

2022

Accident Analysis of Mining Industry in the United States – A retrospective study for 36 years

Author(s) ORCID Identifier:

Elham Rahimi  0000-0002-2898-0616

Younes Shekarian  0000-0001-8240-2895

Naser Shekarian  0000-0001-8225-3631

Pedram Roghanchi  0000-0003-4696-8845

Follow this and additional works at: <https://jsm.gig.eu/journal-of-sustainable-mining>



Part of the [Explosives Engineering Commons](#), [Oil, Gas, and Energy Commons](#), and the [Sustainability Commons](#)

Recommended Citation

Rahimi, Elham; Shekarian, Younes; Shekarian, Naser; and Roghanchi, Pedram (2022) "Accident Analysis of Mining Industry in the United States – A retrospective study for 36 years," *Journal of Sustainable Mining*.

Vol. 21 : Iss. 1 , Article 3.

Available at: <https://doi.org/10.46873/2300-3960.1345>

This Research Article is brought to you for free and open access by Journal of Sustainable Mining. It has been accepted for inclusion in Journal of Sustainable Mining by an authorized editor of Journal of Sustainable Mining.

Accident Analysis of Mining Industry in the United States – A retrospective study for 36 years

Abstract

A retrospective study on accident analysis of the United States mines for 36 years was achieved using statistical analysis on the MSHA's accident databases between 1983 and 2018. A regression model of generalized estimation equation (GEE) was used for unbalanced panel data that provided 95,812 observations for 19,924 mine-ID-year in aggregate, coal, metal, and non-metal mines. The contributions of various parameters, including mine type, injured body part, days lost, age, and experience on the rate of accidents and injuries were investigated across the commodity types. The results showed coal miners in the East region are at a higher risk of accident. The results of regression analysis show that mine-tenured workers have a vital role in accident frequencies. Analysis of the injured body part on the injury rate indicates that the upper body injuries are the most significant among all mine types. Also, the fatality rate is significant in aggregate, and coal mines in comparison with metal and non-metal mines.

Keywords

Mines, Accident, Statistical Analysis, Generalized Estimation Equation (GEE)

Creative Commons License



This work is licensed under a [Creative Commons Attribution 4.0 License](https://creativecommons.org/licenses/by/4.0/).

Accident analysis of mining industry in the United States – A retrospective study for 36 years

Elham Rahimi ^{a,b}, Younes Shekarian ^{a,b}, Naser Shekarian ^c, Pedram Roghanchi ^{a,*}

^a Department of Mineral Engineering, New Mexico Institute of Mining and Technology, Socorro, NM, USA

^b John and Willie Leone Family Department of Energy and Mineral Engineering, University Park, The Pennsylvania State University, State College, PA, 16802, USA

^c Department of Information Systems, Business School, University of Colorado Denver, Denver, CO, 80202, USA

Abstract

A retrospective study on accident analysis of the United States mines for 36 years was achieved using statistical analysis on the MSHA's accident databases between 1983 and 2018. A regression model of generalized estimation equation (GEE) was used for unbalanced panel data that provided 95,812 observations for 19,924 mine-ID-year in aggregate, coal, metal, and nonmetal mines. The contributions of various parameters, including mine type, injured body part, days lost, age, and experience on the rate of accidents and injuries were investigated across the commodity types. The results showed coal miners in the East region are at a higher risk of an accident. The results of regression analysis show that mine-tenured workers have a vital role in accident frequencies. Analysis of the injured body part on the injury rate indicates that the upper body injuries are the most significant among all mine types. Also, the fatality rate is significant in aggregate and coal mines in comparison with metal and nonmetal mines.

Keywords: mines, accident, statistical analysis, Generalized Estimation Equation (GEE)

1. Introduction

Mining is among the major industries that are vital to the economics of a nation. U.S. mines produced an estimated of \$82.2 billion of raw mineral materials in 2018 [1]. Mine production is generally categorized based on the commodity type, such as coal, metals, nonmetals, and aggregate (stone, sand, and gravel). The U.S. mining industry is known as one of the largest industries in terms of active operations, although it has slightly decreased in recent years ([statista.com](https://www.statista.com)¹). Historically, surface and underground mine working environments have been considered to be hazardous worldwide. Today, mine activities are associated with a wide range of risks in both underground and surface while necessary for quality of life and national economies. Asfaw [2] showed an inverse relationship between profitability and reported injuries, in which engineering practices and lack of investment in safety

are probable causes of accidents. According to the International Labor Organization (ILO), the number of work-related accidents has increased, and more people are losing their lives due to workplace injuries and illnesses every year.

An accident occurrence is a result of improper actions by persons and/or insecure physical or mechanical workplace surrounding. An accident is simply defined as an unexpected and unintentional incident that typically results in damage or injury. The risks of the mine practices increase when associated with natural threats from environmental conditions, such as rock falls. In light of this, a detailed investigation of an accident can provides essential information to avoid similar occurrences in the future. A thorough investigation of accidents is necessary for enabling a safe workplace for workers to ensure their health and safety is of all society's priority.

Mine Safety and Health Administration (MSHA) collects and provides data files on mining accidents,

Received 13 September 2021; revised 28 December 2021; accepted 29 December 2021.
Available online 17 January 2022

* Corresponding author.

E-mail address: pedram.roghanchi@nmt.edu (P. Roghanchi).

¹ <https://www.statista.com/statistics/949127/number-active-mines-united-states-by-commodity/> – accessed 9 June 2021.

<https://doi.org/10.46873/2300-3960.1345>

2300-3960/© Central Mining Institute, Katowice, Poland. This is an open-access article under the CC-BY 4.0 license (<https://creativecommons.org/licenses/by/4.0/>).

injuries, fatalities, employment, and other parameters under Part 50 of the U.S. Code of Federal Regulations. Numerous researchers have investigated the relationship between multi variables using MSHA's databases. Due to the complexity and a large amount of data collected, previous researchers have restrained their investigation to particular parameter/s.

Several researchers focused on the role of machinery with accident occurrences in mining operations. Duarte [3] reviewed MSHA's accident-related to machinery between 1995 and 2015. The results indicated that the accident rate in mining has a strong correlation with heavy machinery, including haul trucks, dumpers, and conveyors [4–7]. Also, the highest number of severe accidents are mainly machine-related, including conveyors, bolting machines, and continuous miners in underground coal mines [8]. Among machine-related accidents in underground coal mines, the greatest portion of accident occurrences is related to collision with pedestrians. The main casual factors are pedestrian in the path of a machine and lack of visibility [6].

A general overview of the raw data reveals that a large number of these incidents are related to underground mines, and the main reason could be the confined area in which workers and machines can maneuver [9]. The risks of injuries also are affected by other geological conditions. The strength of geological structures over the coal seam influences the risk of rock falling injuries. The rock falls between the beams, the ribs, and roof failures cause hundreds of accidents and fatalities every year. Notably, 50% of fatalities in underground bituminous mines were associated with falling off a roof and rib pillars [10].

The human factors (e.g., age and mining experience) are also important to be investigated. A previous study showed that the majority of mining accidents are associated with workers having less than five years of experience [11]. Moreover, young workers are at a higher risk of injuries than elderly workers; however, the risk of mortality is higher for workers aged more than 55 years when involved in a mine accident. In a study carried out by Sammarco [12], age and experience were found to be significant factors in intense injuries among roof bolter operators. A short period study between 2007 and 2008 by Moore [13] asserted that there is no relationship between age and severity of the injuries. Among these injuries, a large part of the injury classified

was related sprain and strain of back, arm, and hand, which was associated with handling material [14, 15]. Alessa [16] analyzed the yearly trend of arm and hand injuries and the severity over a period of 18 years between 2000 and 2017. The evaluations showed that 84% of days lost were incurred by 18% of arm and hand injuries resulting in more than 30 days restricted from work.

In this research, valuable information for a retrospective study of a comprehensive analysis of U.S. mine accidents is presented. The study aims to analyze U.S. mine accidents using MSHA data sets between 1983 and 2018. Several hypotheses were developed to investigate any probable relationship between contributing factors to mine accidents. To this approach, descriptive and statistical analyses are performed, which ascertained significant results on involved contributing factors. Although working with such a massive amount of data is complicated, we attempted to prepare these data in a data management system to create a well-organized database. This study consists of all accident records to obtain a comprehensive and better insight into these occurrences in different mines.

2. Materials and method

2.1. Data analysis and preparation

The data for this research was taken from the MSHA database² of mining accidents and injuries. The data was collected in accordance with the *Title 30 Code of Federal Regulations (CFR), Part 50* [17] under which mine operators and independent contractors are required to submit MSHA Form 7000-1 that describes each reportable incident.³ In this study, data analysis included 685,193 reported cases, including fatalities and nonfatal lost-time injuries from 1983 to 2018. The dataset consists of several variables to describe each accident. Relevant variables were identified and selected to investigate the rate of accidents, including accident date, time, mining operation type, states, reported injury and body part, lost workdays (LWD), job experience, age, and accident's narrative. In the studies relying on quantitative data collected over many years, possible epistemic uncertainty includes the limited level of evidence for information related to human factors (e.g., age range, sex, and race). Furthermore, there has been no study investigating the effects of all the contributing mining, environmental, and

² MSHA accident database is available at <https://arlweb.msha.gov/OpenGovernmentData/OGIMSHA.asp>.

³ A reportable incident is anything that happens out of the ordinary in a facility. Specifically, unplanned events or situations that result in or have the potential to result in injury, ill health, damage, or loss (<https://www.ausmed.com/cpd/articles/reportable-incidents> – accessed 27 August 2019).

Table 1. Description of variables in statistical analysis.

