Occupational health and safety and data mining: a bibliometric analysis

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RESUMO

Objetivo – Este artigo tem o objetivo de realizar uma análise bibliométrica sobre o tema de mineração de dados e saúde e segurança do trabalho, contemplando o período compreendido entre os anos de 2008 e 2020, sete bases de dados científicas e 68 registros selecionados.

Referencial teórico – Esta pesquisa se fundamentou teoricamente em conceitos que envolvem a mineração de dados, aprendizado de máquinas e saúde e segurança do trabalho.

Metodologia – Os artigos escolhidos foram submetidos a uma análise estatística, juntamente com a avaliação de uma das leis da bibliometria (Lei de Bradford), sobre a quantidade de citações, periódicos, autores, países de origem, categorias de publicação e avaliação da produtividade ao longo dos anos.

Resultados – Como resultado, constatou-se que o periódico mais influente é a Safety Science, e Taiwan é o país líder na origem dos artigos, com uma média de 115 citações por artigo. As revistas melhor ranqueadas são associadas aos temas Engineering e Health, ambas contendo 30% dos artigos e periódicos selecionados.

Contribuições – Com a pesquisa foi possível identificar insights sobre o crescimento da área de mineração de dados aliada a saúde e segurança do trabalho.

Palavras-chave – Análise de bibliometria. Saúde e segurança no trabalho. Mineração de dados.

ABSTRACT

Purpose - This article aims to carry out a bibliometric analysis on data mining and occupational health and safety, covering the period between 2008 and 2020, for seven scientific databases and 68 articles.

Theoretical framework - This study was theoretically based on concepts that involve data mining, machine learning and occupational health and safety.

Design/methodology/approach - The selected articles were submitted to a statistical analysis, together with the evaluation of one of the bibliometric laws (Bradford's Law), comprising a number of citations, journals, authors, countries of origin, publication categories and an evaluation of production over the years.

Findings - As a result, it was found that the most influential journal was Safety Science, and Taiwan was the leading country in terms of articles produced, with an average of 115 citations per article. The best-ranked journals related to Engineering and Health, both corresponding 30% of the selected articles and journals.

Originality/value - This study provides some insights into the growth of the data mining area together with occupational health and safety.

Keywords - Bibliometrics analysis. Occupational health and safety. Data mining.

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1. INTRODUCTION

Industrial revolutions have brought about innumerable changes within organizations in terms of working conditions, work environments and labor laws. These changes are considered positive in some aspects. For instance, services automation and technological advances have made life more efficient and faster (BADRI; BOUDREAU-TRUDEL; SOUISSI, 2018). However, they have also increased the risks of occupational accidents and diseases by the increasing exposure to machinery and computers. Thus, the work environment has made employees more susceptible to cardiovascular and stress-related diseases (RUSO; STOJANOVIC, 2012).

Regarding labor conditions and legislation, at the beginning of industrialization, commitment to health and safety of workers was not common. Yet, over time, it has become increasingly mandatory, besides being a competitive strategy for organizations, since the welfare of employees results in greater productivity (CIARAPICA; GIACCHIETA, 2009).

The International Labor Organization (ILO) states that Occupational Health and Safety (OHS) protects workers from general and occupational diseases and accidents at work (COMBERTI; DEMICHELA; BALDISSONE, 2018). In this context, OSH has become a recurring issue all around the world, as it represents a competitive strategy for organizations, and also because of the alarming rates of occupational occurrences. According to estimates of the ILO, approximately one employee dies due to occupational accidents or diseases every 15 seconds, and approximately 2.34 million employees die from work-related diseases every year (WANG et al., 2020).

Furthermore, financial loss is not limited to compensations claimed by employees due to accidents and diseases. There is also an economic burden on society, which is imposed, for instance, by Social Security expenditures (YILMAZA; CELEBIB, 2015). Thus, the costs that must be faced by companies and society in general demand occupational safety measures. In
addition to financial losses, accidents, diseases and deaths contribute to excluding thousands of people from the labor market (COLNAGO; SIVOLELLA, 2019).

One of the ways to find solutions for occupational occurrences is to study cases that have already happened by evaluating specific cases or databases. The analysis of the history of occupational occurrences is important because it provides a complete picture of activities to prevent accidents and diseases. Thus, it is a powerful tool to minimize risks (ZHANG; JIANG, 2012).

Data mining (DM) is an alternative to deal with the huge amount of occupational data. It is described as a set of techniques that allow the processing of large amounts of data (Big Data), extracting useful information for a specific purpose. Often, DM is linked to machine learning (ML), since both have automated pattern extraction techniques, which represent knowledge implicitly stored within databases (HAN; KAMBER; PEI, 2012).

