Finding causal paths between safety management system factors and accident precursors

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ABSTRACT

Understanding the causal relationships between safety management system (SMS) factors and accident precursors helps construction organizations identify which factors require improvement upon observing an accident precursor. Previous research has not clearly distinguished between SMS factors and accident precursors. This background examines the relationships between SMS factors and accident precursors using empirical data. Specifically, five structural equation models (SEMs) are developed to map causal paths between SMS factors and accident precursors. Each of the SEMs helps identify what specific SMS factors would have a significant influence on the occurrence of a particular type of accident precursor. These models can thus help describe what specific SMS factors would need to be improved when a certain type of accident precursors appears on site. The SEM results show in particular that the occurrence of accident precursors can be attributed largely to adverse project conditions such as project schedule pressure, reworks, and change orders. Construction organizations may capitalize on these findings by prioritizing safety management resources to address specific observed accident precursors in a more informed and targeted manner.

INTRODUCTION

The causes of accidents are complex, but we may briefly say that an accident occurs when a series of undesired events occur in sequence (Saleh et al. 2013). In an attempt to halt the onset of the sequence of unfortunate events resulting in accidents, multi-pronged and systemic approaches to safety management have been implemented in construction. Known collectively as a Safety Management System (SMS), such multidimensional integrative efforts have involved site management planning, hazard identification and risk mitigation, project safety rules and policies, site inspection, training, consultation, worker engagement, accident investigation/analysis, and safety performance evaluation. This integrated approach has been found effective, and has since significantly contributed to enhancing safety performance on construction sites over the last two decades (Robson et al. 2007; Wachter and Yorio 2014; Bottani et al. 2009).

The factors affecting the performance of SMS can be referred to as SMS factors (Pereira et al. 2018), while the undesirable events that precede and indicate the approach of an accident can be referred to as accident precursors (Kunreuther et al. 2004). Based on these definitions, SMS factors and accident precursors are conceptually distinguishable, and accident precursors can be understood as resulting from the misperformance of SMS with SMS factors being the root causes. However, the understanding of the causal links between SMS factors and accident precursors is currently limited (Patel and Jha 2016). This is problematic because the root causes of an accident precursor can be misidentified if there is no clear understanding of which SMS factors are connected with which specific accident precursors. In turn, misidentification of the causes of accident precursors may result in the inefficient use of safety management resources by addressing less relevant SMS factors. To address this problem, this paper investigates the causal relationships between various SMS factors and accident precursors based on empirical data collected from construction practitioners about the condition of SMS factors and the likelihood of accident precursors. An improved understanding of the relationships between these variables is expected to contribute to advancing proactive safety management approaches in construction projects. With an improved understanding, construction managers can identify the most relevant SMS factors related to an observed accident precursor.

RESEARCH BACKGROUNDS AND KNOWLEDGE GAPS

Safety Management System (SMS)

A SMS can be defined as a set of integrated safety practices designed to achieve occupational health and safety (OHS) objectives on construction sites (Fernandez-Muniz et al. 2007; Robson et al. 2007; Wachter and Yorio 2014). SMSs are multidimensional, inclusive, holistic, proactive, and oriented toward the continuous improvement of safety (Robson et al. 2007). Their integration into organizational processes allows construction organizations to more easily comply with OHS regulations (Fernandez-Muniz et al. 2009). The use of SMSs is mandatory in many countries including the USA, the UK, Australia, Hong Kong, and Singapore (Ai et al 2006); however, SMSs can also be implemented voluntarily by construction organizations in countries where they are not mandated (Robson et al. 2007).

An SMS consists of many components, such as safety management planning, safety policies, safe work practices, safety training, group meetings, incident investigation, safety rules, safety promotion, evaluation, selection and control of subcontractors, safety inspection, machinery maintenance, hazard analysis, and the control of hazardous substances (Teo and Ling 2006; Fernandez-Muniz et al. 2007; Robson et al. 2007; Hinze et al. 2013; Wachter and Yorio 2014). These components of SMS can interact with each other in a complex way to affect the performance of whole SMS (Patel and Jha 2016). Additionally, the performance of an SMS can be affected by many types of project conditions, such as project schedule, safety management budget, worker skill levels, experience of site supervisors, weather (Hinze 1997; Guo et al 2018), and the level of implementation of each component of SMS (Robson et al. 2007).

Accident Precursors

Traditionally, safety performance has been monitored by measuring the frequency and severity of injuries, such as the Recordable Injury Rate and the Days Away Restricted Work or Transfer. Because these measures provide historical information—that is, "after-the-fact" data about incidents (p.24, Hinze et al. 2013b)—they are often referred to as "lagging indicators." Lagging indicators are useful for many purposes, such as safety performance benchmarking; however, they are less useful for proactively mitigating safety risks (Hinze et al. 2013b). Many researchers have noted the limitations of lagging indicators (Hinze et al. 2013b; Salas and Hallowell 2016; Guo and Yiu 2016; Wu et al. 2010), and have consequently argued for the development of new approaches that can signal when a SMS is underperforming and prompt construction managers to intervene prior to accident occurrence (Hinze et al. 2013).

Accident precursors can be defined as conditions, events, or sequences that precede an accident (Phimister et al. 2004, Saleh et al. 2013); more narrowly, they are undesired events *immediately* preceding and leading to an accident (Wu et al. 2010). In this research the latter definition is used to distinguish accident precursors from other undesired conditions or events such as the poor implementation of a safety management process. Since events preceding an accident differ depending on context, accident precursors can generally be identified within a particular industry or sector characterized by similar conditions. For example, accident precursors have been identified for railway sites (Kyriakidis et al. 2012), which differ from those identified in the maritime and ocean freight industry (Grabowski et al. 2007). Similarly, specific accident precursors have been identified for the construction industry. Wu et al. (2010) have identified the lack of protection, workers working without a sufficient operational fall protection, workers working on a scaffold with inappropriate guard railings as the main accident precursors for the 'fall from scaffolding' type accidents. Tixier et al. (2016) indicated that poor housekeeping, poor visibility, improper procedure, and improper use of PPE are the events before the occurrence of an accident in construction. Alexander et al. (2017) identified improvisation in construction processes, poor pre-task plan, limited safety supervision, and fatigue as the precursors to an accident in construction.