Category	Variable	Description
Accident	a. No. accident	Number of the reported accident, which the database is based on
Injury	b. No. injured	Number of reported injuries resulting from the accident
Region	c. East	West Virginia, Kentucky, Pennsylvania, Virginia, Alabama, Tennessee, Florida, Georgia, New York, North Carolina, Maryland, South Carolina, New Jersey, Puerto Rico, Vermont, Massachusetts, Mississippi, Connecticut, New Hampshire, Maine, Virgin Islands, Rhode Island, Delaware
	d. West	California, Nevada, Arizona, Colorado, Wyoming, Utah, Montana, Idaho, Washington, South Dakota, Alaska, Oregon, North Dakota, Hawaii, Northern Mariana Islands
	e. Midwest	Illinois, Texas, Ohio, Indiana, Missouri, Michigan, Minnesota, New Mexico, Oklahoma, Wisconsin, Arkansas, Kansas, Iowa, Louisiana, Nebraska
Mine Type	f. Surface	Surface mining operation
	g. Underground	Underground mining operation
Experience	h. Job experience	Computed years of experience in the job title
Age	i. Age	Age generated from birthdate
Days Lost	j. Days lost	Days lost from work because of injuries
Time	k. 0:00–6:00 am	Time of the day from 0:00–6:00 am
	l. 6:00–12:00 am	Time of the day from 6:00–12:00 am
	m. 0:00–6:00 pm	Time of the day from 0:00–6:00 pm
	n. 6:00–12:00 pm	Time of the day from 6:00–12:00 pm
Injured Body part	o. Head/neck	Head, brain, ear(s), eye(s), face, jaw, mouth, nose, face (multiple parts), scalp, skull, neck, head (multiple)
	p. Arm/hand	arm, upper arm, elbow, forearm, arm (multiple), wrist, hand, finger(s)
	q. Upper body	trunk, abdomen, back, chest, hips, shoulder(s), upper extremities (multiple)
	r. Lower body	leg, thigh, knee, lower leg, multiple, ankle, foot, toe(s), lower extremities (multiple)
	s. Other body parts	body systems, multiple parts, unclassified

human factors to show what factors have the most significant impact on the occurrence of accidents. The description of variables and categories defined are provided in Table 1. Data was categorized and analyzed based on these variables. The injured body part variable includes five classes of body parts, the head/neck, upper extremities, arm/hand, lower extremities, and others.

2.2. Regression analysis

Statistical analysis is the process of analyzing data and interpretation to discover patterns and trends of variables changing. Additionally, it is considered as the mathematical calculation that provides numerical values to represent the property of datasets. Statistical approaches are needed to ensure that data are appropriately understood, and those apparent relationships are meaningful (i.e., “significant”) and not only incidental. It is a technique that uses numbers and attempts to eliminate any biases while analyzing data. There are different ways to fit a straight line to the data when trying to uncover the trends, such as regression analysis, which is a statistical technique for studying linear relationships. Typically, regression analysis is performed to describe the

relationships between a set of independent variables and the dependent variables (number of accidents per employee and the number of injuries per employee). Regression analyses generate a regression equation where the coefficients reflect each independent variable's relationship with the dependent variable. For each possible setting of the independent variables, there is a separate population of response values in a regression model [18, 19].

While the dependent variable's mean value can be modeled by many functions depending on one or more independent variables, this study focuses on a set of models called linear statistical models. The choice of the proper regression model usually depends on the type of dependent variable data and the model type that is the best match. Different regression models have been tried on the panel data to determine the best fit based on the nature of variables, including normal linear, random-effect, zero-inflated, and general estimate equation (GEE) [20, 21]. Finally, GEE is selected to proceed with further analysis.

GEE estimates the marginal effect of covariates averaged across units [22]. This study can be interpreted as the overall effect of the mine operation, geographic location, job experience, and time of accident occurrences per employee. GEE is widely used

for panel data⁴ estimation [23]. The GEE helps to investigate the factors contributing to accident occurrences per mine-year across 35-years of unbalanced panel data. The GEE is used for three reasons [22, 23]. Firstly, GEE accounts for the possible serial correlation.⁵ Secondly, GEE allows for dependent variable distribution specification, which results in a more accurate estimation. Thirdly, robust standard errors in unbalanced panel data can be used [22]. This model is also specifying the covariance structure as exchangeable, implying a shared correlation between observations within each mine [24].

In the first step of this study, the summary and descriptive statistics of estimation models for each commodity are separately provided in Tables 4–7. The collected data sets from MSHA's library were merged by mine-ID using SQL⁶ Server Management. SQL provides a convenient environment to define categories of interests and group data sets to summarize consistent data sets. Throughout this process, a panel data with 19,914 mines from 1983 to 2018 was created that group records of accidents by mine-ID per year [23]. These reports were used in statistical analysis using STATA to provide descriptive statistics of variables, correlation, and regression analysis. The following equation describes the relationship between variables using the proposed GEE regression model:

$$Y_{i,t} = \beta X_{i,t} + \alpha + u_{i,t} + \varepsilon_{i,t} \quad (1)$$

where Y represents the number of accidents; X is a vector of mine-related information, β is the coefficients (values obtained for each variable in GEE result tables); i stand for mine-ID, t indicates the year; therefore, i, t shows the effect of the variable by mine-year; u_i demonstrates mine-specific unobserved heterogeneity (i.e., factors constant over time but unobserved to the econometrician), and ε is the error term (e.g., observation-specific error) [19, 25].

3. Retrospective of MSHA's data

3.1. Accidents distribution per commodity

The panel dataset contained a total number of 685,193 accidents, which resulted in 695,063 reported injuries. The data indicates that 53% of the

accidents (361,289) occurred in coal mines (Fig. 1a). Aggregate mines reported 28% (191,057) of all accidents, followed by metal and nonmetal mines, which reported 13% (87,433) and 6% (45,414) of all accidents, respectively. The proportion of accidents in these commodities based on the mine operation types is shown in Fig. 1b. Underground coal mines reported the majority of underground mine accidents while, on the surface, the majority of accidents were reported in surface aggregate mines.

3.2. Accident type

The distribution of mine accidents based on the type of the accident is shown in Fig. 2. In all the commodities, the majority of the accidents were reported to be related to the struck category (36%) following by over-exertion (23%), fall (13%), caught (10%), and other categories. Furthermore, significant numbers of accidents were struck against an object or by falling/rolling and powered moving objects, particularly in coal. Over-exertion in lifting objects, pulling or pushing, welding or throwing objects were significant in coal and aggregate.

3.3. Accident yearly distribution

The yearly distribution of accidents per commodity is shown in Fig. 3. The trend steadily increased by 1987 and jumped for all commodities in 1988 and 1989, possibly due to a boost in mining production [1]. Figure 3b shows the cumulative number of accidents per month for the whole 35-year period and the average number of 60,000 accidents distributed per month. However, in August, this number raised to more than 7,000 accidents. Moreover, a decrease in the number of accidents has been observed in the last two months of the year, which might be due to the decline in production at the end of the year. According to these observations, the relationship between the number of accidents and time (month) seems not to be significant.

3.4. Geographical location

MSHA performs mine health and safety enforcement activities in three different regions, namely the East, Midwest, and West regions. In this study, the

⁴ A panel data is multi-dimensional data of an observation that is measured repeatedly over time (M. Alam. 2020. VAR and Panel Data Models – the powerhouse of multivariate forecasting techniques. Going beyond univariate time series forecasting, <https://towardsdatascience.com/var-and-panel-data-models-the-powerhouse-of-multivariate-forecasting-techniques-22b8d8888141> – accessed 18 June 2020).

⁵ Serial correlation is the relationship between a given variable and a lagged version of itself over various time intervals. It measures the relationship between a variable's current value given its past values. A variable that is serially correlated indicates that it may not be random (C. Banton. 2021. Serial Correlation – <https://www.investopedia.com/terms/s/serial-correlation.asp#:~:text=Serial%20correlation%20is%20the%20relationship%20between%20> – accessed 24 August 2021).

⁶ Structural Query Language.

Table 2. Total accident distribution in the U.S. mining industry by region and states per commodity in both underground and surface mines between 1983 and 2018 (MSHA accident database).

