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Lagging or leading? Exploring the temporal relationship among lagging indicators in mining establishments 2006–2017

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ABSTRACT

Problem: Safety management literature generally categorizes key performance indicators (KPIs) as either leading or lagging. Traditional lagging indicators are measures related to negative safety incidents, such as injuries, while leading indicators are used to predict (and therefore can be used to prevent) the likelihood of future negative safety incidents. Recent theory suggests that traditional lagging indicators also possess characteristics of leading indicators, and vice versa, however empirical evidence is limited. *Method:* The current research investigated the temporal relationships among establishment-level injuries, near misses, and fatal events using injury and employment data from a sample of 24,910 mining establishments over a 12-year period. *Results:* While controlling for employee hours worked, establishment-level reported injuries and near misses were associated with of future fatal events across the sample of mines and over the time period studied. Fatal events were also associated with increases in future reported near misses, providing evidence of a cyclic relationship between them. *Discussion:* These findings challenge the strict categorization of injuries, near misses, and fatal events as lagging indicators. *Practical applications:* Understanding the KPIs that should be used to manage organizational safety, and how they can be used, is of critical practical importance. The results of the current study suggest that, depending on several considerations, metrics tied to negative safety incidents may be used to anticipate, and possibly prevent, future negative safety events.
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1. Introduction

Although key performance indicators (KPIs) are fundamentally important to organizational safety management and a wealth of theory and practical guidance surrounding KPIs has been published, consensus has yet to be achieved regarding the basic elements of their definitions, nature, and utility (Almost et al., 2018; Sinelnikov, Inouye, & Kerper, 2015; Reiman & Pietikäinen, 2012). The safety management literature generally groups KPIs into *leading* or *lagging* categories. Traditional lagging indicators are measures related to negative safety incidents such as injuries. Conversely, leading indicators, such as management practices, safety culture, and safety climate, are used to predict the likelihood of future lagging indicators and, therefore, can be used to anticipate and prevent future negative safety incidents (Grabowski, Ayyalasomayajula, Merrick, & McCafferty, 2007). Given these characteristics, increased emphasis has recently been placed on the importance of leading indicators within organizational safety management (Almost et al., 2018; Bitar, Chadwick-Jones, Lawrie, Nazaruk, & Boodhai, 2018; Nazaripour, Halvani, Jahagiri, Fallahzadeh, & Mohammadzadeh, 2018).

1.1. Problem

Recent research has challenged the notion that leading and lagging indicators neatly conform to their traditional characteristics (Lingard, Hallowell, Salas, & Pirzaheh, 2017; Kongsvik, Johnsen, & Sklet, 2011; Payne, Bergman, Beus, Rodriguez, & Henning, 2009). Specifically, theory and evidence suggest that incidents and injuries (traditionally classified as lagging indicators) are also able to predict a significant portion of the variability in future levels of traditional leading indicators. Thus, metrics traditionally defined as lagging indicators may possess characteristics of both lagging and leading indicators. The objective of the current research was to explore the temporal relationship between traditional lagging indicators using a large longitudinal, establishment-level injury surveillance database, thereby further informing the ongoing discussion related to the concept and use of KPIs in organizational safety.

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1.2. Theoretical background

How to measure organizational safety has been, and continues to be, an important question for organizations around the globe. The types of KPIs that should be used to measure organizational safety have been debated by safety theorists, researchers, and practitioners (BSI, 2018; Parmenter, 2015; Podgórski, 2015; ILO, 2001). Numerous KPI frameworks specific to organizational safety have been proposed (e.g., Bitar et al., 2018; Nazaripour et al., 2018; Haas & Yorio, 2016; Podgórski, 2015; Sinelnikov, Inouye, & Kerper, 2015; Laitinen, Vuorinen, Simola, & Yrianheikki, 2013; Reiman & Pietikäinen, 2012; Körvers & Sonnemans, 2008; ILO, 2001). With few exceptions, most of these proposed frameworks broadly categorize KPIs as either *lagging* or *leading*.

