Perceiving Interactions on Construction Safety Behaviors: Workers' Perspective

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Abstract: This paper presents a systematic approach that incorporates structural equation modeling (SEM) and exploratory factor analysis (EFA) to perceive and verify causal-relationships and interactions between enablers and goals of construction workers' safety behaviors (CWSB). A sample of 450 questionnaire surveys regarding CWSB was collected from construction workers in several Chinese construction companies. EFA was used to extract eight common factors in order to identify the model structure among 28 questionnaire items. Then, SEM was employed to investigate the interrelationships among variables in the hypothesized safety behavior model. The built causal model was verified in terms of the hypothesis test and goodness-of-fit test. The impact of the path coefficient on CWSB was investigated and analyzed in detail. Results indicate that *management-oriented supervision and system* (F_3) and *leadership* (F_8) exert obvious positive impacts on CWSB in accordance with the path coefficients analysis, whereas *psychological workers' condition* (F_5) and w*orkplace conditions* (F_6) exert obvious negative influences. *Individual differences among workers* (F_2) do not perform statistically significantly with workers' safety behaviors. The developed approach is capable of revealing causal-relationships, testing hypothesized models, and determining leading factors in complex project environments. This research provides insights into cause-effect relationships among the workers' perceived influential factors and goals, and the results can be used to understand the factors that the construction workers perceive as important factors in safety behaviors. This can further provide decision support on the improvement of construction safety performance in the context of the Chinese construction industry. **DOI: 10.1061/(ASCE)ME.1943-5479.0000454.** *© 2016 American Society of Civil Engineers.*

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Introduction

Construction is one of the most dangerous industries in the world (Fang et al. 2004; Fung et al. 2005; Guo and Yiu 2015). In recent years, statistics from the United States, the United Kingdom, and Hong Kong reveal no significant reduction in the number of fatalities in the construction industry (Fung et al. 2005; Zhang and Fang 2013). The ramifications of construction accidents are growing with a trend toward more larger-scale and more complex construction projects (Lee et al. 2012), especially in developing countries, like China. For instance, in order to alleviate increasing urban traffic volumes, tunnel construction has presented a measure of the powerful momentum of the rapid economic development of China's metropolitan areas in the last ten years (Zhang et al. 2014). However, safety violations occur frequently in tunnel construction practices, which cause huge losses of life and property (AFP 2008; Zhang et al. 2013). This supports the importance of construction safety management, and suggests a need for a better approach to construction accident prevention (Yu et al. 2014).

A thorough understanding of accident generation mechanisms is necessary for accident prevention. As many scientific studies have concluded, unsafe behavior is a major cause of accidents (Garavan and O'Brien 2001). Heinrich et al. (1950) estimated that 85% of accidents can be attributed to unsafe acts. Fleming and Lardner (2002) revealed that 80–90% of all workplace accidents and incidents were attributed to unsafe behaviors. Choudhry (2012) indicated that reducing accidents and improving safety performance can be achieved by systematically focusing upon those unsafe behaviors on construction sites. The traditional approach to evaluate construction workers' safety behaviors (CWSB) is through the measurement and statistical analysis of incident-related data (such as number of injuries and ill-health, accident frequency and severity rates, and accident costs), which are often referred to as retrospective or lagging indicators (Sgourou et al. 2010). However, these indicators have often been criticized as measuring system failures without revealing cause-effect relationships that would drive system improvement, and therefore appear to have little predictive value (Carder and Ragan 2003; Cooper and Phillips 2004). Choudhry (2014) indicated traditional indicators focused on the analysis afterward, but paid less attention to internal factors such as attitudes, awareness, values, and personal characteristics. Generally, the criticism of incident-based indicators coincided with increased attention on exploring leading factors and cause-effect relationships between internal factors and CWSB. In the meantime, workers on site play an important role contributing to the accomplishment of the construction, and the awareness and perceptions of the workers are important aspects to improve the conditions around the construction (Hassan et al. 2007). Unfortunately, little attention

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has been given to workers' perceptions on safety behaviors because workers' perceptions are of soft type, and difficult to measure and quantify (Gyekye 2015).

Various factors may affect the final outcome of CWSB, and a better understanding of safety behavior and its key determinants (enablers), will definitely help construction organizations to strategically allocate resources and concentrate their efforts to ensure improvement of the overall safety performance (Lee et al. 2012; Wu et al. 2015). The empirical validation of the way its key enablers are interrelated is rarely studied in previous literature. The interactions between what construction workers are doing and how unsafe behaviors influence safety performance appear to be ignored (Chinda and Mohamed 2008). Moreover, causal links between those internal enablers and external goals have not been properly addressed (Chinda and Mohamed 2007).

In recent years, two statistical analyses have been proposed to empirically reveal and test interrelationships in the hypothetical model: exploratory factor analysis (EFA) and structural equation modeling (SEM). The EFA can be used to identify the structure among the questionnaire items, where no prior knowledge of factors or patterns of measured variables exists (Finch and West 1997). The SEM is able to handle complex relationships among variables and estimate all coefficients in the model simultaneously (Xiong et al. 2015). This paper therefore intends to present a systematic approach that incorporates SEM and EFA to get rid of the above dilemma. It aims to identify, test, and verify the internal causal-relationships and interactions between enablers and goals of CWSB in construction industry in China. The research results can be used to understand the factors that the construction workers perceive as important factors in safety behaviors and further provide decision support on the improvement of construction safety performance in the context of the Chinese construction industry.

Previous Studies

Research on workers' perceptions on safety behaviors began in the early 1980s with Zohar's (1980) study and has since received considerable attention in organizational and psychological literature. Psychological science defines perception as a cognitive process of inferential and constructive character, by which a subject can generate an interior representation of what happens in the exterior, from information collected by the senses and information from memory (Merleau-Ponty and Smith 1996). In the construction industry, workers are exposed to a riskier environment compared to other industries. Safer behaviors are reflected by good attitudes and provide one way of identifying characteristics that might distinguish between employers with high or low injury rates. Actually, many accidents/incidents that occurred in the jobsite were because of inadequate adherence of workers to work procedures. Workers' perceptions on safety behaviors provide another dimension of the perceived organizational climate in which they work through the measure items of trust, cohesion, pressure, innovation, and fairness between the workers themselves and organization (Zohar 1980).

A number of studies have shown that, in general, the perceptions of management and workers usually differ. Chen et al. (2012) investigated discrepancies between perceptions of administrators and workers regarding safety practices in construction sites, in which the statistical analyses revealed a significant difference between the two groups in their reflexive knowledge of workplace safety. Reese and Eidson (2006) explored the perceptions of construction workers and their bosses and found different perceptions between the two groups in concepts relating to the worker, such as the value conceded to the worker, his productivity, and the quality of his competencies. Some doubted that the perceptions of a worker might contain specific components that could seem absurd to other people. Nevertheless, these components are part of that worker's reality, which are projected based on his knowledge and values (Solís-Carca and Franco-Poot 2014). Thus, some authors concluded that the safety behaviors in construction sites are closely related to the perceptions and beliefs of the workers regarding the phenomenon of safety (Mohamed 2002).

