Miners work injury determination using Bayesian structural equation model

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Abstract

This paper develops a Bayesian structural equation model for miners work injury in an underground coal mine India. The technical and behavioural variables for work injury were identified and causal relationships were developed. The prior distributions of the causal parameters were obtained from the data obtained from the experts opinions and fitting the sample distribution with theoretical distribution by Chi-squared method. The posterior distributions of these parameters were obtained by applying Bayesian rule. The Markov Chain Monte Carlo simulation in the form of Gibbs sampling was performed for sampling the data from the posterior distribution. The results revealed that 19 parameters out of 33 causal parameters are statistically significant. The results of expert opinion based on priors and maximum likelihood priors revealed that the parameters bound were converged towards the expected value in spite of wrong or bad initialization of priors distributions. The error statistics reveals that Bayesian structural model provides reasonably good fit of work injury with high coefficient of determination (0.91) and less mean squared error (0.025).

Keywords: *injury, Bayesian analysis, conditional probability, coal mine*

1.0 Introduction

Mining is one of the hazardous professions and associated with a high level of accidents and injuries. As per NIOSH (2011) report 2011, mine accident statistics of USA shows a decreasing trends for last 10 years (1992-2002) periods; however mining industry is still occupying the top spot as per accident statistics out of all industries with an average fatality rate of 25 per 100,000 full-time equivalent employees (NIOSH, 2011). The injuries and accident statistics in India is significantly high.

The major cause of high accident and injury rates are due to unsafe conditions, unsafe practices, or combination of these two (Harrell 1990; Sherry 1991). Unsafe conditions are due to engineering and geological aspects of the mines and arise through wrong engineering design, unanticipated geological consequence etc (Bhattacherjee 1990). Unsafe practices mainly take place due to human errors (Shaw et al. 1989). The study shows that the human error is the major causative factor in mine accidents (Shaw et al. 1989). The past studies also revealed that a large proportion of accidents are experienced by a relatively small percentage of the work force (McKenna 1993). Therefore, a systematic method or model is required to see the effects of these individual characteristics (physiological and psychological) along with the characteristics of the work environment to understand how all these factors contribute to mining accident.

A few studies already conducted to quantitatively analyse the miners work injuries. Bhattacherjee et al. (1997) and Ghosh et al. (1998) investigated the system dynamics model to capture the complex dynamic behaviour of the mine safety system involving the feedback process such as safety programs and direct management actions. Maiti (1999), Maiti and Bhattacherjee (1999) and Maiti et al. (1999) evaluated the risk of occupational injuries among underground coal miners through investigation of multivariate statistical models. Maiti et al. (2004) and Paul et al. (2005) investigated multivariate models using structural equation modeling (SEM) techniques to investigate the relationship of engineering and behavioural factors on mining accident.

The generalized least square (GLS) and maximum likelihood (ML) are used in the standard SEM model within the covariance structure analysis framework. The GLS and ML approaches are based on the sample covariance matrix. Hence, these approaches work well under certain assumptions. The observations are assumed to be identically and independently distributed according to a multivariate normal distribution. If some of the assumptions are violated, the covariance matrix and its asymptotic properties may be difficult to derive. The real mining accident/injury model is a complicated problem and the required assumptions may not be satisfied. Moreover, when the output variable is categorical standard SEM is no more applicable for causal mode. Hence, there is a strong demand for new developments of new statistical methods for handling more general models and complex data structures.

The statistical properties of the ML approach are asymptotic. Hence, they are valid for situations with large sample sizes. Researchers (Hu et al. 1992; Hu and Bentler 1995) show that the properties of the statistics are not robust for small sample sizes. The Bayesian methods depend less on asymptotic theory, and hence have the potential to produce reliable results even with small samples. Moreover, the posterior distributions of parameters can be estimated by using a sufficiently large number of observations that are simulated from the posterior distribution of the unknown parameters through Markov chain Monte Carlo (MCMC) methods. The Bayesian approach gives a more flexible and natural statistic for model comparison than the classical likelihood ratio test (Kass and Raftery, 1995).

The aim of this paper is to introduce a Bayesian approach for analyzing the standard SEMs for work injury model of mines. The Bayesian SEM uses the raw observations rather than the sample covariance matrix for the injury modeling.