Lagging indicators represent outcomes of events that have already happened. In the context of organizational safety, traditional lagging indicators are those that reflect the frequency and/or severity of negative safety incidents such as loss of property or injuries. Alternatively, leading indicators are used to predict the likelihood of future lagging indicators or objective levels of safety performance. Thus, they provide actionable information that can be used to prevent future negative safety incidents (Sinelnikov et al., 2015; Grabowski, Ayyalasomayajula, Merrick, & McCafferty, 2007). Examples of traditional leading indicators include the frequency and quality of management practices; the values, attitudes, and beliefs related to safety within the organization; worker perceptions of the importance and priority that workplace safety has in an organization; and observable safe and healthy behaviors (Lingard et al., 2017; Hinze, Thurman, & Wehle, 2013).

Historically, incidents and injuries (i.e., lagging indicators) have represented the most common performance indicator of organizational safety (Reiman & Pietikäinen, 2012; Grabowski et al., 2007). Within the last decade the importance of leading indicators has been emphasized as the drawbacks of relying on lagging indicators have been voiced (Bitar et al., 2018). The most commonly voiced criticism is the argument that, while lagging indicators are generally less resource-intensive to obtain, they only provide information about negative safety events that have already occurred and are not useful for predicting or anticipating future negative events (Bitar et al., 2018; Brauer, 2016; Hinze et al., 2013; Grabowski et al., 2007; Chen & Yang, 2004). Nazaripour et al. (2018) argued that, "lagging indicators such as incident statistics are passive and do not have the ability to predict possible incidents" (p. 285). With this assumption in mind, Grabowski et al. (2007) argued that a focus on 'after-the-fact' lagging indicators may convey the message that preventing future incidents and injuries is less important.

In recent years, however, the academic literature has provided some evidence that the time dependent, causal dichotomy between traditional leading and lagging indicators may not be black and white (e.g., Lingard, et al., 2017; Haas & Yorio, 2016; Kongsvik et al., 2011; Payne et al., 2009). Through a literature review and theoretical reasoning, Payne et al. (2009) argued that safety climate, a traditional leading indicator, is both a leading and lagging indicator of organizational safety outcomes. This finding was also supported in an analysis of KPIs conducted by Haas and Yorio (2016). As a leading indicator, safety climate represents perceptions of the priority of safety in the workplace that, in turn, drives expectations regarding appropriate behavior. Therefore, safety climate should influence the occurrence or non-occurrence of occupational incidents and injuries. The recognition that safety climate can also function as a lagging indicator, however, acknowledges that worker perception of the priority of workplace safety can be influenced by incidents and injuries previously witnessed or experienced within an organization.

Likely due to research design complexity, only two published empirical studies were found that directly examined these assertions. In the context of the oil and gas industry, Kongsvik et al. (2011) examined the relationship between safety climate and incidents in 28 offshore installations. The study gathered incident information for a 12-month period, measured the safety climate perceptions of 2188 oil and gas workers, and then tracked incident events over the next 12 months. The authors found that safety climate significantly predicted incident events that occurred in the 12 months following the survey. They also found that the incident events that had occurred during the preceding 12 months significantly predicted safety climate. Given the results, the authors concurred with Payne et al., (2009) and concluded that safety climate can act as both a leading and lagging indicator of incident events in the oil and gas industry.

In a separate study, Lingard, Hallowell, Salas, and Pirzadeh (2017) collected five years of leading and lagging safety metrics from a single infrastructure project. They found that expected leading indicators (e.g., number of toolbox talk meetings, behavioral observations, and audit results) could be used to significantly predict future injury rates. They also found that injury rates could be used to significantly predict future changes in, for example, the frequency of toolbox talks, audits, procedural reviews, and behavioral observations. The authors concluded that the traditional assumptions underpinning the leading and lagging terms should be reconsidered.