Given the critical importance of workers' perceptions on safety behaviors in the work environment, research on this topic has been studied meticulously and refined in various industrial settings in the last 30 years. Typical examples include safety analyses in health care systems (Flin et al. 2006) and manufacturing sectors (Bosak et al. 2013), particularly in the construction industry (Meliá et al. 2008). For instance, Glendon and Litherland (2001) investigated the relationship between safety perceptions and safety performance in a road construction organization, in which supervision and guidance, workforce stability, and industrial relations were identified as major factors through factor analysis. Han et al. (2014) stated that the reward system, work pressure, and intensity were critical factors affecting workers' perceived safety performance on a construction site. Liao et al. (2014) indicated that the communication could be a key factor that determined the shared safety perception.

The awareness and perception of the workers toward safety behaviors play an important role in enhancing construction safety performance and must be considered in order to move the existing research forward. The current studies focus on identifying important factors that affect the workers' perceived safety performance from an organization perspective, but pay less attention to the internal factors such as attitudes, awareness, and personal characteristics from a worker's perspective. As a matter of fact, workers are direct receptors for the measurement of safety behavioral performance within an organization. More attention and priority should be given to the factors that are perceived as important factors by workers themselves, in order to improve the construction workers' safety behaviors in an efficient manner. This research therefore intends to develop a more exhaustive approach to investigate causal interactions on construction safety behaviors from a worker's perception perspective.

Research Methodology

SEM is considered a theory-driven technique, as the number of dimensions and the items-factors relationship in which the covariance matrix exists can be explained and supported by a strong theory. The SEM represents causal processes that generate observations on multiple variables. The advantages of using SEM include: (1) it can handle complex relationships among variables, where some variables can be hypothetical or unobserved (latent variables), (2) it estimates all coefficients in the model simultaneously and thus, one is able to assess the significance and strength of a particular relationship in the context of the complete model, and (3) the hypothesized model can be tested statistically in a simultaneous analysis of the entire system of variables to determine the extent to which it is consistent with the data (Dion 2008; Martínez et al. 2010). SEM enables the testing of measurement invariance (Vandenberg and Lance 2000); however, the main limitation of SEM is the restrictive assumption that the factor structure is fully simple (Asparouhov and Muthén 2009). Thus, multicollinearity that leads to bias and unstable findings is thought to exist because of the expected intercorrelations among predictors within the model's constructs (Chinda and Mohamed 2008).

EFA is generally referred to as a data-driven technique, and can be used to discover the factor structure of a measure and to examine its internal reliability. EFA serves to identify a set of latent constructs underlying a battery of measured variables (Fabrigar et al. 1999), and should be used when the researcher has no prior hypothesis about factors or patterns of measured variables (Finch and West 1997). In order to overcome the limitation of the traditional SEM, EFA can be conducted to determine the number of constructs and the loadings of items before moving on to the construction of SEM (Mattsson 2012). Therefore, an integration of EFA and SEM can be developed to address the aforementioned deficiencies.

In this research, a conceptual model for CWSB in the Chinese construction industry is first hypothesized and empirically tested using information gathered via a questionnaire survey. The statistical technique of EFA is then conducted to check the appropriateness of the proposed grouping of attributes. Next, SEM is used to gain insights into the interactions and associations among different enablers of the conceptual model. Finally, a greater understanding of interdependence in CWSB is provided, which, in turn, facilitates safety performance improvement in the construction industry.

Data Collection

Data collection aims to gather and measure information on variables of interest and capture evidence that can be translated to data analysis. Basically, questionnaires, which enable one to answer the stated questions, test hypotheses, and evaluate the outcomes, are commonly used for data collection. This process provides both a baseline from which to measure and a target on what to improve.

Influential Factors

Safety behaviors can prevent accidents and injuries from happening and have attracted broad attention from researchers over the last two decades (Al-Hemoud and Al-Asfoor 2006; Feng et al. 2014). Some previous studies on safety behaviors in the construction industry are summarized in Table 1; these can provide practical and theoretical guidance for setting up frame variables in the questionnaire design. More precisely, Martínez-Córcoles et al. (2011) conducted a study in Spanish with 566 employees involved, in which many factors were considered, such as presence of a safety management system, management commitment, an incentive mechanism, and coworkers' influences. Hsu et al. (2012) indicated that employee participation, safety education and training, on-site supervision and guidance, and protective gears were identified as important factors for workers' safety behaviors in Taiwan. The empirical study conducted by Al-Refaie (2013) in Jordan took safety management system, management commitment, and supervisor and coworkers' influences into account, and the results revealed that management commitment and interrelationship harmony were significantly affecting CWSB. Yu et al. (2014) and Shin et al. (2014) also conducted relevant investigations in China and Korea, respectively. Despite scholars not having produced a consensus on the index system regarding CWSB, there are similarities in the most commonly used measures for evaluation of safety behaviors, which provide a certain level of reference significance on proposing relevant hypotheses and constructing the safety behavior–based model in this research.

In those studies as shown in Table 1, the relationship between the actual influential factors (like the presence of a safety management system and times of safety training) and safety behaviors is mainly investigated in different companies and different countries. The perceived influential factors by workers (like inertia of worker's habits, susceptibility to accidents, and job satisfaction) also play a significant role in contributing to the high performance level of safety behaviors; however, they are rarely studied. Those perceived influential factors act as soft factors to generate inputs for collaborating in construction safety management practices. Compared to the actual influential factors that act as hard factors, those soft factors are more difficult to measure and quantify. As a matter of fact, workers are considered as direct receptors for the measurement of safety behavioral performance within an organization. Thus, in order to improve the construction workers' safety behaviors in an efficient manner, more attention and priority should be given to the factors that are perceived as important factors by workers themselves. In this research, a more comprehensive framework that considers both actual influential factors (acting as hard factors) and the perceived influential factors (acting as soft factors) is therefore developed for identifying interactions within construction worker's safety behaviors. Those influential factors are fully incorporated in the following design of the questionnaire in this research.

Questionnaire Design

As mentioned above, many kinds of factors, including hard and soft factors should be involved in the measurement of safety behaviors of construction workers. Those relevant factors can be identified by referring to a variety of sources in both academy and industry, such as literature reviews (as shown in Table 1), standard specifications, technical manuals, and reports. Finally, a total of 28 influential factors were covered in the questionnaire design, with all kinds of knowledge sources taken into account. In order to elicit respondents' perceptions towards both hard and soft factors on a unified basis, most of the items were evaluated by the five-point

Table 1. Relevant Factors on Measurement of Safety Behaviors Involved in Previous Literature

		Spain	Taiwan	Jordan	China	Korea
Number	Factors	Martínez-Córcoles et al. (2011)	Hsu et al. (2012)	Al-Refaie (2013)	Yu et al. (2014)	Shin et al. (2014)
1	Safety management system	X	X	X	X	X
2	Employee participation	—	X	—	X	—
3	Safety awareness	—	X	—	X	X
4	Management commitment	X	—	X	—	—
5	Safety education and training	X	X	X	X	X
6	On-site supervision and guidance	—	X	X	X	—
7	Safety incentive mechanism	X	—	X	—	X
8	Adequate protective gears	—	X	—	X	—
9	Risk-taking mindset	X	—	—	X	X
10	Coworkers' influences	—	X	X	X	—