2. 0 Variables of causal Accident Model

Many factors are associated with accident/injury occurrences in mines. The following represents the various variables addressed in safety studies in mines.

2.1 Personality

The personality is represented by variables negative affectivity, rebelliousness, impulsivity, risk-taking and depression. Negative affectivity refers to the chronic experience of negative emotional states and lack of emotional stability. Researchers suggest that individuals with high negative affectivity suffer from attention lapses on the job, which make them more susceptible to accidents/injuries. Rebelliousness represents the degree of frustration of an individual when they are exposed to regulation. It increases the possibility of experiencing injuries at work. Impulsivity represents the extent to which individuals behave at the spontaneous with little anticipation for the consequence of their behaviours. Therefore, impulsive employees may rush to complete a task without adequate consideration of following safe operating procedures, resulting in an increased risk of injuries. Risk-taking is an undesired behaviour which may leads to work injuries but the workers seldom repeat this behavior to complete the work fast. Depression represents the frequencies with which individuals have symptoms such as a depression mood, feeling of worthlessness, poor concentration, and loss of appetite and sleep disturbance.

2.2 Social supports

Social supports in mining include the variables like Management-worker interaction, coworker supports, and supervisory supports. Management–worker interaction includes the variables such as overall labour relations climate, management concern for labour, and labour supports for safety disciplinary actions. A considerable amount of evidence suggests that there is a significant positive relationship between poor management–worker interaction and work injuries (Gaertner et al. 1987; DeMichiei et al. 1982; Pfeifer et al. 1976). National Academy of Science studies showed that at all the low accident rate mines the union generally supported the company's enforcement of safety rules (1982). Co-worker support is defined as the degree of consideration expressed by coworkers and it plays an import role in work injury.

2.3 Safety environment

Safety environment is an important area for minimizing work injuries. Safety environment represents an organisation's safety practices and safety training.

Researchers suggested that although training has a major role to play in accident/injuries reduction, it is very difficult to evaluate its effect in a short span of time (Phiri 1989). Bhattacherjee et al. (1997) found that the training given to miners is mostly classroom oriented and on-the-job training; they recommended that specific task training is to be implemented to improve the safety of workers. Proper safety practices lead to fewer accidents/injuries in mines. Safety equipment availability and maintenance have immediate effects on safety performance.

2.4 Job hazards

The job hazards include physical hazards, production pressure, job boredom, job dissatisfaction, and job stress. Physical hazards represent the extent to which individuals are exposed to dangerous equipment, unsafe working conditions and poor environmental conditions (Dawson et al. 1983). Job boredom represents the degree to which individuals find their job boring and uninteresting (Frone and McFarlin 1989). Job dissatisfaction represents individuals' overall thoughts towards their job. The job overload, job ambiguity, and job conflict are the major job stressors in mining industry.

2. 5 Job involvement

Job involvement indicates the degree to which the workers are concerned about their work for improving safety and productivity. Researchers show that job involvement has direct impact on the accident and injury in mines.

3.0 Structural Equation model

Structural equation models provide a broad framework for modeling of means and covariance relationships in multivariate data. In social science and behavioural study, it is not clear whether each of variables in the model causally influence the other variables; hence, the model allows them to co vary. In SEMs, such a relationship is typically depicted by a double headed curved arrow (Maruyama et al. 1980). Variables of these types, whose causes are unknown in the model, are termed exogenous. The exogenous variables are considered to be affected by other variables in the model; and, they are termed endogenous. In the path diagram, a straight line with a single arrowhead indicates that the variable closest to the arrowhead is proposed to be caused by the variable from which the line emanates. The relationship between exogenous and endogenous variables are denoted by gamma (γ) and between the endogenous variables are denoted by beta (β) parameters. Zeta (ζ) parameter represents the residual variance.