Region (States)	Coal		361,289				Aggregate				191,057				Metal				87,433				Nonmetal				45,414							
			Underground		Surface		Other		Total		Underground		Surface		Other		Total		Underground		Surface		Other		Total		Underground		Surface		Other		Total	
East	364,198						271,717								71,314								4,224								16,943			
West Virginia	91,178	67,969	8,541	12,774	89,284	117	518	1,146	1,781	—	—	73	73	5	3	32	40																	
Kentucky	83,034	59,329	9,417	9,305	78,051	962	1,413	2,346	4,721	—	—	—	—	—	92	170	262																	
Pennsylvania	65,159	37,000	5,613	8,304	50,917	454	5,971	7,501	13,926	11	3	104	118	6	15	177	198																	
Virginia	33,350	21,637	1,739	4,174	27,550	84	2,264	2,614	4,962	—	44	47	91	34	142	571	747																	
Alabama	26,344	16,350	1,819	2,270	20,439	25	1,510	3,764	5,299	—	1	7	8	—	107	491	598																	
Tennessee	10,507	2,690	371	394	3,455	103	1,842	2,228	4,173	1,584	—	582	2,166	—	98	615	713																	
Florida	9,997	—	—	—	—	—	2,927	2,771	5,698	—	7	358	365	—	2,271	1,663	3,934																	
Georgia	9,947	1	1	—	2	71	2,379	2,091	4,541	—	5	26	31	2	847	4,524	5,373																	
New York	7,705	—	—	5	5	29	2,828	2,297	5,154	514	16	229	759	549	171	1,067	1,787																	
North Carolina	5,425	—	—	—	—	—	2,429	1,288	3,717	—	3	24	27	—	482	1,199	1,681																	
Maryland	5,244	1,434	179	349	1,962	39	1,404	1,837	3,280	—	—	—	—	—	1	1	2																	
South Carolina	3,403	—	—	—	—	—	1,194	1,264	2,458	—	155	167	322	—	121	502	623																	
New Jersey	2,712	—	—	—	—	—	1,187	1,365	2,552	22	3	49	74	—	4	82	86																	
Puerto Rico	2,229	—	—	—	—	—	1,180	1,048	2,228	—	—	—	—	—	1	0	1																	
Vermont	1,859	—	—	—	—	19	949	679	1,647	—	—	—	—	19	35	158	212																	
Massachusetts	1,545	—	—	—	—	—	1,041	454	1,495	—	—	—	—	—	31	19	50																	
Mississippi	1,393	—	52	—	52	—	476	319	795	—	—	—	—	—	54	492	546																	
Connecticut	1,139	—	—	—	—	—	559	520	1,079	—	—	—	—	—	13	47	60																	
New Hampshire	1,028	—	—	—	—	—	912	115	1,027	—	—	—	—	—	—	1	1																	
Maine	588	—	—	—	—	—	398	162	560	—	—	—	—	—	1	27	28																	
Virgin Islands	159	—	—	—	—	—	26	1	27	—	—	132	132	—	—	—	—																	
Rhode Island	149	—	—	—	—	—	140	9	149	—	—	—	—	—	—	—	—																	
Delaware	104	—	—	—	—	—	5	40	45	—	—	58	58	—	1	—	1																	
Midwest	184,691						65,555								78,576								27,477								13,083			
Illinois	41,906	29,192	2,245	3,485	34,922	193	2,383	3,367	5,943	—	—	86	86	98	74	783	955																	
Texas	25,515	0	4,592	64	4,656	11	7,227	6,929	14,167	2	77	4,531	4,610	244	508	1,330	2,082																	
Ohio	21,793	8,598	2,524	1,705	12,827	70	3,369	4,058	7,497	—	—	—	—	756	167	546	1,469																	
Indiana	14,720	3,766	3,769	870	8,405	206	2,673	3,110	5,989	—	—	—	—	129	46	151	326																	
Missouri	14,264	—	571	39	610	542	3,013	7,363	10,918	1,287	8	867	2,162	3	48	523	574																	
Michigan	11,389	—	—	—	—	—	2,949	2,646	5,595	1,045	1,398	3,111	5,554	57	116	67	240																	
Minnesota	10,721	—	—	—	—	—	1,714	271	1,985	0	2,863	5,724	8,587	5	41	103	149																	
New Mexico	10,563	—	1,440	875	2,315	—	1,197	303	1,500	1,016	1,263	1,097	3,376	1,480	225	1,667	3,372																	
Oklahoma	6,148	353	819	38	1,210	26	2,086	2,551	4,663	—	—	—	—	—	211	64	275																	
Wisconsin	6,026	—	—	—	—	25	3,533	2,071	5,629	—	10	12	22	20	141	214	375																	
Arkansas	6,010	115	11	11	137	13	2,026	1,978	4,017	—	39	1,618	1,657	1	100	98	199																	
Kansas	5,684	—	69	13	82	88	1,351	2,991	4,430	—	—	—	—	304	45	823	1,172																	
Iowa	4,371	24	93	7	124	294	1,495	2,038	3,827	—	—	8	8	177	69	166	412																	
Louisiana	3,974	—	263	4	267	—	148	730	878	—	1	1,379	1,380	689	25	735	1,449																	
Nebraska	1,607	—	—	—	—	129	276	1,133	1,538	—	—	35	35	—	1	33	34																	
West	136,304						24,017								41,167								55,732								15,388			
California	22,815	—	9	13	22	14	10,409	6,232	16,655	333	1,071	1,595	2,999	141	761	2,237	3,139																	
Nevada	18,873	—	—	—	—	1	1,014	574	1,589	2,923	7,275	5,506	15,704	4	283	1,293	1,580																	

(continued on next page)

Table 2. (continued)

Region (States)	Coal			Aggregate			191,057			Metal			87,433			Nonmetal			45,414					
	Underground			Surface			Other			Total			Underground			Surface			Other			Total		
	Underground	Surface	Total	Underground	Surface	Total	Underground	Surface	Total	Underground	Surface	Total	Underground	Surface	Total	Underground	Surface	Total	Underground	Surface	Total			
Arizona	18,626	—	18,626	550	80	630	2,831	987	3,818	2,451	6,089	5,440	13,980	—	144	54	198	—	144	54	198			
Colorado	15,151	5,448	20,599	801	1,012	1,813	3,030	1,291	4,403	1,584	473	1,197	3,254	76	62	95	233	—	62	95	233			
Wyoming	13,884	541	14,425	4,795	564	5,900	667	492	1,159	35	75	169	279	2,444	311	3,791	6,546	—	311	3,791	6,546			
Utah	12,743	5,700	18,443	25	949	6,674	1,289	403	1,692	270	1,098	1,866	3,234	344	137	662	1,143	—	137	662	1,143			
Montana	8,198	71	8,269	1,210	116	1,397	738	542	1,280	2,890	653	1,203	4,746	159	174	442	775	—	174	442	775			
Idaho	6,724	—	6,724	—	—	—	916	180	1,096	3,399	472	870	4,741	8	558	321	887	—	558	321	887			
Washington	5,974	—	5,974	914	44	958	2,587	950	3,537	778	11	429	1,218	—	57	204	261	—	57	204	261			
South Dakota	5,355	—	5,355	—	—	—	1,494	777	2,271	1,846	448	524	2,818	—	41	225	266	—	41	225	266			
Alaska	3,105	—	3,105	134	26	160	266	23	289	573	920	1,154	2,647	—	9	—	9	—	9	—	9			
Oregon	2,539	—	2,539	0	—	—	1,696	425	2,121	35	39	38	112	—	—	—	306	—	—	—	306			
North Dakota	1,374	—	1,374	985	30	1,015	314	1	315	—	—	—	—	—	1	43	44	—	1	43	44			
Hawaii	941	—	941	—	—	—	507	433	940	—	—	—	—	—	1	—	1	—	1	—	1			
Northern Mariana Islands 2	—	—	—	—	—	—	2	—	2	—	—	—	—	—	—	—	—	—	—	—	—			

mine accident analysis based on the geographical locations was conducted according to the MSHA enforcement regions. Despite its smaller geographic size, more than half of the accidents occurred in the East region. Those states with the highest number of accidents, in general, are located in the eastern part of the U.S., including West Virginia, Kentucky, Pennsylvania, Virginia, and Alabama (Fig. 4 and Table 2). Following the East region, Midwest states had a significant number of accidents. Those states include Illinois, Texas, and Ohio. Coal mines reported a higher number of accidents (i.e., more than 50,000 accidents in West Virginia, Kentucky, and Pennsylvania (Fig. 5 a)). Aggregate mines in California, Texas, Pennsylvania, and Missouri reported the considerable number of accidents (Fig. 5 b). The West region states, which are known for large metal

Table 3. Demographic information on fatalities by year in the U.S. mining industry per Coal and other commodities between 1983–2018 (MSHA fatality database).

Year	Coal			Noncoal			
	Miners	Fatalities	Rate	Year	Miners	Fatalities	Rate
1983	200,199	70	0.350	1983	214,661	62	0.289
1984	208,160	125	0.600	1984	219,727	80	0.364
1985	197,049	68	0.345	1985	218,112	57	0.261
1986	185,167	89	0.481	1986	209,638	49	0.234
1987	172,780	63	0.365	1987	213,532	67	0.314
1988	166,278	53	0.319	1988	225,422	49	0.217
1989	164,929	68	0.412	1989	234,459	48	0.205
1990	168,625	66	0.391	1990	235,690	56	0.238
1991	158,677	61	0.384	1991	230,107	53	0.230
1992	153,128	55	0.359	1992	224,567	43	0.191
1993	141,183	47	0.333	1993	219,320	51	0.233
1994	143,645	45	0.313	1994	225,498	40	0.177
1995	132,111	47	0.356	1995	229,536	53	0.231
1996	126,451	39	0.308	1996	229,045	47	0.205
1997	126,429	30	0.237	1997	235,915	61	0.259
1998	122,083	29	0.238	1998	235,561	51	0.217
1999	114,489	35	0.306	1999	238,852	55	0.230
2000	108,098	38	0.352	2000	240,450	47	0.195
2001	114,458	42	0.367	2001	232,770	30	0.129
2002	110,966	28	0.252	2002	218,148	42	0.193
2003	104,824	30	0.286	2003	215,325	26	0.121
2004	108,734	28	0.258	2004	220,274	27	0.123
2005	116,436	23	0.198	2005	228,401	35	0.153
2006	122,975	47	0.382	2006	240,522	26	0.108
2007	122,936	34	0.277	2007	255,187	33	0.129
2008	133,828	30	0.224	2008	258,918	23	0.089
2009	134,089	18	0.134	2009	221,631	17	0.077
2010	135,500	48	0.354	2010	225,676	24	0.106
2011	143,437	20	0.139	2011	237,772	16	0.067
2012	137,650	20	0.145	2012	250,228	16	0.064
2013	123,259	20	0.162	2013	251,263	22	0.088
2014	116,010	16	0.138	2014	250,574	30	0.120
2015	102,804	12	0.117	2015	247,091	17	0.069
2016	81,485	8	0.098	2016	247,107	16	0.065
2017	82,843	15	0.181	2017	236,622	13	0.055
2018	82,699	12	0.145	—	—	—	—

Table 4. Descriptive statistics and correlation matrix of variables for aggregate mines.