This limited empirical evidence suggests that traditional leading indicators can be predicted by—and, therefore, can 'lag' behind—lagging indicators. It also suggests that traditional lagging indicators can be used to predict other indicators of organizational safety. Although there are several studies that force us to question the traditional theoretical notions of the leading and lagging framework, they are limited in scope by both the number of establishments/projects studied and/or the length of time studied.

1.3. Research question

To that end, the current study further addressed the notion of organizational KPIs being interdependent and, perhaps, cyclical. The current study presents the results of statistical models designed to examine whether occupational injuries and near misses can be used to predict the probability of future fatal events—and vice versa—using safety information from 24,910 mining establishments over a 12-year period. This research design allows us to directly examine whether traditional lagging indicators are associated with future fatal events, and if fatal events are associated with future counts of injuries and near misses, thereby further informing the ongoing discussion related to the concept and use of KPIs in organizational safety. Within this context, exploring the prospect of a predictive relationships between OSH incidents over time is not synonymous with an examination of causation. Rather, an examination of prediction—through adjusted, longitudinal regression models within the sample over the time period studied— quantifies the relationship between establishment-level lagging indicators and the negative safety events that preceded them.

2. Methods

2.1. Databases used for analysis

Publicly available data collected and maintained by the Mine Safety and Health Administration (MSHA) were used to examine the research question. For each year between 2006 and 2017, the MSHA Mine Address and Employment (AE) and the Mine Incident, Injury, and Illness (AII) databases were obtained from MSHA's online statistics portal (MSHA, 2019). MSHA databases were selected because of the detail provided for negative safety events and the employment statistics they provide for each mining establishment in the United States. Because the databases include a fixed unique mine identification code, events and employment at each mine can be tracked over time.

2.1.1. AE database

The AE database is created from a required mine-level quarterly report (MSHA Form 7000-2) and is essentially a list of all the existing mines within the United States. Each case within this database represents information for a single mine and includes variables that denote, for example, the mine identification code, the geographic location of the mine, whether the mine was active or inactive, hours worked throughout the year, and other employment statistics. A distinct AE database is available for each year given that the number and status of mines can change over time.

2.1.2. AII database

The AII database includes each reportable occupational safety and health (OSH) incident that a mine experienced during the course of a given year. Each case within the database represents an individual OSH incident and, therefore, each case exists at the individual worker level. However, each reportable OSH incident is linked to a specific mine through their unique mine identification code, as assigned by MSHA. Using the MSHA-required form 7000-1 (MSHA's Mine Incident, Injury, and Illness Report), mines must record and report each of the following events:

- fatality
- injury with the potential to cause death
- worker entrapment of 30 min or more
- unplanned mine inundation by liquid or gas
- unplanned ignition or explosion of dust or gas
- unplanned mine fire not extinguished within 30 min of discovery
- unplanned ignition of a blasting agent or explosive
- unplanned roof fall; a coal or rock outburst that causes the withdrawal of miners
- unstable condition at an impoundment, refuse pile, or culm bank
- hoisting equipment failure or damage
- off-site injuries due to an incident event

This list includes incidents that resulted in worker injury as well as events that did not result in an injury but could have (i.e., a near miss). Within the AII database, there are numerous variables associated with each reported incident. For example, the degree of injury variable codes each OSH incident as a fatal injury, an injury that resulted in a permanent disability, an injury that resulted in days lost or restricted duty (herein referred to as days lost injuries), or a reportable injury (those without lost or restricted days), or a near miss.

Each of the datasets demarcated by year were summarized individually. For each mine, the total number of fatalities, near misses, and each type of injury was summed. Given that the AII database includes information only if a mine reported an OSH event during a given year, an active and operating mine with zero reportable OSH incidents during a given year would not have any associated cases in the AII database. To correct this, all active status mines were isolated using the AE databases for each year during the time period studied. The number of fatalities, permanently disabling injuries, days lost injuries, near misses, and total number of lost and restricted days each mine experienced were added to the set of active mining establishments. Zeros were then imputed for each of the OSH incident variables for the years in which a mine was active but had no case identified within the AII database.