The best-known techniques used in DM are Association Rules (AR), Artificial Neural Networks (Neuro-Fuzzy) and Regression Trees (RT). All these techniques have a common path: data preparation stages, model execution and analysis of the results (BUCZAK; GUVEN, 2016; FAYYAD; PIATETSKY-SHAPIRO; SMYTH, 1996). DM can help with OSH by extracting patterns from databases where records are stored, so that, studies can be conducted and preventive measures can be taken. As an example, Sanmiquel, Rossell and Vintró (2015) carried out a case study in the Spanish mining sector in which decision tree techniques and Bayesian classifiers were applied to explore occupational accidents in mines. The study contributed to the development of safety policies in the mine where the research took place.

DM and OSH are interconnected and represent a recurring issue. That leads to an increase in the scientific production on the subject (RUSO; STOJANOVIĆ, 2012). In this context, conducting a bibliometric analysis of the studies available on the topic is important to identify trends and research growth. Moreover, it is a way to identify the main journals related
to the topic and predict productivity of individual authors and countries, as well as analyze the emergence of new study areas (PIMENTA et al., 2017; QUEVEDO-SILVA et al., 2016).

In light of the foregoing, this study aims to present a bibliometric analysis to identify the most impactful articles, authors, journals, countries and publication categories associating OSH to DM. The selected articles were identified through a systematic mapping conducted by a research group whose goal was to answer the following question: “How does DM support decision-making in OSH?” The mapping was performed to identify what bases and types of OSH data, in addition to techniques and tools, are used by DM.

This bibliometric study has an investigative and quantitative approach, a descriptive objective and bibliographic research procedures. It is divided into five sections. Section 1 introduces the topic for research contextualization. Section 2 briefly presents a theoretical framework on OSH and DM. Section 3 details the methodology. Section 4 provides research results through statistical analysis. Finally, section 5 presents final considerations with some insights for future research on the topic.

2. THEORETICAL FOUNDATION

2.1 Occupational Safety and Health (OSH)

The occupational safety and health concept has risen in the academic and business environments in recent decades, mainly influenced by an increase in cases of work-related incidents all over the world (SÁNCHEZ-HERRERA; DONATE, 2019). Attention to OSH has become fundamental for the survival of organizations. It aims to identify, manage and mitigate the risks involving workers’ health and safety (MUTLU; ALTUNTAS, 2019).

As employees are the pillars of organizations development, the concern with health and safety has led to the creation of new policies, laws and regulations, both by private and public organizations (AZIZ; OSMAN, 2019; CHEN et al., 2020). Those measures have been taken not only due to the damage suffered by workers and their families, but also due to economic losses. The ILO estimates that losses caused by occupational accidents and diseases...
correspond to US $ 3.3 trillion, which represents about 4% of the global gross domestic product (WANG et al., 2020).

To reduce human and financial losses, it is necessary to understand the concepts involved in OSH. A risk means the possibility of an occurrence whose outcome is detrimental to an employee. That can be an injury or loss caused by a dangerous situation (MUTLU; ALTUNTAS, 2019). Regarding diseases, they are divided into two classes. Profession-related diseases are those associated with the profession of the victim, whereas occupational diseases are the ones caused by special conditions a worker is subject to (AZZOLIN et al., 2012).

As for accidents, there are five categories according to the NBR 14280: 2001: working, commuting, without injury, impersonal and personal. However, the most serious outcome is death. A work death is that related to one’s profession, regardless of the interval between accident and death confirmation (ASSOCIAÇÃO BRASILEIRA DE NORMAS TÉCNICAS, 2001).

All occurrences must be registered for companies’ control, but also for the government and regulatory organizations monitoring. In Brazil, all diseases, accidents and deaths related to work must be registered through a Work Accident Communication (Comunicação de Acidentes de Trabalho - CAT). Then, the information is formalized, stored and made publicly available (BATISTA; SANTANA, FERRITE, 2019).

Other countries also register and disclose their data publicly, such as Taiwan, with the Council of Labor Affairs (Executive Yuan) (CHENG; YAO; WU, 2013; LIAO; PERNG, 2008), Italy with the Istituto nazionale per l’assicurazione contro gli infortuni sul lavoro (INAIL) (COMBERTI; DEMICHELA; BALDISSONE, 2018; PALAMARA; PIGLIONE; PICCININI, 2011) and the United States, with the Occupational Safety and Health Administration (OSHA) (SHIN et al., 2018; TIXIER et al., 2017).

Creation and dissemination of these occupational data sets are useful in investigating the OSH scenario, developing actions, supporting new legislation and assisting organizations in decision-making (DEL POZO-ANTÚNEZ et al., 2018; YANAR; LAY; SMITH, 2019).
order to carry out these analyses, some tools should be used, such as the exploratory analysis of data and statistical methods (CHENG et al., 2010) and computational resources, such as data mining (CHOI et al., 2020).

2.2 Data Mining (DM)

According to Witten and Frank (2016), DM covers the use of ML techniques to extract knowledge from large amounts of data, with applications in several areas, such as medicine, finances, retail, manufacturing, engineering and others. Medical diagnostics, credit analysis and fraud detection are examples of applications in some of these areas. The term "mining" was chosen because this process of extracting knowledge from data leads us, metaphorically, to perform mineral processing activities that extract economic interest products from large deposits.

