T9	.298**	.262**	−0.023	.238**	.220**	.255**	.461**	.455**		.213**	.717**			.274**		.249**	.283**	.210**		.422**	.294**
T10	.123**	.077**	.091**	.218**	.284**	.211**	.281**	.306**	.213**		.327**			.313**		.113**	.207**	.063**		.284**	.195**
T11	.190**	.142**	0.009	.285**	.318**	.290**	.553**	.602**	.717**	.327**				.308**		.161**	.284**	.087**		.381**	.292**
T12	.072**	.090**		.337**	.504**	.237**		.353**	.421**		.314**			.432**	.589**	.569**	.421**	.777**	.715**	.209**	.345**
T13	.509**	.526**					.588**	.362**	.657**		.477**	.669**				.670**	.670**		.522**	.629**	
T14	.228**	.168**	.106**	.425**	.432**	.413**	.388**	.321**	.274**	.313**	.308**					0.009	.220**	.140**		.424**	.310**
T15	.440**	.421**		.533**	.639**	.404**		.340**	.414**		.414**	.589**		.510**		.727**	.591**	.711**	.666**	.434**	.549**
T16	.526**	.534**	.334**	0.024	.028*	.066**	−.140**	.025*	.249**	.113**	.161**			0.009			.606**	.508**		.372**	.205**
T17	.370**	.341**	.292**	.194**	.217**	.182**	.125**	.276**	.283**	.207**	.284**			.220**		.606**		.304**		.457**	.245**
T18	.498**	.496**	.223**	.159**	.123**	.230**	−.062**	−0.021	.210**	.063**	.087**			.140**		.508**	.304**			.304**	.216**
T19	.154**	.151**		.400**	.530**	.322**		.222**	.407**		.261**	.715**		.345**	.666**	.798**	.521**	.740**		.319**	.445**
T20	.365**	.286**	.222**	.429**	.377**	.402**	.397**	.410**	.422**	.284**	.381**			.424**		.372**	.457**	.304**			.356**
T21	.195**	.148**	.231**	.589**	.528**	.632**	.328**	.243**	.294**	.195**	.292**			.310**		.205**	.245**	.216**		.356**	

**Correlation is significant at the 0.01 level 2-tailed.
*Correlation is significant at the 0.05 level 2-tailed.

Table 9. Correlation value between gas and gas.

Gas sensors	Gas sensor	Correlation value
T2,T3,T16,T17,T18,T20	T1	0.971, 0.425, 0.526, 0.370, 0.498, 0.365
T1,T3,T16,T17,T18	T2	0.971, 0.376, 0.534, 0.341, 0.496
T1,T2,T16	T3	0.425, 0.376, 0.334
T5,T6,T7,T8,T14,T20,T21	T4	0.708, 0.816, 0.552, 0.410, 0.425, 0.429, 0.589
T4,T6,T7,T8,T11,T14,T20,T21	T5	0.708, 0.662, 0.563, 0.499, 0.318, 0.432, 0.377, 0.528
T4,T5,T7,T8,T14,T20,T21	T6	0.816, 0.662, 0.507, 0.357, 0.413, 0.402, 0.632
T4,T5,T6,T8,T9,T11,T14,T20,T21	T7	0.552, 0.563, 0.507, 0.761, 0.461, 0.553, 0.388, 0.397, 0.328
T4,T5,T6,T7,T9,T10,T11,T14,T20	T8	0.410, 0.499, 0.357, 0.761, 0.455, 0.306, 0.602, 0.321, 0.410
T7,T8,T11,T20	T9	0.461, 0.455, 0.717, 0.422
T8,T11,T14,	T10	0.306, 0.327, 0.313
T5,T7,T8,T9,T10,T14,T20	T11	0.318, 0.553, 0.602, 0.717, 0.327, 0.308, 0.381
T4,T5,T8,T9,T11,T14,T15,T16,T17,T18,T19,T21	T12	0.337, 0.504, 0.353, 0.421, 0.314, 0.432, 0.589, 0.569, 0.421, 0.777, 0.715, 0.345,
T1,T2,T7,T8,T9,T11,T12,T16,T17,T19,T20	T13	0.509, 0.526, 0.588, 0.362, 0.657, 0.477, 0.669, 0.670, 0.670, 0.522, 0.629
T4,T5,T6,T7,T8,T10,T11,T20,T21	T14	0.425, 0.432, 0.413, 0.388, 0.321, 0.313, 0.308, 0.424, 0.310
T1,T2,T4,T5,T6,T8,T9,T11,T14, T16,T17, T18,T19,T20,T21	T15	0.440, 0.421, 0.533, 0.639, 0.404, 0.340, 0.414, 0.589, 0.510, 0.727, 0.591, 0.711, 0.666, 0.434, 0.549
T1,T2,T3,T17,T18,T20	T16	0.526, 0.534, 0.334, 0.606, 0.508, 0.372
T1,T2,T16,T18,T20	T17	0.370, 0.341, 0.660, 0.304, 0.457
T1,T2,T16,T17,T20	T18	0.498, 0.496, 0.508, 0.304, 0.304
T4,T5,T6,T9,T12,T14,T15,T16,T17,T18,T20,T21	T19	0.400, 0.530, 0.322, 0.407, 0.715, 0.345, 0.666, 0.798, 0.521, 0.740, 0.319, 0.445
T1,T4,T5,T6,T7,T8,T9,T11,T14,T16,T17,T18,T21	T20	0.365, 0.429, 0.377, 0.402, 0.397, 0.410, 0.422, 0.381, 0.424, 0.372, 0.457, 0.304, 0.356
T4,T5,T6,T7,T14,T20	T21	0.589, 0.528, 0.632, 0.328, 0.310, 0.356