In factor models, a vector of observed variables $\boldsymbol{Y_i}$ is considered to obtain by random sampling from a multivariate normal distribution denoted by $\boldsymbol{N}$ ($\nu + \Lambda \boldsymbol{f_i}$;$\Sigma$), where $\boldsymbol{f_i}$ is the vector of latent variables; Λ is the factor loadings matrix describing the effects of the latent variables on the observed variables; ν is the vector of intercepts and Σ is the covariance matrix. In SEMs the focus is also on studying relationships among the factors. For this purpose, the distinction between the measurement model and structural (latent) model is common. The measurement model specifies the relationships of the latent to the observed variables, whereas the structural model specifies the relationships among the latent variables. Following the standard structural equation modeling notation, as in Bollen (1989) and JÄoreskog and SÄorbom (1996), the measurement model is, for i = 1,…, N observations,

$$\boldsymbol{y}_i = \boldsymbol{\nu}_y + \boldsymbol{\Lambda}_y \boldsymbol{\eta}_i + \boldsymbol{\delta}_i^y, \qquad (1)$$

$$\boldsymbol{x}_i = \boldsymbol{\nu}_x + \boldsymbol{\Lambda}_x \boldsymbol{\xi}_i + \boldsymbol{\delta}_i^x, \qquad (2)$$

where model (1) relates the vector of indicators $y_i = (y_{i1},\dots, y_{ip})$ to an underlying m-vector of latent variables $\eta_i = (\eta_{i1},\dots,\eta_{im})$, $m \le p$, through the p x m factor loadings matrix Λ_y. Similarly, (2) relates $x_i = (x_{i1},\dots, x_{iq})$ to an n-vector of latent variables $\xi_i = (\xi_{i1},\dots,\xi_{in})$, $n \le q$, through the q x n matrix Λ_x. The vectors δ_i^y and δ_i^x are the measurement error terms, with dimensions p x 1 and q x 1, respectively. The vectors ν_y, px1 and ν_x, qx1 are the intercept terms of the measurement models.

On the other hand, the structural (latent variable) model is focused on studying the relationships among latent variables, η and ξ. This is performed by regressing the dependent vector, η, on the explanatory vector ξ as follows, i = 1,…,N

$$\underset{(m\times1)}{\eta} = \underset{(m\times m)\,(m\times1)}{B\eta} + \underset{(m\times n)\,(n\times1)}{\Gamma\xi} + \underset{(m\times1)}{\zeta} \qquad (3)$$

where, η is an m×1 random vector of endogenous variable, ξ is a n×1 random vector exogenous variable, Γ is an m×n matrix of coefficient of the ξ - variables in the structural relationship, B is an m×m matrix of coefficient of the η - variables in the structural relationship, ζ is an m×1 vector of equation errors (random disturbances) in the structural relationship between η and ξ, m is the number of endogenous variables, n is the number of exogenous variables

The main limitation of the standard SEM is the assumption of multi-variate normality of the latent variables. Therefore, to model the causal relationship with categorical or binary data, direct use of standard SEM gives an erroneous result.

Researchers have proposed different preprocessing steps for handling categorical variables in SEM. Browne (1984) proposed an asymptotic distribution free (ADF) estimator by taking into account kurtosis in joint multivariate distribution. The ADF estimation generally requires large samples and difficult to handle binary variable with sufficient precision. Bollen and Stinein (1993) suggested using resampling techniques like jacknife or bootstrap with robust maximum likelihood estimator (MLE) to obtain the standard errors of SEM parameters. Since, the parameters are estimated using MLE, the samples generated by resmapling algorithm will be close to normally distributed. Joreskog and Soerbom (1994) proposed a preprocessing step for standard SEM where polyserial correlations for pairs of variables used instead of covariance by assuming that these variables have an underlying (latent) continuous scale whose large sample joint distribution is bivariate normal. Muthén (1994) proposed a method where in first step a probit or logit model is estimated for observed categorical variables and then probit and logit score values are used as input for standard SEM. The last two strategies critically depend on how well the first-level model fits the data.

3.1 Bayesian approach for parameters estimation

Instead of ML or GLS estimator of standard structural equation model and the preprocessed SEM models, the Bayesian approach is based on exact posterior distributions for the parameters and latent variables estimated by Markov chain Monte Carlo. As sample sizes increase, Bayesian and standard estimators of the parameters should converge. However, an appealing feature of the Bayesian approach is that posterior distributions are obtained not only for the parameters, but also for the latent variables.

