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Identifying the Safety Risk Factors of Falsework during Building Construction Project through Partial Least Square Structural Equation Modelling

Mohd Rafe Abdul Majid[1], Haikal Afies Mohammed Samsudin[2], Raja Nor Husna Raja Mohd Noor[3], Juzailah Nur Yunus[4]

[1,2,3,4]School of Civil Engineering, College of Engineering, Universiti Teknologi MARA, Cawangan Pulau Pinang, Malaysia

Corresponding Author Email: rafebanu@uitm.edu.my

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Abstract

A temporary structure known as falsework is crucial for supporting the weight of building materials, labor, and equipment during building construction projects. However, falsework also poses significant safety risks to both workers and the public. The collapse of falsework can lead to serious injuries, fatalities, and substantial financial losses. Therefore, it is imperative to identify safety risk factors associated with falsework to minimize accidents and ensure a secure working environment. This study, focused on territory of Seberang Perai Tengah, Penang, with utilizes Structural Equation Modeling (SEM) to ascertain safety risk factors related to falsework in Malaysian building construction projects. The aim of this research is to help stakeholders in term of reducing accidents and promoting a safe working environment for workers. The research combines a quantitative approach through a questionnaire survey and a case study project to achieve its goals. The data collection process involves distributing questionnaires to selected individuals with experience related to falsework. The targeted study area comprises skilled workers competent in handling falsework, including Architects, Quantity Surveyors, Project Managers, Falsework Specialists, Safety Officers, and Falsework Installers. Surveys were disseminated to a sample size of 119 individuals, targeting companies located in Seberang Perai Tengah, Penang. Furthermore, the study incorporates a literature review to identify key variables related to stakeholders' behavior towards technology changes and safety performance, encompassing human, technical, management, and environmental factors. A conceptual framework is developed as the final product of this research, and hypotheses are formulated to establish relationships between these variables. Data collected through the survey is analyzed using SEM techniques to validate the hypotheses. Based on the developed framework, the main findings of research

show the most contributing factors to the falsework failure are technical factors combined with either management factors or environment factors. By referring to the developed framework, guidelines can be utilized by companies in the construction industry and government regulators to ensure that safety standards are met, thereby safeguarding workers from undue injury. This research is instrumental in enhancing the safety and well-being of construction workers in Malaysia by understanding the relationship between safety risk factors associated with falsework and their causes.
Keywords: Safety Risk Factors, Falsework, Partial Least Square, Structural Equation Modelling, Accident.

Introduction

Construction projects often need temporary structures to hold up the building or structure while it is being built. These temporary structures are called falsework, and they are very important for keeping the construction site stable and safe. But if falsework fails or falls, it can pose serious safety risks that could lead to serious injuries or even death (International Organization for Standardization, 2020). In infrastructure projects, figuring out the risks of falsework structures that could cause them to fail or fall is called "identification of falsework risk failure." This process involves evaluating the installation and the condition of the falsework, as well as the environmental conditions and site-specific factors that could affect the stability of the structure. This involves a thorough analysis of the falsework's failure factor and how it will affect the falsework structure's failure. For example, excessive loading on the falsework structure and poor installation of the falsework structural can both be harmful to the falsework structure. This evaluation should also consider any environmental factors, like wind loading, that could affect the stability of falsework structure. In addition to the risk assessment, the falsework structure needs to be checked and maintained regularly so that any signs of instability or possible failure can be found. This includes visually inspecting the structure, testing how much weight it can hold, and looking for signs of damage or wear. By figuring out how likely it is that falsework will fail in infrastructure projects, construction professionals can take steps to reduce the risks and keep workers and the public safe. According to the National Institute for Occupational Safety and Health (NIOSH), one of the most important parts of construction safety is to find and deal with falsework risks. NIOSH recommends that employers do regular inspections and risk assessments of all falsework structures to make sure they are safe and sound, and that workers get proper training on how to spot and report potential hazards (NIOSH, 2018).

To prevent accidents, we need to know the causes and types of accidents in the working environment, such as technical factors, management factors, and environmental factors that lead to accidents. So, this research aims to identify the significant relationship between safety risk factors of falsework and types of accidents that occurred during a building construction project.

Literature Review

An accident can be defined as an unplanned, undesirable, unexpected, and uncontrolled event. An accident does not necessarily result in an injury. It can be in term of damage to equipment and materials and especially those that result in injuries receive the greatest attention (Hinze et al., 1997). In high-rise building construction project, accidents mostly occur at temporary structures that the failure prone than the permanent structure because it is easily getting damaged due to frequent dismantle and reuse (Sofwan et al., 2016). It is extremely difficult to talk about construction safety management in the absence of an understanding of the causes of accidents. Before one can embark on effectively and efficiently improving safety on the project site, one must first understand the theory of accident causation and prevention. Theories of accident causation are used to predict and prevent accidents in construction project. The famous accidents causation models started from domino theory produced by Heinrich in 1930 and multiple causation theory developed by Petersen in 1971.