the results of correlation analysis studies (see Figures 7–9). The Correlation Analysis Theoretical Framework alleges 328 significant correlations (also called correlation analysis rules), including analyses between gas and gas (163), gas and temperature (130), and gas and wind (35). No correlations exist between gas and dust (FC1 and FC2), as discussed in section 4.4. Data repository was provided (see Data Repository 2021).

Thus, a warning sub-system was embedded and deployed into the current gas monitoring system. A Unified Modeling Language (UML) model was finally developed by integrating a Correlation Analysis Theoretical Framework (see Figure 10) into the existing gas monitoring system (see Figure 2). Figure 11 demonstrates the Innovative Integrated Gas Warning System's UML model to understand better the system's architectural design comprising three layers: the view layer, domain layer, and data access layer.

As a result of this research, an Innovative Integrated Gas Warning System was deployed in the Case Study mine for user acceptance testing to increase coal mining safety in Dec 2020 (see Figure 12). The system includes three sub-systems (alarming, warning, and monitoring) that were developed incorporating the 328 correlation analysis rules and three activated decision rules, including analyses between gas and gas (163), gas and temperature (130), and gas and wind (35). The three decision processes (Data acquisition, Correlation analysis, and Activated decision) will systematically and constrainedly follow as:

- Data acquisition: This logic flow was run between the Data Access Layer to the Domain Layer. The data were obtained from gas, temperature, and wind databases.

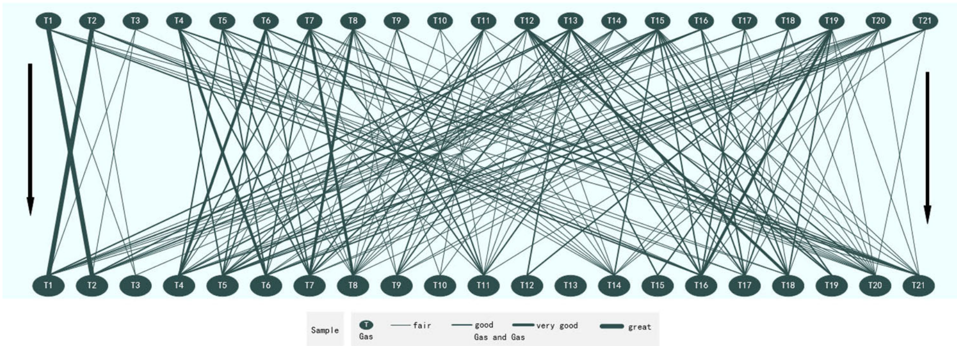

Figure 7. The result of significant correlations between gas and gas.

- Correlation analysis: Within the Domain Layer, triple-correlation analyses were conducted separately between data upstream of gas and gas, gas and temperature, and gas and wind. The 328 correlation analysis rules will constrain the correlation analysis.
- Activated decision: This step was established between the Domain Layer and the View Layer. Three activated decision rules were be followed:
- If the outputs of data reach or exceeding TLV, the alarm system will immediately alert the safety-responsive team.
- If the real-time correlation analysis value (CAV) exceeds the correlation analysis limit value (CALV) between gas and gas, gas and temperature, or gas and wind. In that case, the warning system will be alerted.
- If the CAV does not reach CALV, the original data would be forwarded to the monitoring system.

The Entropy algorithm calculated the real-time CAV using the real-time data obtained from the correlated sensors of gas and gas, gas and temperature, and gas and wind. The Entropy algorithm calculated the CALV using the upper-limit and lower-limit values obtained from the correlated sensors between gas and different gas, gas and temperature, and gas and wind. The Entropy algorithm followed the step-by-step weight estimation by Mukhametzyanov (2021, 79–80) as:

The intensity (p_{ij}) of the j-th attribute of the i-th alternative is calculated for each criterion (Sum-method):

$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}, \forall_i = 1, \ldots, m, j = 1, \ldots, n; \sum_{i=1}^{m} p_{ij} = 1 \tag{1}$$

To calculate the entropy (e_j) and the key indicator (q_j) of each criterion:

$$e_j = -\frac{1}{\ln m} \cdot \sum_{i=1}^{m} p_{ij} \cdot \ln p_{ij}, j = 1, \ldots, n; (if\ p_{ij} = 0 \Rightarrow p_{ij} \cdot \ln p_{ij} = 0) \tag{2}$$

$$q_j = 1 - e_j, j = 1, \ldots, n \tag{3}$$

Table 10. Correlation analysis between gas and temperature.