Table 2. Descriptions of 30 Variables Involved in Design of Questionnaire

Item	Description
Item01	Worker's inertia of habit (I think the safety operations are largely dependent on the inertia of my habits)
Item02	Attentiveness to work (I think the quality of total attentiveness to work at hand is helpful to reduce mistakes)
Item03	Education (Well educated workers are doing better than the less educated in complying with safety principles)
Item04	Susceptibility to accidents (I have seen or experienced real-life accidents which keep me from risky behaviors)
Item05	Working experience (I have rich working experience in construction which helps me to finish the task correctly)
Item06	Self-control ability (In the face of exciting or frustrating events, I can well control my emotion and actions)
Item07	Know-how and skills (I have enough know-how and skills to recognize and avoid unsafe behaviors)
Item08	Staff's participation in decision making (I often attend safety meetings and get involved in safety decisions)
Item09	Staff are motivated to improve skills (We are motivated to improve our skills and to be active learners)
Item10	Job satisfaction (Job satisfaction contributes to the improvement of work efficiency and operational safety)
Item11	Safety awareness (I fully understand the potential dangers and keep an extra careful watch on them)
Item12	Management commitment (Top management adopts the right resource allocation and governance to safety)
Item13	Management involvement (The right level of management involvement is required to make better policies)
Item14	Teamwork (Teamwork is well coordinated and I have to work closely with my group to perform well)
Item15	Safety management system (The organization has an efficient SMS to formulate safety procedures)
Item16	On-site supervision and guidance (Supervisor revises my behaviors, reports cases, or experiences periodically)
Item17	Clear task assignments (I fully understand the work contents, key link, and responsibilities in my position)
Item18	Safety training (I'm willing to participate in the safety training, from which I can benefit and learn a lot)
Item19	Talents-job fit degree (The performers of critical process are working with valid qualification certificates)
Item20	Safety incentive mechanism (Proper incentives can encourage me to perform my work safely and efficiently)
Item21	Lack of safeguards (I rarely operate at the edge of danger for the lack of available protective gear)
Item22	Fluky psychology (I rarely take chances / bend the rules / ignore some rules to get the job done)
Item23	Risk-taking mindset (I rarely underestimate the risk and take shortcuts that involve little or no risk)
Item24	Messy conditions (Workplace conditions there are neat and in order instead of dirty and messy)
Item25	Bad emotional state (I am rarely in a bad emotional state and that keep me working with all my heart)
Item26	Work intensity (I can well accept the state of high intensity work and strong in compression)
Item27	Coworkers' influences (Coworkers often help me with safety-related issues and correct my unsafe behavior)
Item28	Interpersonal relationship (I have a good relationship with my colleagues and get confirmation from leaders)
B1	Personal safety score (What is the average of your safety scores during last three months?)
B2	Team safety score (What is the average safety score of your team during last three months?)

Likert-type scale ranging from 1 (*completely disagree*) to 5 (*completely agree*).

For instance, as shown in Table 2, *worker's inertia of habit* (Item01) is a soft factor, and the question on this factor is stated as "*I think the safety operations are largely dependent on the inertia of my habits.*" A respondent then chooses a number from 1 to 5 based upon his working experience and understanding. This question can enable respondents to evaluate the "perceived importance" of the inertia of the workers' habits in safety operations. We assume that workers will consciously adjust their habit inertias to a reasonable level to improve safety operations, if they highly value the factor of habit inertia. Accordingly, this soft factor can then be measured from a perspective of the worker's perception. As for the hard factors, such as *working experience* (Item05), the question on this factor is stated as "*I have rich working experience in construction which helps me to finish the task correctly.*" A respondent with a high value on this question indicates that he holds long years of working experience in actual practice, and vise versa. In this way, both hard and soft influential factors can be measured by using a uniform criterion and scale, which can provide a consistent basis for model construction and analysis later in subsequent sections.

In order to further measure the performance level of CWSB, another two factors are identified and selected, namely, personal safety score (B1) and team safety score (B2). Specifically, B1 records the average of each respondent's safety scores during the last three months, whereas B2 records the average safety score of the respondent's working team. These two factors are evaluated by a five-point scale, where "1" stands for a low performance level, and "5" stands for a high performance level. These two factors serve as the observed outcomes of CWSB from a respondent's perspective, which provide a feasible and user-friendly way to assess the performance level of CWSB. In total, there are 30 observed variables (Table 2) that are involved in the measurement of safety behaviors of construction workers.

Questionnaire Response

In this research, all the surveyed respondents are front-line workers on construction sites that are located in south, central, and northeast China. Most of the respondents were from rural areas, and this survey was completely anonymous and voluntary. A total of 600 questionnaires were distributed with 454 responses returned, representing a response rate of 75.8%. Out of all the returned responses, only four were deemed unusable because of unanswered items and were subsequently dropped from the collected data. According to the statistical analysis among valid respondents as shown in Fig. 1, 39% of the respondents were between the ages of 30 and 39, 41% had 3–5 years of working experience in the construction industry, 74% completed high school or above, and 50% had at least three times of actual participation in safety training every year. In general, the majority of the respondents were very familiar with construction engineering practices, which increased the quality of the questionnaire data and the persuasiveness of the following analysis results to some extent.

Exploratory Factor Analysis (EFA)

The EFA is a parsimonious information technology, mainly aimed at using a smaller number of dimensions to render the original data structure in order to explain the complex phenomenon of relevant variables. It can be used to identify the structure among questionnaire items, and also for data reduction (where appropriate). The

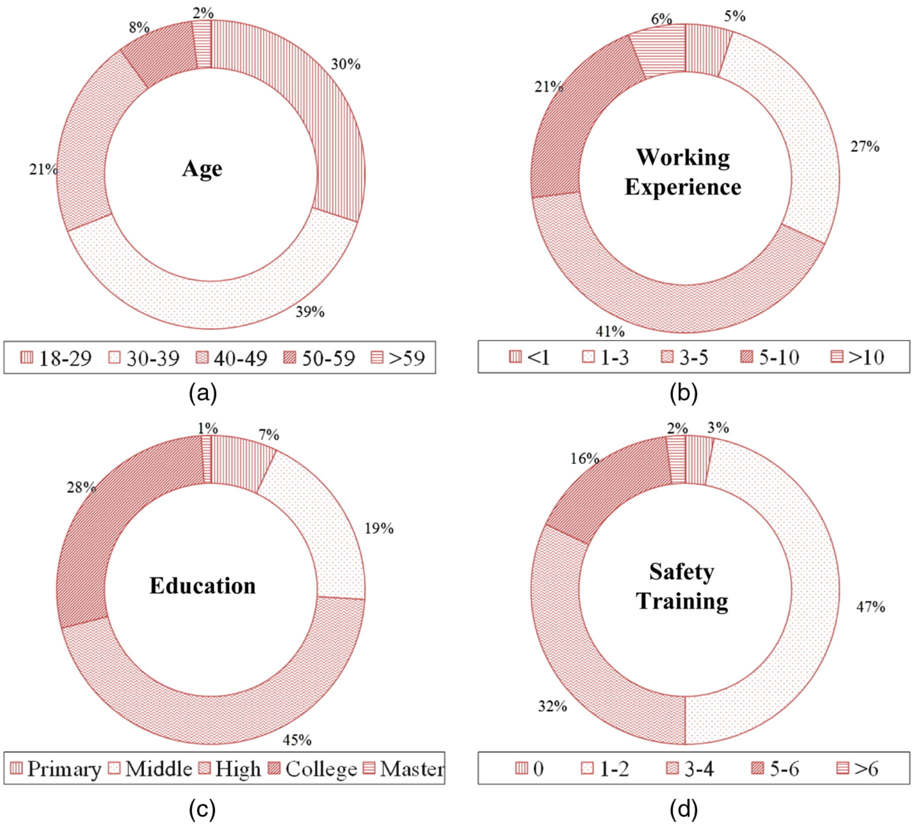

Fig. 1. Statistics analysis among 450 valid respondents in terms of (a) age; (b) working experience; (c) education; (d) safety training

appropriate number of factors can then be extracted in order to examine the dimensionality of the safety behavior model. This procedure was used to assess the common factors of the scale in this study.