2.2. Aggregated database

Given that the research question of interest was to examine if OSH incidents could be used to predict future fatalities, new variables reflecting the mine-level, one-year lagged counts of injuries, and near misses were created. This step allowed fatalities that a mine experienced during a given year to be included in the same row as the counts of OSH incidents the same mine experienced in the preceding year. In order to examine for the presence of a cyclic relationship, a lagged fatalities variable was also created. The resulting database included lagged and unlagged mine level counts of fatalities, injuries, and near misses by year.

The resulting database included 24,910 distinct mining establishments that were active during the designated time period: 4511 coal mines (18.1%); 770 metal mines (3.1%); 1155 nonmetal mines (4.6%); 6930 stone mines (27.8%); and 11,544 sand and gravel mines (46.3%). The average number of mine-level yearly hours worked during the time period was 35,972.29 (SD = 136,163.19).

Within the dataset of active mines, there were 469 fatalities, 83.58% ($N = 392$) of which were cases in which a mine experienced a single fatality in a single year. Given this distribution, counts of fatalities each establishment experienced for each year were dichotomized: 0 if no fatal event was experienced, and 1 if a mine experienced one or more fatalities in a given year. This step operationalizes the dependent variable as a fatal event rather than counts of fatalities and thereby eliminates possible statistical bias that may be introduced in the instance that a single event caused multiple fatalities. To illustrate, the Crandall Canyon Mine incident in 2007 in which nine mine workers died and the Upper Big Branch Mine incident in 2010 that resulted in 29 mine worker fatalities were both recoded as a 1 to represent a single fatal incident. Table 1 shows the sum, mine-level average, standard deviation, and minimum/maximum for each of the OSH metrics reported by the sample of mines. The table shows that there were 469 fatalities and 413 fatal events after dichotomization.

2.3. Analytical approach

Two sets of models were used to examine the temporal relationships between establishment level injuries, near misses, and fatalities. Given that repeated measures of yearly establishment-level metrics resulted in a nested dataset, four longitudinal logistic statistical models were initially used to estimate the change in probability for an establishment to experience a fatal event in a given year as a function of counts of OSH incidents in the previous year (t−1). The models were fit in IBM SPSS version 25 using generalized estimating equations (GEE)—a form of generalized linear models that accounts for statistical dependence among sets of observations resulting from repeated measures over time. Given that increased employee hours worked may also theoretically increase the probability of a fatal event, each of the models controlled for mine level counts of hours worked during the same year of the dependent variable (fatal events).

Within the four models, each of the incident variables (i.e., permanent disabling injuries; days lost injuries; reportable injuries; and near misses) were entered as independent variables predicting the probability of a subsequent fatal event year while controlling for employee hours worked. Models 1 – 4 took the form of:

$$logit(P[fatal\,event_{i,t}] = B_0 + B_1(number\,of\,injuries\,of\,given\,degree)_{i,t-1} + B_2 * \log(employee\,hours\,worked)_{i,t}$$

Table 1
Descriptive statistics for 2006–2017 OSH metrics used in the model.

Variable	Total	Mine-Level average	Standard Deviation	Minimum/Maximum
Fatalities—before dichotomization	469	<0.01	0.09	0/29
Fatalities—after dichotomization	413	<0.01	0.05	0/1
Permanently disabling Injuries	1010	0.01	0.08	0/4
Days lost injuries	60,735	0.34	1.92	0/155
Reportable injuries	29,534	0.16	0.94	0/69
Near Misses	13,754	0.08	0.94	0/95

Table 2
Longitudinal Logistic Regression Results—Establishment level fatal events predicted by prior year counts of injuries and near misses.