	WD1	WD2	WD3	WD4	WD5	WD6	WD7	WD8	WD9	WD10	WD11	WD12	WD13	WD14	WD15	WD16
T1	.271**	.459**	.383**	−.080**	.684**	−.062**	.346**	−.132**	.341**	0.015	.517**	.181**			.029*	.320**
T2	.202**	.383**	.337**	−.160**	.704**	−.142**	.335**	−.207**	.287**	−.061**	.511**	.168**			−.050**	.345**
T3			.691**		.363**				.777**		.261**	.063**			0.009	.160**
T4	.828**	.830**		.640**	.174**	.623**	.311**	.551**		.580**	.105**	.230**			.618**	.405**
T5	.650**	.794**		.556**	.146**	.538**		.480**		.586**	−0.012	.159**			.509**	.293**
T6	.687**	.701**	.133**	.615**	.176**	.596**	.345**	.543**	.252**	.549**	.149**	.199**			.592**	.296**
T7	.566**	.632**		.690**	.312**	.638**		.682**		.556**	−.087**	.315**		.270**	.582**	
T8	.501**	.586**		.410**		.353**		.442**		.473**	−0.017	.349**		.198**	.353**	
T9				.249**	.441**	.218**		.223**		.181**	.271**	.523**		.478**	.199**	.158**
T10				.267**		.254**		.230**		.371**	.160**	.062**			.236**	
T11				.293**		.248**		.304**		.302**	.152**	.403**		.373**	.208**	.156**
T12					.747**		.695**						.948**	.775**		.468**
T13																
T14	.471**	.606**	.482**	.542**		.553**	.275**	.404**	.480**	.559**	.101**	.042**			.400**	.473**
T15	.249**	.423**	.310**				0.032		.311**							.414**
T16	.555**	.506**	.506**	−.293**	.340**	−.287**	.407**	−.255**	.543**	−.048**	.586**	.235**		.323**	−.054**	.252**
T17	.440**	.448**	.436**	−.027*		−0.019	.222**	−.061**	.448**	.200**	.388**	.275**		.249**	.109**	.381**
T18	.592**	.610**	.386**	−.034**	.441**	−0.023	.230**	−.089**	.314**	.086**	.394**	.153**			.032*	.606**
T19	.524**	.615**	.459**				.434**		.570**					0.024		.303**
T20	.380**	.485**	.383**	.354**		.337**	.198**	.310**	.349**	.436**	.343**	.369**		.188**	.420**	.185**
T21			.332**	.367**	.171**	.355**	.230**	.322**	.156**	.317**	.259**	.196**		.382**	.425**	.462**

**Correlation is significant at the 0.01 level 2-tailed.
*Correlation is significant at the 0.05 level 2-tailed.

Table 11. Correlation value between gas and temperature.

Gas sensors	Temperature sensor	Correlation value
T4,T5,T6,T7,T8,T14,T16,T17,T18,T19,T20	WD1	0.828, 0.650, 0.687, 0.566, 0.501, 0.471, 0.555, 0.440, 0.592, 0.524, 0.380
T1,T2,T4,T5,T6,T7,T8,T14, T15,T16,T17, T18,T19,T20	WD2	0.459, 0.383, 0.830, 0.794, 0.701, 0.632, 0.586, 0.606, 0.423, 0.506, 0.448, 0.610, 0.615, 0.485
T1,T2,T14,T15,T16,T17,T18,T19,T20,T21	WD3	0.383, 0.337, 0.691, 0.482, 0.310, 0.506, 0.436, 0.386, 0.459, 0.383, 0.332
T4,T5,T6,T7,T8,T14,T20,T21	WD4	0.640, 0.556, 0.615, 0.690, 0.410, 0.542, 0.354, 0.367
T1,T2,T3,T7,T9,T12,T16,T18	WD5	0.684, 0.704, 0.363, 0.312, 0.441, 0.747, 0.340, 0.441
T4,T5,T6,T7,T8,T14,T20,T21	WD6	0.623, 0.538, 0.596, 0.638, 0.353, 0.553, 0.337, 0.355
T1,T2,T4,T6,T12,T16,T19	WD7	0.346, 0.335, 0.311, 0.345, 0.695, 0.407, 0.434
T4,T5,T6,T7,T8,T11,T14,T20,T21	WD8	0.551, 0.480, 0.543, 0.682, 0.442, 0.304, 0.404, 0.310, 0.322
T1,T3,T14,T15,T16,T17,T18,T19,T20	WD9	0.341, 0.777, 0.480, 0.311, 0.543, 0.448, 0.314, 0.570, 0.349
T4,T5,T6,T7,T8,T10,T11,T14,T20,T21	WD10	0.580, 0.586, 0.549, 0.556, 0.473, 0.371, 0.302, 0.559, 0.436, 0.317
T1,T2,T16,T17,T18,T20	WD11	0.517, 0.511, 0.586, 0.388, 0.394, 0.343
T7,T8,T9,T11,T20	WD12	0.315, 0.349, 0.523, 0.403, 0.369
T12	WD13	0.948
T9,T11,T12,T16,T21	WD14	0.478, 0.373, 0.775, 0.323, 0.382
T4,T5,T6,T7,T8,T14,T20,T21	WD15	0.618, 0.509, 0.592, 0.582, 0.353, 0.400, 0.420, 0.425
T1,T2,T4,T12,T14,T15,T17,T18,T19,T21	WD16	0.320, 0.345, 0.405, 0.468, 0.473, 0.414, 0.381, 0.606, 0.303, 0.462