The Bayesian approach yields estimates of the exact joint posterior distribution of the latent variables. This posterior distribution can be used for: (a) to obtain point and interval estimates for the factor scores of each individual; (b) formally compare the factor scores for different subjects (e.g., through a posterior probability that the score is higher for a particular subject); (c) assess whether a particular subject's factor score has changed over time; (d) Identify outlying subjects in the tails of the latent variable distribution; and (e) assess relationships that may not be fully captured by the basic modeling structure.

The Bayesian model requires the specification of a full likelihood and prior distributions for the parameters. The complete data likelihood, including the latent variables, has the following form:

$$\mathcal{L}(\boldsymbol{y},\boldsymbol{x},\boldsymbol{\eta},\boldsymbol{\xi};\Theta) = \prod_{i=1}^{N} \Big\{ N_p\left(\boldsymbol{y}_i;\boldsymbol{\nu}_y + \boldsymbol{\Lambda}_y\boldsymbol{\eta}_i, \boldsymbol{\Sigma}_y\right) N_q\left(\boldsymbol{x}_i;\boldsymbol{\nu}_x + \boldsymbol{\Lambda}_x\boldsymbol{\xi}_i, \boldsymbol{\Sigma}_x\right) \times \times N_m\left(\boldsymbol{\eta}_i;\boldsymbol{\alpha} + \boldsymbol{B}\boldsymbol{\eta}_i + \boldsymbol{\Gamma}\boldsymbol{\xi}_i, \boldsymbol{\Omega}_\zeta\right) N_n(\boldsymbol{\xi}_i;\boldsymbol{\mu}_\xi, \boldsymbol{\Omega}_\xi) \Big\} \tag{4}$$

where $\Theta = (\alpha, b, \gamma, \nu_x, \nu_y, \lambda_x, \lambda_y, \sigma_y^2, \sigma_x^2, \omega_\zeta^2, \mu_\xi, \omega_\xi^2)$ is the vector of model parameters.

To complete a Bayesian specification of the model, the priors for each of the parameters in Θ has to specify. For convenience, normal or truncated normal priors are selected for the free elements of the intercept vectors, ν_x, ν_y and α, the factor loadings λ_x and λ_y, and the structural parameters b and γ. For the variance component parameters, including the diagonal elements of $\Sigma_y, \Sigma_x, \Omega_\zeta$, and Ω_ξ, the inverse-gamma priors are selected. The reason of selecting the inverse-gamma prior is for avoiding high variance priors for the latent variable variances. The bounds on the truncated normal are chosen to restrict parameters that are known from the collected sample.

The joint posterior distribution for the parameters and latent variables is computed, applying Bayes' rule

$$\pi(\Theta, \xi, \eta | y, x) = \frac{\mathcal{L}(y, x, \eta, \xi; \Theta)\pi(\Theta)}{\int \mathcal{L}(y, x, \eta, \xi; \Theta)\pi(\Theta) d\eta d\xi d\Theta}, \quad (5)$$

The Bayesian formulation of SEM implies that the posterior distribution of parameters is computed by the complete data likelihood multiplied by the prior and divided by the marginal likelihood. The data likelihood and priors can be easily calculated; however, the calculation of the marginal likelihood is very challenging, because it typically involves a high dimensional integration of the likelihood over the prior distribution. In this paper, instead of calculating the marginal likelihood mathematically, MCMC technique has been applied to numerically obtain the marginal likelihood values by generating random draws from the joint posterior distribution. Due to the conditionally normality structure of the SEM and to the choice of conditionally conjugate truncated normal and inverse-gamma priors for the parameters, MCMC computation can be performed by Gibbs sampling algorithm (Geman and Geman,1984; Gelfand and Smith,1990).

The conditional posterior distributions for the latent variables, $\eta_{i,}$ ξ_i and the structural parameters α , b and γ are derived to obtain the joint posterior of Eq. (5) which is used for random sampling by MCMC methods.