Kaiser-Meyer-Olkin and Bartlett Tests

The initial variables having a strong correlation with each other is a necessary precondition during factor analysis. Thus, in order to verify the precondition was met, both the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity should be carried out. To be specific, the KMO test measures the adequacy of a sample in terms of the distribution of values for the execution of factor analysis. A value of 0.8 is generally accepted as the minimum desired value of the KMO coefficient (Pallant 2013). Bartlett's test of sphericity determines whether the correlation matrix is an identity matrix. If an identity matrix exists, the exploratory factor analysis will then be meaningless. In this study, the data was deemed to be appropriate for the analysis because the KMO measurement value of sampling adequacy was calculated to be 0.922. Furthermore, the Sig. (significant probability) of Bartlett's test of sphericity inspection was calculated to be 0.000, which is less than the significance level of 0.01. Accordingly, the data was considered to be relevant and suitable for the further exploratory factor extraction.

Exploratory Factor Extraction

Factor loadings are correlations of the variables with a factor. The realistic meaning of a factor can be synthesized by combining those variables that have a relatively high factor loading after performing a principal component factor analysis. In order to determine the underlying dimensions of the safety behavior model, the principal components factor analysis was performed on the 28-item safety behavior questionnaire data from 450 respondents. The factor analysis yielded an eight-factor solution, which accounts for 70.205% of the total variance. Table 3 illustrates the interpretation of the total variance within EFA in the safety behavior model.

In order to enhance the factor interpretability, a cut-off factor loading of 0.45 was used to screen out items that are weak indicators of common factors. Varimax rotation was then performed, and items with factor loadings greater than 0.45 were selected as the extracted common factors. Table 4 illustrates the factor load matrix after rotation and the extracted eight common factors in the safety behavior model. According to the concrete items contained in each factor, the following labels were assigned to reflect factors' common and latent properties (in line with the SEM model's latent variables):

- Factor 1 (F_1) accounted for 15.737% of the total variance and included five items (11, 07, 19, 05, 03), namely, safety awareness, know-how and skills, talents-job fit degree, working experience, and education. Thus, we named this factor "*knowledge and skills*";
- Factor 2 (F_2) accounted for 13.323% of the total variance and covered four items (01, 02, 04, 06), namely, inertia of habit, attentiveness to work, susceptibility to accidents, and self-control ability. Thus, we named this factor "*individual differences among workers*";
- Factor 3 (F_3) accounted for 13.141% of the total variance and included four items (15, 16, 18, 20), namely, safety management system, on-site supervision and guidance, safety training, and safety incentive mechanism. Thus, we named this factor "*management-oriented supervision and system*";
- Factor 4 (F_4) accounted for 9.885% of the total variance and covered five items (17, 28, 10, 27, 14), namely, clear task assignments, interpersonal relationships, job satisfaction, coworkers'

Table 3. Interpretation of Total Variance during EFA in Safety Behavior Model

Factor	Initial eigenvalues			After extracted			After rotated		
	Total	Variance (%)	Accumulation (%)	Total	Variance (%)	Accumulation (%)	Total	Variance (%)	Accumulation (%)
1	12.761	31.124	31.124	12.761	31.124	31.124	6.452	15.737	15.737
2	4.312	10.517	41.641	4.312	10.517	41.641	5.462	13.323	29.059
3	3.394	8.278	49.919	3.394	8.278	49.919	5.388	13.141	42.201
4	2.724	6.645	56.564	2.724	6.645	56.564	4.053	9.885	52.086
5	2.104	5.131	61.695	2.104	5.131	61.695	2.440	5.951	58.037
6	1.223	2.984	64.679	1.223	2.984	64.679	2.203	5.373	63.410
7	1.196	2.918	67.597	1.196	2.918	67.597	1.686	4.113	67.524
8	1.069	2.608	70.205	1.069	2.608	70.205	1.099	2.681	70.205
…	…	…	…	…	…	…	…	…	…
28	0.116	0.282	100.000	—	—	—	—	—	—

Note: The principal component analysis was adopted in the factor extraction process.

Table 4. Factor Load Matrix after Rotation and the Extracted Eight Common Factors in Safety Behavior Model

Factors	Factor load matrix								Extracted common factors
	1	2	3	4	5	6	7	8	
Item 11. Safety awareness	**0.836**	0.169	0.047	0.156	0.023	0.153	−0.099	0.010	F_1: Knowledge and skills
Item 07. Know-how and skills	**0.835**	0.155	0.096	0.156	−0.005	0.111	−0.038	0.020	
Item 19. Talents-job fit degree	**0.816**	0.116	0.143	0.120	0.127	0.153	0.027	−0.024	
Item 05. Working experience	**0.783**	0.101	0.214	0.136	0.088	0.105	−0.042	−0.085	
Item 03. Education	**0.672**	0.288	0.152	0.252	0.085	0.015	−0.166	0.124	
Item 01. Inertia of habit	0.154	**0.829**	0.188	0.145	0.02	0.026	−0.001	0.067	F_2: Individual differences among workers
Item 02. Attentiveness to work	0.14	**0.820**	0.138	0.129	0.074	0.023	−0.034	0.125	
Item 04. Susceptibility to accidents	0.173	**0.797**	0.176	0.117	0.129	0.191	0.011	−0.044	
Item 06. Self-control ability	0.039	**0.749**	0.123	0.127	0.079	0.095	0.081	0.095	
Item 15. Safety management system	0.103	0.105	**0.841**	0.145	0.0290	0.131	−0.062	0.049	F_3: Management-oriented supervision and system
Item 16. On-site supervision and guidance	0.119	0.142	**0.820**	0.111	−0.020	0.132	0.083	0.048	
Item 18. Safety training	0.073	0.107	**0.772**	0.210	−0.026	0.023	0.086	−0.005	
Item 20. Safety incentive mechanism	0.037	0.114	**0.728**	0.248	0.136	0.078	−0.192	0.064	
Item 17. Clear task assignments	0.129	0.178	0.168	**0.865**	−0.026	0.028	0.032	−0.009	F_4: Organizational climate
Item 28. Interpersonal relationship	0.092	0.134	0.200	**0.796**	−0.029	0.052	0.077	0.021	
Item 10. Job satisfaction	0.109	0.152	0.11	**0.764**	0.025	0.107	0.246	−0.027	
Item 27. The coworkers' influences	0.049	0.216	0.146	**0.739**	−0.015	0.148	0.131	0.043	
Item 14. Teamwork	0.223	0.145	0.226	**0.673**	0.043	−0.097	−0.033	−0.042	
Item 22. Fluky psychology	0.086	0.074	−0.029	−0.026	**0.874**	0.109	0.002	−0.027	F_5: Psychological workers' condition
Item 23. Risk-taking mindset	0.034	0.03	−0.048	−0.058	**0.867**	0.080	0.017	−0.006	
Item 25. Bad emotional state	0.102	0.113	−0.061	0.009	**0.766**	0.031	0.112	0.128	
Item 21. Lack of safeguards	0.296	0.334	0.117	0.061	0.065	**0.716**	0.076	0.005	F_6: Workplace conditions
Item 24. Messy conditions	0.37	0.238	−0.023	0.097	0.047	**0.697**	0.059	−0.012	
Item 26. Work intensity	0.128	0.457	0.069	0.087	0.148	**0.676**	−0.055	0.077	
Item 08. Staff's participation in decision making	0.153	0.209	0.121	0.432	0.019	0.037	**0.722**	0.050	F_7: Employee empowerment
Item 09. Staff are motivated to improve skills	0.122	0.191	0.103	0.482	0.031	−0.002	**0.661**	−0.010	
Item 12. Management commitment	−0.061	−0.023	0.007	0.013	0.010	−0.003	0.033	**0.921**	F_8: Leadership
Item 13. Management involvement	0.312	−0.194	0.152	0.193	0.101	0.143	0.018	**0.666**	