By making use of ML algorithms, DM is often linked to Artificial Intelligence (AI). This relationship is based on the fact that DM models can have learning and adaptation capacities. These models can provide solutions for situations which they were not explicitly programmed for. They make use of mathematical and statistical theories and are programmed (as well as parameterized) to optimize a performance criterion. This optimization uses data as examples, based on past experiences and with the ultimate goal of making predictions (WITTEN; FRANK, 2016).

DM can also be associated with the KDD (Knowledge Discovery in Databases) process, as it is one of the stages involved in the entire process. However, there are nine steps that compose the KDD procedure, as presented by Fayyad, Piatetsky-Shapiro and Smyth (1996): understanding the customer's demand; selecting the data set; performing cleaning and pre-processing; reducing and projecting; aligning methods to the demand; defining the model and its elements; performing data mining; interpreting results; and using the knowledge discovered.
A way to classify data mining methods refers to model learning, which can be supervised or unsupervised. The first method is guided by the developer, while the second is not (HAJAKBARI; MINAEI-BIDGOLI, 2014; ZHAO et al., 2019). In addition, DM methods have two main objectives, namely, prediction of future events, based on the mined data, and description, in which there is a search for patterns that can be understood by the decision-makers (FAYYAD; PIATETSKY-SHAPIRO; SMYTH, 1996). The application of data mining to OSH is often associated with forecasting and extracting patterns. In those cases, the techniques may be related to injury risk prediction, accidents or even to predict the seriousness of those events (SARKAR; MAITI, 2020).

3. METHODOLOGICAL PROCEDURES

The 68 articles selected for bibliometric analyses were identified through a systematic mapping of the literature, conducted by a research group. The selected articles (also used in this research) addressed topics related to DM and ML, with applications in health and safety at work. These records were selected by using IEEE Xplore, Ingenta, Science Direct, Scopus, SpringerLink, PubMed and ProQuest databases.

The inclusion criteria met the following restrictions: published since 2008; English-language publications; and showing an application of DM in OSH. The exclusion criteria were: not peer reviewed; not showing an application of DM in OSH; and not responding satisfactorily to our research questions. As for duplicate articles, only the most complete one was selected.

The initial search on the seven databases, based on the aforementioned inclusion and exclusion criteria, resulted in 1424 articles from which 474 duplicate studies were excluded. After partial and total reading of the remaining articles, the final set reached 68 articles. By exploring them, we sought to answer five questions:

(i) What kind of occupational safety and health data are explored?
(ii) What types of data mining tasks, techniques and tools are used?
(iii) What industrial activity sector is explored in the research?
(iv) Which occupational safety and health database was used?
(vi) Does the study use OSH data in a way that is related to other information?

This research was carried out by using the same 68 articles. Figure 1 shows all the steps of the research methodology, from the identification of the articles to the final analysis.

**Figure 1 – Research method used**

Source: Authors (2021).

Based on the selected articles, it was possible to start the analysis of the records, in which the publications were cataloged considering ten variables, namely, Code; Title of the article; Journal title; Authors; Year of publication; JCR; Source; Scimago; CiteScore; and Index H. After a synthesis of the information, Bradford's Law was applied to verify the degree of attraction of the journals by adopting their reputation as a criterion to identify the most relevant ones, as well as the ones that give more attention to a specific topic.

The titles and the number of articles published by each journal are organized in a table in descending order of productivity, divided into three zones, each of them containing one third of the total of journals. Thus, each zone averaged 22 articles. The analysis also considered the impacts of the productions, journals, authors and countries.
4. RESULTS AND DISCUSSION

4.1. Productivity evaluation over the years

Statistical analysis showed that, within the period of publication of the articles (2008 - 2020), the amount of research had an increase. The increase in the number of publications on OSH and DM in recent years can be explained by the following factors: a) the number of researchers has grown exponentially and, thus, the number of submissions to journals has also increased; b) the use of technologies, such as computers connected to the internet, facilitates the access to updated information sources; c) nowadays, workers' health has been a very discussed topic and has gained emphasis in large companies that try to promote health, safety, comfort and satisfaction of their employees. There are some other factors that have influence on efficiency and productivity, such as reducing compensation costs due to work accidents.

All of these factors led to an increase in research and publications in the area, with an average growth of 17% in the last 4 years, which is shown in Figure 2.

**Figure 2 – Number of publications per year**

![Number of publications per year](image)

Source: Authors (2021).

A projection of the total production in 2020 was also made based on the exponential growth of the previous years, and the average number was 14 publications.
4.2. Journals evaluation

Regarding the journals themselves, Bradford’s Law was used to assist us in their evaluation. By arranging the 48 journals in descending order of productivity and separating them into three zones, with an average of 22 articles each zone, it was possible to identify the most relevant and productive journals on the list. Figure 3 shows the distribution of the accumulated sum of articles indicating that, as the number of journals increases, production decreases.