Falsework means the temporary structure used to support a permanent structure, material, plant, equipment and people until the construction of the permanent structure has advanced to the stage where it is self-supporting. The utilization of temporary structures, such as falsework, is becoming more widespread to accommodate the growing complexity of infrastructure projects. Temporary structures are systems designed for brief durations of time, as in the case of staged performances, maintenance, or retrofitting. Other than that, A falsework is also temporary structure that is used to support building activities. If it is not planned and maintained correctly, it poses a considerable risk to the construction workers' safety. During infrastructure projects, it is essential to identify and mitigate any safety risks that are associated with falsework. This will ensure the safety of construction workers as well as the general public. As a result, the purpose of this literature review is to identify and evaluate the existing research on the safety risk factors associated with falsework in construction projects.

Previous research from 2021 has found a number of safety risk concerns that are connected with falsework. Some of these risk factors include faulty design, inadequate inspections, and inadequate worker training. For instance, (Alshammari, 2021) discovered that insufficient inspections of falsework might lead to undetected corrosion or deterioration, which can raise the probability of failure in the structure. In a similar vein, discovered that faulty design of falsework can lead to structural failure, which in turn can result in personal injuries or even fatalities. Because workers may lack the necessary knowledge or skills to safely work with falsework, inadequate training of workers can also increase the risk of injury or fatality (Zhang et al., 2019).

Although earlier research has pinpointed a few potential safety hazards associated with falsework, there is still a requirement for a more in-depth examination of the published research in this field. This gap in knowledge will hopefully be filled by this literature review, which will provide a comprehensive analysis of the published research on safety risk factors associated with the use of falsework in construction projects. The purpose of this evaluation is to provide a better knowledge of the safety hazards connected with falsework and to propose new pathways for future research and the improvement of safety in infrastructure projects. This will be accomplished by identifying and analyzing the research that has already been conducted. The findings of this literature review can, in the long run, be used to inform the establishment of best practices for the safe design and maintenance of falsework, hence enhancing the safety outcomes of construction projects.

Methodology

The research instrument is a questionnaire. This method is chosen as it is one of the most widely used and accepted instruments for research purposes (Sekaran, 2006). The items from the existing literature and former researches were adopted and adjusted to construct the questionnaire items in order to make sure that all the important points are covered during measurement. The total number of 50 copies of questionnaire was distributes personally and others via google form. The sample size for this research was 255 companies in Penang. Quantitative method was used in this research as it is more structured than the qualitative method of data collection. Hence, the data was collected by using the questionnaire. As stated above, the method used in this research for data collection process was the questionnaire as it is found to be easier for the collection of data from the respondents. The answers to the questions were recorded by taking input from the respondents and without the need for an interview. In analyzing the data, SPSS software version 26.0 was used for respondents' demographics such as nature of company, types of company, age of company, gender, position in the company, working experience and qualification. The data analysis adopted for both independent and dependent variables was Smart PLS version 3.3.7. Five- point Likert scale was adopted to measure the independent and dependent variables which range from (1) strongly disagree, (2) disagree, (3) moderately, (4) agree, to (5) strongly agree.

Result and Discussion

Demographic Respondents

A total of 119 questionnaires were distributed via Google Form by forwarding the online form's link to respondents' emails or WhatsApp's. The aim of the survey was to gather data on select construction projects in Penang, involving clients, consultants, contractors, and workers. The survey targeted consultants and contractors, including skilled workers that are competent in handling falsework such as Architect, Quantity Surveyor, Project Manager, Falsework Specialist, Safety Officer, and Falsework Installer. By including a diverse range of professionals, the survey aimed to capture insights from different perspectives within the construction industry. As shown in Table 1, respondents with work experience of 1-3 years, 3-5 years, 5-10 years, and more than 10 years were approximately 39.7%, 44.4%, 15.9%, and 5.3%, respectively. The highest respondents' groups (44.4%) had 3-5 years of experience and more than 65% of respondents had more than 3 years' experience. These results collectively indicate the high qualifications and experience level of the respondents. As such, some level of confidence in their input can be exercised. Most respondents were site supervisor (35.1%) followed by project manager (31.8%), project directors (19.9%), safety officer (11.9%), falsework specialist (7%) and others (7%). The respondents' academic credentials were 45.0%, 41.7%, 13.2, and 6.94% for DIP, BS, MS degrees, secondary school, respectively.

