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Using Structural Equation Modelling to Predict Safety and Health Status among Stone Industries

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Keywords: Organizational structure; safety and health; structural equipment modelling; stone industry

Abstract

Background: *The creation of a working organization with a high safety level facilitates the employees' health in their workplaces; therefore, the current study evaluated the effect of the organizational structure on safety and health in the stone industry.* **Methods:** *This study was conducted among 100 stone industries in Isfahan, Iran. The participants were requested to complete the organizational structure questionnaire and ELMERI checklists. Smart PLS 3.0 used to test the hypothesis.* **Results:** *The model fit index showed the standardized root mean square (SRMR=0.08), the normalized fit index (NFI=0.9), the coefficient of determination (R2=0.362), effect size (f2 was less than 0.2), and the Predictive relevance of the model (Q2=0.216) which is considered a good fit for mode. In addition, the relation between formalization and health and safety was significant (β=-0.47).* **Conclusions:** *The findings suggest that organizational factors are the basic reasons for occupational accidents and the main indicator of safety and health performance.*

1. Introduction

The modern economy is led by agriculture, manufacturing, and services. Regardless of the deciding factors, each country's economic growth and improvement based on a weak labour protection system is an invitation to accidents [1]. In the European Union (EU), more than 5,500 people die annually from workplace accidents. Based on the estimates by the International Labour Organization, 159,000 people in the EU lose their lives annually as result of occupational diseases. Companies in the EU lose about 143 million working days because of workplace accidents annually. All these injuries, deaths and occupational diseases cost the EU economy at least 490 billions euros annually [2]. Occupational safety and health in working groups at the workplace play a basic role in successful business management in many studies [3]. Arthur Schopenhauer, a German philosopher (1788-1860), emphasized health importance and stated, "Health is not everything, but without health, everything is nothing" [4]. Hence, the definition of health and safety and integration of these terms can be considered occupational health and safety and a holistic approach to staff's welfare in the workplace. According to

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WHO's definition, occupational health involving occupational hygiene, occupational medicine, safety, physiotherapy, rehabilitation, occupational psychology, ergonomics, etc. Safety, on the contrary, is defined as safeguarding a person from physical harm. International Occupational Health Association defines Occupational Safety and Health (OSH) as the science of anticipating, evaluating, and controlling hazards arising in or from the workplace that could impair the health and well-being of workers [5, 6].

Regarding workplace safety issues, some researchers say that each workplace has a specific environment, which may indirectly affect the industry's accident rate, e.g., decisions made in politics and management, leadership and management skills, education level, mutual communications, etc. [7, 8], are under the employer's responsibility. On the other hand, the employer or industry management is responsible for this area based on industry safety rules and workplace protection. Therefore, OSH requirements must be inseparable from modern industries' performances [2]. In addition, many papers written by famous management theorists (Frederick W. Taylor, Henry L. Gantt, Frank and Lilian Gilbreth, Henry Fayol, Hugo Münsterberg, George E. Mayo, and others) explain that the interests of workers, managers, and owners must be matched and aligned [9]. Hence, organizational improvement is among the crucial elements of occupational safety. Creating a working organization with a high safety level ensures employees' health in their workplaces, so fewer staff leave their jobs or decide to change their occupations. In this case, employees become satisfied, which leads to higher individual and organizational performance and productivity. In this case, the organization achieves its organizational goals.

1.1 Research Hypotheses

Proposed Research Model and Hypotheses Based on the above theoretical assumptions is schematically illustrated in Figure 1. The following hypotheses are formulated: (i) H1: Complexity is positively related to health and safety in the stone industry; (ii) H2: Formality is positively related to health and safety in the stone industry; (iii) H3: Concentration positively affects health and safety in the stone industry.

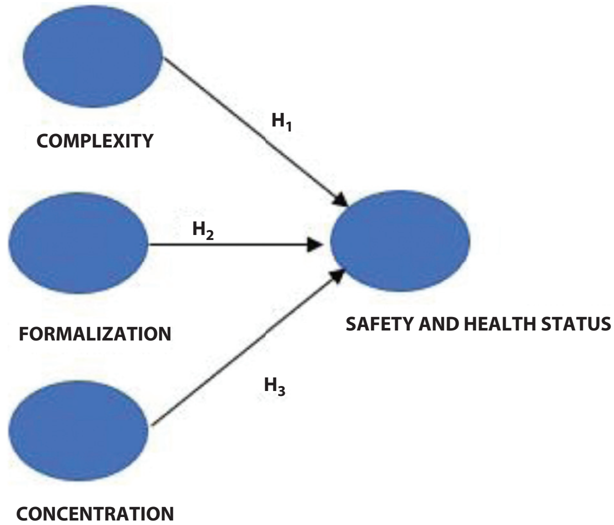

Figure 1. The study conceptual model.