Note: Bold values indicate the factor loadings are greater than 0.45.

influences, and teamwork. Thus, we named this factor "*organizational climate*";

- Factor 5 (F_5) accounted for 5.951% of the total variance and included three items (22, 23, 25), namely, fluky psychology, risk-taking mindset, and bad emotional state. Thus, we named this factor "*psychological workers' condition*";
- Factor 6 (F_6) accounted for 5.373% of the total variance and covered three items (21, 24, 26), namely, the lack of safeguards, messy conditions, and work intensity. Thus, we named this factor "*workplace conditions*";
- Factor 7 (F_7) accounted for 4.113% of the total variance, and included two items (08, 09), namely, staff's participation in decision making and staff motivation to improve skills. Thus, we named this factor "*employee empowerment*"; and
- Factor 8 (F_8) accounted for 2.681% of the total variance and included two items (12, 13), namely, management commitment and management involvement. Thus, we named this factor "*leadership*."

In order to ensure the appropriateness of the groupings of the extracted eight factors, Cronbach's α test was subsequently adopted. Cronbach's α values are shown in Table 5. The overall α values with a range [0.83, 0.92] are greater than the minimum desired value of 0.70, indicating that the internal consistency of each dimension maintains a high level of performance.

Table 5. Results of Cronbach's α Reliability Test

Common factor	Cronbach's α
F_1: Knowledge and skills (five items)	0.85
F_2: Individual differences among workers (four items)	0.92
F_3: Management-oriented supervision and system (four items)	0.83
F_4: Organizational climate (five items)	0.86
F_5: Psychological workers' condition (three items)	0.94
F_6: Workplace conditions (three items)	0.91
F_7: Employee empowerment (two items)	0.84
F_8: Leadership (two items)	0.87

SEM

The traditional incident-based indicators regarding CWSB are criticized as measuring system failures without revealing cause-effect relationships that would drive system improvement and therefore appear to have little predictive value (Carder and Ragan 2003; Cooper and Phillips 2004). The SEM technique proves to be an efficient tool for testing complex casual relationships among variables, and overpass multiple regression analysis by avoiding excessive multicollinearity (Chinda and Mohamed 2008). This procedure is used to investigate the interrelationships between enablers and the goals of CWSB. Generally, SEM comprises two types of models: namely, a measurement model and a structural model.

Model Hypotheses

Reasonable hypotheses are very crucial for the establishment of a SEM. In the last section, the EFA method processed the data by dimension reduction and item classification, which can provide more understanding on causal-relationships for measurement and structural models to be constructed. In order to examine relationships among the extracted eight common factors (Table 4), the following eight hypotheses are developed:

- Hypothesis H_1: F_1 (*Knowledge and skills*) positively affects safety behaviors;
- Hypothesis H_2: F_2 (*Individual differences among workers*) positively affects safety behaviors;
- Hypothesis H_3: F_3 (*Management-oriented supervision and system*) positively affects safety behaviors;
- Hypothesis H_4: F_4 (*Organizational climate*) positively affects safety behaviors;
- Hypothesis H_5: F_5 [*Psychological workers' condition (bad mood)*] negatively affects safety behaviors;
- Hypothesis H_6: F_6 [*Workplace conditions (poor conditions)*] negatively affects safety behaviors;
- Hypothesis H_7: F_7 (*Employee empowerment*) positively affects safety behaviors; and
- Hypothesis H_8: F_8 (*Leadership*) positively affects safety behaviors.

Measurement Model

The measurement model is concerned with how well the variables measure the latent factors addressing their reliability and validity. Based on the data collected from front-line workers on construction sites, SEM and *AMOS 21.0* software packages were applied to test the hypotheses and gain insights on the relationships between the above variables. Establishing good measurement models is a prerequisite to testing the structural model. As mentioned above, EFA serves to identify a set of latent constructs underlying a battery of measured variables (Fabrigar et al. 1999) and can be used where no prior knowledge of factors or patterns of measured variables exists (Finch and West 1997). In this research, EFA was conducted to establish the relationships between latent factors and their observed indicator variables before moving on to the construction of structural models. As shown in Table 4, the results of EFA indicated that a total of eight measurement models needed to be developed for the measurement of CWSB. Taking the latent factor F_1 (*knowledge and skills*) for an example, there were five observed indicator variables for this measurement model, namely, Item11 (*safety awareness*), Item07 (*know-how and skills*), Item19 (*talents-job fit degree*), Item05 (*working experience*), and Item03 (*education*). The same procedure can be extended to other measurement models, including $F_2 - F_8$.

Structural Model

The structural model is concerned with modeling the relationships between the latent factors by describing the amount of explained and unexplained variance, which is akin to the system of simultaneous regression models (Wong and Cheung 2005). Having established confidences in the measurement model, a SEM that combines the measurement model and the structural model is then developed and tested to examine the direction of the assumed relationships between the aforementioned eight latent variables. With regard to the required minimum sample size for the construction of a SEM, some of the following principles should be taken into account: (1) Thompson (2000) indicated that the sample size should be at least 10 times as much as that of the observed variables, (2) Byrne (2001) noted that the maximum likelihood (that was the default method used in *AMOS*) required the samples to be more than 400 so as to better estimate the proposed model, and (3) Tabachnick and Fidell (2007) suggested that the sample number should be at least 200 to construct a SEM to make an empirical research on it, with the sample number ranging from 200 to 500. For instance, Fernandez-Muniz et al. (2009), Martinez-Corcoles et al. (2012), and Al-Refaie (2013) conducted relevant investigations using SEM, and their sample sizes were 455, 495, and 324, respectively. In our study regarding causal-relationships in CWSB, there are 30 observed variables (Table 2), and the sample with a size of 450 is enough to meet all the above requirements.

Based upon the established hypotheses and data collected from 450 valid respondents, arrows connecting the eight factors with "safety behaviors" were developed to examine their effects on workers' safety behaviors. The multidimensional structural model should have acceptable convergent validity and discriminant validity; only then will the path coefficients provided by the model (best-fit) have high predictability and practical value. When we combine the measurement model and the structural model together, the initial structural equation model for CWSB in China is presented in Fig. 2.