Current Knowledge Gaps

In previous work, the undesirable state of SMS factors (e.g., the lack of a worker safety behavior program) and accident precursors (e.g., improper use of PPE) were not clearly distinguished; consequently, the causal links that may exist between them have been overlooked. For instance, several researchers (Patel and Jha 2016; Robson et al. 2007; Wachter and Yorio 2014; Bottani et al. 2009; Akroush and El-adaway 2017; Gui and You, 2016; Eteifa and El-Adaway 2018) investigated the impact of specific SMS components (e.g., budget for safety management, hazard management practices, site safety rules and worker behavior management efforts) on accident rates, but they paid limited attention to accident precursors resulting from the undesirable state of the SMS factors. Some researchers highlight the difference in safety performance between adopters and non-adopters of SMS (Castillo et al, 2018; Li et al, 2015; Hinze et al 2013). But these previous studies did not consider the breadth of SMS implementation and its impact on safety performance. Therefore, an important knowledge gap exists regarding the cause of accident precursors in relation to SMS implementation and factors affecting SMS performance.

METHODS

To investigate the complex associations between the condition of SMS factors and the occurrence of specific types of accident precursors in a quantitative manner, a structural equation modeling (SEM)-based approach was used in this research. Specifically, the research was conducted in the following two stages: (1) defining constructs and collecting empirical data for each measure of SMS factors and accident precursors, and (2) constructing and testing SEMs to connect each type of accident precursor with SMS factors. The data analysis stage was further divided into two steps: (1) Confirmatory Factor Analysis (CFA), and (2) Structural Equation Modeling (SEM) and analysis, as outlined by Hair et al. (2014).

Measures and Data Collection

Based on a comprehensive review of the construction safety management literature, a total of 28 SMS factors (Table 1) and 24 accident precursors (Table 2) were selected for inclusion in the questionnaire. As indicated in Tables 1 and 2, *a priori* categories of the SMS factors and accident precursors were developed based on the literature. The resulting SMS factors were grouped into six categories: project administration for safety (e.g. safety goals setup (Hislop 1999), subcontractor assessment (Al Haadir and Panuwatwanich 2011)), risk assessment and control (e.g. incident investigation, pre-task hazard assessment, site inspection (Hinze 1997)), worker behavior improvement efforts (e.g., employee engagement behavior-based safety program (Hinze et al. 2013)), commitment (e.g., management team's priority on safety over schedule or cost (Lee et al. 2012; Lee et al. 2005; Choudhry et al. 2008; Han et al. 2014)), resources (both budget and personnel) (Zou and Zhang 2009), and project adverse condition (reworks (Han et al. 2014); tight contract schedule (CII 2012; Mitropoulos et al. 2005), lack of availability of skilled workers (Zou and Zhang 2009)).

The accident precursors were grouped into five categories as suggested by Wu et al. (2010): worker-related precursors (workers' failure to identify hazards (Rodrigues et al., 2015) and fatigue (Alexander et al. 2017)), work team-related precursors (lack of attention for coworkers (Zou and Zhang 2009), insufficient foremen experience (Toole 2002)), workplace-related precursors (housekeeping (Khanzode et al. 2012) or inadequate safety guards and barriers (Reiman and Pietikäinen 2012; Alexander et al. 2017)), site organization-related precursors (unclear emergency procedures (Sun et al. 2008) or inadequate site information (Suraji et al 2001)), and materials and equipment-related precursors (inadequate use of tools (Toole 2002) and workers' exposure to hazardous materials (Hallowell et al. 2013)).

The questionnaire items were designed specifically to collect data on both the condition of SMS factors and the likelihood of accident precursors as perceived by the construction practitioners in their most current construction projects. A more detailed description of questionnaire items, data collection and preprocessing is provided in Pereira et al. (2018). The final questionnaire (available at https://ascelibrary.org/action/downloadSupplement?doi=10.1061%2F%28ASCE%29ME.1943-5479.0000562&attachmentId=5758332) was administered as an online survey. Some items were measured with a high value (a desirable state) while others were measured in the opposite way. After data collection, the data were pre-processed so that all variables could be interpreted such that a higher value means a more undesirable state, whether or not the measure is related to a SMS factor or accident precursor.

A link to the online survey questionnaire form was distributed to key contact individuals of 15 major construction companies in Alberta, Canada, who were asked to circulate the questionnaire link to site managers, safety managers, and other construction practitioners in their companies.

Survey participation was voluntary, anonymous, and confidential. Respondents were asked to respond to items based on their experience from their current or most recent project to reflect a single project. A total of 102 responses were received, of which 6 were removed due to incompleteness; therefore, 96 responses were used in the analysis stage. While the majority (60%) of the respondents were currently working on an industrial construction project, 31% were in the heavy construction sector, 6% in the building industry, and 3% in the other construction sectors of the construction industry. Of those respondents, 24% were also health, safety, and environment (HSE) managers, 25% were project managers, 21% were superintendents, 19% were other safety staff members, and 11% had other managerial positions in the construction industry. The respondents were predominantly from Alberta, Canada.

Data Analysis and Modeling

The data analysis process of this research was guided by the widely adopted SEM process suggested by Hair et al. (2014). In the process, a confirmatory factor analysis (CFA) is first performed to confirm that the small number of predetermined constructs (i.e., “Groups;” see Tables 2 and 3) represent the measures (i.e., individual SMS factors and accident precursors). In CFA, the reliability of the factors and the convergent and discriminant validity of the scales used to measure the variables are assessed to ensure the appropriateness of the measures for use in SEM analysis (Hair et al. 2014).