2. Methods

2.1 Data Collection, Participants, and Study Design

This cross-sectional study was conducted among the 100 stone industries in Isfahan, Iran. Data collection started on 1 January 2019 and ended on 28 June 2019. Participants were employees and employers. The selected participants were requested to complete the questionnaire. Participants completed the OSQ and ELMERI checklists and provided demographic information from the work system. Of the 100 questionnaires, 10 did not return measurements or contained more than 20% missing data. This study used statistical frequency analysis to determine central trend measurements (mean) and variance measurements (standard deviation). We tested the research hypothesis using structural equation modelling.

2.2. Instruments

We used the ELMERI checklist developed by the Finnish Institute of Occupational Health (2000) to measure safety and health status. The result is calculated as a percentage. The level safety performance index is classified into four levels: good (75 to 100%), medium (50 to 75%), poor (25 to 50%), and very poor (0 to 25%) [10].

Stephen Robbin's questionnaire was applied to measure organizational structure [11]. This questionnaire has 24 questions, 5-choice, with scores from 1 to 5 in three subscales of complexity, formality, and concentration. The increase in scores in this questionnaire indicates the increase in the scores of each of the subscales of organizational structure. The validity of the questionnaire was measured using Cronbach's alpha coefficient and was evaluated as 0.725 [12].

As shown in the Conceptual Framework (Figure 1), the dependent variable for this study is health and safety, and the independent variables are complexity, formalization, and concentration.

"Health and safety status" is selected as an exogenous latent variable. Therefore, "unsafe behaviors of the worker", "order and tidiness", "machine safety", "industrial hygiene", "ergonomic", "walkways", and "fire and health aid" are selected as the endogenous latent variables. These latent variables include one observable indicator of "unsafe worker behavior", four indicators for "order and tidiness", "machine safety", "ergonomics", and "fire and health aid". In addition, three indicators of "walkways" and five indicators for "Industrial hygiene", complexity, formalism, and concentration are defined as endogenous latent variables. These include 7 observable indicators of complexity and formalism and 10 observable indicators of concentration.

2.3 Statistical Analysis

Karl G. Jöreskog (1935) defines causal modelling as a linear structural, relational model comprising a structural and a measurement model. Structural models elaborate on the association among the latent variables via a series of linear equations. However, the measurement model explains the unobservable measurement of latent variables with the observable predictors or manifest variables, allowing the measurement characteristics of the indicators to be evaluated (Lomax, 1982, 1983) [13-15].

The database turned into Smart PLS 3.0 (https://www. smartpls.com/smartpls3), and the study's hypotheses were tested with the bootstrap method. Since few data had been available, PLS-SEM turned into employed. The technique of statistics evaluation with PLS-SEM for verifying the theoretical version was achieved in 2 steps.

The first step was to evaluate the quality of the measurement model. Various indicators were employed in the analysis of the measurement model, depending on the type of indicator in the model. We used the indicator weights to determine which indicators to remove and which to keep in the model [16]. The measurement model was analyzed based on the developed criteria for the reflective method, convergent validity; internal consistency; and discriminant validity. The standards of convergent validity and internal consistency are suggested by [17]. The validity of the convergence of the reflection structure was verified by the external load and the extracted mean-variance AVE; its value should be more than 0.5. Internal consistency was confirmed by Cronbach's alpha factor composite reliability and rho_A factor. Cronbach's alpha factor measures reliability based on the correlation between the index variables, and composite reliability considers the various loads of these variables [16]. Diagonal elements must be significantly greater than the corresponding row and column off-diagonal elements to achieve proper identification validity [18, 19].

Then measuring the Inner Structural Model outcomes comes afterward, which comprises observation of the model's predictive relevancy and the association between the constructs. The coefficient of determination (R2), Path coefficient (b value) and T-statistic value, Effect size ($f2$), and the Predictive relevance of the model (Q2) are the key standards for evaluating the inner structural model [17].

3. Results

3.1. Assessment of Measurement Model

According to the least square's structural equation modelling, the measurement model was initially assessed by employing Smart PLS 3.0. The convergence validity, discriminant validity and reliability of the measurements used were evaluated to analyze the measurement model.

Table 1 shows that loading above 0.4 on each variable is considered significant. Indicators that have very low loadings below 0.40 must be removed.

Table 1. Measurement model for the research constructs.