To calculate the weight of each criterion:

$$w_j = \frac{q_j}{\sum_{k=1}^{n} qk}, j = 1, \ldots, n \tag{4}$$

The programming code for running the above Entropy algorithm was provided (see Supplementary material, Appendix 5).

6. Discussions

6.1. Feasibility verification

For verifying the research method adopted in this research, two rounds of feasibility verification studies were conducted. The first round of studies aimed to examine whether the method proposed in this research might be used at other periods at the Case Study mine. The second round of studies aimed to investigate whether this proposed method might be used simultaneously at the same periods in different mines.

The first round of studies used data collected in a Case Study mine on 14 September 2020. The outcomes were to compare with data collected between 25 September and 16 October 2020. This round aimed to confirm whether this proposed method might be used at different periods in the same Case Study mine for verification. The reason was that the Case Study mine kept the continuing mining production. Sensors might be changed to the different physical addresses on average one month at the same working face, including adding, moving, and removing. 53,760 data points for each sensor on 14 September 2020 with 11 days ahead compared to the case study. After data pre-processing (eliminating extreme values, eliminating outliers, and standardizing data) to the raw data, 5,753 data points were obtained from

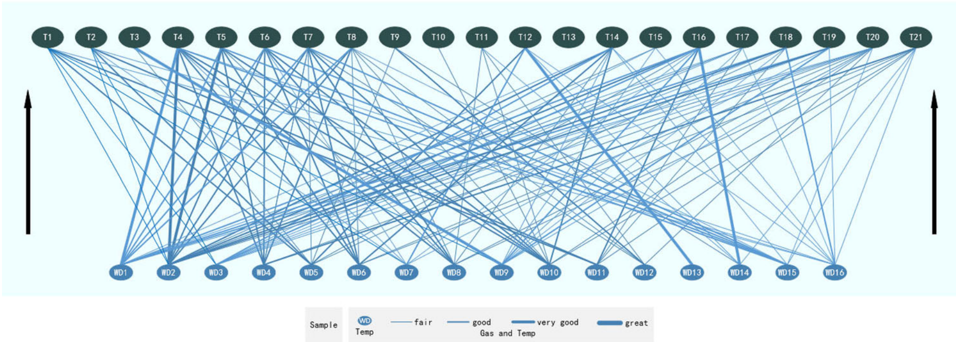

Figure 8. The result of significant correlations between gas and temperature.

Table 12. Correlation analysis between gas and wind.

	FS1	FS2	FS3	FS4	FS5	FS6	FS7	FS8	FS9	FS10
T1			.227*	.601**		.486**	.729**	.480**	.393**	
T2				.699**	.584**	.465**	.733**	.515**	.388**	
T3						.533**	.359**	.267**		0.087
T4						.119**		.189**	.164**	
T5						0.039	.130**	.397**	.208**	
T6						.107**		.170**	.159**	
T7						.164**	.115**	.269**	.340**	
T8							.088*	.365**	.222**	
T9					.707**	.349**	.139**	.316**	.370**	
T10								.547**		0.149
T11						.169**	.165**	.408**	.317**	
T12				.598**		.557**	.550**		.253**	0.126
T13					.569**					.198*
T14							.256**	.280**		.270**
T15							.518**	.621**	.225**	
T16			0.208			.395**			.394**	
T17			0.179				.247**		.200**	.199*
T18						.218**			.243**	
T19			.449**				.258**	.543**		
T20							.321**	.294**	.349**	
T21						.128**	.128**		.085**	

**Correlation is significant at the 0.01 level 2-tailed.
*Correlation is significant at the 0.05 level 2-tailed.

Table 13. Correlation value between gas and wind.