Category	Variables	Mean	SD	Min	Max	a	b	c	d	e	f	g	h	i	j	k	m	n
Geographical location	a. No. accident	2	3	1	107													
	b. No. injured	2	8	1	996	0.48												
	c. East	0	0	0	1	-0.03	-0.02											
	d. West	0	0	0	1	0.00	0.01	-0.41										
	e. Midwest	0	0	0	1	0.03	0.01	-0.66	-0.42									
Mine operation type	f. Surface mines	1	0	0	1	-0.21	-0.10	-0.11	0.21	-0.06								
	g. Underground	0	0	0	1	0.00	0.00	0.04	-0.06	0.02	-0.19							
	h. Other	0	0	0	1	0.22	0.10	0.10	-0.19	0.06	-0.96	-0.10						
Job experience	i. Job experience	7	7	0	65	-0.03	-0.01	0.02	-0.03	0.01	-0.01	-0.03	0.02					
Age	j. Age	39	12	0	93	-0.02	-0.01	0.00	0.00	0.00	-0.02	-0.02	0.03	0.50				
Time of accident	k. 0:00-6:00 am	0	0	0	11	0.59	0.27	-0.03	0.01	0.02	-0.18	0.01	0.17	-0.02	-0.01			
	m. 6:00-12:00 am	1	2	0	41	0.86	0.40	-0.02	0.00	0.02	-0.17	-0.01	0.17	-0.01	-0.01	0.41		
	n. 0:00-6:00 pm	1	1	0	30	0.80	0.37	-0.03	0.00	0.03	-0.16	-0.01	0.17	-0.03	-0.02	0.37	0.52	
	o. 6:00-12:00 pm	0	1	0	45	0.71	0.38	-0.04	0.02	0.02	-0.17	0.01	0.17	-0.03	-0.01	0.40	0.45	0.42

Note: Numbers in bold implies correlation is significant at the 0.01 level ($p < 0.01$).

Table 5. Descriptive statistics and correlation matrix of variables for coal mines.

Category	Variables	Mean	SD	Min	Max	a	b	c	d	e	f	g	h	i	j	k	m	n
Geographical location	a. No. accident	6	11	1	301													
	b. No. injured	6	16	1	1122	0.74												
	c. East	1	0	0	1	-0.12	-0.09											
	d. West	0	0	0	1	0.02	0.02	-0.54										
	e. Midwest	0	0	0	1	0.12	0.08	-0.78	-0.09									
Mine operation type	f. Surface mines	0	0	0	1	-0.15	-0.11	-0.29	0.13	0.24								
	g. Underground	0	0	0	1	0.23	0.16	0.19	-0.07	-0.17	-0.73							
	h. Other	0	0	0	1	-0.12	-0.09	0.10	-0.06	-0.07	-0.28	-0.43						
Job experience	i. Job experience	8	6	0	90	-0.08	-0.06	0.04	-0.05	-0.01	0.16	-0.20	0.06					
Age	j. Age	39	10	0	91	0.04	0.02	-0.05	0.00	0.06	0.08	-0.19	0.12	0.46				
Time of accident	k. 0:00-6:00 am	1	3	0	63	0.91	0.67	-0.08	0.01	0.09	-0.12	0.27	-0.17	-0.08	0.02			
	m. 6:00-12:00 am	2	3	0	93	0.92	0.68	-0.11	0.02	0.11	-0.05	0.22	-0.18	-0.06	0.02	0.79		
	n. 0:00-6:00 pm	1	3	0	64	0.91	0.68	-0.11	0.03	0.11	-0.06	0.23	-0.19	-0.07	0.02	0.79	0.80	
	o. 6:00-12:00 pm	2	4	0	106	0.91	0.68	-0.06	0.01	0.06	-0.11	0.29	-0.20	-0.06	0.03	0.78	0.75	0.76

Note: Numbers in bold implies correlation is significant at the 0.01 level ($p < 0.01$).

Table 6. Descriptive statistics and correlation matrix of variables for metal mines.

Category	Variables	Mean	SD	Min	Max	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>	<i>i</i>	<i>j</i>	<i>k</i>	<i>m</i>	<i>n</i>	
Geographical location	<i>a.</i> No. accident	7	13	1	178														
	<i>b.</i> No. injured	8	24	1	1080	0.68													
	<i>c.</i> East	0	0	0	1	-0.06	-0.04												
	<i>d.</i> West	1	0	0	1	-0.10	-0.07	-0.46											
Mine operation type	<i>e.</i> Midwest	0	0	0	1	0.15	0.11	-0.16	-0.81										
	<i>f.</i> Surface mines	0	0	0	1	0.01	0.00	-0.12	0.13	-0.06									
	<i>g.</i> Underground	0	0	0	1	0.06	0.04	0.08	-0.01	-0.04	-0.31								
Job experience	<i>h.</i> Other	1	0	0	1	-0.06	-0.04	0.04	-0.10	0.08	-0.63	-0.54							
	<i>i.</i> Job experience	6	6	0	50	0.05	0.03	-0.02	-0.12	0.15	0.00	0.03	-0.03						
Age	<i>j.</i> Age	38	10	0	93	0.03	0.01	0.03	-0.15	0.15	-0.01	-0.05	0.05	0.44					
Time of accident	<i>k.</i> 0:00–6:00 am	1	2	0	53	0.76	0.57	-0.05	-0.04	0.08	0.01	0.12	-0.10	-0.02	-0.01				
	<i>m.</i> 6:00–12:00 am	3	5	0	69	0.94	0.62	-0.06	-0.12	0.17	0.01	0.01	-0.02	0.07	0.04	0.62			
	<i>n.</i> 0:00–6:00 pm	2	4	0	48	0.92	0.60	-0.06	-0.08	0.14	0.01	0.03	-0.04	0.04	0.02	0.65	0.85		
	<i>o.</i> 6:00–12:00 pm	2	4	0	96	0.88	0.64	-0.04	-0.08	0.12	0.01	0.11	-0.10	0.04	0.02	0.65	0.73	0.72	

Note: Numbers in bold implies correlation is significant at the 0.01 level ($p < 0.01$).

Table 7. Descriptive statistics and correlation matrix of variables for non-metal mines.

Category	Variables	Mean	SD	Min	Max	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>	<i>i</i>	<i>j</i>	<i>k</i>	<i>m</i>	<i>n</i>	<i>n</i>
Geographical location	<i>a.</i> No. accident	3	4	1	93														
	<i>b.</i> No. injured	3	10	1	873	0.56													
	<i>c.</i> East	0	0	0	1	-0.02	-0.02												
	<i>d.</i> West	0	0	0	1	0.05	0.04	-0.53											
Mine operation type	<i>e.</i> Midwest	0	0	0	1	-0.03	-0.02	-0.54	-0.42										
	<i>f.</i> Surface mines	0	0	0	1	-0.17	-0.08	0.03	0.02	-0.05									
	<i>g.</i> Underground	0	0	0	1	0.15	0.10	-0.18	0.01	0.18	-0.21								
Job experience	<i>h.</i> Other	1	0	0	1	0.07	0.02	0.09	-0.03	-0.06	-0.82	-0.39							
	<i>i.</i> Job experience	7	7	0	50	-0.02	-0.01	0.07	-0.02	-0.06	0.05	-0.02	-0.04						
Age	<i>j.</i> Age	39	11	0	88	-0.05	-0.02	0.03	-0.03	-0.01	0.06	-0.02	-0.04	0.52					
Time of accident	<i>k.</i> 0:00–6:00 am	0	1	0	18	0.65	0.39	-0.06	0.05	0.01	-0.16	0.17	0.05	-0.04	-0.05	0.00			
	<i>m.</i> 6:00–12:00 am	1	2	0	33	0.84	0.42	0.01	0.02	-0.04	-0.12	0.11	0.05	0.00	-0.03	-0.04	0.41		
	<i>n.</i> 0:00–6:00 pm	1	2	0	39	0.81	0.40	0.00	0.03	-0.04	-0.11	0.08	0.05	-0.02	-0.05	-0.04	0.42	0.54	
	<i>o.</i> 6:00–12:00 pm	1	1	0	34	0.75	0.53	-0.07	0.07	0.00	-0.16	0.15	0.06	-0.03	-0.03	-0.02	0.48	0.45	0.45

Note: Numbers in bold implies correlation is significant at the 0.01 level ($p < 0.01$).

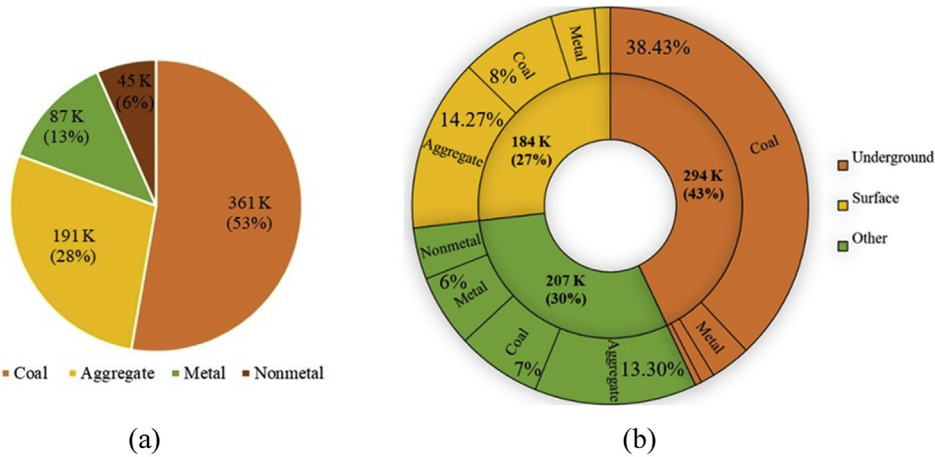


Fig. 1. (a) Accident distribution of the U.S. mining industry between 1983 and 2018 by commodity; (b) The proportion of accident occurrences of commodities by mine type (subunit in the database).