Table 1
Demographic Respondents

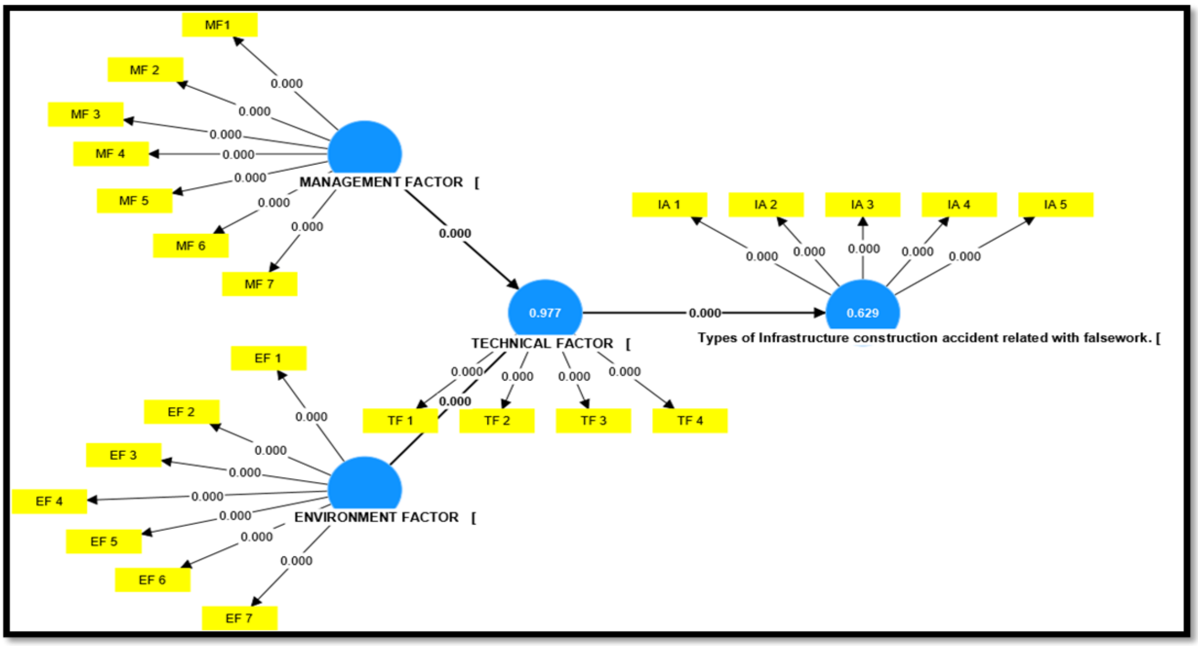
Type	Items	Percentage (%)
Gender	Female	45
	Male	55
Age	20 29 Years	31.1
	30- 39 Years	54.3
	40-49 Years	18.0
	>50 Years	2.6
Qualification	Unknown	11.11
	Secondary School	6.94
	Diploma	45.0
	Bachelor	41.7
	Master	13.2
Position	Project Director	19.9
	Project Manager	31.8
	Safety officer	11.9
	Falsework Specialist	7
	Site Supervisor	35.1
	Others	7
Working Experience (Years)	1 - 3 Years	39.7
	3 - 5 years	44.4
	5 - 10 Years	15.9
	> 10 Years	5.3
Number of years in construction field	1 - 3 Years	50.7
	3 - 5 years	25.0
	5 - 10 Years	8.3
	> 10 Years	16.0
Major types of construction involved	Bridges construction	14.6
	Commercial Building	23.6
	construction	58.3
	High Rise Building	3.5
	construction	
	Hospital	

Developing a Framework Model

Smart PLS 3.3.7 vision validated the model, and the Tenenhaus et al (2005), criteria were used to assess the model's overall quality. The framework model consists of three stages: a first-stage measurement model test, a second-stage structural model test, and a third-stage quality test model.

Stage 1: Measurement Model Test Result

Figure 1 below show the result from measurement model test. The developed measures' convergent and discriminant validity assures both the reliability of the scales and the distinction of various sub-factors tested separately inside the measurement model. To examine the measuring model's convergent and discriminant validity, scale reliability and



construct sub-factors were evaluated. Henderson et al. (2012) conducted validity tests to demonstrate the measurement model's dependability, as well as assessments of convergent and discriminant validity.