Gas sensors	Wind sensor	Correlation value
T19	FS3	0.449
T1,T2,T12	FS4	0.601, 0.699, 0.598
T2,T9,T13	FS5	0.584, 0.707, 0.569
T1,T2,T3,T9,T12,T16	FS6	0.486, 0.465, 0.533, 0.349, 0.557, 0.395
T1,T2,T3,T12,T15,T20	FS7	0.729, 0.733, 0.359, 0.550, 0.518, 0.321
T1,T2,T5,T8,T9,T10,T11,T15,T19	FS8	0.480, 0.515, 0.397, 0.365, 0.316, 0.547, 0.408, 0.621, 0.543
T1,T2,T7,T9,T11,T16,T20	FS9	0.393, 0.388, 0.340, 0.370, 0.317, 0.394, 0.349

each sensor between 00:00:00 am on 14 September and 23:59:59 on 14 September 2020. The outcomes of correlation analysis identified that this study step built the same UML model and confirmed the relations between gas and gas, gas and temperature, and gas and wind.

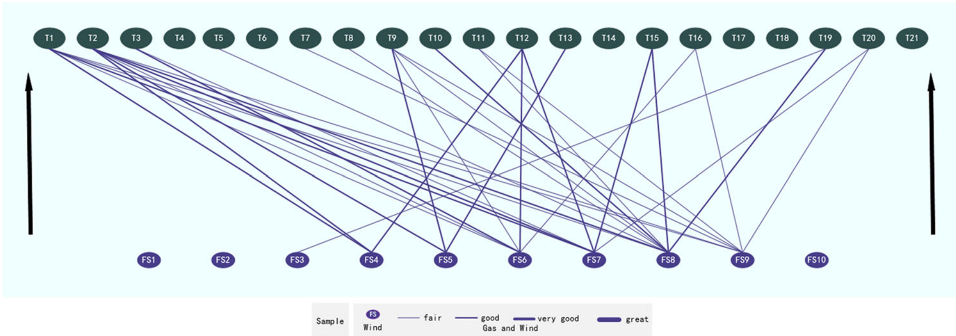

Figure 9. The result of significant correlations between gas and wind.

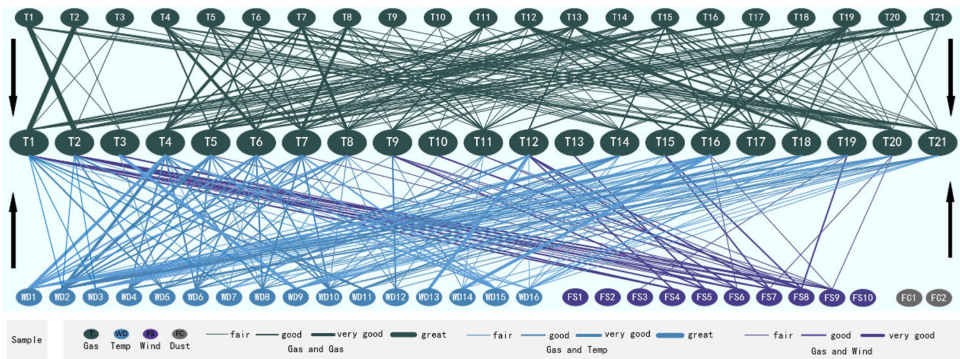

Figure 10. The correlation analysis theoretical framework.

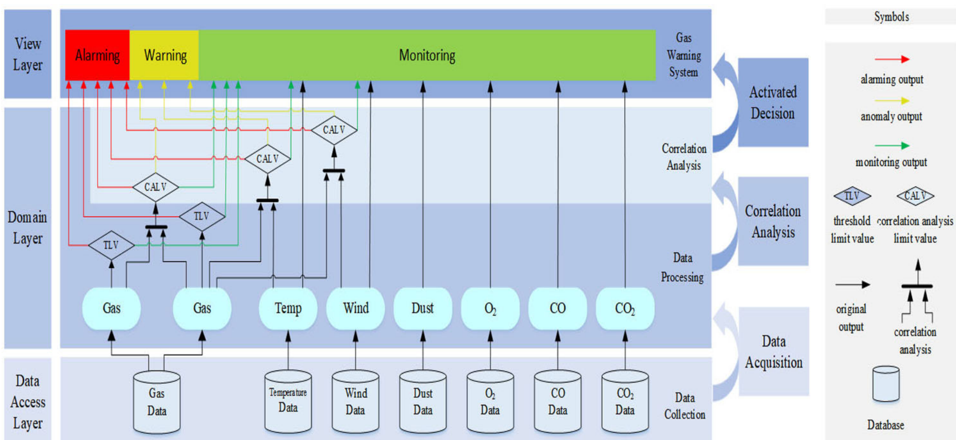

Figure 11. A UML model of the innovative integrated gas warning system.