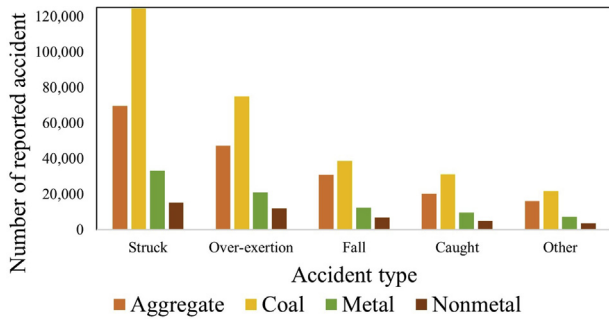
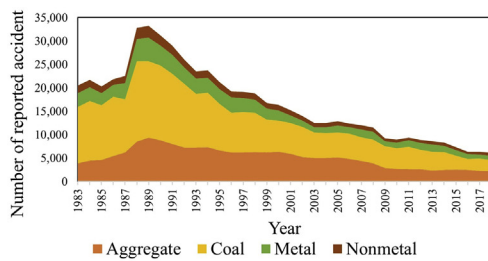
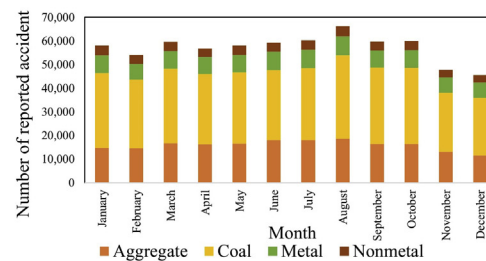


Fig. 2. The frequency of accidents classified by four main accident type categories per commodity.

mining such as gold and copper, reported the high number of accidents (Fig. 5 c). Nonmetal mines have inconspicuous linkage with geographical location (Fig. 5 d).



(a)



(b)

Fig. 3. (a) The total number of accidents in the U.S. mining industry by commodity between 1983 and 2018; (b) The distribution of accidents by months of the year per commodity.

3.5. Job experience

The analysis of mining tenured as a contributing factor shows that less tenured workers were involved in a large portion of mine accident occurrences. The majority of accidents in all the commodities were reported to involve miners with less than five years of job experience. However, this portion declined by 280% in metal miners with 5–10 years of job experience, followed by 278% in nonmetal, 260% in aggregate, and 174% in coal mines. The frequency of accident occurrences was inversely affected by obtaining more job experiences (Fig. 6).

3.6. Injury severity and injured body part

Arms and hands are the body parts of most potentially injured in aggregate, metal, and nonmetal mines (Fig. 7). However, in coal mines, the

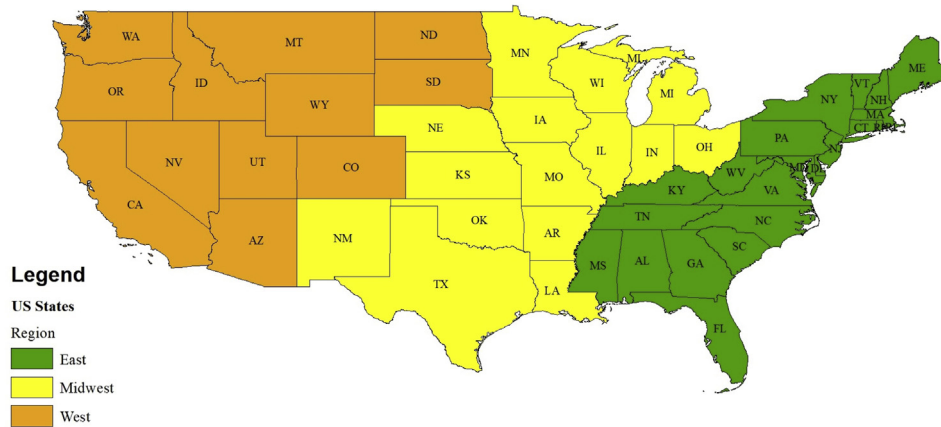


Fig. 4. The United States by classified regions of East, Midwest, and West.

worker's upper body is more injury-prone and accounted for more than 31% of all accidents (Fig. 7). In the analysis of injured body parts, all commodities other than coal showed a similar distribution, followed by arm/hands are upper body, lower body, and head/neck, respectively.

3.7. Accident analysis by days lost

Yearly trends of the number and severity of injuries were investigated based on the total days lost.

Despite a declining trend for the number of accidents as well as the severity of injuries (number of days lost), the ratio of intense injuries for coal mines (Fig. 8a) is remained remarkable (Fig. 8). However, in aggregate (Fig. 8b), metal (Fig. 8c), and nonmetal mines (Fig. 8d), the majority of accidents were occupational injuries with no workday lost.

The severity of injuries is investigated regarding those with more than seven days lost. Body part categories are analyzed to determine the potential of the high-risk body part as a mine worker. These

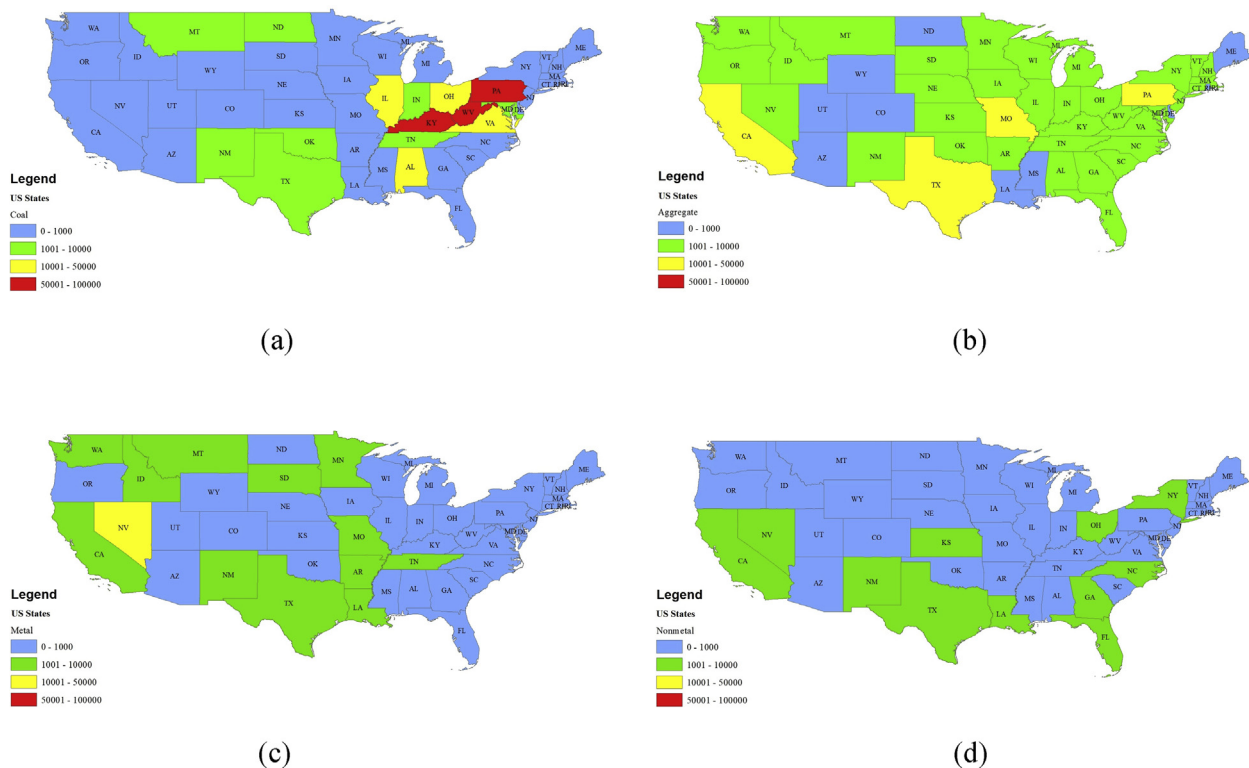


Fig. 5. Schematic view of accidents incidence by geographical location per commodity for: (a) coal; (b) aggregate; (c) metal; and (d) nonmetal.

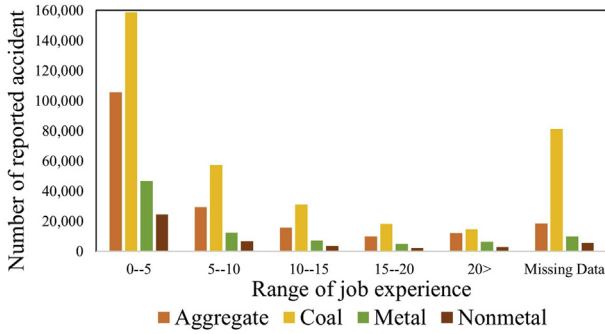


Fig. 6. Accident incidence versus ranges of miner's job experience.

analyses indicate that proportionally, upper and lower bodies are more intensely prone to injury, which mainly include the back, chest, shoulder, leg, and foot (Fig. 9). Following that, severe injuries of arm and hand were considerable in coal and aggregate mines and partially in the metal and nonmetal mines.

3.8. Age and gender analysis

The number of accidents based on the age of the workers in different commodities is shown in Fig. 10a. In all commodities, the workers with age between 30 and 50 years old were injured more than workers in other age ranges. The number of missing data in coal is noticeable. As expected, the number of reported injuries among female workers is significantly lower because the number of female workers to men are relatively smaller (Fig. 10 (b)).

3.9. Fatality in mining

The number of fatal accidents in the mining industry has been considerably decreased. For example, MSHA data reports that the fatalities have

been decreased from 242 in 1977 to 28 in 2017. This remarkable decrease has been achieved by continuously monitoring accidents and improving regulations for the safety of workers.

Fatality analysis of U.S. mine accidents from 1983 to 2018 showed that, on average, approximately 0.03% of coal workers and nearly 0.017% of mine-workers in other commodities lost their lives (Table 3). Figure 11 shows the number of fatalities compared to the number of employees in coal mines and other commodities. Generally, the number of employees in coal mines has decreased to the present (although there was a jump between 2003 and 2011). This diminishing number of coal workers was infected by the pulsation of legislation and the chain of supply and demand. However, the total number of employee in other commodities has been steady. According to the rate of fatalities per employees, there is the primary concern on coal mines, which indicates this rate is four times in coal compared to noncoal mines.