After the factors (i.e., “groups”) are confirmed through CFA, SEM is used to model the associations between the factors. The structural components of SEM enable the rendering of statements about relationships between factors and the mechanisms underlying a process or phenomenon (Byrne 2009). The SEM method investigates complex inter-relations between observed or factors by systematically incorporating CFA, multiple regression analysis, and path analysis (Hair et al. 2014). The actual structural modeling portion of SEM begins with the construction of hypothetical structural models, each of which consists of a set of hypothesized relationships between the factors. The hypothesized structural model is then tested against the dataset using several goodness-of-fit indices.

Several recommendations regarding the appropriate sample size for SEM have been suggested by many researchers (Iacobucci 2010; Bagozzi 2010; Lam et al. 2016; Ozorhon and Oral 2016; Zafar et al. 2018; Sideridis et al. 2014). The sample size in SEM is particularly important to produce realiable assessment of the model overall fit (Jiang and Yuan 2017). A low sample size can produce misleading results or in unattainable parameter estimates due to non-convergences in computation (Deng et al. 2018). As most of the recommendations suggest at least 100 samples for SEM, this research adopted a bootstrapping technique to address the issue of its modest sample size. Specifically, 5,000 bootstrap samples were used to test the stability and appropriateness of the models, as recommended by Hair et al (2011).

RESULTS

Confirmatory Factor Analysis

Because the measurements used in this research are self-reported and collected through the same questionnaire during the same period of time, a common method variance (a variance that is attributed to the measurement method rather than the constructs of interest) could cause systematic measurement errors. To ensure that the data is not substantially influenced by a common method variance, the Harman's single factor test was applied. The result suggests that 23.54% of the dataset variance could be explained by one latent factor, which is much lower than the 50% threshold for common method variance (Podsakoff et al, 2003).

The CFA was conducted, and the results of the analysis on the SMS factors are summarized in Table 3. To examine the factor models' reliability, the internal consistency of the measures for each group was tested. Items with a factor loading of greater than 0.6 were accepted to be unidimensional (Hair et al. 2014). The following SMS factors had a factor loading less than 0.6 and, therefore, were excluded from the factor models: *Emergency Planning* (RISK5), *Substance Abuse Prevention Program* (BEHAV5), *Safety Performance Incentive Programs* (ADMIN4), *Design Complexity* (ADV4), *Availability of Skilled Workers* (ADV5), and *The Level of Required Worker Compensation Rate* (ADV6).

In addition, the convergent validity—the degree to which indicator variables correlate and share variance with each other—was tested using the Average Variance Extracted (AVE) metric. According to Fornell and Larcker (1981), it is recommended that AVE be 50% or greater. In addition, the Composite Reliability (CR) test was used to evaluate the convergent validity of reflective constructs. According to Hair et al (2014), CR has a threshold value of 0.7. The following factors (Table 3) satisfied all these criteria, and were used in the SEM analysis process: *Project Administration for Safety* (ADMIN), *Risk Assessment and Control* (RISK), *Worker Behavior Improvement efforts* (BEHAV), *Project*, *Commitment* (COM), *Resources* (RES), and *Adverse Project Conditions* (ADV).

Table 4 summarizes the results of the CFA for accident precursor measures. Among these measures, the following had a factor loading of less than 0.6 and were therefore excluded from the factor models: *Worker's Low-Skill Level* (WOR6), *Worker's Exposure to Extreme Weather Conditions* (PLACE4), *Inadequate/Inaccurate Site Information* (SITE5), and *Workers' Exposure to Hazardous Material* (MATEQ4). The same tests used for SMS factor measures—Internal Consistency, Convergent Validity, and CR—were also applied to the accident precursor factors.

All accident precursor factors also satisfied these criteria, and the factor models were therefore deemed acceptable.

Hypotheses for Structural Models

Based on the CFA results, five SEMs were hypothesized: one for each accident precursor factor. Each model was designed to examine the associations between one type of accident precursor and the SMS factors. According to Ullman and Bentler (2003), the first phase in a SEM analysis is the specification of a model. Although the factor analysis for each construct can be built based on exploratory or confirmatory approaches, the researcher should hypothesize the causal paths and directionality between the variables in the model specification (Gunzler and Morris 2015). That is, a researcher is more likely to use SEM to determine whether a certain model is valid, rather than using SEM to "find" a suitable model. In this research, the hypothesized relationships for each structural model were constructed based on the research findings reported in the construction safety management literature. The hypotheses tested in the structural models are summarized in Table 5.

Final Causal Path Models between SMS Factors and Accident Precursors

The structural models based on the hypotheses were built using *AMOS 24*. The internal validity test—the discriminant validity between the factors—was analysed to verify if each construct is truly distinct from the others so as to avoid the issue of multicollinearity. According to Hair et al (2011), the discriminant validity of two constructs is secured if both of their AVEs are larger than the squared correlation between them (Hair et al. 2011). This condition was met in all five hypothesized models. Following the internal validity check, two methods were used in the modeling process for testing, refining, and finalizing the structural models. Firstly, the

Modification Index technique, the most commonly used method for refining a SEM (Chen et al. 2012), was used to select the variables to improve the fit. Secondly, all models were tested through a number of goodness-of-fit (GOF) tests. Finally, a bootstrapping technique was conducted to estimate the significance relationship between factors. The final model validation results are summarized in Table 6.

The final model for the worker-related precursors (WOR) is illustrated in Figure 1 (Model 1). Worker-related precursors (WOR) were found to be significantly affected by adverse project conditions (ADV). Although the standardized coefficient (0.44) of the causal link from worker behavior improvement efforts (BEHAV) to worker-related precursors (WOR) was higher than that of the adverse project conditions (ADV) (0.42), the significance of this relationship was not supported by the bootstrapping test ($p > 0.05$). As a note, the positive value of the coefficient between BEHAV and WOR means that worker behavior improvement efforts can reduce worker-related precursors since all data were pre-processed such that a high value means an undesirable state regardless of whether the variable is a SMS factor or an accident precursor. Similarly, the causal link from resources for safety management (RES) to worker-related precursors (WOR) was not supported by the test. The final model suggests that commitment to safety (COM) can significantly affect resources for safety management (RES) as well as worker behavior improvement efforts (BEHAV).