**Figure 3 – Number of publications per year**

![Figure 3](image)

Source: Authors (2021).

Thus, it was possible to identify that the first zone (core) gathered the most productive journals, totaling four with 21 articles, followed by zone 2, with 20 journals and 23 articles. The third zone, which was the least productive, reached only one publication per journal, with 24 journals and 24 articles. As provided by Bradford's law, “few produce much and many produce little” (ARAÚJO, 2006).

Calculation of the Minimum Bradford Zone (MBZ) also justifies the number of articles in each zone:

\[
MBZ = \frac{NR1a}{2}; MBZ = \frac{41}{2}; MBZ = 20.5
\]
where NR1a is the total number of journals with a single article.

Table 1 shows the most productive and relevant journals on the list, found in the core zone, as well as their TP (total publications), hi% (relative frequency) and Hi% (cumulative frequency) indexes.

| Ranking | Journals                                         | TP | \(\sum\) Cum. | hi\% | Hi\% | Citation < 2020 |
|---------|--------------------------------------------------|----|---------------|------|------|-----------------|
| 1°      | Safety Science                                   | 10 | 10            | 14.70| 14.70| 493             |
| 2°      | Accident Analysis & Prevention                   | 5  | 15            | 7.35 | 22.05| 242             |
| 3°      | Environmental Science and Pollution Research     | 3  | 18            | 4.41 | 26.46| 10              |
| 4°      | Int. J. of Environmental Research and Public Health | 3  | 21            | 4.41 | 30.87| 27              |

Source: Authors (2021).

Although the core zone contains only four journals, it corresponds to about 30% of the total number of articles. Safety Science leads the ranking of publications with 10 of the 68 articles, showing a strong influence on OSH and DM. The journal addresses multidisciplinary research on employees’ health and safety, involving aspects related to social studies, technologies, legislation, control, safety techniques and others.

The second most productive journal is Accident Analysis & Prevention, which deals with specific issues involving occupational accidents and diseases. It covers medical research, studies of human and environmental factors that can cause diseases, injuries and fatalities.

The third and fourth journals, in terms of relevance, are also multidisciplinary. They discuss issues related to occupational hygiene, public health research and engineering sciences, such as programming.

4.3. Evaluation of citations between articles
Regarding evaluation of the articles, the number of citations each publication had was analyzed, with a total of 1291. Figure 4 shows the 15 articles that were most referenced by other publications. Three of them stood out (S2, S7 and S10), with 32% of the total of citations, but only 4% of the total number of articles.

![Figure 4 - Ranking of the 15 most cited articles](image)

Source: Authors (2021).

It is noteworthy that articles S2 and S7 had the maximum number of citations. They were referenced by 145 publications. In addition, the two articles were published by Safety Science, which was the most influential journal among those selected for the research, as previously reported. Details of the characteristics of the 15 most cited articles are presented in Table 2, as well as the data mining techniques and tools used, the sector of application, country of origin and type of result presented.

| ID | Techniques | Tools | Application sector | Country | Results |
|----|------------|-------|---------------------|---------|---------|
| S2 | **Association Rules** | Not Specified | Civil Construction | Taiwan | Data visualization and analysis only |

Table 2 - Characteristics of the 15 most referenced articles (to be continued)
### Table 2 - Characteristics of the 15 most referenced articles (continued)

| ID  | Techniques          | Tools                  | Application sector | Country      | Results                                      |
|-----|---------------------|------------------------|--------------------|--------------|----------------------------------------------|
| S1  | Regression tree     | Not Specified          | Petrochemical      | Italy        | Visualization and analysis with suggestions of actions and/or tools |
| S8  | Hierarchical        | MATLAB®                | Timber sector      | Italy        | Data visualization and analysis only           |
| S20 | Neuro-fuzzy, Naive  | TextMiner®             | Not Specified      | United States| Visualization and analysis with suggestions of actions and/or tools |
| S12 | Naive-Bayes         | Not Specified          | Not Specified      | United States| Data visualization and analysis only           |
### Hierarchical Clustering

| Source   | Method            | Feature(s) Used       | Location   | Visualization and Analysis |
|----------|-------------------|-----------------------|------------|---------------------------|
| S37      | Hierarchical clustering | Not Specified | Civil Construction, France | Visualization and analysis with suggestions of actions and/or tools |
| S17      | Naive-Bayes, Decision tree | SMOTE®      | Not Specified, Canada      | Visualization and analysis with suggestions of actions and/or tools |
| S57      | Decision tree (C 5.0) | Not Specified | Steel sector, India        | Visualization and analysis with suggestions of actions and/or tools |

Source: The Authors (2021).

1 Clustering, also known as grouping, is a data mining task used when there are no predefined classes for dividing the data. In these cases, the algorithm itself decides which groups (clusters) will be used to classify the data (WITTEN; FRANK, 2016).