The second-round study used data collected in Feasibility Verification Study Mine at ZhongXing mine, which used the data obtained with the same periods from the different mine – No.1209 at ZhongXing mine. This step investigated whether this proposed method might be used in other mines for verification at the same time. Ten gas sensors were installed in Feasibility Verification Study Mine (Figure 12). Table 14

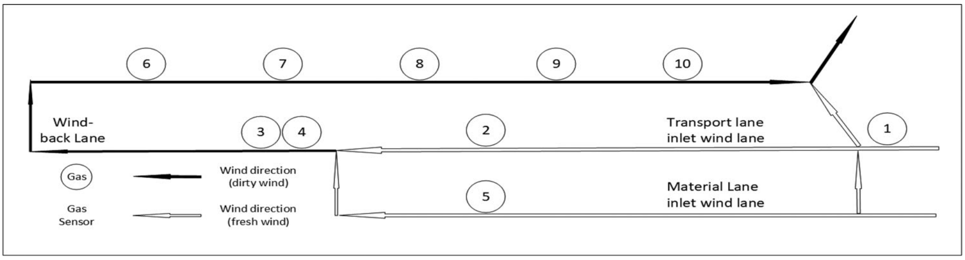

Figure 12. Ten gas sensors installed in feasibility verification mine.

shows the codes of the sensors used. This step initially obtained 17,280 data outputs from each gas sensor. After data pre-processing to the raw data, the final data was 7,265 for each gas sensor. Thus, 72,650 datasets in total were collected for ten sensors (see Supplementary material, Appendix 6). The outcomes of the correlation analysis identified that this study step built the same UML model and confirmed the relationships between gas and gas, gas and temperature, and gas and wind.

Thus, both rounds of feasibility verification studies confirmed existing correlations between gas and gas, gas and temperature, and gas and wind. The two-round studies also verified that the proposed method in this research might feasibly be adopted at ZhongXing mine. Further research should be conducted to examine whether the Innovative Integrated Gas Warning System might be effectively adopted in other coal mining companies and further clarify the adaptive application conditions.

6.2. Discussion

This study conducted correlational research on integrating gas, temperature, wind, and dust into gas separately. Table 15 summarizes the significant differences between this research and other fourteen recent works discussed in section 2.1 Related Works, fourteen studies focused on temperature, wind, dust, C_2H_2, CO_2, CO, O_2, humidity, gas pressure, and other parameters to predict gas concentrations.

Among them, some studies used temperature, wind, and/or dust to predict gas concentrations. For example, Ma and Zhu (2016, 7) alleged that wind speed and temperature were the critical factors that affect gas concentration distribution. Fan et al. (2017, 50) asserted that the adsorbed gas in the coal seam took more than 80% of the total, while adsorbed gas content mainly depended on the porosity of coal, gas pressure, and temperature. Zhang et al. (2017, 1) attested that the variance of seepage velocity with time and temperature could provide an early warning for coal containing gas failing and gas disasters in a coal mine. Jo et al. (2019, 190) observed a strong correlation between temperature and humidity sensors. Song et al. (2019, 11, 13) discussed physical parameters of coal spontaneous combustion and gas migration, including wind speed and fresh air temperature. Wang et al. (2019, 1722) highlighted that historical monitoring data of coal seam depth, coal seam thickness, temperature, and gas concentration significantly impacted gas prediction. Sun and Li (2020, 7) developed a new gas safety evaluation model based on the sensor data of gas concentration, wind speed, dust, and temperature obtained from the coal mine safety monitoring system. Wang et al. (2020, 9) indicated that the coal seam's temperature was

Table 14. Code of sensors in feasibility verification study mine.

No.	Sensor name	Code
1	Coal Bin T	T030601
2	Transport Lane T	T030602
3	Working Face T	T030603
4	Upper Corner T	T030604
5	Material Lane T	T030701
6	1000m Refuge Chambers T	T030801
7	middle of Wind-back Lane T	T030802
8	500m Refuge Chambers T	T030803
9	Wind-back Lane T	T030804
10	Wind-back Lane Mixing T	T030805

considered one of the parameters of coal and gas. Zhang et al. (2020, 2) proposed an SRWNN model to make a gas concentration prediction mode based on gas CO, air volume, temperature, pressure, the number of continuous mining days, mining volume and mining depth. Zhang et al. (2020a) researched temperature variation during coal and gas outbursts as the implication for outburst prediction.