Using Eq. (5) and factoring the joint posterior, the conditional posterior for the endogenous latent variable can be calculated as:

$$\pi(\eta_i | \nu_y, \Lambda_y, \Sigma_y, \widetilde{\mu}_{\eta i}, \widetilde{\Omega}_\eta,\ y_i) \propto \pi(y_i; \nu_y + \Lambda_y \eta_i, \Sigma_y) \cdot \pi(\eta_i; \widetilde{\mu}_{\eta i}, \widetilde{\Omega}_\eta)$$

where, $\widetilde{\mu}_{\eta i} = A[\alpha + \Gamma \xi_i],\ \widetilde{\Omega}_\eta = A\ \Omega_\zeta A'$ and $A = [I_{m \times m} -\ B]^{-1}$

The conditional posteriors of exogenous latent variables, structural parameters and intercepts are also be calculated and discussed in Dunson et al. (2003). Once all the full conditional posteriors are computed, the Gibbs sampling algorithm can be implemented. The Gibbs sampling is an iterative algorithm by initializing the parameters and updating all conditional posterior and thus the join posterior to converge the true parameters value.

4. 0 Methods and Materials

4.1 Data collection

The study was conducted in an underground coal mine in India. The mine employs 592 underground workers. The sample comprised of 160 employees who were randomly selected from all the employees. The higher management of the mine was excluded from the study since they were not directly exposed to the mine environment on daily basis. The multiple-item worker response devices were prepared to assess the socio-physical behaviour of mine workers. The null hypothesis was framed assuming there is no significant difference in the technical and behavioural parameters between accident and no-accident group. Sixteen (16) variables were identified which might have causal relationship with work injuries and questionnaires were framed to obtain responses from the participants workers for each of the variables. A five-Point Likert-type scale format was used to measure employees' participation of each item. Injury data was then matched with each employee's questionnaire responses. Injuries refer to accidents at work, which result in physical incapacitation, absence from work, and compensation paid to the injured worker. The basic statistics of the 16 measured variables based on the questionnaires survey are presented in Table 1.

Table 1 Basic statistics of measured variables

	INV	SPR	JB	JD	JS	PHZ	PDPR	REB	IMP	RISK	NA	DEP	COS	SOS	MWI
Mean	42.92	68.56	8.1	23.1	26.26	28.81	8.54	7.8	19.39	28.55	25.8	8.78	18.79	10.22	35.5
SD	7.55	8.68	2.97	7.03	5.45	6.71	2.82	1.77	3.45	7.56	6.84	3.10	2.03	2.24	7.14

*REB-Rebelliousness, IMP-Impulsivity, RISK-Risk-taking, NA-Negative affectivity, DEP-Depression, JB-Job boredom, JD-Job dissatisfaction, JS-Job stress, PHZ-Physical hazards, PDPR-Production Pressure, COS-Coworker support, SOS-Supervisory support, MWI-Management worker interaction, SPR-Safety practice, INJ-Injury, INV-Involvement.

4.2 Bayesian structural model

The proposed work injury model is presented as a path diagram in Figure 1. The diagram shows there are thirteen *x*-variables such as job boredom, job dissatisfaction, job stress, physical hazards, production pressure, rebelliousness, impulsivity, risk-taking, negative affectivity, depression, co-worker support, supervisory support, and management–worker interaction and three exogenous latent such as job hazards, personality, and social support. There are three endogenous latent variables such as work injuries, safety practices, and job involvement each with one *y*-indicator. The three latent variables personality, job hazards and social support are considered as important factors causing injury.

In the Bayesian structural equation modeling, the prior specification involves quantifying expert's uncertainty in the model parameters Θ. In the cases where not much information is available other than the observed data, objective priors are generally selected (Berger, 1985; Bernardo and Smith, 1994). Here, the priors based on expert opinion were considered. All the opinions collected on the priors distribution of the parameters for this study were expert based. A total number of 30 officials including overman and mining sirdar were selected randomly as experts from the case study mine. The experts are requested to evaluate individual workers against the response to the sixteen variables based on their daily performances. The experts' opinions are rescaled within 0 to 10. The frequency distribution of the opinion results were fitted with proper theoretical distribution function using χ^2 method. Based on the prior distribution, the posterior distribution of work injury was computed using the Bayesian rule as discussed earlier. A Gibbs sampling algorithm was applied to obtain samples from the posterior distributions of work injuries. The R2WINBUGS software is used for posterior calculation and Gibbs sampling. The algorithm is run for 20,000 iterations.