4. Results

An attempt was made to identify the various causal factors of work injuries in mines. During the observed 36-year period, there were 95,812 observations on accident records in the United States mining industry. This number divided into 46,470 observations in 9,749 aggregate mine-year, 36,678 observations in 8,075 coal mine-year, 5,811 observations in 987 metal mine-year, and 6,853 observations in 1,113 nonmetal mine-year. A multiple linear regression analysis was conducted to identify any patterns or trends in accident occurrences in each commodity. Figure 12 illustrates the research model that includes four hypotheses on geographical location, mine operation, job experience, and time of accident contributed to accident incidences. Reported injuries were also analyzed by developing

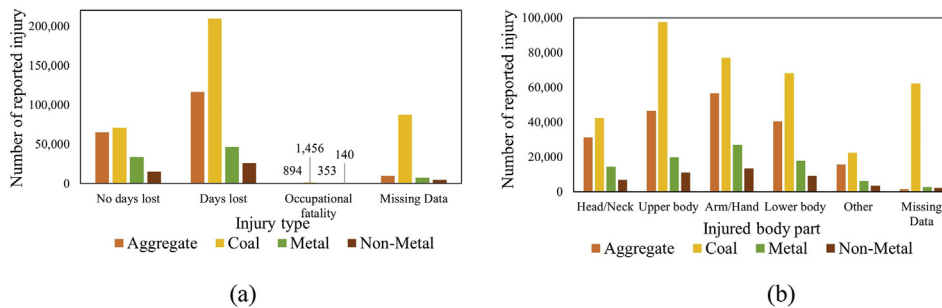


Fig. 7. (a) Injury severity of accident by commodity is classified as fatal, days lost, and no days lost; (b) The occurrence of accidents that had days lost is illustrated by portion of injured body parts.

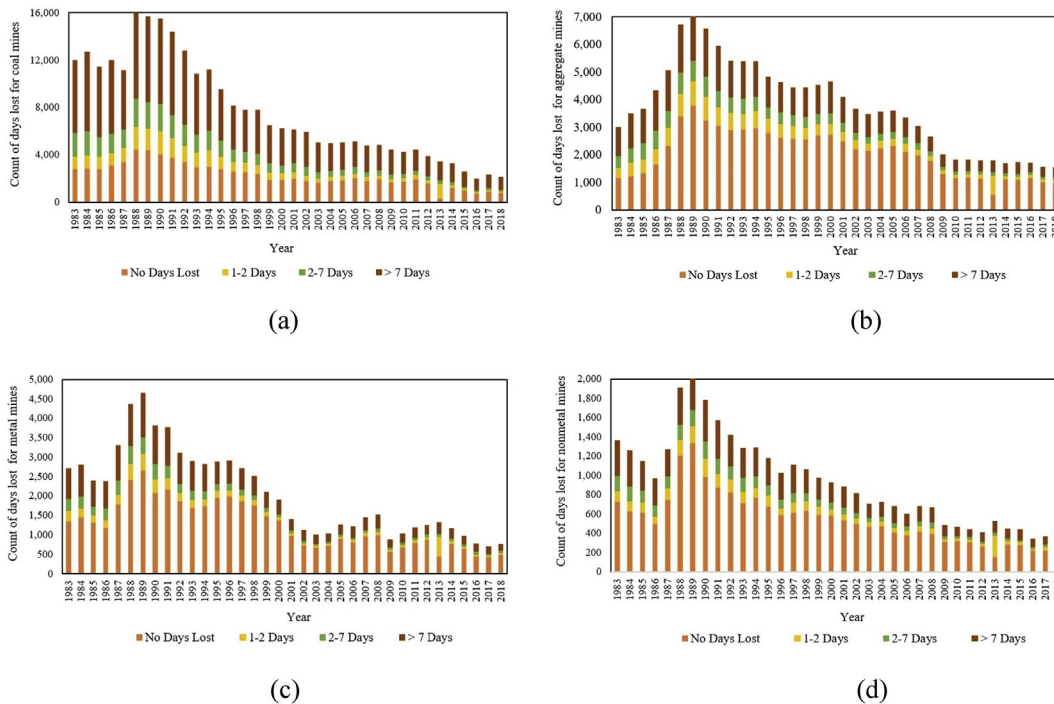


Fig. 8. Yearly analysis of days lost per commodity for: (a) coal; (b) aggregate; (c) metal; (d) nonmetal; which accounts for 37% of accident database.

hypotheses on days lost, fatality, and injured body parts.

A comprehensive study was conducted to develop hypotheses and examine the relationship between accident occurrences and contributing factors in the U.S. mining industry from 1983 to 2018. This study found several factors that may contribute to the occurrence of the accident and consequently the reported injuries. The selected database allows for studying the effects of contributing factors, including geographic location, mine operation type, miner's job experience, time of day, days lost, fatality, and injured body parts. Therefore, the model was utilized to test the following hypotheses:

H1. Geographic location contributes to accident occurrences.

H2. Mine type (underground/surface) contributes to a higher risk of accident occurrence.

H3. There is no relationship between the miner's job experience with accident occurrence.

H4. The time of day contributes to a higher risk of accidents.

H5. Days lost (severity) contribute to higher reported injuries.

H6. Fatality is associated with higher reported injuries.

H7. Body part contributes to the rate of reported injuries.

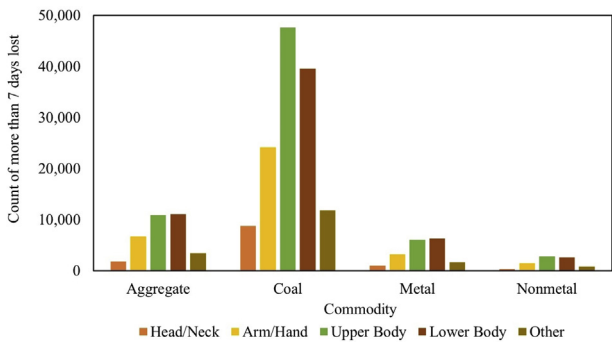


Fig. 9. The severe injuries distributed by body part for each commodity (includes 37% of recorded accidents).

4.1. Descriptive statistics

In this section, the summary and descriptive statistics of estimation models for each commodity are

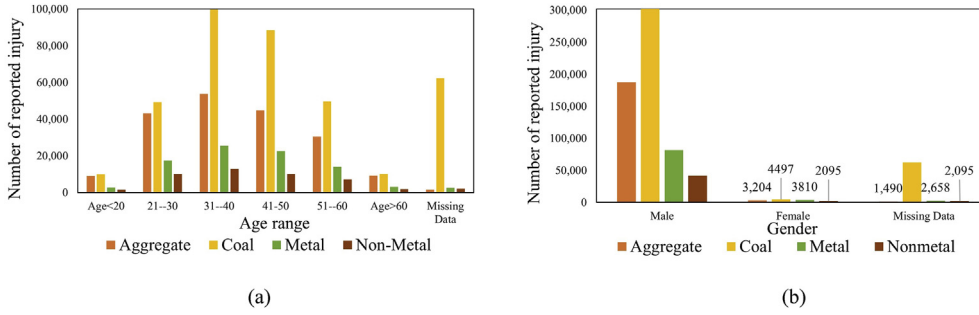


Fig. 10. Analysis of accidents distribution per: (a) age ranges and (b) gender.

separately provided through Tables 4–7. There was a positive correlation between the West region with accident occurrences, as well as injuries during the 6:00 am–12:00 pm in aggregate mines (Table 4). Table 5 indicates a positive correlation between accident/injuries and underground coal mines. A positive correlation is seen between underground metal

mines and accident occurrences (Table 6). Also, there is a positive correlation between job experience and the Midwest region. Table 7 shows a positive correlation between underground nonmetal mines and injuries. Moreover, there is a positive correlation between the West region with accident occurrences, as well as the Midwest region with the underground.

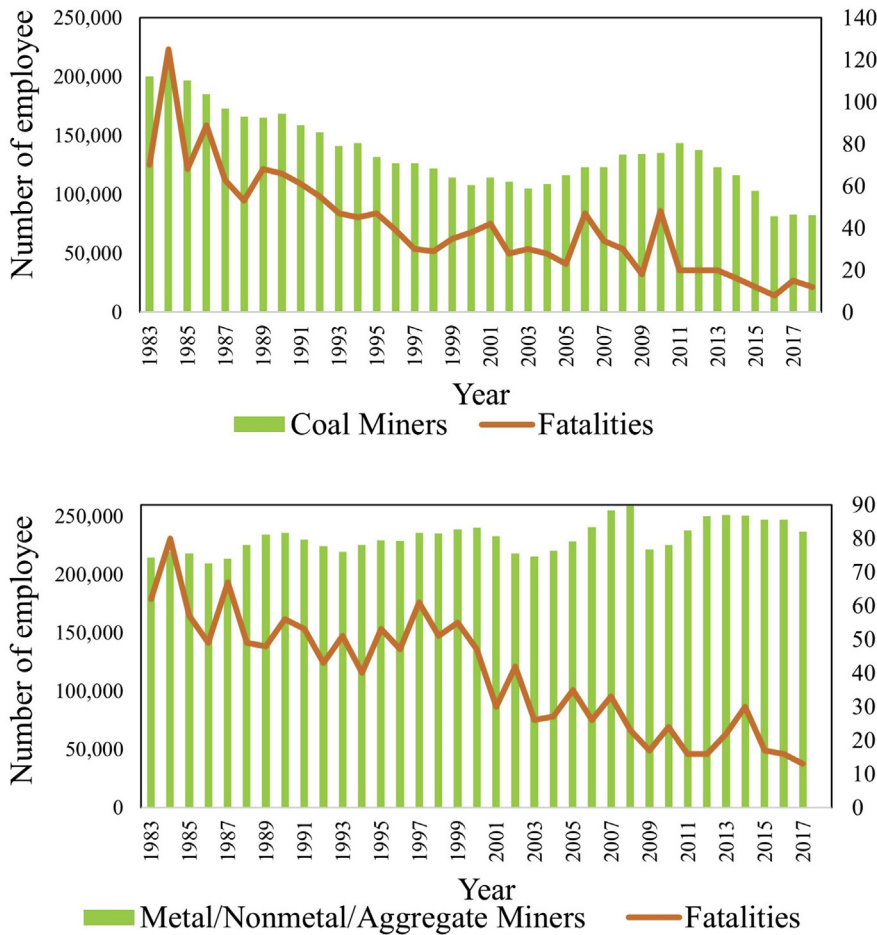


Fig. 11. The number of miners and fatality portion by year.