Some studies focused on C_2H_2, CO_2, CO, O_2, gas pressure, and other parameters to predict gas concentrations, including parameters of dynamic geological environments, simulation parameters, coal spontaneous combustion, gasometric and ventilation, gas emission, mining, etc. For example, Xia et al. (2018, 3) focused on monitoring the concentration of CO and believed that it was one of the main reasons for explosion and fire accident in the coal mine. They also examined other concentrations from the environmental monitoring system as an example, such as O_2, C_2H_2, and Simulation parameters. Jo et al. (2019, 190, 192) clarified that the variations of concentration of mine gases (CO_2 and CO) are of extreme importance to the real-time monitoring system. A strong correlation was also observed for temperature and humidity sensors. Song et al. (2019, 11, 13) discussed the CO concentration, O_2 concentration, and O_2/N_2 and confirmed that the CH_4/O_2 ratio changes could characterize the variation of gas indicators. Tutak and Brodny (2019, 6, 9, 18) used data from the mine's gasometric system for forecasting gas concentration levels. Sun and Li (2020, 7) developed a new gas safety evaluation model for the Qing Gang Ping coal mine. The data analysis was based on the sensor data of gas concentration, wind speed, dust, and temperature obtained from the coal mine safety monitoring system. Zhao et al. (2020, 1982) built a model for predicting gas outbursts to the working surface, including gas geology, mining influence, daily forecast, gas emission, mine pressure, and anti-burst measures. Zhang et al. (2021) combined geological structure and gas pressure as key indicators for developing a warning system. Data collected from CO_2, CO, and O_2 sensors had almost measured no variations in this research. They were maintained at a constant level from the current gas monitoring system so that there is no value to be investigated (see section 3.1). This research did not include other parameters as this project focused mainly on the current gas monitoring system rather than other coal mining information systems.

This research found the existing relations between gas and temperature in gas monitoring systems. Only one recent study by Lu et al. (2021, 9, 10) reported that gas concentrations increased with the increased temperature from 30 °C to 60 °C. It exponentially surged with the temperature after 60 °C. However, their research

Table 15. Comparisons between this research and other literatures.

Comparisons	*Corr* (Gas, Gas) ⇒ Gas	*Corr* (Gas, Temp) ⇒ Gas	*Corr* (Gas, Wind) ⇒ Gas	*Corr* (Gas, Dust) ⇒ Gas	Temperature	Wind	Dust	O2	CH4/O2	O2/N2	C2H2	CO	CO2	Humidity	Gas pressure	Other parameters
Ma and Zhu (2016)					*	*										
Fan et al. (2017)					*										*	*
Zhang et al. (2017)					*										*	*
Xia et al. (2018)								*			*	*				*
Jo et al. (2019)					*							*	*	*		
Song et al. (2019)					*	*		*	*	*		*				*
Tutak and Brodny (2019)																*
Wang et al. (2019)					*											*
Sun and Li (2020)					*	*	*									*
Wang et al. (2020)					*											*
Zhang et al. (2020)					*	*						*				*
Zhang et al. (2020a)					*										*	*
Zhao et al. (2020)															*	*
Zhang et al. (2021)															*	*
This research	*	*	*	*												

(Notes:
- *Corr*(X, Y) stands for the correlation of random variables X and Y.
- A ⇒ B stands for if A is true, then B is also true; if A is false, then nothing is said about B.
- Other parameters include parameters of dynamic geological environments, simulation parameters, coal spontaneous combustion, gasometric and ventilation, gas emission, mining, and so on)