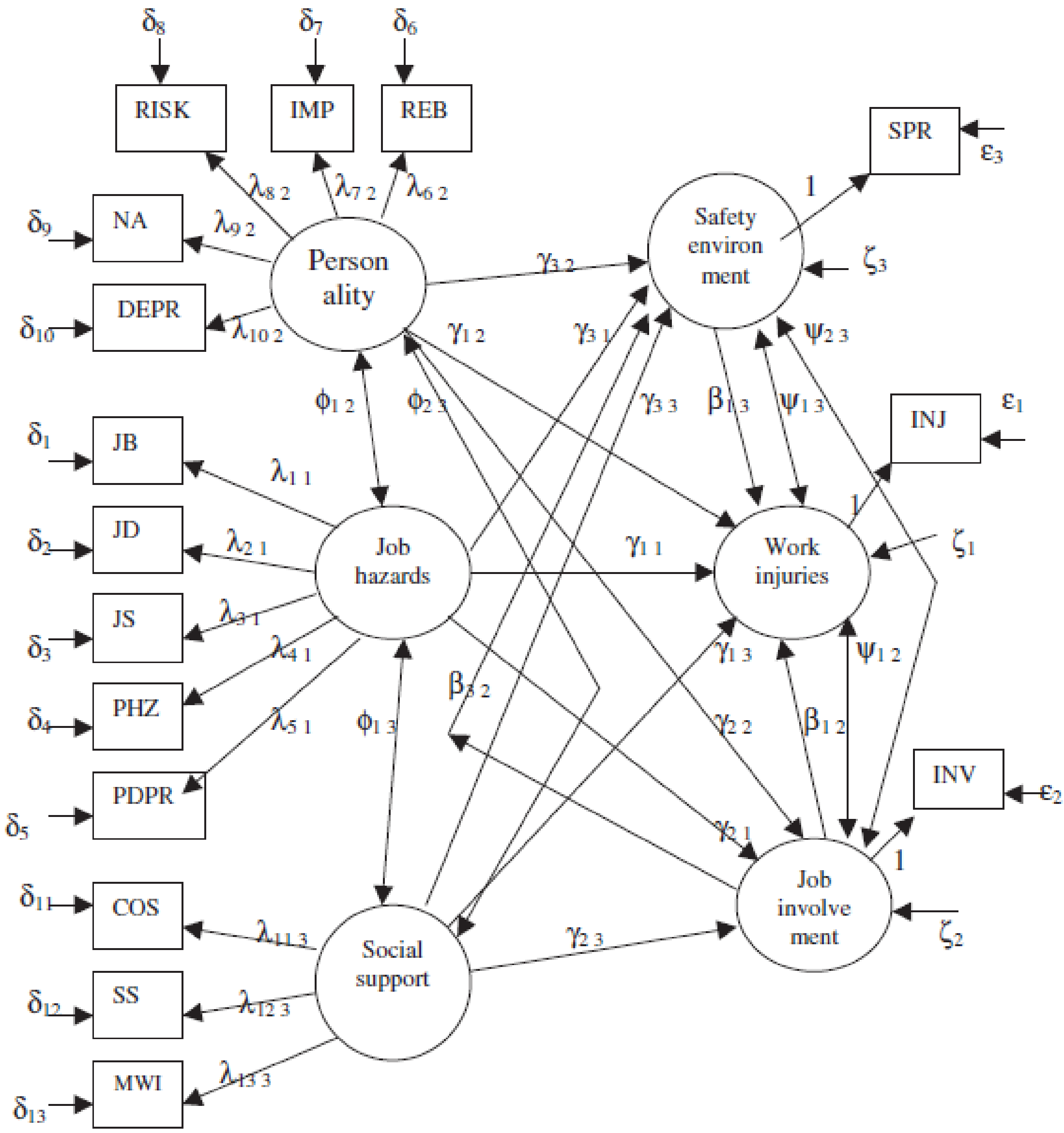

Figure1. Hypothesized path diagram of the casual accident model (Maiti et al. 2004)