The model for *Work team-related precursors* (TEAM) is illustrated in Figure 2 (Model 2). The pattern of relationships between SMS factors and the accident precursor factor is very similar to that of Model 1. According to the model, *work team-related precursors* (TEAM) would be significantly affected by the adverse project conditions (ADV). Model 2 also confirms that commitment to safety (COM) can significantly affect resources for safety management (RES) and worker behavior improvement efforts (BEHAV), as shown in Model 1.

The model for the *Workplace-related precursors* (PLACE) is illustrated in Figure 3 (Model 3). Model 3 did not support the hypothesis that *workplace-related precursors* (PLACE) would be affected by resources for safety management (RES). However, the model suggests that adverse project conditions (ADV) and risk assessment and control efforts (RISK) can significantly affect this type of accident precursor. Additionally, the model indicates strong relationships between the following SMS factors: between commitment to safety (COM) and *project administration for safety* (ADMIN); and, between *project administration for safety* (ADMIN) and *risk assessment and control efforts* (RISK).

Figure 4 illustrates Model 4, the model for the *site organization-related precursors* (SITE). Model 4 supports the hypothesis that *Site organization-related precursors (SITE)* are affected by *Resources for safety management* (RES), and also by adverse project conditions (ADV); however, it did not support the hypothesis that *site organization-related precursors (SITE)* would be affected by *risk assessment and control efforts* (RISK). As with Model 3, Model 4 confirms a strong relationship between the following variables: between commitment to safety (COM) and *project administration for safety* (ADMIN); and, between *project administration for safety* (ADMIN) and *risk assessment and control efforts* (RISK); and lastly, between commitment to safety (COM) and *Resources for safety management* (RES).

Finally, Figure 5 illustrates Model 5, the model for the Materials and equipment-related precursors (MATEQ). Model 5 did not support the hypothesis that materials and equipment-related precursors (MATEQ) are affected by risk assessment and control efforts (RISK), resources for safety management (RES) or worker behaviour improvement efforts (BEHAV). However, the model does support the hypothesis about the influence of the adverse project conditions (ADV) on the accident precursors. As was the case in the previous models, strong relationships were observed between commitment to safety (COM) and project administration for safety (ADMIN); and between project administration for safety (ADMIN) and risk assessment and control efforts (RISK).

DISCUSSION

The five structural models presented in this paper imply that the occurrence of accident precursors is systemic. The models also suggest that each of the accident precursors may be linked with one or two specific upstream SMS factors. Specifically, Model 1 suggests that the accident precursors related to workers' conditions and behavior (fatigue, stress and misbehavior) would be mainly influenced by adverse project conditions such as tight schedules and reworks. This finding can be supported by the accident causation model proposed by Mitropoulos et al (2005) and Han et al (2014), which explains that delays in production and tight project schedules can increase workers' working hours and consequently lead to the occurrence of incident precursors. Interestingly, the SEM suggests that the SMS factors thought to be directly related to worker behavior improvement (worker engagement programs, behavior-based safety programs, and training programs) may have a limited impact on those worker-related incidents. However, the authors suggest exercising caution in interpreting this result: the statistical insignificance ($p>0.05$ from the bootstrapping) of the relationship does not necessarily mean the non-existence of the relationship. The model also confirms the idea that the level of commitment to safety in general that project participants have would have a strong impact on the efforts and resources for safety performance improvement. Model 2 suggests that the accident precursors related to the understanding and communication of safety matters at the team-level (miscommunication/misunderstanding of safety requirements by subcontracts/foremen/safety management personnel) would follow a very similar pattern of causation as was the case in Model 1. The teamwork-related accident precursors would also be strongly influenced by the adverse project conditions while only a marginally significant influence was observed between behavior-focus safety programs and the teamwork-related accident precursors. Again, accident causation models such as the one proposed by Mitropoulos et al (2005), Han et al (2013), and Jiang et al (2015) can provide some explanation for this observation. Adverse project conditions can create production pressure and, in turn, such pressure will increase the chance that important safety-related information is miscommunicated or misunderstood at the team-level. The results of Model 1 and 2 indicate the importance of change management, minimization of reworks, and the development of a reasonable timeframe for the project to prevent accident precursors represented as undesirable worker and workgroup safety conditions and behaviors.

Model 3 suggests that the accident precursors related to the conditions of a construction workplace (poor housekeeping, inadequate safety barriers, and congestion) would be significantly reduced by proper on-site risk assessment and mitigation efforts. For example, pre-task hazard assessment, site inspection, and constructability review can all mitigate incidents (Patel and Jha, 2016; Eteifa and El-adaway 2018). In other words, this model tells us that this type of precursor can be effectively prevented by a well-designed safety risk assessment and with management best-practices. Additionally, this model suggests that a 'causal path' exists starting from project participants' commitment to safety, mediated through project administrative settings for safety management (setting safety performance goals and procedures, safety risk-management efforts), and ultimately to the prevention of workplace-related accident precursors such as poor housekeeping and inadequate safety guards/barriers.

Model 4 suggests that the accident precursors related to site organisation, such as unclear emergency procedures and the lack of mitigation of site environmental/ergonomic hazards, contribute significantly to the amount of resources dedicated to safety management, such as safety-management budget and specialized personnel. According to these results, site-level efforts to address environmental or ergonomic hazards can be very costly (Yiu et al 2019) and may require an significant early-stage endeavor to organize the construction site for better safety , such as site-mobilisation (Shapira et al. 2012). Similar to the case of Model 3, a causal path would begin at a high-level commitment to safety shown to all project participants, then lead to dedicating a good portion of budgetary and human resources to achieve high-level safety goals, which may lead to organizing a site with minimal environmental or ergonomic risks. As site organization is part of construction pre-planning, this causal path would need to work from the very beginning of a construction project for it to be effective in improving the setting and overall conditions of the site.