							95% Confidence Interval for the Odds Ratio	
Model	Predictor	B	Std. Error	Wald Chi-Square	Significance	Odds Ratio	Lower	Upper
Model 1	Prior Year Disabling Injuries	0.12	0.16	0.56	0.45	1.13	0.83	1.54
Model 2	Prior Year Days Lost Injuries	0.02	0.01	4.74	0.03	1.02	1.01	1.03
Model 3	Prior Year Reportable Injuries	0.04	0.02	5.96	0.01	1.04	1.01	1.07
Model 4	Prior Year Near Misses	0.03	0.01	8.98	<0.001	1.03	1.01	1.05

Note: In each of the Models 1–4 the log of total hours worked variable was a significant, positive, and strongest predictor of fatal events at the $p < 0.001$ level. All models were equivalent when using the raw counts ($N = 469$) in count regression models.

Table 3
Longitudinal Count Regression Results—Establishment level counts of injuries and near misses predicted by prior year fatal events.

							95% Confidence Interval for the Risk Ratio	
Model	Outcome	B	Std. Error	Wald Chi-Square	Significance	Risk Ratio	Lower	Upper
Model 5	Disabling Injuries	0.19	0.18	1.12	0.29	1.21	0.80	1.70
Model 6	Days Lost Injuries	0.80	0.05	2.39	0.12	1.08	0.94	1.19
Model 7	Reportable Injuries	0.12	0.07	3.03	0.10	1.12	0.97	1.25
Model 8	Near Misses	0.51	0.15	12.14	<0.001	1.67	1.25	2.22

Note: Grounded in an analysis of fit statistics, longitudinal (Generalized Estimating Equations) negative binomial count regression models were used to estimate the results. In each of the Models 5–8 the log of employee hours worked was significant, positive, and the strongest predictor of injuries and near misses at the $p < 0.001$ level.

Within the model, i is the individual mining establishment, and t is the year. Each of the models allows for a single odds ratio to be generated for each of the OSH incident types for the time span. In all models, the injury and near miss predictor variables were entered into the regression equation untransformed to allow for straightforward interpretation of the results. The interpretation of each exponentiated regression coefficient (i.e., the odds ratio) represents the change in probability for a mining establishment to experience a fatal event in a given year for every single additional OSH incident in a previous year.

Four additional longitudinal statistical models were used to examine for evidence of a cyclic relationship between fatal events and injury counts and near misses. Within the four additional models, each of the incident variables (i.e., permanent disabling injuries; days lost injuries; reportable injuries; and near misses) were regressed on fatal events at t-1 while controlling employee hours worked. Models 5–8 were as follows:

$$log(P[number\ of\ injuries\ of\ a\ given\ degree_{i,t}] = B_0 + B_1(fatal\ event)_{i,t-1} + B_2 * \log(employee\ hours\ worked)_{i,t}$$

Similar to the longitudinal logistic models, each of the models allows for a single risk ratio to be generated that summarizes the predictive effect of a fatal event on subsequent year counts of injuries and near misses for the time span. The interpretation of each exponentiated regression coefficient in this case represents the change in probability for a mining establishment to report a near miss or injury type depending on whether a fatal event occurred in the previous year. Like the previous models, these effects are derived while controlling for the log number of hours worked.

3. Results

Table 2 reports the results of Models 1–4 in which fatal events were predicted by previous year counts of injuries and near misses while controlling for the log of the total number of hours worked. Within these models, the effect of disabling injuries on future fatal events was not significant. While controlling for the log of hours worked, days lost injuries, reportable injuries, and near misses were significantly associated with future fatal events: days lost injuries, Odds Ratio (OR) = 1.02, $p = 0.03$; reportable injuries, OR = 1.04, $p = 0.01$; and near misses, OR = 1.03, $p < 0.001$. This implies that there was a 2% increase in the probability for an establishment to experience a fatal event for each additional days lost injury, a 4% increase for each reportable injury, and a 3% increase for each near miss.