Table 2 presents the mean and standard deviation of estimated parameters using the Bayesian SEM. To calculate the priors, two methods were adopted: (a) by using the estimates of SEM where polyserial correlations are as inputs for SEM model (Joreskog and Soerbom, 1994); and (b) from expert opinions. The frequency distribution of the experts' opinion fitted with an appropriate theoretical distribution by Chi-squared method and the mean and standard deviation were calculated from the fitted distribution. The prior standard deviation value of method (a) was selected arbitrarily. The reason for arbitrarily selecting the standard deviation values is that the distribution of the prior doesn't have much influence on Bayesian SEM model. It can clearly be observed from Table 2 results. For an example, the priors 95% probability interval for the influence job involvement on the work injuries is [-5.15, 4.85] under the MLE priors and [-3.63, 3.49] under expert's opinion priors. The posterior interval of these probability intervals are narrow to [-0.246, 0.546] and [-0.262, 0.582]. This results show the convergence of the posterior after observing the data, regardless of the starting prior knowledge.

Table 2 Estimated mean and standard deviation of parameters of SEM using different techniques

	Bayesian SEM with MLE priors				Bayesian SEM with expert's opinion prior			
	Prior		Posterior		Prior		Posterior	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
λ_{11}	0.02	1.5	0.019	0.96	1.0	1.1	0.02	0.98
λ_{12}	0.55	2.5	0.56	0.122	1.5	2.05	0.55	0.13
λ_{13}	-0.11	2.5	-0.13	0.19	0	1.22	-0.12	0.18
λ_{21}	-0.25	2.5	-0.26	0.269	0.5	1.53	-0.23	0.28
λ_{22}	-0.62	2.5	-0.63	0.298	-0.5	1.07	-0.60	0.31
λ_{23}	0.32	2.5	0.30	0.285	1.0	0.98	0.33	0.295
λ_{31}	-0.50	2.5	-0.51	0.322	0.08	1.5	-0.52	0.35
λ_{32}	-0.02	1.5	-0.02	0.082	0.1	1.25	-0.01	0.079
λ_{33}	0.19	2.5	0.2	0.19	0.16	1.11	0.21	0.2
β_{12}	-0.15	2.5	-0.15	0.198	0.07	1.78	-0.16	0.211
β_{13}	-0.03	1.5	-0.02	0.1	0.5	1.9	-0.02	0.12
β_{32}	0.02	1.5	0.02	0.12	0.2	2.1	0.03	0.121

The goodness-of-fit indices for the causal accident model for Bayesian SEM are presented in Table 3 for parameter work injury. Root mean squared error, mean absolute error, and R^2 are considered for performance measures of the developed model. The root means squared error for the model by Bayesian SEM is.025, indicating an acceptable fit of the model. The root mean squared error is a measures of the average variance unaccounted for by the model (Hansen, 1989). The high R^2 value revealed that the model developed by using Bayesian approach can provide reasonably good fit model of work injury.

Table 3 Goodness-of-fit indices for work injury

Statistics	Bayesian SEM
R^2	0.91
Mean absolute error	0.26
Root mean squared error	0.025

The Bayesian estimate of SEM also reveals that out of 33 considered causal parameters 19 variables are significant.

Job stress is a significant parameter in Bayesian SEM having influenced negatively by work environment. Job stress doesn't have any significant impact on safety practices; however anxiety is significantly related to job stress.

The relation of job satisfaction with safety environment and social support with work injury are significant in Bayesian analysis. The results support the general concept that good social support can reduce the work injury by significant amount.

5. Conclusion

This paper presents the work injury modeling using structural equation model within the Bayesian framework. The causal relationship of the different technical and behavioral factors was developed and the relationship was analysed via structural equation modeling. The model was applied in an underground coal mine in India. The SEM was iteratively solved in Bayesian context and the sample was randomly drawn from the posterior distribution using Gibbs sampling. The prior distribution of these parameters were obtained by two ways: (a) obtaining mean values from the MLE based SEM with poly-serial correlation as input parameter and assuming arbitrary standard deviation with Gaussian distribution; (b) mean and variance were obtained from experts' opinions and fitted the sample distribution with an appropriate theoretical distribution by Chi-squared method. The comparative results of MLE-based estimation and experts' opinions based estimation revealed that the second approach provides better results in terms of minimizing the errors. The error statistics results revealed that the Bayesian framework in the structural equation model provide reasonably good fit model with high coefficient of determination (0.91). The Bayesian model is a robust approach for SEM since it doesn't need any assumption of the distribution function like normality.

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