Model 5 suggests that the accident precursors related materials and equipment usage, (inadequate use of construction materials, plants, tools, and PPE) can again be significantly influenced by adverse project conditions (tight schedule and rework) (Guo et al 2018). Contractors might not be able to provide all adequate equipment, tools, and materials when the project is under the stress of tight budget, schedule, or major rework. Workers and operators also may start to 'cut corners' in using heavy equipment and tools ignoring best practices for safety performance. Contractors would, therefore, need to manage project conditions such as time, changes and rework, effectively to prevent accident precursors related to inadequate construction materials and equipment usage.

One notable finding of this study is the significant influence that adverse project conditions such as tight contract schedule, a large number of change orders and reworks can have on the occurrence of most types of accident precursors. The models demonstrate that even when a SMS is implemented, adverse project conditions can still cause the occurrence of accident precursors. This finding indicates the importance of a holistic approach to safety management. The mere implementation of several safety improvement programs/practices may not be powerful enough on its own to offset the impact of adverse project conditions. Therefore, SMSs should be integrated into the larger project administration and planning framework, including project design, project planning, human resources, change management, and quality assurance to ensure their effectiveness in improving safety performance.

CONCLUSIONS

This study has developed five structural models to explain causal links between SMS factors and five types of observable accident precursors on construction sites. This research used empirical data on SMS factors and accident precursors collected from experienced site safety managers, and analyzed the data using an established and rigorous SEM analysis process. The results of the SEMs enhance our understanding of the relationships between SMS factors and accident precursors by (1) demonstrating that adverse project conditions should be controlled, concomitantly, with traditional safety programs to avoid the occurrence of incident precursors and 2) identifying SMS factors of interest for each particular type of accident precursors.

The contributions of this research would be three-fold. First, from a practical perspective, the final structural models can be used to address specific observable accident precursors in a more informed and proactive manner. This evidence-based, focused approach is expected to enhance the value for money of safety management resources by prioritizing measures and interventions most relevant to specific conditions. Second, this research contributes to the understanding of the complex cause-and-effect relationship between SMS factors and incident precursors. The results reinforce that improving the SMS using a comprehensive approach (considering factors such as performance and design) can reduce the occurrence of incident precursors and, consequently, allow for a proactive approach for improving safety performance. Third, the models' results also contribute to engineering management practice by corroborating or suggesting approaches to enhance safety management onsite. The results reinforce that resources available for safety, and implementation of safety programs to control unsafe behavior or to enhance risk assessments and control on site, highly depend on organizational commitment to safety. The results also suggest that merely enhancing traditional safety management programs to reduce the likelihood of accident precursors may not be sufficient on its own. Therefore, organizations should adopt a holistic approach in all project phases to avoid incidents

The findings of this study should be interpreted in consideration of the following limitations. The SEM was built based on a sample size of 96 participants, which may be on the lower side for the SEM analysis. Therefore, it is possible that the models developed in this research were influenced by the biases that the respondents could have. It is recommended that the models are viewed as most reflective of the circumstances in which they were gathered: Alberta, Canada. While this research has used a bootstrapping method to enhance the reliability of the models by introducing random sampling within the analysis process, further studies based on a larger sample size would enable further reinforcement of the findings from this research to a greater degree of confidence.

Also, because the respondents were recruited from various types of construction projects, further research may be warranted to identify project-specific SMS factors and accident precursors.

Additionally, efforts can be invested to test un-confirmed relationships. The cross-sectional design of the current study can lead one only to infer causality, rather than prove causality. Future studies should focus on identifying accident precursors that have a high level of predictive power for actual accidents. Furthermore, future studies should advance the predictive power of accident precursors with further validation to select the most relevant accident precursors when investigating their relationships with SMS factors. Additional empirical testing is recommended to increase the generality of the models. As different forms of empirical models can be constructed depending on the dataset, additional testing will assist with validating the generality of the models and the findings of this research. Causal relationships proposed by the model should be confirmed using alternate approaches. Currently, causal relationships were hypothesized and tested based on literature and surveys; direct observations and measurement-based research will increase confidence of the causal links discussed in this paper.

DATA AVAILABILITY STATEMENT

Some or all data, models, or code generated or used during the study are available from the corresponding author by request (SEM and Interview data).

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Fig. 1. Model for *Worker-Related* Accident Precursor (WOR) Where: ** $p < 0.01$; * $p < 0.05$

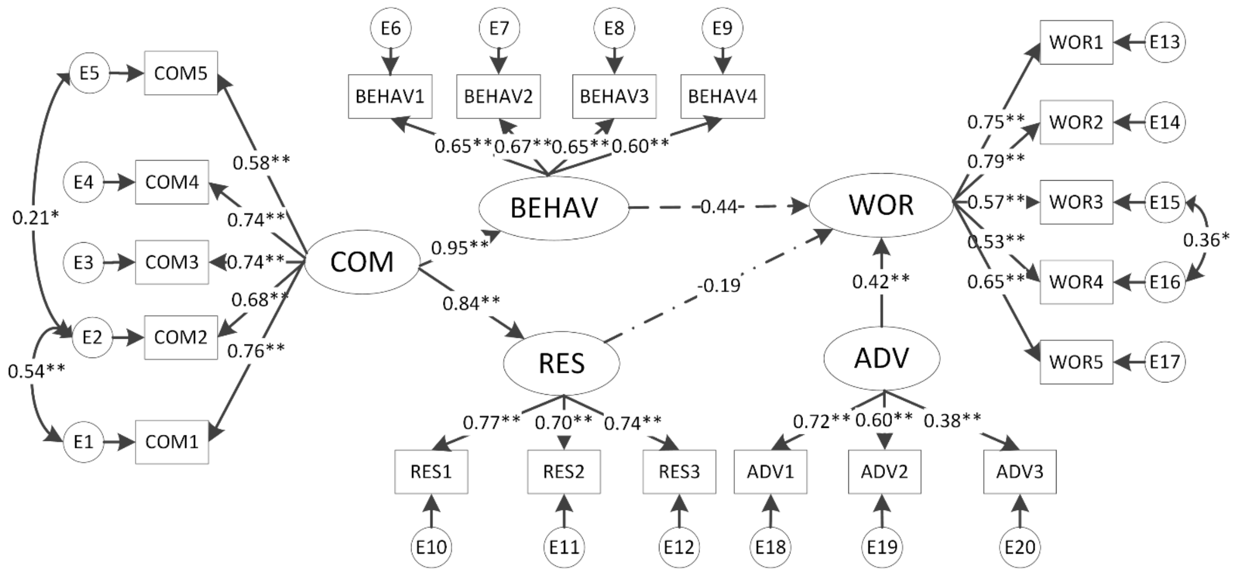

Fig. 2. Model for *Work Team*-related Precursor (TEAM) Where: ** $p < 0.01$; * $p < 0.05$