Liao and Perng (2008), authors who lead the ranking (S2), address in their research some DM techniques used to identify characteristics of work accidents in the construction industry. Their research revealed that many accidents are related to weather conditions. The second article (S7), by Cheng et al. (2010), who also lead the ranking, discusses the possible patterns of accidents in civil construction to be detected by using DM. Their study listed some risky combinations responsible for many accidents, such as working in heights without the necessary safety equipment.

In the third most referenced article (S10), which was cited 126 times, Cheng et al. (2012) address the most serious occupational accidents, such as injuries and fatalities, which have a high rate of occurrence in the construction sector worldwide. The authors also address prevention measures.

Another classification applied to the 15 articles refers to the tasks used in the DM process, divided into four types: three of them related to supervised learning (association, classification and regression) and one linked to unsupervised learning (clustering¹). Data processing during ML, with previously labeled inputs and outputs, can be understood as supervised learning. It means that the types of data and their meaning are already known.
Unsupervised learning, however, refers to ML whose data are unknown, presenting several results.

Most articles presented supervised learning tasks. Classification task was the most used. It was found in 78% of the records, in some cases as a single task and, in others, in comparisons or in association with other types. Clustering was used in 15 studies (22%), and association was found in eight studies (12%). Regression was the least applied task, corresponding to only 7%.

4.4. Evaluation of the impact of the articles considering the number of authors

In order to determine whether the number of authors in each article directly affects the impact of the production, some parameters were collected (Table 3). In this study, articles written by one to 12 authors and their respective indexes TP, TC (Total citations), hi% and Hi% were identified.

| Number of authors | TP | hi%  | Hi%  | Citations < 2020 | TC/TP |
|-------------------|----|------|------|------------------|-------|
| 1                 | 3  | 4.41 | 4.41 | 55               | 18.33 |
| 2                 | 11 | 16.18| 20.59| 279              | 25.36 |
| 3                 | 18 | 26.47| 47.06| 454              | 25.22 |
| 4                 | 14 | 20.59| 67.65| 208              | 14.86 |
| 5                 | 10 | 14.71| 82.35| 163              | 16.30 |
| >5                | 12 | 17.65| 100  | 129              | 10.75 |
| Σ                 | 68 | 100  | -    | 1288             | -     |

Source: Authors (2021).

Productions with up to three authors represented almost 50% of the total number of publications (Hi%). When comparing the total number of citations that the articles had in other publications, those written by up to three authors were the most referenced ones in the academic environment. In contrast, articles produced by five or more authors had an average of citations per published article (TC / TP) of 10.75. This corresponds to the lowest average in
the table, which shows that the smaller the number of authors in the articles, the greater the impact and the number of publications on the topic addressed.

4.5. Evaluation of the publication category of the journals

According to the classification category for journals, by Scimago Journal & Country Rank (Table 4), there were two main areas: Engineering (25 journals) and Health (19 journals). When analyzing the h-index (Hirsch index) of the categories, Engineering still remains the most productive area, with a score of 17. It means that there were, at least, 17 articles with, at least, 17 citations. Engineering was followed by Health, with a score of 15. Social Sciences, which previously had the lowest score in number of publications, ranked third in the h-index, with 13.

| Category            | Journals | Articles | Citations | TC/TP | h-index |
|---------------------|----------|----------|-----------|-------|---------|
|                     | TP       | hi%      | TP        | hi%   | < 2020  |         |
| Engineering Health  | 25       | 32.05%   | 41        | 31.78%| 1105    | 26.95   | 17      |
| Computer Science    | 19       | 24.36%   | 36        | 27.91%| 916     | 25.44   | 15      |
| Social Sciences     | 19       | 24.36%   | 19        | 14.73%| 191     | 10.05   | 7       |
| Others              | 7        | 8.97%    | 20        | 15.50%| 822     | 41.10   | 13      |

Source: Authors (2021).

4.6. Scientific production by country

In total, about 20 countries produced the 68 articles selected for this study. As a way of evaluating the productivity of each country that contributed with an article on OSH and DM, some parameters were identified, as shown in Table 5.
Table 5 - Classification of countries