Table 3 shows the results of Models 5–8 in which fatal events were used to predict future counts of injuries and near misses. While controlling for the number of hours worked, only the number of reported near misses (Model 8) was significantly influenced by whether a fatal event was experienced in the preceding year (Risk Ratio = 1.67, $p < 0.001$). This implies that there was a 67% increase in the likelihood of a reported near miss if a fatal event occurred in the previous year over the time period studied. Models

5–7 suggest that counts of the remaining injury categories (disabling, days lost, and reportable injuries) were not systematically influenced by the occurrence of a fatal event in the preceding year.

4. Discussion

While controlling for the total number of employee hours worked in the context of the mining industry, increased counts of reportable injuries, days lost injuries, and near misses were significantly associated with fatal events in future years over a 12-year period across 24,910 establishments. These findings share some commonalities with similarly situated longitudinal statistical models using data from an overlapping, but distinct sample of mines during the 2000–2012 time period (Yorio & Moore, 2018). Collectively, both studies provide strong evidence that traditional lagging indicators can be used to predict future indicators of organizational safety. The results are consistent with the fundamental conclusions drawn by Payne et al. (2009), Kongsvik et al. (2011), Lingard et al. (2017), and Haas and Yorio (2016) that highlight potential limitations of the traditional terminology.

Evidence of a cyclic relationship was found between fatal events and near misses. This finding suggests that following a fatal event, mine workers are much more likely to report occurrences of near miss events; and increased reports of near misses are associated with an increased probability of a future fatal event.

Although the results of the study can be used to inform the ongoing dialogue regarding terms used to describe KPIs important to the organization, the utility of incidents and injuries as predictive indicators remains open to debate and is subject to future research. In what follows is a discussion regarding the potential utility of using incident and injury data as a leading indicator in lieu of findings of the current and previous studies.

4.1. Near misses and fatal events

Interestingly, previous theoretical work has shown that near miss incidents share properties with both traditional leading and lagging indicators. They are unwanted and unplanned incident events that did not result in an injury but, under slightly different circumstances, could have (Sinelnikov, Inouye, & Kerper, 2015). Although some theorists argue that near misses share more in common with a traditional leading indicator given the absence of an injury event (e.g., Hinze et al., 2013), with respect to near miss instances that resulted in damage to materials, machinery, equipment, and/or the work environment, a loss event and/or negative outcome related to organizational safety has occurred. In these circumstances, near misses possess properties consistent with traditional lagging indicators. In the context of mining, the reporting of near misses is mandated for serious incident events such as roof and face falls, unplanned explosions, and hoisting equipment failures—all of which involve some type of loss event that did not result in an injury event. Both the current study and Yorio and Moore (2018) found that near misses were significantly associated with future fatal events. The current study also found that reported near misses were substantially higher for establishments that experienced a fatal event in the preceding year. This empirical finding of a cyclic pattern between fatal events and near misses over time is consistent with notions that they theoretically possess properties of both traditional leading and lagging indicators.

4.2. Injury counts and fatal events

Although evidence of a cyclic relationship was not present for days lost and reportable injuries, while controlling for employee hours worked, increased counts of both days lost and reportable injuries were significantly associated with future fatal events. These findings were in contrast with the results of Yorio and Moore (2018) these effects were not significant. Also distinct from the current study, Yorio and Moore (2018) found a significant effect for counts of permanently disabling injuries. The fact that different periods of time and an overlapping but distinct sample of establishments resulted in these distinctions, questions the notion of a systematic relationship between their occurrence and future catastrophic incident events. However, the effect of traditional leading indicators (e.g., safety climate) on future fatal events is largely anecdotal (see Christian, Bradley, Wallace, & Burke, 2009 for a review of the outcomes involved in safety climate empirical studies to date) and chance variations are theoretically expected to disrupt a consistent and systematic effect on future incident and injuries (Zohar, 2010). Thus, although some inconsistencies were found between distinct samples and time frames, when both the current study and Yorio and Moore (2018) are considered, the fact that days lost injuries, reportable injuries, and permanently disabling injuries were found to, at some point, be significantly associated with future fatal incidents provides evidence that they possess properties of predictive indicators.