Subscales			**Factor loading**	**Cronbach's α>0.7**	**AVE>0.5**	**CR>0.7**	**rho_A>0.7**
Safety & health status		Safety behavior	0.871	0.897	0.653	0.926	0.927
		Order and tidiness	0.725				
		Machine safety	0.335				
		Industrial hygiene	0.875				
		Ergonomics	0.877				
		Walkways	0.953				
		Fire and health aid	0.858				
Organization structure	*Complexity*	P1	0.809	0.678	0.598	0.846	0.894
		P2	0.833				
		P3	0.675				
		P4	0.615				
		P5	0.845				
		P6	0.875				
		P7	-0.720				
	Formalization	R1	0.843	0.924	0.703	0.941	0.946
		R2	0.902				
		R3	0.914				
		R4	0.897				
		R5	0.836				
		R6	0.491				
		R7	0.903				
	Concentration	T1	0.828	0.924	0.703	0.941	0.946
		T2	0.794				
		T3	0.785				
		T4	0.791				
		T5	0.826				
		T6	0.84				
		T7	0.836				
		T8	0.797				
		T9	0.853				
		T10	0.812				

Table 2. Discriminant validity: Fornell-Larcker criterion test.

	Complexity	Formalization	Concentration	Safety and health status
Complexity	0.773			
Formalization	0.824**	0.838		
Concentration	-0.779**	-0.864**	0.816	
Safety and health status	-0.479**	-0.593**	0.560**	0.808

No indicators were below 0.40, and as a result, no indicators were deleted. All of the AVEs are above 0.50, which is the recommended cut-off value. The composite reliability for all variables is above 0.60, which is the acceptable cut-off value. So, the measurements employed in this research for each variable are considered reliable.

The Discriminant validity was analysed by employing the Fornell-Larcker criteria. Table 2 represents the Fornell-Larcker criterion comparing the correlation between constructs with the square root of the AVE for each construct.

3.2 Model Fit Test

PLS-SEM does not have a global goodness of fit index. To date, important thresholds are not fully understood. Therefore, a bootstrap and blindfold approaches are implemented to solve these issues. Moreover, these analyses, testing the reliability and validity of the measurement model, are conducted in the first step. The goodness of fit index is usually not shown. However, some researchers have proposed a Standardized Root Mean Square residual (SRMR) and a Normalized Fit Index (NFI) as performance metrics to assess model fit without model specification errors. It is regarded appropriate if the SRMR is less than 0.10 or 0.08 and the NFI range is 0 to 1 (close to 1). In this study, the SRMR was 0.08, considered acceptable. Moreover, the NFI was approximately 0.9, which is considered a good fit for our mode.

3.3 Measuring the Value of R^2

The coefficient of determination measures the model's predictive accuracy because it measures the size of the overall effect and variance described in the structural model's endogenous construct. The R2 value in Figure 2 indicates that the combined three factors of concentration, complexity, and formalization account for 36.2% of the variance in satisfaction. (R2=0.362). See R2 classification by Hair et al. [17]. The power of these factors to safety and health can be explained between the weak and the moderate.

3.4. Estimation of Path Coefficients (β) and T-statistics

Partial least squares statistical significance was determined using resampling techniques such as bootstrap. This procedure provides t-test results for all pass coefficients. The model's path coefficients (β) and t-statistics were used to evaluate the relationship between the independent and dependent variables. The beta coefficient of the structural model between formalization and health and safety was significant, with a p-value of 0.01 and β=-0.47 [20, 21]. See table 3 for more.

3.5 Effects Sizes for Path Coefficients (f^2)

The effect size of the path coefficient between independent and dependent construct (f2). Effect size is a change in R-squared (R2) examined to determine if the effect of the independent structure on the dependent structure has a significant effect (f2), which is automatically calculated by the Warp PLS-SEM software. According to Cohen (1988), the effect size between formalization and health and safety conditions was less than 0.2, which was regarded as small effect [22].