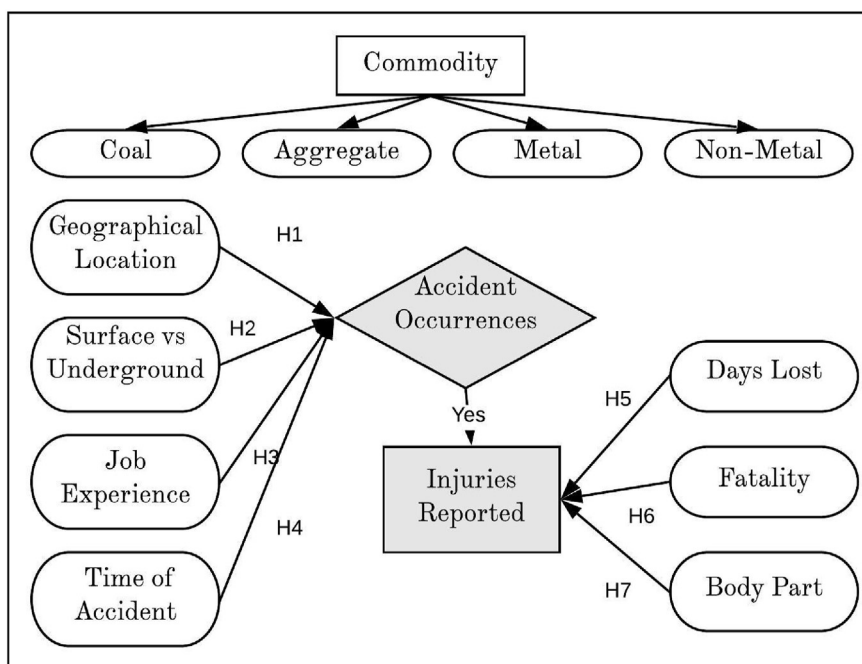


Fig. 12. Research framework modeling for developed hypotheses and contributing factors.

The hypothesis was tested by GEE regression and the main results are presented in Tables 8 and 9. Here, the analysis of results for each commodity is separately provided as the following:

4.2. Aggregate

In the statistical analysis for the aggregate mine operations, a total number of 46,470 observations

Table 8. Main results of GEE estimation model for accident variables.

Accident variable		(1) Aggregate	(2) Coal	(3) Metal	(4) Nonmetal
Mine operation type	Surface (reference)				
	Underground	−0.296 (0.215)	0.201*** (0.227)	0.489*** (0.103)	−0.354** (0.172)
Job experience		0.001** (0.001)	0.009*** (0.001)	0.016*** (0.005)	0.004*** (0.002)
	Geographical location				
Geographical location	East (reference)				
	West	0.286*** (0.025)	−0.361*** (0.060)	0.046 (0.168)	0.517*** (0.093)
	Midwest	0.193*** (0.024)	−0.298*** (0.038)	−0.354** (0.178)	0.244*** (0.092)
Time of accident	0:00–6:00 am (reference)				
	6:00 am–12:00 pm	0.124*** (0.004)	0.019*** (0.005)	0.003 (0.006)	0.065*** (0.006)
	12:00 pm–6:00 pm	0.137*** (0.004)	0.014*** (0.006)	0.011 (0.010)	0.077*** (0.010)
	6:00 pm–12:00 am	0.089*** (0.006)	0.019*** (0.009)	0.112* (0.006)	0.021* (0.011)
	Constant	−2.069*** (0.029)	−2.577*** (0.047)	−2.480*** (0.180)	−2.045*** (0.142)
Observations	46,470	36,678	5,811	6,853	
Number of ID	9,749	8,075	978	1,113	
Wald Chi-2	2593.17***	1038.15***	435.70***	532.73***	
Year	1983–2018				

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9. Main results of GEE estimation model for injury-related variables.

Injury variable		(1)	(2)	(3)	(4)
		Aggregate	Coal	Metal	Nonmetal
Body Part	Days lost	−0.001* (0.000)	−0.001*** (0.000)	0.001 (0.001)	−0.001 (0.000)
	Fatality	0.279*** (0.070)	0.112*** (0.199)	0.053 (0.662)	0.092 (0.078)
	Head/neck (reference)				
	Arm/hand	0.099*** (0.007)	−0.009 (0.006)	−0.015* (0.009)	0.047*** (0.007)
	Upper body	0.109*** (0.007)	0.355*** (0.007)	0.021*** (0.008)	0.075*** (0.008)
	Lower body	0.087*** (0.009)	−0.005 (0.006)	0.001 (0.011)	0.022* (0.012)
	Other organs	0.121*** (0.014)	0.537*** (0.013)	0.102*** (0.024)	0.081*** (0.014)
	Constant	−2.053*** (0.032)	−2.327*** (0.029)	−2.135*** (0.428)	−1.961*** (0.131)
	Observations	46,470	36,678	5,811	6,853
	Number of ID	9,749	8,075	978	1,113
	Wald Chi-2	978.93***	870.52***	394.05***	567.54***
	Year	1983–2018			

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

were associated with 9,749 mine-IDs. The regression analysis showed that aggregate mine workers in West and Midwest regions are more susceptible to mine accidents compared to workers in the East region (Table 8, column (1), $\beta = 0.286$ and $\beta = 0.193$, $p < 0.01$). As for mining operation type, the results of the regression analysis were not statistically significant to conclude. Furthermore, the statistical analysis result was significant, although the coefficient is close to zero. In addition, a hypothesis related to the time of the accident was significant in diurnal shifts compared to nocturnal shifts. The results indicate a significant negative value for days lost with the number of injured people, although the coefficient is a low number to make a conclusion. Finally, a significant relationship was found with the injuries, which need to be considered by mine operators ($\beta = 0.279$, $p < 0.01$). Also, a hypothesis on the body part is supported by the result of the regression analysis in the way that mine injuries are more likely to include the upper body and arm/hands (Table 9).

4.3. Coal

To conduct the statistical analysis for coal, a total number of 36,678 observations associated with 8,075 mine-IDs were included. The regression analysis supported the coal miners in the East region are more susceptible to mine accidents in comparison with workers in the West and Midwest regions (Table 8, column (2), $\beta = -0.361$ and $\beta = -0.298$, $p < 0.01$). The result of the regression analysis was significant for underground mine operations compared to surface operations ($\beta = 0.201$, $p < 0.01$). Moreover, the hypothesis on job experience was significant, while the coefficient value was meager. In addition, a hypothesis on the time of the accident was significant in diurnal shifts compared to nocturnal shifts. According to Fig. 7, the number of days lost is considerable for coal compared to other injury severities. Table 9 indicates a significant negative value for days lost with the number of injured people. Similarly, the hypothesis on fatality shows a significantly negative number with the injuries. In addition, the hypothesis on the body part was supported by the results of regression analysis so that coal mine accidents result in injuries in the upper body and other organs ($\beta = 0.355$, $p < 0.01$).

Table 10. The result of Variance Inflation Factor (VIF).

Variable	VIF
Underground	1.30
Other	1.08
Job experience	1.32
West	1.19
Midwest	1.22
6:00 am–12:00 pm	2.98
12:00 pm–6:00 pm	2.87
6:00 pm–12:00 am	2.57

Table 11. Homoscedasticity test.

Test	Statistics	Pr > ChiSq	Variables
White's Test	1339.45	<0.0001	across all variables
Breusch–Pagan	1966.69	<0.0001	across all variables

4.4. Metal

A total number of 5,811 observations associated with 978 mine-IDs were considered. The regression analysis supported the hypothesis that coal workers in the East region are more susceptible to mine accidents in comparison with the Midwest region (Table 8, column (3), $\beta = -0.354$, $p < 0.01$). The result of regression analysis was also significant for underground coal operations ($\beta = 0.489$, $p < 0.01$). Moreover, the statistical analysis confirmed that the job experience was significant, although the coefficient value was meager. In addition, the hypothesis on the time of the accident was significant in diurnal shifts compared to the nocturnal shift. Table 9 indicates a nonsignificant positive value for days lost and fatality with the number of injured people; hence a conclusion cannot be based on that. In addition, the hypothesis on the body part was supported by the result of regression analysis in the way that mine injuries were associated with upper body parts ($\beta = 0.021$, $p < 0.01$).

4.5. Nonmetal

A total number of 6,853 observations were associated with 1,113 mine-IDs. The regression analysis supported the hypothesis that nonmetal mine workers in West and Midwest regions are more susceptible to mine accidents compared to East region Table 8 column (4), $\beta = 0.517$ and $\beta = 0.244$, $p < 0.01$). The result of regression analysis indicates a significant negative value for underground mine operations in comparison with surface mines ($\beta = -0.354$, $p < 0.05$). Moreover, a hypothesis on job experience was significant while the coefficient value was meager. In addition, the hypothesis on the time of the accident was significant in diurnal shifts compared to nocturnal shifts. The number of days lost is considerable for nonmetal compared to other injury severities. Table 9 indicates a nonsignificant negative value for days lost and a nonsignificant positive value for fatality with the number of injured people that cannot make a conclusion based on that. As for body part, the result of statistical analysis was significant for all the body parts.

VIF measures the inflation in the variances due to collinearities that exist among the explanatory variables [18, 26]. All VIF values are below the recommended threshold of 10, indicating that

multicollinearity is not a concern. Each of the VIF scores for the dataset met this requirement (the average of VIF is 1.82). Table 10 shows the VIF⁷ value for variables.