| Citations | Articles | Citations < 2020 | TC/TP | h-index |
|-----------|----------|------------------|-------|---------|
|           | TP       | hi%              | Hi%   |         |
| United States | 14 | 20,59%           | 20,59% | 157     | 11,21   | 6     |
| India     | 8        | 11,76%           | 32,35% | 85      | 10,63   | 5     |
| Italy     | 6        | 8,82%            | 48,53% | 170     | 28,33   | 6     |
| Spain     | 5        | 7,35%            | 39,71% | 99      | 19,80   | 4     |
| Brazil    | 4        | 5,88%            | 54,41% | 17      | 4,25    | 3     |
| China     | 4        | 5,88%            | 60,29% | 6       | 1,50    | 2     |
| South Korea | 4   | 5,88%            | 66,18% | 11      | 2,75    | 2     |
| Taiwan    | 4        | 5,88%            | 72,06% | 460     | 115,00  | 4     |
| Canada    | 3        | 4,41%            | 76,47% | 33      | 11,00   | 2     |
| Iran      | 3        | 4,41%            | 80,88% | 22      | 7,33    | 1     |
| Turkey    | 3        | 4,41%            | 85,29% | 59      | 19,67   | 2     |
| France    | 2        | 2,94%            | 88,24% | 48      | 24,00   | 2     |
| Saudi Arabia | 1 | 1,47%            | 89,71% | 14      | 14,00   | 1     |
| Slovenia  | 1        | 1,47%            | 91,18% | 17      | 17,00   | 1     |
| Finland   | 1        | 1,47%            | 92,65% | 55      | 55,00   | 1     |
| Hong Kong | 1        | 1,47%            | 94,12% | 5       | 5,00    | 1     |
| Japan     | 1        | 1,47%            | 95,59% | 3       | 3,00    | 1     |
| Serbia    | 1        | 1,47%            | 97,06% | 2       | 2,00    | 1     |
| Singapore | 1        | 1,47%            | 98,53% | 22      | 22,00   | 1     |
| Thailand  | 1        | 1,47%            | 100,00%| 6       | 6,00    | 1     |

Source: Authors (2021).

The first parameter to be assessed was the total number of publications by country (TP). The United States leads the ranking, with 20% of the articles. In addition, more than 50% of the publications were produced by only five countries, namely, the United States, India, Italy, Spain and Brazil, an index called “cumulative frequency of publications” (Hi%).
Based on the h-index, it was possible to analyze the production capacity of the countries and its scientific-academic impact. As a result, it was noticed that Italy and the United States were the leading countries with the same score, reaching the h-index of six. It means that the two countries have, at least, six articles with, at least, six citations in each publication. The main works are, respectively, from the United States (S20, S12, S32, S35, S29 and S3) and Italy (S4, S8, S1, S42, S63 and S28).

India comes in second place, with a score of five (S57, S33, S50, S26 and S38). Then come Spain (S22, S54, S40 and S52) and Taiwan (S2, S7, S10 and S14), with the same score, reaching an h-index of four. For the analysis, the average of citations is also evaluated by the number of publications per country (TC / TP). In first place, comes Taiwan, with an average of 115 citations for each publication (Table 5), followed by Finland and Italy, which had 55 and 28 citations per article published, respectively. Among the 15 most cited articles, Taiwan has four, Italy three and the United States two, while Spain, Finland, Turkey, France, Canada and India have only one.

6. CONCLUSION

This research shows the importance of bibliometric literature reviews, not only as an instrument to identify and classify a wide variety of studies within areas related to OSH and DM, but also to analyze information and search for trends. Based on the results, it was possible to raise some insights and possibilities for future research.

The results of this study show an increasing trend in the number of annual publications, despite the reduction in the number of articles published in the last two years. For that reason, this area presents itself as an area of great interest among academics. Another indicator of interest is the progressive increase in the number of citations that the articles had, with three articles standing out from the rest: S2 - Data mining for occupational injuries in the Taiwan construction industry (LIAO; PERNG, 2008), S7 - Use of association rules to explore
cause–effect relationships in occupational accidents in the Taiwan construction industry (CHENG et al., 2010), S10 - Applying data mining techniques to explore factors contributing to occupational injuries in Taiwan's construction industry (CHENG et al., 2012).

Classification of the number of authors per article can be useful for researchers who need to carry out an initial review of the literature. In that sense, it is evident that the smaller the number of authors, the greater the relevance of the article, since the average number of citations per publication was high. In contrast, articles with five or more authors had the lowest average and, thus, were considered less relevant.

Regarding the analysis of the journals based on Bradford's law, only four journals belonged to zone 1, which was the most influential. Safety Science was the most productive among the 48 selected journals, once it had 10 of the 68 articles. Thus, we can infer that it has a strong influence on OSH and MD studies.

Regarding the number of articles per country, the United States stood out with the highest number of publications (14). However, it was not the country with the highest average number of citations per article. Taiwan leads this ranking with an average of 115 citations for each of its four articles. The countries' h-index shows that both the USA and Italy had a minimum of six articles with six citations.

Finally, this study revealed that there are two main areas among the publication categories of the journals: Engineering and Health. Engineering has the best performance, since it had, on average, 30% of the articles and journals selected. In addition, it has the highest h-index, reaching a score of 17 articles with, at least, 17 citations. The second best classified area was Health, with 25 citations on average for each article. Both areas have a strong influence on issues related to technology, data analysis, accidents and occupational diseases.

In light of the above, this research enabled the understanding of publications on data mining associated with health and safety, as well as insights and future research possibilities.
It was also possible to identify the increasing use of DM techniques to understand and predict behaviors of occupational incidents. That results in an improvement in the OSH scenario.