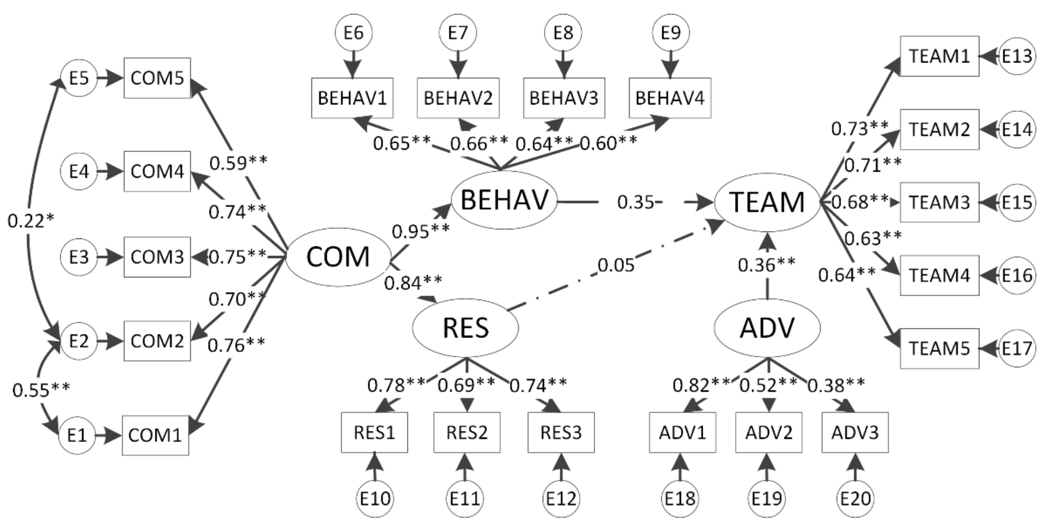

Fig. 3. Model for *Workplace -Related Precursors* (PLACE) Where: ** $p < 0.01$; * $p < 0.05$

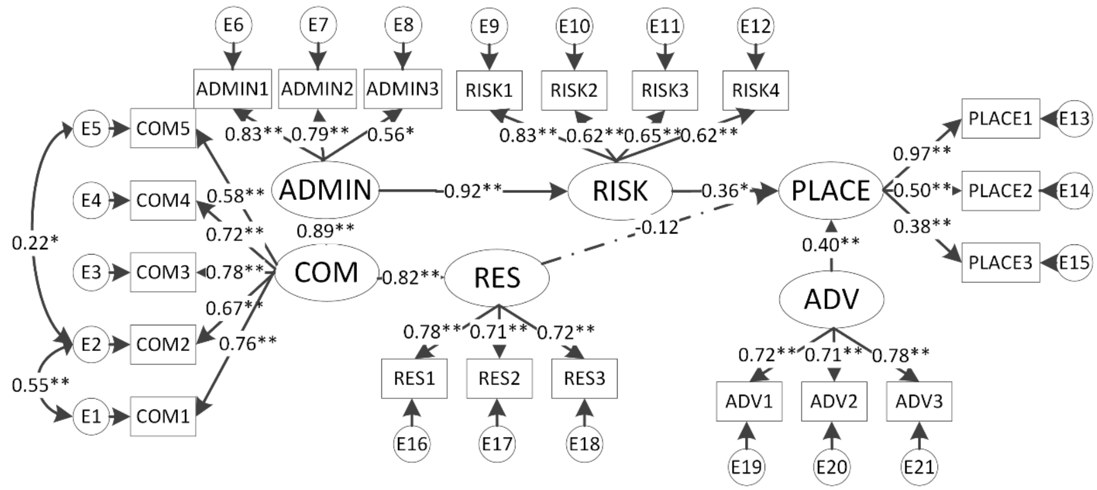

Fig. 4. Model for *Site Organization*- related Precursor (SITE) Where: ** $p < 0.01$; * $p < 0.05$

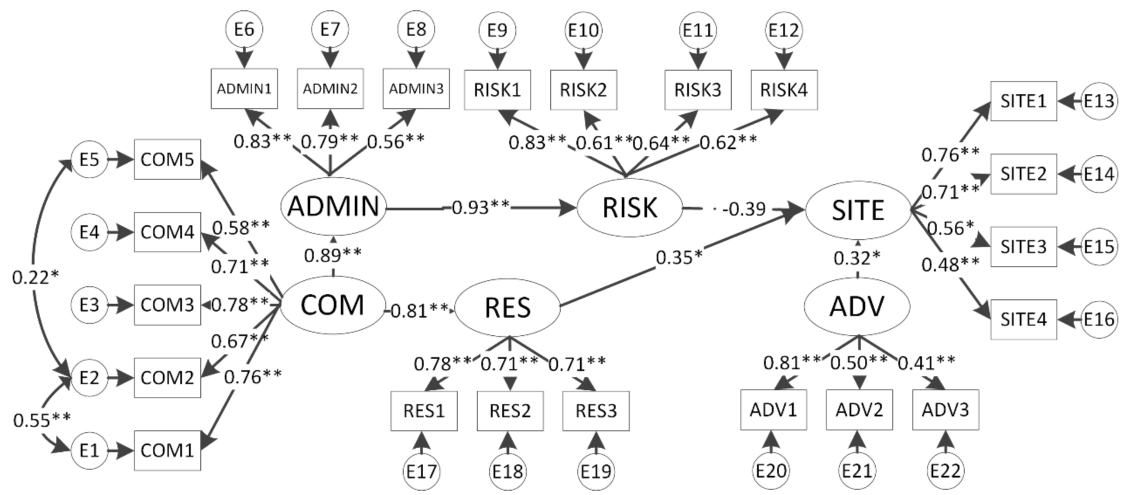

Fig. 5. Model for *Material and Equipment-related* Precursor MATEQ Where: ** $p < 0.01$; * $p < 0.05$