Analysis of Results

Hypothesis Test Analysis

Hypothesis testing is the primary content of the structural equation model, and the results of regression weights in the initial model are summarized in Table 6. The hypothesis is considered to be acceptable for the model establishment if and only if the value of P, that is, the significance level, is less than 0.05. In this study, the following results are obtained: Hypotheses H_1, H_3, H_4, H_5, H_6, H_7, and H_8 were clearly confirmed. However, the P value of hypothesis H_2 was calculated to be 0.886, which exceeded 0.05, leading to the rejection of hypothesis H_2. To be specific, the individual

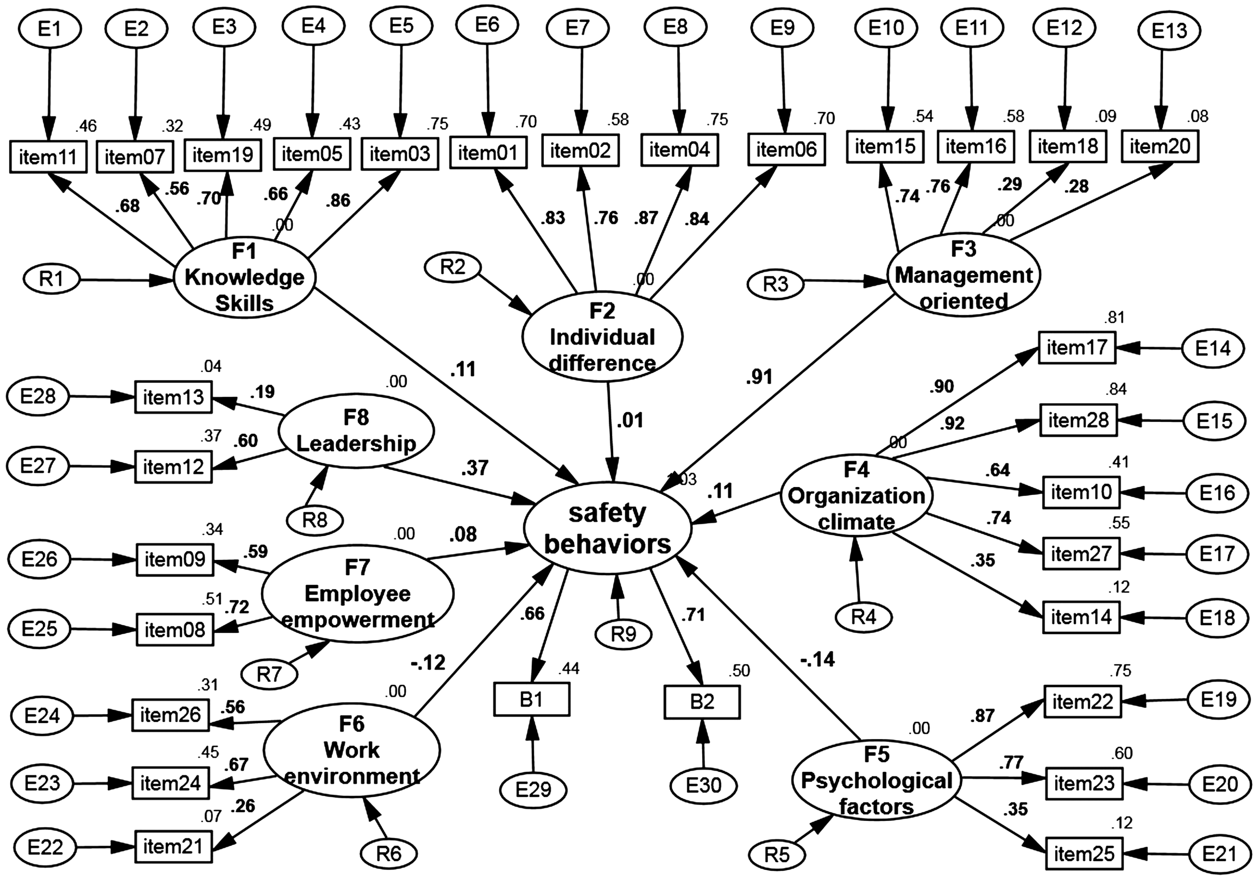

Fig. 2. Initial structural equation model for CWSB in China

Table 6. Results of Regression Weights in Initial Structural Equation Model for CWSB

Relationship	Regression weight				Test results
	Estimate	Standard error	Critical ratio	P	
F_5 (knowledge and skills) → safety behaviors	−0.105	0.037	−2.863	0.04	Supported
F_2 (individual difference among workers) → safety behaviors	0.005	0.033	0.144	0.886	Unsupported
F_4 (organizational climate) → safety behaviors	0.099	0.039	2.521	0.012	Supported
F_3 (management-oriented supervision and system) → Safety behaviors	1.628	0.311	5.242	[a]	Supported
F_1 (knowledge and skills) → safety behaviors	0.125	0.052	2.396	0.017	Supported
F_8 (leadership) → safety behaviors	1.074	0.272	3.949	[a]	Supported
F_7 (employee empowerment) → safety behaviors	0.093	0.029	3.207	[a]	Supported
F_6 (workplace conditions) → safety behaviors	−0.152	0.325	−4.468	[a]	Supported

[a] $P < 0.001$.

differences among workers, such as inertia of habit, attentiveness to work, susceptibility to accidents, and self-control ability slightly influence the workers' safety behavior. In contrast, psychological workers' condition, organizational climate, management-oriented supervision and system, knowledge and skills, leadership, employee empowerment, and workplace conditions have greater impacts on the front-line workers' thoughts and behaviors.

The outcome of hypothesis testing can provide basic references on correcting invalid assumptions. Thus, it is essential to modify the initial structural equation model (Fig. 2). The latent factor, namely the individual differences among workers (F_2), is then deleted from the initial model entirely because it does not perform statistically significantly with workers' safety behaviors. Finally, the optimized structural equation model for CWSB that passes the hypothesis test is shown in Fig 3.

The assessment of the overall model fit is a critical issue in any SEM, and each parameter in the hypothetical model should be successfully estimated. Hus et al. (2012) indicated that the overall model can be assessed by a variety of statistical goodness-of-fit indicators. With regard to assessment indicators of model goodness-of-fit, the SEM model should pass through the following three types of assessment indices, namely, absolute fit indices, incremental fit indices, and parsimonious fit indices (Hooper 2008). Generally, the meaning of the three types of assessment indices can be explained and distinguished as follows: (1) absolute fit indices provide the most fundamental indication of how well the proposed theory fits the data, and they do not use an alternative model as a