4.3. Comparing findings from other industries

A handful of studies outside of the mining industry have also found relationships between injuries and future catastrophic incident events. In the construction industry, for instance, efforts to bring residual low-injury numbers (close) to zero led to a greater likelihood of fatalities (Saloniemi & Oksanen, 1998; Sheratt & Dainty, 2017). One explanation for the negative relationship is that the pressure to show low numbers of injuries can help create cultures of risk secrecy in which incident potential is allowed to build up behind an image or façade of low injury numbers (Turner, 1978). A similar finding was revealed within the commercial aviation industry (Dekker, 2011; Amalberti, 2001; O'Leary & Chappell, 1996). These researchers found that the number of incidents reported was found to be significantly and negatively predictive of fatalities. Another cross-industry study (Mendelhoff & Burns, 2013) found that higher fatality rates in the majority of U.S. states were associated with low nonfatal injury rates, and vice-versa.

Differences in the direction of the predictive relationship between counts of injuries and future catastrophic incidents highlight complexities involved in their empirical relationship. The current results compared with results of previous studies in high-risk industries demonstrate that the strength and direction of the empirical relationship between injuries and future KPIs may largely depend on the industrial setting of the empirical study, the norms related to managerial responses to workplace injury, the frequency with which the outcome(s) takes place, the number of months/years of lag time, and the outcome used in the empirical study. Given the nature of the surveillance dataset used, the current study considered fatal events—a relatively rare event—as the foci around which temporal associations with injuries and near misses were examined.

When the relationship between fatal events and injuries/near misses are contemplated, a few considerations should be reflected upon. First, the time lag chosen may influence the effect found. Lingard et al.'s, (2016) finding that a systematic cyclic relationship between injuries and traditional leading indicators over time, suggests a positive or negative relationship may be uncovered depending on the exact time lag chosen between measurements. Although the pattern of OSH incidents and their interrelationships with safety climate and/or the frequency of management practices, as a function of time is largely theoretical, the general notion that choosing different time lags (e.g., weeks, months, or years) may result in effects of different directionality is intriguing. Thus, strong theory and reasoning may be needed to support directional hypotheses between counts of injuries and future KPIs in context specific studies.

Second, managerial interventions to identify and correct the root causes of injuries and illnesses can alter the likelihood of future negative events of the same cause that may have occurred in the future. The importance of a direct link through common cause has been routinely identified within the literature. For example, Bellamy (2015), concluded on the basis of 23,000 serious reportable incidents that low-severity, high-frequency incidents can provide information about the direct and underlying causes of high–severity incidents—but only within the same hazard category. The notion that most safety incidents and low severity injuries do not share common causes with high severity incidents has led to policy conclusions that managing low severity injury events with the goal of preventing future fatalities may not be effective. For example, the Chemical Safety Board (CSB) found that the "BP Texas City explosions was an example of a low-frequency, high-consequence catastrophic incident. Total recordable incident rates and lost time incident rates do not effectively predict a facility's risk for a catastrophic event" (CSB, 2007, p. 202). Based on its investigation, the CSB advised that regulatory inspection targeting should not rely on traditional injury data.