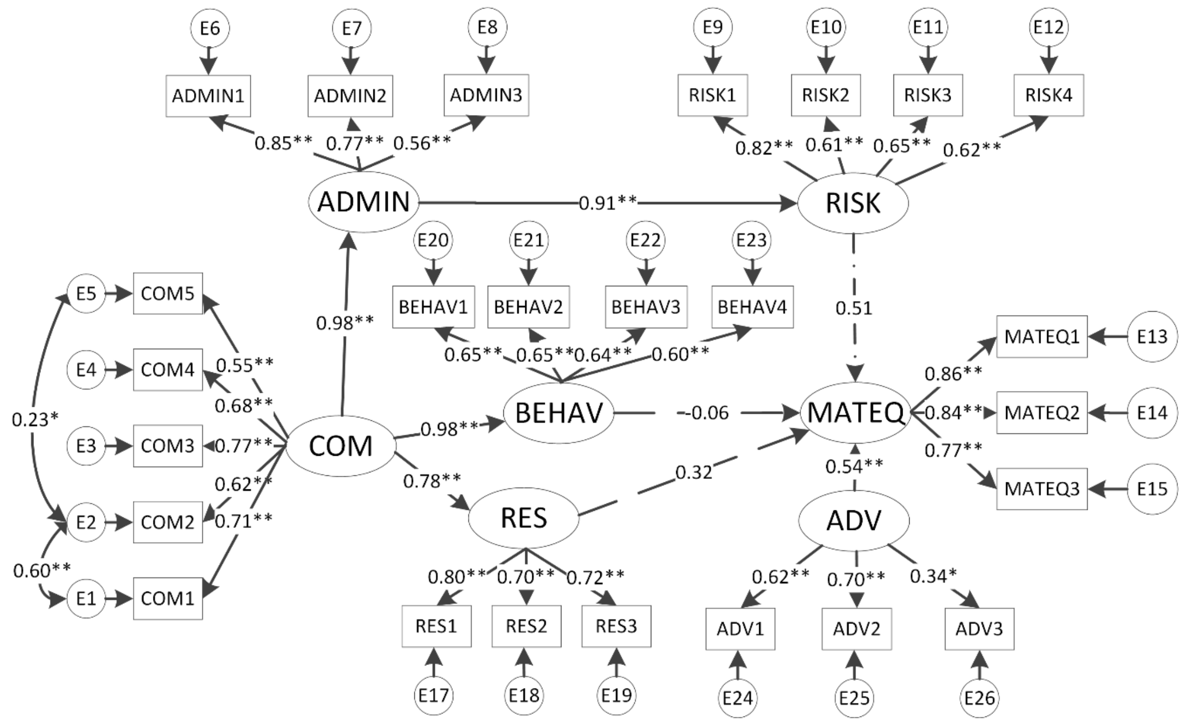

Table 1. List of SMS Factors included in research (adapted from Pereira et al. 2018)

Group	Code	SMS Factor
Project administration for safety	ADMIN1	Subcontractor safety performance assessment and screening
	ADMIN2	Establishment of clear safety goals and procedures
	ADMIN3	Establishment of safety committee
	ADMIN4	Safety performance incentive program
Risk assessment and control	RISK1	Incident investigation
	RISK2	Pre-task hazard assessment
	RISK3	Site inspection and auditing
	RISK4	Pre-construction safety and constructability review
	RISK5	Emergency planning
Worker behavior improvement efforts	BEHAV1	Employee engagement program
	BEHAV2	Behavior-based safety program
	BEHAV3	Safety awareness meetings with workers
	BEHAV4	Formal safety training
	BEHAV5	Substance abuse prevention program
Commitment to safety	COM1	Management team’s priority with safety over schedule
	COM2	Management team’s priority with safety over cost
	COM3	Subcontractors’ commitment to safety
	COM4	Management team’s commitment to safety
	COM5	Owner’s commitment to safety
Resources for safety management	RES1	Budget for safety management practices
	RES2	Number of safety management personnel
	RES3	Number of foremen
Adverse Project Conditions	ADV1	Number of reworks
	ADV2	Tightness of contract schedule
	ADV3	Frequency of change orders
	ADV4	Design Complexity
	ADV5	Availability of skilled workers
	ADV6	The level of required worker compensation rate

Table 2. List of accident precursors included in research (adapted from Pereira et al. 2018)

Group	Code	Accident precursor
Worker-related precursors	WOR1	Workers under the influence of drugs or alcohol
	WOR2	Workers' ignorance of hazards
	WOR3	Workers' high level of fatigue
	WOR4	Workers under high levels of stress due to schedule pressure
	WOR5	Workers' failure to identify hazards
	WOR6	Workers' low skill level
Work team-related precursors	TEAM1	Inadequate communication/enforcement of safety rules within teams
	TEAM2	Misunderstanding of safety requirements by worker or subcontractor
	TEAM3	Insufficient experience of foremen
	TEAM4	Insufficient experience of safety management personnel
	TEAM5	Lack of attention to coworkers' safety
Workplace-related precursors	PLACE1	Poor housekeeping
	PLACE2	Inadequate safety guards or barriers
	PLACE3	Site congestion
	PLACE4	Workers' exposure to extreme weather conditions
Site organization-related precursors	SITE1	Lack of mitigation of hazardous site environments (e.g., noise)
	SITE2	Unclear emergency procedures
	SITE3	Low level of ergonomic consideration of workspace
	SITE4	The newness of site conditions to workers
	SITE5	Inadequate/inaccurate site information
Materials and equipment-related precursors	MATEQ1	Inadequate use of personal protective equipment
	MATEQ2	Inadequate use of tools
	MATEQ3	Inadequate use of heavy equipment
	MATEQ4	Workers' exposure to hazardous materials