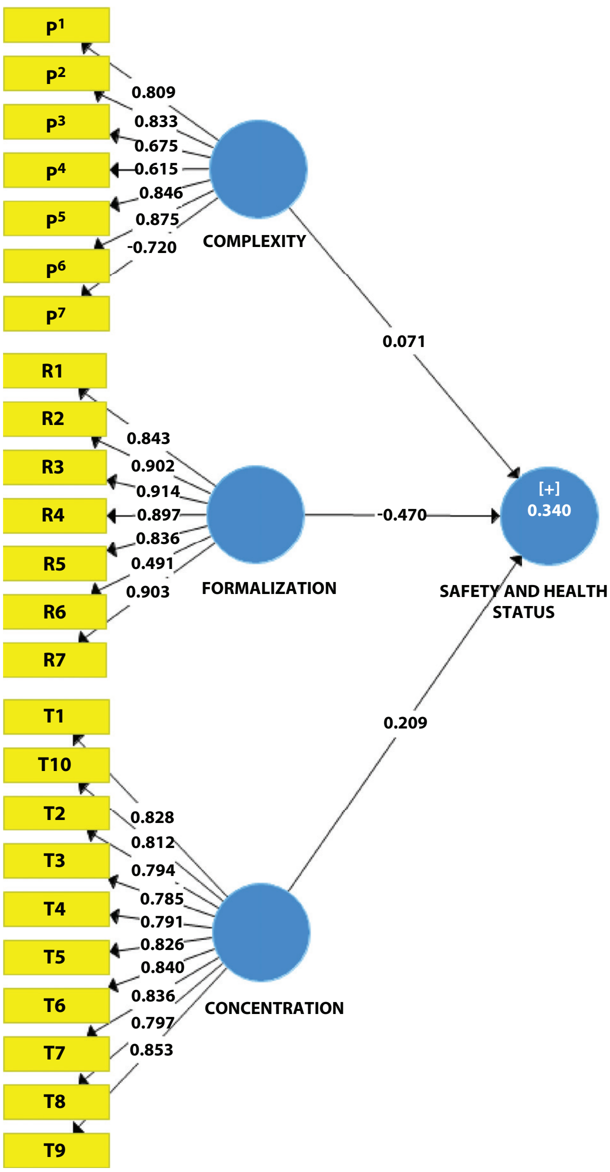

Figure 2. SEM Model for the relationship between safety and health status and organization structure dimensions.

3.6. Predictive Relevance of the Model (Q^2)

The model's accuracy can be evaluated using predictive validity (Q2). This is also known as the Stone-Geisser indicator or redundancy of cross validity (Q2). The Q2 criteria recommend that the conceptual model be able to predict the latent structure. In SEM, the measured Q2 value must be greater than zero for a particular endogenous latent structure [23]. The result shows that the Q2 value for this study model is equal to 0.216. This is above the threshold and confirms that the predictive relevance of the path model of the endogenous construct is valid.

4. Discussion

According to the model's results, there was only a significant and direct relation between the formality of organizational structure and safety. Cox and Cheyne (2000) and Mearns et al. (2003) express that safety rules and regulations have a crucial role in safety level management in organizations [24, 25]. Moreover, Otieno et al. (2019) explain that increased occupational accidents reduce firm performance and show that safety and health regulations moderates the relation between occupational accidents and firms' performance, so they act as a moderator [26]. However, Patel and Jha (2016) indicated that safety regulation had no considerable effect on the safe behaviors of workers [27]. So, Patel and Jha (2014) implanted safety regulations and procedures as the less important determinants of safe work behavior. Fielder's theory (1983) debates that human resources actions affect organizational performance only if they are subjected to strategic policy. In other

Table 3. Path coefficient (β), T-statistics, and P-value.

Hypothesized Path	Standardized Beta	T-Statistics	p Values
Complexity → Safety and health status	0.071	0.496	0.6
Formalization → Safety and health status	-0.47	2.555	0.01
Concentration → Safety and health status	0.2	1.3	0.19

words, effective OSH performance in those corporations that decrease occupational accidents to enhance firm performance requires vertical integration of OSH regulations.

Aliabadi et al. (2018) explain that although unsafe actions of workers are usually introduced as the main reason for industrial accidents, humans are just one of the components in complex systems. Hence, the whole system must be considered to detect accidents source. Aliabadi et al. pointed out that organizational deficiencies do not have a direct impact on unsafe behavior by workers [28]. Other studies have shown that organizational factors such as lack of safety management, organizational involvement, and unsafe regulations directly influence hazardous worker behaviour [29, 30]. In addition, Hoła and Nowobilski (2019) assert that most accidents occur in small- and medium-sized firms that do not have a regular and systematic organizational structure. Because owners and their family members work in such corporations and there is high employee turnover in these firms, many employees leave their jobs every year, and new employees are recruited [31]. These employees do not have sufficient professional experience, so the mentioned reasons result in high occupational accident rates in these firms.

5. Conclusion

Organization factors and organizational structure-related factors are the most basic reasons associated with occupational injuries and accidents and the main indicator of safety and health performance. These variables may, in turn, cause work safety enforcement and problems or indirectly affect occupational accidents and injuries under the influence or in interaction with other factors.

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Conflicts of interest: The authors have no conflicts of interest to declare for this study.

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