In theory, however, managerial efforts to correct root causes can influence the occurrence of future negative events even when the causes are not consistent in lieu of several mitigating factors. For example, if a strict focus on low severity incidents decreases or eliminates efforts to control the risks related to fatal events—the probability of future catastrophic safety events may increase. In addition, the influence of OSH incidents on safety climate and culture may also play a mitigating role in the absence of a common cause. For example, as theorized by Payne et al. (2009) and demonstrated by Kongsvik et al. (2011), safety climate perceptions can be influenced by previous negative safety incidents, which, in turn may increase the probability of a future catastrophic incident regardless of cause. Alternatively, one must also consider the potential benefit of implementing corrective actions for lower severity events that occur more frequently. Because these events occur more frequently, they offer an organization the opportunity to exercise key behaviors incorporated within the SHMS and to collect routine data that can be used to evaluate the effectiveness of this system. Moreover, the interest in characterizing and correcting these events will undoubtedly impact worker perceptions on an organization's view of safety and health as a priority. Collectively the challenge may be for organizations to find a balanced investment strategy—perhaps one that does not over-invest in low severity events while ignoring non-common risks that could result in a future fatal event; while at the same time not ignoring the potential benefits of leveraging the more frequently occurring lower severity events for the benefit of safety climate and culture and exercising response behaviors included within the SHMS.

5. Limitations, conclusions and directions for future research

A few important limitations and directions for future research should be highlighted. First, we relied solely on reported establishment-level metrics included within the MSHA database between 2006 and 2017. A consistent limitation when using this type of surveillance data is the potential for underreporting, and perhaps increased error variance in reporting due to potential changes of mine ownership and reporting norms over time.

Second, the primary goal of the study was to examine for mere evidence of a significant association between traditional lagging indicators on future lagging indicators and no direct empirical examination was made regarding the reasons behind the relationship. As implied, the predictive relationship between OSH incidents and fatalities—or vice versa in the case of near misses—does not argue that direct causation between the two can or should be made. Logically OSH incidents should not be understood to directly cause the occurrence of a future fatal event in the context of this research. Most traditional leading indicators (e.g., management communications, training, safety climate, toolbox talks, pretask safety audits) also do not directly cause a future incident. In both instances, there are unmeasured proximal/indirect mechanisms through which a prediction is realized. Future studies may be designed to empirically focus on the indirect mechanisms through which OSH incidents influence future negative events.

Given the nature of the surveillance dataset used, the current study considered fatal events—a relatively rare outcome—as the foci used to examine the temporal relationship with injuries and near misses. Therefore, a level of temporal association among fatal events and injuries and near misses was not certain and the small effect sizes observed for most of the relationships is not surprising. Future studies may examine the predictive effects of fatal events, injuries, and near misses on KPIs with greater variability such as safety climate (Payne et al., 2009). No such examination could be made in the current study given that metrics related to traditional leading indicators are not included within the MSHA databases.

6. Practical applications

The purpose of this research was to explore the empirically grounded theoretical assertions that questions the traditional notions of KPIs used in OSH management (Lingard et al., 2017; Haas & Yorio, 2016; Kongsvik et al., 2011; Payne et al., 2009). Through predictive models based on data from a sample of 24,910 mining establishments over a 12-year period, increased instances of establishment-level injuries and near misses were found to be significantly associated with future fatal events. Given the critical importance of identifying metrics that can be used to predict occupational fatalities, these findings have significant practical implications. The finding that fatal events trigger significant increases in reported near misses highlights the impact these events can have on management and worker awareness, perception, and the importance attributed to reporting and sharing near injury events.

These findings support previously voiced notions that the temporal relationships among organizational safety indicators may be more complicated than previously understood. Given the broad-based appeal and use of the leading and lagging typology in practice, the degree to which these findings, and other supporting research, can have a practical impact is yet to be decided. Almost certainly, additional research is needed to theoretically develop OSH KPI frameworks that do not integrate the nuances associated with the leading/lagging terminology. Building from the theoretical work of Juglaret et al (2011), Haas and Yorio (2016) empirically developed indicator categories that were neither explicitly categorized based on time nor causally related. In doing so, they argued that the newly developed categories are ideally positioned to manage the full breadth of SHMS practices, while satisfactorily recognizing OSH and its management as a complex, emergent property of an organization. The work of Haas and Yorio (2016) demonstrates that the potential for alternative frameworks do exist, the utility of which may be considered from a practical perspective in the future.

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