Table 3. Results of CFA for SMS Factors

Code	Component – Factor Loading						AVE[a]	CR[b]
	1	2	3	4	5	6		
ADMIN1	0.814						62.25	0.813
ADMIN2	0.809							
ADMIN3	0.742							
RISK1		0.826					59.74	0.786
RISK2		0.754						
RISK3		0.767						
RISK4		0.742						
BEHAV1			0.783				55.31	0.734
BEHAV2			0.763					
BEHAV3			0.761					
BEHAV4			0.662					
COM1				0.864			62.66	0.817
COM2				0.841				
COM3				0.782				
COM4				0.757				
COM5				0.703				
RES1					0.816		69.56	0.883
RES2					0.865			
RES3					0.821			
ADV1						0.746	55.12	0.786
ADV2						0.730		
ADV3						0.687		

a) Average variance extracted (AVE) = (summation of the square of the factor loadings)/[(summation of the square of the factor loadings) + (summation of the error variances)] * 100 b) Composite reliability (CR) = (square of the summation of the factor loadings)/[(square of the summation of the factor loadings) + (square of the summation of the error variances)].

Table 4. Results of CFA for Accident Precursors

Code	Component – Factor Loading					AVE	CR
	1	2	3	4	5		
WOR1	0.819					56.37	0.747
WOR2	0.789						
WOR3	0.711						
WOR4	0.704						
WOR5	0.673						
TEAM1		0.790				56.41	0.748
TEAM2		0.767					
TEAM3		0.758					
TEAM4		0.721					
TEAM5		0.717					
PLACE1			0.843			59.74	0.785
PLACE2			0.779				
PLACE3			0.689				
SITE1				0.814		54.26	0.720
SITE2				0.799			
SITE3				0.682			
SITE4				0.636			
MATEQ1					0.910	79.41	0.949
MATEQ2					0.891		
MATEQ3					0.872		

Table 5. List of the hypotheses included in each structural model

Hypothesis	Included-in Model	References
H1: Worker behaviour improvement efforts (BEHAV) reduce worker-related precursors (WOR).	1	Li et al. (2015); Zhang and Fang (2013); Choudhry and Fang (2008)
H2: Resources for safety management (RES) reduce worker-related precursors (WOR).	1	Cameron and Duff (2007)
H3: Adverse project conditions (ADV) increase worker-related precursors (WOR).	1	Mitropoulos et al. (2009); Nepal et al. (2006)
H4: Commitment to safety (COM) increases resources for safety management (RES).	1,2,3,4,5	Mitropoulos et al. (2005)
H5: Commitment to safety (COM) increases worker behaviour improvement efforts (BEHAV).	1,2,5	CII (2003)
H6: Worker behavioural improvement efforts (BEHAV) reduces work team-related precursors (TEAM).	2	Cheng (2016); Wirth and Sigurdsson (2008)
H7: Resources for safety management (RES) reduces work team-related precursors (TEAM).	2	Jiang et al. (2015)
H8: Adverse project conditions (ADV) increase work team-related precursors (TEAM).	2	Mitropoulos and Memarian (2012)
H9: Risk assessment and control efforts (RISK) reduce workplace-related precursors (PLACE).	3	El-gohary and Aziz (2014)
H10: Resources for safety management (RES) reduces workplace-related precursors (PLACE).	3	Reiman and Pietikäinen (2012); Mitropoulos et al. (2009)
H11: Adverse project conditions (ADV) increase workplace-related precursors (PLACE).	3	Spillane et al. (2011); Mitropoulos et al. 2009)
H12: Project administration for safety (ADMIN) increase risk assessment and control efforts (RISK)	3,4,5	Hinze (1997); Park et al. (2015)
H13: Commitment to safety (COM) increase project administration for safety (ADMIN)	3,4,5	Choudhry et al. (2008)
H14: Risk assessment and control efforts (RISK) reduce site organization-related precursors (SITE).	4	(Salas and Hallowell (2016)
H15: Resources for safety management (RES) reduce site organization-related precursors (SITE).	4	Hinze (1997)
H16: Adverse project conditions (ADV) increase site organization-related precursors (SITE).	4	(Hinze 1997)

H17: Risk assessment and control efforts (RISK) reduce materials and equipment-related precursors (MATEQ).	5	Ahmed et al. (2000); Koh and Rowlinson (2012)
H18: Resources for safety management (RES) reduce materials and equipment-related precursors (MATEQ).	5	(Patel and Jha 2016; Guo and Yiu 2016; Hinze et al. 2013)
H19: Worker Behavior Improvement efforts (BEHAV) reduce materials and equipment-related precursors (MATEQ).	5	(Wachter and Yorio 2014; Hinze et al. 2013b)
H20: Adverse project conditions (ADV) increase materials and equipment-related precursors (MATEQ).	5	(Mitropoulos et al. 2009)

Table 6. Model Validation Results

GOF	Criteria	Model 1	Model 2	Model 3	Model 4	Model 5
Relative χ2	< 2 is acceptable model	1.179	1.156	1.198	1.203	1.253
RMSEA	<<0.08, not bad fit; <0.05, good fit	0.043	0.040	0.046	0.046	0.052
IFI	>0.9 is satisfactory	0.960	0.964	0.955	0.951	0.941
TLI	>0.9 is satisfactory	0.951	0.956	0.946	0.942	0.931
CFI	>0.9 is satisfactory	0.958	0.964	0.954	0.950	0.939
PGFI	>0.5 is satisfactory	0.648	0.660	0.653	0.651	0.651
PNFI	>0.5 is satisfactory	0.668	0.675	0.671	0.667	0.675
PCFI	> 0.5 is satisfactory	0.817	0.831	0.822	0.826	0.832

Where: RMSEA (Root Mean Square Error of Approximation); IFI (Incremental Fit Index); TLI (Tucker-Lewis Index); CFI (Comparative Fit Index); PGFI (Parsimonious Good of Fit Index); PNFI (Parsimonious Normed Fit Index); PCFI (Parsimonious Comparative Fit Index)