Regarding future research, this study suggests deepening into the selected articles, in order to carry out a comparative analysis of their results. Due to the increasing interest of the academia and the industry in OSH and MD, research with applications is also recommended to understand the behavior of real data and specific sectors of the industry, or even predictions of future accidents. That can be useful, for it would support new norms and policies, both for public and private organizations.

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## Appendix

Appendix A - Table with the articles selected in the systematic mapping, their respective identification and citation codes.

| Study ID | Title of Articles                                                                 | Citation                                       |
|----------|------------------------------------------------------------------------------------|------------------------------------------------|
| S1       | Industrial and occupational ergonomics in the petrochemical process industry: A regression trees approach | Bevilacqua et al., 2008                        |
| S2       | Data mining for occupational injuries in the Taiwan construction industry          | Liao e Perng, 2008                            |
| S3       | Prioritizing Health Promotion Plans with k-Bayesian Network Classifier             | Ueno et al., 2008                             |
| S4       | Classification and prediction of occupational injury risk using soft computing techniques: An Italian study | Ciarapica e Giacchetta, 2009                   |
| S5       | Application of data mining in classification analysis of safety accidents based on alternate covering neural network | Qu, 2009                                       |
| S6       | Signal processing and machine learning for real-time classification of ergonomic posture with unobtrusive on-body sensors; application in dental practice | Olsen et al., 2009                            |
| S7       | Use of association rules to explore cause–effect relationships in occupational accidents in the Taiwan construction industry | Cheng et al., 2010                            |
| S8       | Self-Organizing Map and clustering algorithms for the analysis of occupational accident databases | Palamara et al., 2011                         |
| S9       | Spatial clustering applied to health area                                         | Valêncio et al., 2011                         |
| S10      | Applying data mining techniques to explore factors contributing to occupational injuries in Taiwan's construction industry | Cheng et al., 2012                            |
| S11      | Application of Pharmacovigilance Methods in Occupational Health Surveillance: Comparison of Seven Disproportionality Metrics | Bonneterre et al., 2012                       |
| S12      | Development and evaluation of a Naïve Bayesian model for coding causation of workers’ compensation claims | Bertke et al., 2012                           |
| S13      | Occupational Health and Safety using Data Mining                                  | Russo et al., 2012                            |
| S14      | Applying data mining techniques to analyze the causes of major occupational accidents in the petrochemical industry | Cheng et al., 2013                            |
| S15      | Analysing factors related to slipping, stumbling, and falling accidents at work: Application of data mining methods to Finnish occupational accidents and diseases statistics database | Nenonen, 2013                                  |
| S16      | Analytical study using data mining for periodical medical examination of employees | Waghmare and Pai, 2013                        |
| Study ID | Title of Articles                                                                 | Citation                      |
|---------|-----------------------------------------------------------------------------------|-------------------------------|
| S17     | Development of a computer-based clinical decision support tool for selecting appropriate rehabilitation interventions for injured workers | Gross et al., 2013           |
| S18     | A new scoring system for assessing the risk of occupational accidents: A case study using data mining techniques with Iran's Ministry of Labor data | Hajakbari e Minaei-Bidgoli, 2014 |
| S19     | Office workers syndrome monitoring using kinect                                      | Paliyawan et al., 2014        |
| S20     | Near-miss narratives from the fire service: A Bayesian analysis                      | Taylor et al., 2014           |
| S21     | An information fusion framework for context-based accidents prevention               | Sanchez-Pi et al., 2014       |
| S22     | Study of Spanish mining accidents using data mining techniques                       | Sanmiquel et al., 2015        |
| S23     | Decision tree analysis of construction fall accidents involving roofers             | Mistikoglu et al., 2015       |
| S24     | A Dimensionally Reduced Clustering Methodology for Heterogeneous Occupational Medicine Data Mining | Saadaoui et al., 2015         |
| S25     | Assessing ergonomic and postural data for pain and fatigue markers using machine learning techniques | Shein et al., 2015            |
| S26     | Assessment of Risk of Musculoskeletal Disorders among Crane Operators in a Steel Plant: A Data Mining-Based Analysis | Krishna et al., 2015          |
| S27     | Data-mining and expert models for predicting injury risk in ski resorts               | Bohanec e Delibasic, 2015     |
| S28     | Workplace accidents analysis with a coupled clustering methods: S.O.M. and K-means algorithms | Comberti et al., 2015          |
| S29     | Bayesian decision support for coding occupational injury data                        | Nanda et al., 2016            |
| S30     | Analyzing Arizona OSHA Injury Reports Using Unsupervised Machine Learning           | Chokor et al., 2016           |