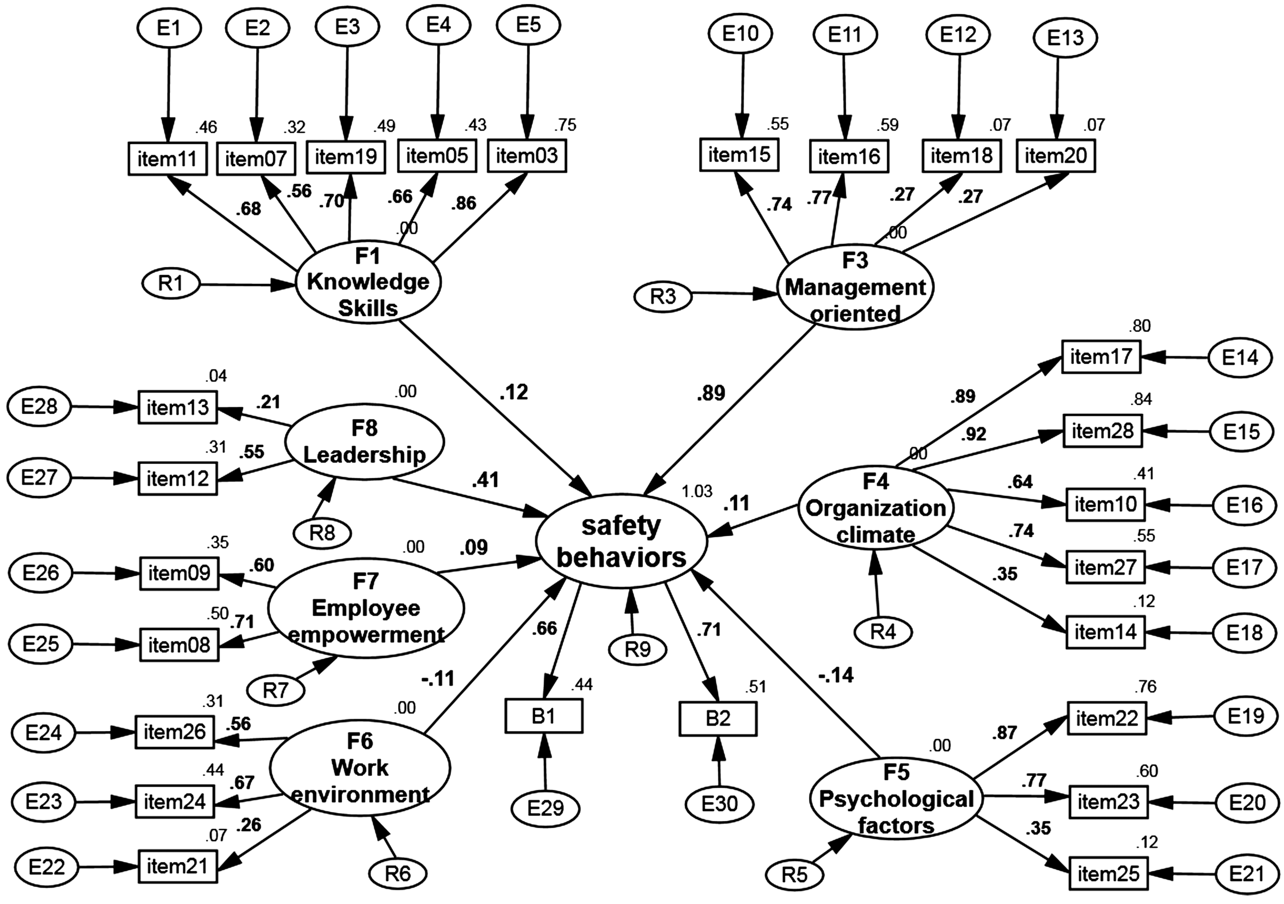

Fig. 3. Optimized structural equation model for CWSB in China

Table 7. Results of Goodness-of-Fit Verification in Optimized Structural Equation Model

Type of fit indices	Indicators	Fit standards and applicability	Values	Test results
Absolute fit indices	χ^2 test	<0.05, good fit	0.000 < 0.05	X
	RMR	<0.05, good fit	0.044	X
	RMSEA	<0.08, not bad fit; <0.05, good fit	0.045	X
	GFI	>0.90, good fit	0.922	X
	AGFI	>0.90, good fit	0.918	X
Incremental fit indices	NFI	>0.90, good fit	0.928	X
	RFI	>0.90, good fit	0.732	X
	IFI	>0.90, good fit	0.913	X
	TLI	>0.90, good fit	0.928	X
	CFI	>0.90, good fit	0.913	X
Parsimonious fit indices	PGFI	>0.50, good fit	0.664	X
	PNFI	>0.50, good fit	0.746	X
	PCFI	>0.50, good fit	0.736	X

Note: AGFI = adjusted goodness-of-fit index; CFI = comparative fit index; GFI = goodness-of-fit index; IFI = incremental fit index; NFI = normed fit index; PCFI = parsimony comparative fit index; PGFI = parsimony goodness-of-fit index; PNFI = parsimony normed-fit index; RFI = relative fit index; RMR = root mean square residual; RMSEA = root mean square error of approximation; TLI = Tucker-Lewis index; χ^2 test = Chi-square test.

base for comparison, (2) incremental fit indices are a group of indices that do not use the chi-square in its raw form and their calculation should rely on comparison with a baseline model, and (3) parsimonious fit indices seriously penalize for model complexity, which results in parsimony fit index values that are considerably lower than other goodness-of-fit indices, and it's strongly recommend that the use of parsimony fit indices should in tandem with other measures of goodness-of-fit. Moreover, some specific indicators are selected for each type of the fit indices in this study.

Table 7 illustrates the results of goodness-of-fit verification in the optimized structural equation model. Taking the absolute fit indices for instance, the values of RMR (root mean square residual), RMSEA (root mean square error of approximation), GFI (goodness-of-fit index), and AGFI (adjusted goodness-of-fit index) are 0.044, 0.045, 0.922, and 0.918, respectively, which are all in line with the recommended values. Among all the indicators, only the RFI (relative fit index) with a value of 0.732 is below the recommended value of 0.9. In conclusion, the model is considered to be

Table 8. Results of Direct Path Coefficients for Seven Latent Variables in Optimized Structural Equation Model for CWSB in Descending Order

Factor	Relationship	Direct path coefficient
F_3	Management-oriented supervision and system → safety behaviors	0.89
F_8	Leadership → safety behaviors	0.41
F_1	Knowledge and skills → safety behaviors	0.12
F_4	Organizational climate → safety behaviors	0.11
F_7	Employee empowerment → safety behaviors	0.09
F_6	Workplace conditions → safety behaviors	−0.11
F_5	Psychological workers' condition → safety behaviors	−0.14

acceptable because most of the goodness-of-fit indices are fairly good.

Path Coefficients Analysis

The SEM is capable of depicting direct or indirect effects between factors. Path coefficients are standardized versions of linear regression weights that can be used in examining possible causal linkages between statistical variables in the SEM-based approach (Shipley 2002). The term "path coefficient" derives from Wright (1921), where a particular diagram-based approach was used to consider the relations between variables in a multivariate system. Path coefficients analysis estimates the effects of variables in a causal system, which starts with a structural equation—a mathematical equation representing the structure of variables' relationships to each other. In the established safety behavior model (Fig. 3), all the latent variables have relationships with workers' safety behaviors; however, the direct path coefficients might be different among different latent variables. Table 8 illustrates the results of direct path coefficients for the seven latent variables in the optimized structural equation model for CWSB in a descending order. Latent variables that exert obvious positive or negative impacts on the safety behaviors are picked up and analyzed as follows:

- Management-oriented supervision and system (F_3): This latent variable is considered as the top factor that has significant direct relationships with safety behaviors (path coefficient = 0.89); F_3 covers four observed indicator variables: Item15 (*safety management system*), Item16 (*on-site supervision and guidance*), Item18 (*safety training*), and Item05 (*safety incentive mechanism*). This indicates that safety management plays a very important role in supervising and examining the implementation of every safety rule and regulation, conducting safety education and training of newcomers and front-line workers, duly correcting unsafe deeds, and eliminating accident potential;
- Leadership (F_8): This latent variable also performs obvious positive impacts on workers' safety behaviors (path coefficient = 0.41); F_8 includes two observed indicator variables: namely, Item12 (*management commitment*) and Item13 (*management involvement*). This indicates that the top management involvement and commitment to safety are vital to inspire employees' interest in adopting the right process and realizing reasonable resource allocation, in order to guarantee construction safety;
- Psychological workers' condition (F_5): This latent variable has significant negative influence on safety behaviors (path coefficient = −0.14); F_5 includes three observed indicator variables: namely Item22 (*fluky psychology*), Item23 (*risk-taking mindset*), and Item25 (*bad emotional state*). Presently, many small construction enterprises in China have weak links in safety management, where bad or risk-taking behaviors go unpunished, leading to fluky psychology. Workers that have to put up with long hours and heavy physical labors are more likely to get vocational sluggishness, such as emotional exhaustion, negative attitudes, and become mentally dull. Those turn out to be serious obstacles to realizing high performance regarding CWSB; and
- Workplace conditions (F_6): This latent variable also performs negatively on safety behaviors (path coefficient = −0.11); F_6 covers three observed indicator variables: namely Item21 (*lack of safeguards*), Item24 (*messy conditions*), and Item26 (*work intensity*). Whether in factories, mines, or construction sites, workplace conditions in China are very harsh, and workers have to endure hot, dirty, and dusty ambient conditions. Even worse, a lack of adequate safety devices (such as protective suits, helmets, or shoes) and long working hours increases the risk of human injury accidents. From a long-term perspective, improving workplace conditions can greatly promote positive health and safety behaviors of construction workers.

Discussions

This paper develops a systematic hybrid approach that integrates EFA and SEM so as to verify causal-relationships and interactions between enablers and goals of CWSB. A total of 450 valid responses were collected on construction sites and further used for exploratory factor extraction, model construction, model verification, and model analysis. The impacts of research hypothesis and path coefficient on CWSB were investigated and analyzed in detail. The capacities and potential application of the developed approach are as follows:

1. Revealing causal-relationships by using survey data. In most countries, the incidence rate of fatal accidents in the construction industry is higher than any other industry (Duff 1998; ves Dias 1999). Causality is the relation between a set of factors (causes) and a phenomenon, and a thorough understanding of the incident causal mechanism is necessary for prevention. However, how to determine and verify causal-relationships among relevant variables in an effective way is a challenging problem because a large number of complex processes/behaviors are involved in the management practice of workers' safety behaviors. In the developed approach, the data-driven technique that is EFA is first used to discover the factor structure of a measure and for data reduction. Using a survey of 450 valid respondents, eight common factors were extracted as potential latent variables in constructing the SEM for CWSB, and accounted for 70.205% of the total variance. Next, SEM was used to investigate the interrelationships between the constructs of the hypothesized model. At the same time, the established model passed both the hypothesis test and the goodness-of-fit test, and could be considered acceptable because most of the verification indices were fairly good. In this way, a hypothetical model can be validated using a large amount of survey data, and it is thus rational and reliable to apply the verified model to further analysis.
2. Determining leading factors in terms of path coefficients. A large number of factors/processes/behaviors are involved in the management practice of workers' safety behaviors in the construction industry. Which factor plays a leading role in ensuring the satisfactory workers' safety performance is unknown exactly (Demirkesen and Arditi 2015; Guo and Yiu 2015). The approach developed in this research is capable of depicting causal effects, including direct and indirect effects between factors in terms of path coefficient analysis. The factor with a high path coefficient can then be identified as a leading factor in ensuring

the satisfactory performance of workers' safety behaviors. In this study, *management-oriented supervision and system* (F_3) and *leadership* (F_8) were identified as leading factors with direct path coefficients of 0.89 and 0.41, respectively, whereas *individual differences among workers* (F_2) did not perform statistically significantly with workers' safety behaviors. In this way, the factors leading to the satisfactory performance of CWSB can be determined on a quantitative basis.

3. Improving construction safety performance by increasing workers' safety behaviors. Preventing construction disasters can be achieved via analysis of safety behavior factors and an integrated long-term plan can then be created (Seo et al. 2015; Wu et al. 2015). In this study, results indicated both *management-oriented supervision and system* (F_3) and *leadership* (F_8) exerted obvious positive impacts on CWSB, whereas *psychological workers' condition* (F_5) and *workplace conditions* (F_6) exerted obvious negative impacts on CWSB. Some corresponding programs in response to those factors can be developed for increasing workers' safety behaviors. For instance, improving workplace conditions can greatly promote positive health and safety behaviors of construction workers. Those research findings can provide insights into cause-effect relationships among safety behavior factors and goals, which, in turn, can facilitate the improvement of construction safety performance in the context of the Chinese construction industry.

Conclusions and Future Work

This paper presents a systematic hybrid approach, with EFA and SEM fully incorporated, for the analysis of CWSB from a workers' perception perspective in the construction industry in China. A questionnaire survey was used to gather and measure information on variables of interest, with previous literature and engineering practices taken into account. The EFA was conducted to extract the exploratory factors for data reduction in order to identify the structure among the questionnaire items, and SEM was used to investigate the interrelationships between the constructs of the hypothesized model. Results provide a clear understanding of the interdependence and causal-relationships for the safety behaviors on construction working sites, which can, in turn, facilitate safety performance improvement in the construction industry.

In light of empirical findings, some conclusions can be drawn as follows: (1) the principal components factor analysis with varimax rotation was conducted to yield eight common factors, namely *knowledge and skills* (F_1), *individual differences among workers* (F_2), *management-oriented supervision and system* (F_3), *organizational climate* (F_4), *psychological workers' condition* (F_5), *workplace conditions* (F_6), *employee empowerment* (F_7), and *leadership* (F_8); (2) these eight factors were extracted as potential latent variables in constructing the SEM model for CWSB, and account for 70.205% of the total variance; (3) in terms of hypothesis testing, all the above eight factors had greater impacts on the front-line workers' thoughts and behaviors, except *individual differences among workers* (F_2); this factor was deleted from the qualified structural equation model because it did not perform statistically significantly with workers' safety behaviors; and (4) F_3 and F_8 exerted obvious positive impacts on CWSB, whereas F_5 and F_6 exerted obvious negative impacts on CWSB. These research findings can provide insights into interactions among safety behavior factors and causal-relationships between those factors and safety behavior goals in the context of the Chinese construction industry.

The approach developed in this research also has some limitations. Large amounts of data were obtained through a questionnaire survey. Numerous front-line workers in the construction industry participated in the data collection work, making an essential contribution to securing a reliable input dataset for the subsequent safety behavior-based modeling and analysis. This on-site questionnaire process is laborious and expensive. Given a high number of people involved in data collection, the questionnaire process would probably lose control of respondents. In addition, great fuzziness and uncertainty exist during the measurement of respondents' perceptions on some hard and soft influential factors. How to address underlying uncertainties during questionnaire design and implementation is still a serious issue. Subsequent research will develop an automation acquisition technique for data collection and use simulation knowledge to reduce underlying respondents' perceptions. A more comprehensive approach that is capable of analyzing CWSB among different countries regarding different safety cultures and identifying sensitivity factors to CWSB will also be investigated in future studies.

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