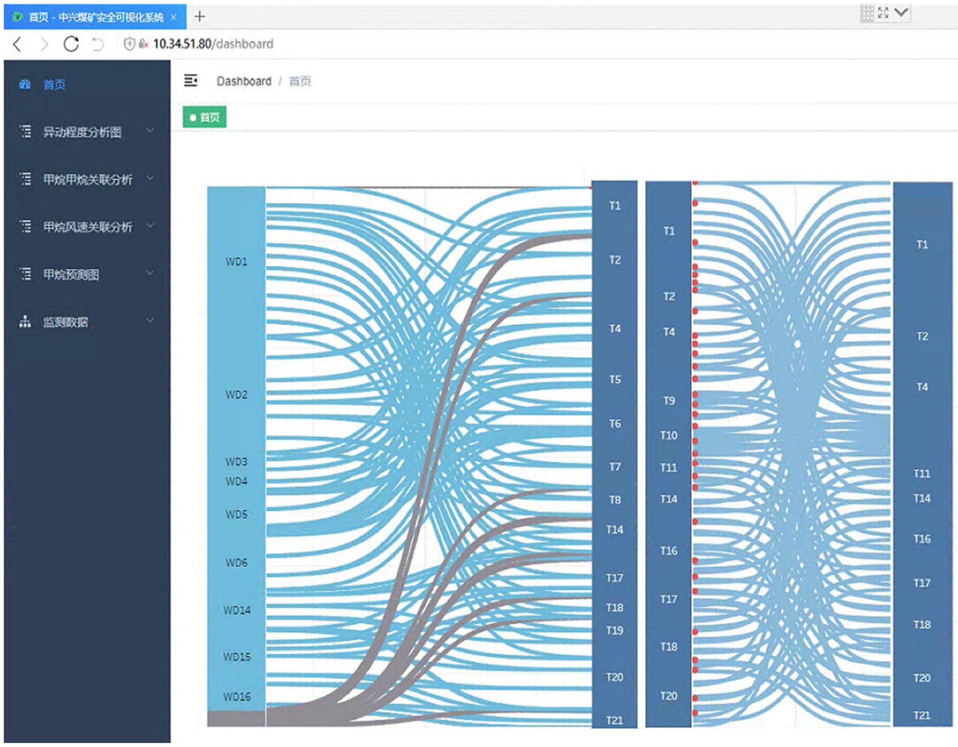

Figure 13. The screenshot of home page of the innovative integrated gas warning system deployed to the case study mine.

studied gas transport characteristics of positive pressure beam tube systems to spontaneous coal combustion warning rather than gas monitoring systems. This research also found the existing relations between gas and gas, and gas and wind. Similar findings were not reported or uncovered by up-to-date literature and the above studies (Table 15). The research outcomes will be valuable for field experts in coal mining safety with different scenery to further probe the relevant mechanisms. The proposed method used in this research mainly focused on correlational research. However, the correlational study does not provide the best evidence regarding causal mechanisms between two variables (Messerli 2012, 1563; Luft 2018, 159). Therefore, there is also a need for field experts to further conduct causal studies for investigating the cause-and-effect grounded theory to the findings of relations between gas and wind and probe the relevant mechanisms.

7. Conclusions, limitations, and further research

This research aims to develop an innovative gas warning system for increasing mining safety in the underground coal mine industry. The existing gas monitoring systems focus on detecting real-time data obtained from gas sensors and do not analyze whether other sensors' outputs affect gas data. The literature search did not find existing alarms or warning systems incorporating correlation analysis of gas data and data acquisition from temperature sensors and wind sensors in practice; this research aimed to fill this gap.

A mixed qualitative and quantitative research methodology was adopted in this research, including a case study, observation approach, boxplot technique, and correlational research. 3,211,215 data outputs were obtained from 49 sensors, including gas sensors (21), temperature sensors (16), wind sensors (10), and dust sensors (2). The study found 328 strong correlations between gas and gas (163), gas and temperature (130), and gas and wind (35). No correlations exist between gas and dust. This research suggested that integrating data on temperature and wind into gas would improve warning systems' sensitivity and reduce the incidence of explosions and other adverse events.

On the basis of the research outcomes, a warning sub-system was explored and embedded in the current gas monitoring system. Thus, three sub-systems (alarming, warning, and monitoring) are deployed in the Case Study mine. A UML model was finally developed by integrating the Correlation Analysis Theoretical Framework to the existing gas monitoring system in the Case Study to demonstrate an innovative gas warning system. An Innovative Integrated Gas Warning System was developed incorporating the 328 correlation analysis rules and three activated decision rules as a research outcome. The proposed method used in this research mainly focused on correlational research. For enhancing feasibility verification, this research conducted two rounds of verification studies to verify the feasibility of the proposed method. The first-round research proved that the proposed method might successfully be used at other periods at the Case Study mine. The second-round study verified that the proposed method might also fruitfully be used simultaneously at the same periods in different mines. As a result, an Innovative Integrated Gas Warning System was deployed in the Case Study mine for user acceptance testing to increase coal mining safety in Dec 2020. A screenshot of the homepage of this deployed system was provided for verification of this research project (see Figure 13).

The main contributions of this study can be stated as:

- This research attempts to use a correlational research method rather than ML methods to develop the gas warning system due to the current ML limitations. As a case study, this research utilized correlation analysis for developing an Innovative Integrated Gas Warning System.
- This research also attempts to find the existing relations between gas and gas, gas and temperature, and gas and wind in gas monitoring systems. The research outcomes will be valuable for field experts in coal mining safety with different scenery to further probe the relevant mechanisms.

The main limitation is that the result outcomes are mainly focused on the Case Study mine. Further research should be performed to examine whether the Innovative Integrated Gas Warning System might be effectively adopted in other coal mining companies and further clarify the adaptive application conditions. Another limitation is that this research uses correlational analysis to indicate significant relationships between gas and gas, gas and temperature, and gas and wind. However, the correlational research does not provide the best evidence regarding causal mechanisms between two variables (Messerli 2012, 1563; Luft 2018, 159). Therefore, there is a need for field experts in coal mining safety to further conduct causal studies for investigating the cause-and-effect grounded theory to the findings and explore the relevant mechanisms.

Nomenclature

a_{ij}	elements of decision matrix (DM)
r_{ij}	normalized elements of decision matrix
w_j	weight or importance of criteria ($j = 1, \ldots, n$)

Disclosure statement

No potential conflict of interest was reported by the authors.

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