| S31     | A novel hidden danger prediction method in cloud-based intelligent industrial production management using timeliness managing extreme learning machine | Luo et al., 2016              |
| S32     | Automatic Detection of Helmet Uses for Construction Safety                           | Rubaiyat et al., 2016         |
| S33     | Text mining based safety risk assessment and prediction of occupational accidents in a steel plant | Sarkar et al., 2016           |
| S34     | Classifying construction site photos for roof detection                              | Siddula et al., 2016          |
| S35     | Classifying injury narratives of large administrative databases for surveillance—A practical approach combining machine learning ensembles and human review | Marucci-Wellman et al., 2017  |
| Study ID | Title of Articles                                                                 | Citation                      |
|---------|-----------------------------------------------------------------------------------|-------------------------------|
| S36     | Coupling risk attitude and motion data mining in a preemptive construction safety framework | Rashid *et al*., 2017         |
| S37     | Construction Safety Clash Detection: Identifying Safety Incompatibilities among Fundamental Attributes using Data Mining | Tixier *et al*., 2017         |
| S38     | Predictive model for incident occurrences in steel plant in India                  | Sarkar *et al*., 2017         |
| S39     | Construction accident narrative classification: An evaluation of text mining techniques | Goh e Ubeynarayana, 2017      |
| S40     | Bayesian Decision Tool for the Analysis of Occupational Accidents in the Construction of Embankments | Gerassis *et al*., 2017       |
| S41     | Safety in ready mixed concrete industry: Descriptive analysis of injuries and development of preventive measures | Akboğa e Baradan, 2017        |
| S42     | A combined approach for the analysis of large occupational accident databases to support accident-prevention decision making | Comberti *et al*., 2018       |
| S43     | Wearable insole pressure system for automated detection and classification of awkward working postures in construction workers | Antwi-Afari *et al*., 2018    |
| S44     | Application of Inertial Measurement Units for Advanced Safety Surveillance System Using Individualized Sensor Technology (ASSIST): A Data Fusion and Machine Learning Approach | Baghdadi, 2018                |
| S45     | Does background really matter? Worker activity recognition in unconstrained construction environment | Jiang *et al*., 2018          |
| S46     | Estimation of probability of harm in safety of machinery using an investigation systemic approach and Logical Analysis of Data | Jocelyn *et al*., 2018        |
| S47     | Association Rules Mined from Construction Accident Data                              | Shin *et al*., 2018           |
| S48     | A Bayesian assessment of occupational health surveillance in workers exposed to silica in the energy and construction industry | Abad *et al*., 2018           |
| S49     | Evaluation of genotoxic effects in Brazilian agricultural workers exposed to pesticides and cigarette smoke using machine-learning algorithms | Tomiazzi *et al*., 2018       |
| S50     | Prediction of Occupational Incidents Using Proactive and Reactive Data: A Data Mining Approach | Sarkar *et al*., 2018         |
| S51     | A Bayesian Network Application in Occupational Health and Safety                     | Pekel *et al*., 2018          |
| S52     | Effect of a job demand-control-social support model on accounting professionals’ health perception | Del Pozo-Antúnez *et al*., 2018 |
| Study ID | Title of Articles | Citation |
|----------|-------------------|----------|
| S53 | Prediction of return-to-original-work after an industrial accident using machine learning and comparison of techniques | Lee e Kim, 2018 |
| S54 | Analysis of occupational accidents in underground and surface mining in Spain using data-mining techniques | Sanmiquel et al., 2018 |
| S55 | Predicting the outcome of occupational accidents by CART and CHAID methods at a steel factory in Iran | Shirali et al., 2018 |
| S56 | Applying machine learning to workers’ compensation data to identify industry-specific ergonomic and safety prevention | Meyers et al., 2018 |
| S57 | Application of optimized machine learning techniques for prediction of occupational accidents | Sarkar et al., 2019c |
| S58 | Predicting types of occupational accidents at construction sites in Korea using random forest model | Kang e Ryu, 2019 |
| S59 | Evaluating machine learning performance in predicting injury severity in agribusiness industries | Kakhki et al., 2019 |
| S60 | Discovering Latent Psychological Structures from Self-Report Assessments of Hospital Workers | Kao et al., 2019 |
| S61 | Deep Learning Algorithms with Demographic Information Help to Detect Tuberculosis in Chest Radiographs in Annual Workers’ Health Examination Data | Heo et al., 2019 |
| S62 | Performance of machine-learning algorithms to pattern recognition and classification of hearing impairment in Brazilian farmers exposed to pesticide and/or cigarette smoke | Tomiazzi et al., 2019 |
| S63 | Supervised machine learning techniques and genetic optimization for occupational diseases risk prediction | Di Noia et al., 2019 |
| S64 | Intelligent Wearable Occupational Health Safety Assurance System of Power Operation | Xie e Chang, 2019 |
| S65 | An optimization-based decision tree approach for predicting slip-trip-fall accidents at work | Sarkar et al., 2019b |
| S66 | Machine Learning Models for the Hearing Impairment Prediction in Workers Exposed to Complex Industrial Noise: A Pilot Study | Zhao et al., 2019 |
| S67 | Text-clustering based deep neural network for prediction of occupational accident risk: A case study | Sarkar et al., 2019a |
| S68 | Decision support approach to occupational safety using data mining | Khosrowabadi and Ghousi, 2019 |