An essential assumption of GEE is the existence of homogeneity of the variance of the residuals. In this case, the variance of the residuals is almost similar to the predicted dependent variable. To address this concern, we used Breusch–Pagan and White's tests. As shown in Table 11, the results for both tests are statistically significant, which rejects the null hypothesis; therefore, we have heteroscedasticity in our data. According to Wooldridge [18, 27] clustering the standard errors will address the heteroscedasticity issues. Thus, we used robust regression in our estimation models.

5. Conclusions

Accident investigation and prevention is crucial, and it must be a priority to all mine executives to enable a safe workplace for employees and ensure their health and safety. There has been no comprehensive study that investigates and compares accident/injury for commodities including aggregate, coal, metal, and nonmetal. This study provided significant results on various factors involved in accident occurrence and consequent injuries. Analysis of accidents indicated that workers are in the higher risk of accident occurrences when working in underground coal and metal mines. However, there is a higher risk of accident in surface mines when working in the aggregate and nonmetal mines. Analysis of geographic location within the accident occurrences revealed the greater risk of an incident in the East region when working in coal mines. However, workers are more susceptible to the mine accidents in the West region if working in aggregate, metal, and nonmetal mines. Considering the importance of this study, better insight into the root causes of the accident and the consequences of injuries is vital to reduce the mining occupational fatalities to zero. Following this, the fatality is of serious concern in aggregate and coal mines compared to other commodities. Therefore, considering further contributing environmental and workers' factors may also provide substantial information to better analyze the causes of severe injuries and fatalities. The results of regression analysis on injury severity (days lost) were not

⁷ VIF for a regression model variable is equal to the ratio of the overall model variance to the variance of a model that includes only that single independent variable. This ratio is calculated for each independent variable ([https://www.investopedia.com/terms/v/variance-inflation-factor.asp#:~:text=Variance%20inflation%20factor%20\(VIF\)%20is,only%20that%20](https://www.investopedia.com/terms/v/variance-inflation-factor.asp#:~:text=Variance%20inflation%20factor%20(VIF)%20is,only%20that%20) – accessed 24 August 2021).

significant to conclude. However, analysis on body part injuries revealed that the upper body is at a higher risk of accident occurrence for all commodities. According to this analysis, if workers are aware of probable risks for their body part injuries when an accident occurs, they would perform their tasks with further caution and follow safety protocols particularly. Moreover, mine operators and mine executives could provide a safer environment by predicting probable incidents in advance and being well-prepared to protect workers from any hazardous incidents. Finally, conducting such an accident analysis in each mine particularly could provide valuable information to develop a predictive model.

Conflicts of interest

None declared.

Ethical statement

The authors state that the research was conducted according to ethical standards.

Funding body

This research was funded by National Institute for Occupational Safety and Health (NIOSH), grant number 75D30119C06390.

Acknowledgment

The authors would like to thank the Mine Safety and Health Administration for providing the accident/injury/employee databases and also express immeasurable appreciation to the National Institute for Occupational Safety and Health (NIOSH) for funding this study [75D30119C06390]. Expressed thanks to Dr. Pierre Mousset-Jones and Dr. Arvin Ebrahimkhanlou for all precise technical and editorial comments related to this paper.

References

- [1] United States Geological Survey (USGS). U.S. mines produced an estimated \$82.2 billion in minerals during 2018 [internet]. U.S. Department of the Interior, USGS; 2019. Retrieved from: <https://www.usgs.gov/news/national-news-release/us-mines-produced-estimated-822-billion-minerals-during-2018/retrieved>.
- [2] Asfawa A, Mark C, Pana-Cryan R. Profitability and occupational injuries in U.S. underground coal mines. *Accid Anal Prev* 2013;50:778–86. <https://doi.org/10.1016/j.aap.2012.07.002>.
- [3] Duarte J, Baptista JS, Marques AT. Occupational accidents in the mining industry - a short review. *Occup Environ Saf Health* 2019;202:61–9. https://doi.org/10.1007/978-3-030-14730-3_7.
- [4] Zhang M, Kecojovic V, Komljenovic D. Investigation of haul truck-related fatal accidents in surface mining using fault tree analysis. *Saf Sci* 2014;65:106–17. <https://doi.org/10.1016/j.ssci.2014.01.005>.
- [5] Dindarloo SR, Pollard J, Siami-Irdemoos E. Off-road truck-related accidents in US mines. *J Saf Res* 2016;58:79–87. <https://doi.org/10.1016/j.jsr.2016.07.002>.
- [6] Noll J, DeGennaro C, Carr J, DuCarme J, Homce G. Causal factor of collision accidents involving underground coal mobile equipment. In: Proceedings of the ASME 2017 International Mechanical Engineering Congress and Exposition. Tampa, Florida: IMECE, 2017; 2017. <https://doi.org/10.1115/IMECE2017-70714>.
- [7] Nasarwanji MF, Pollard J, Porter W. An analysis of injuries to front-end loader operators during ingress and egress. *Int J Industr Ergon* 2017;65:84–92. <https://doi.org/10.1016/j.ergon.2017.07.006>.
- [8] Ruff T, Coleman P, Martini L. Machine-related injuries in the US mining industry and priorities for safety research. *Int J Inj Control Saf Promot* 2011;18(1):11–20. <https://doi.org/10.1080/17457300.2010.487154>.
- [9] Javadi M, Saeedi G, Shahriar K. Developing a new probabilistic approach for risk analysis, application in underground coal mining. *J Fail Anal Prev* 2017;17(5):989–1010. <https://doi.org/10.1007/s11668-017-0325-0>.
- [10] Mark C, Pappas DM, Barczak TM. Current trends in reducing ground fall accidents in U.S. coal mines. *Min Eng* 2011;63(1):60–5. Retrieved from: <https://www.cdc.gov/niosh/mining%5C/UserFiles/works/pdfs/ctirgf.pdf/retrieved>.
- [11] Groves WA, Kecojovic VJ, Komljenovic D. Analysis of fatalities and injuries involving mining equipment. *J Saf Res* 2007; 38:461–70. <https://doi.org/10.1016/j.jsr.2007.03.011>.
- [12] Sammarco JJ, Podlesny A, Rubinstein EN, Demich B. An analysis of roof bolter fatalities and injuries in U.S. mining. *Trans Soc Min Metall Explor* 2016;340(1):11–20. <https://doi.org/10.19150/trans.7322>.
- [13] Moore SM, Porter WL, Dempsey PG. Fall from equipment injuries in U.S. mining: identification of specific research areas for future investigation. *J Saf Res* 2009;40(6):455–60. <https://doi.org/10.1016/j.jsr.2009.10.002>.
- [14] Santos BR, Porter WL, Mayton AG. An analysis of injuries to haul truck operators in the U.S. Mining industry. In: Proceedings of the Human Factors and Ergonomics Society Annual Meeting; 2010. p. 1870–4. 54(21).
- [15] Pollard J, Heberger J, Dempsey PG. Maintenance and repair injuries in US mining. *J Qual Mainten Eng* 2014;20(1):20–31. <https://doi.org/10.1108/JQME-02-2013-0008>.
- [16] Alessa FM, Nimbarte AD, Sosa EM. Incidences and severity of wrist, hand, and finger injuries in the U.S. mining industry. *Saf Sci* 2020;129:e104792. <https://doi.org/10.1016/j.ssci.2020.104792>.
- [17] Mine safety and health administration (MSHA). Mission Washington, DC: United States Department of Labor; 2016 [internet]. <https://www.msha.gov/about/mission>.
- [18] Wooldridge JM. *Econometric analysis of cross-section and panel data*. MIT press; 2010.
- [19] Shekarian N, Ramirez Ronald, Khuntia J. The impact of data analytics on hospital performance. AMCIS 2020. Proceedings 3, https://aisel.aisnet.org/amcis2020/data_science_analytics_for_decision_support/data_science_analytics_for_decision_support/3.
- [20] Schall R. Estimation in generalized linear models with random effects. *Biometrika* 1991;78(4):719–27. <https://doi.org/10.2307/2336923>.
- [21] Diggle P, Heagerty P, Liang KY, Zeger S. *Analysis of longitudinal data*. Oxford University Press; 2002.
- [22] Fitzmaurice GM, Laird NM, Ware JH. *Applied longitudinal analysis*. Hoboken: John Wiley & Sons; 2004.
- [23] Shekarian Y, Rahimi E, Shekarian N, Rezaee M, Roghanchi P. An analysis of contributing mining factors in coal workers' pneumoconiosis prevalence in the United States coal mines, 1986–2018. *Int J Coal Sci Technol* 2021;8: 1227–37. <https://doi.org/10.1007/s40789-021-00464-y>.

- [24] Rahimi E. Investigation of respirable coal mine dust (RCMD) and respirable crystalline silica (RCS) in the U.S. Underground and surface coal mines. New Mexico Institute of Mining and Technology; 2020. In PROQUESTMS: <http://libproxy.uoregon.edu/login?url=https://www.proquest.com/dissertations-theses/investigation-respirable-coal-mine-dust-rcmd/docview/2468128535/se-2?accountid=14698>.
- [25] Benfratello L. Random effects regression for panel data. In: Michalos AC, editor. Encyclopedia of quality of life and well-being research. Dordrecht: Springer; 2014. https://doi.org/10.1007/978-94-007-0753-5_2402.
- [26] Shekarian N, Ramirez R. Resilience through technology intensity and international related management experience: An explorative examination of European firms during the COVID-19 crisis. Digit 2021. Proceedings. <https://aisel.aisnet.org/digit2021/>.
- [27] Shekarian Y. An investigation of the effects of mining parameters on the prevalence of coal worker's pneumoconiosis (CWP) risks among the US coal miners. New Mexico Institute of Mining and Technology; 2020. <https://doi.org/10.13140/RG.2.2.22358.27205>. In PROQUESTMS: <http://libproxy.uoregon.edu/login?url=https://www.proquest.com/dissertations-theses/investigation-effects-mining-parameters-on/docview/2467855260/se-2?accountid=14698>.