Figure 1. Measurement Model

i. Loading Factor

Acceptance of outer loadings in Smart-PLS and structural equation modelling is conditional on meeting particular requirements. To validate the signs, researchers often seek considerable and substantial outer loadings. Adequate outer loadings, generally more than a predefined threshold such as 0.7, indicate that the indicator accurately represents the underlying concept. These loadings demonstrate a strong link between observed variables and underlying components in the model. Verifying that exterior loadings satisfy established criteria is critical for proving the measurement model's reliability and validity in structural equation modelling.

The Table 2 shows the result for outer loadings in the structural equation model was deemed acceptable based on the set criterion, which is normally 0.7 or higher. The loadings for indicators representing multiple latent constructs—Environment (EF), Management (MF), Technical (TF), and Accident (TA)—show consistently strong connections. All Environment indicators had loadings more than 0.7, ranging from 0.823 to 0.884, indicating strong connections to the latent construct. All loadings in the Management indicators surpass 0.7 (range from 0.772 to 0.878), indicating substantial correlations. Similarly, the Technical and Accident indicators show loadings greater than 0.7, with values ranging from 0.823 to 0.908 and 0.795 to 0.882, respectively. Overall, the consistently high loadings across all latent components show that the presented data supports the measurement model's reliability and validity.

Table 2
Loading Factor

	Environment	Management	Technical	Accident
EF 1	0.823			
EF 2	0.883			
EF 3	0.88			
EF 4	0.884			
EF 5	0.869			
EF 6	0.871			
EF 7	0.848			
MF 1		0.772		
MF 2		0.868		
MF 3		0.878		
MF 4		0.856		
MF 5		0.849		
MF 6		0.838		
MF 7		0.798		
TF 1			0.908	
TF 2			0.823	
TF 3			0.877	
TF 4			0.897	
TA1				0.795
TA2				0.882
TA3				0.829
TA4				0.844
TA5				0.806

ii. Composite Reliability

During this phase, the evaluation focuses on internal consistency reliability, with Jöreskog's (1971) composite reliability being often used. Increased values indicate a better level of reliability. Ratings of dependability between 0.60 and 0.70 are regarded as "acceptable in exploratory research," while ratings between 0.70 and 0.90 are rated "satisfactory to good." Values greater than 0.95 indicate the possibility of item duplication, which might have an influence on construct validity, as observed by Diamantopoulos et al (2012), and Drolet (2001). Furthermore, convergence validity assesses how well a group of variables measures a notion.

iii. Convergent Validity

Convergence validity evaluates the ability of a group of variables to measure a notion. All loadings greater than 0.5 were approved. According to Hari (2010), the Composite Reliability (CR) assesses the group's ability to uncover latent components inside a model. The CR and Average Variance Extracted (AVE) details are shown.

iv. Average Variance Extracted (AVE)

Each experimental element had an AVE greater than 0.5, suggesting that the research constructs achieved convergent validity under the stated conditions. Ridwan et al. (2020) used Cronbach's alpha and composite reliability to analyze the measurement model's internal consistency. All variables in Table 3 exceeded the 0.5 criterion, with the "Effect of Delay" variable having the highest value at 0.572. According to Silaparasetti et al. (2017), composite reliability was crucial in determining construct reliability and internal consistency. The composite dependability of these three components is emphasized in build reliability assessments and internal stability estimates. Notably, all research constructs had a composite reliability greater than 0.70.

Table 3
Average Variance Extracted (AVE)

	Cronbach's alpha	Composite reliability (rho’a)	Composite reliability (rho’c)	Average variance extracted (AVE)
EF	0.944	0.946	0.954	0.75
MF	0.929	0.935	0.943	0.702
TF	0.899	0.907	0.93	0.768
TA	0.888	0.89	0.918	0.692

v. Discriminant Validity

Hulland (1999) defines discriminant validity as the extent to which a construct inside a model demonstrates variations unique from other constructs. It needs distinct distinctions between the sub-factors of each construct inside the model. Fornell (1981) claimed that diagonal elements in a matrix have greater relevance than columns and rows, and that this might be used to establish discriminant validity. The experimental evaluation of discriminant validity seeks to assess an idea's distinctiveness in the context of other structural model concepts. Fornell (1981) proposed a standard measure that compares each construct's Average Variance Extracted (AVE) to the squared inter-construct correlation, which represents shared variance with all other reflectively assessed structural model components. The shared variances are expected to be lower than the AVEs for each project. Recent study, however, calls this metric's efficacy in determining discriminant validity into question.

Table 4
Cross Loading

	EF	MF	TF	TA
EF1	**0.823**	0.765	0.804	0.604
EF2	**0.883**	0.818	0.848	0.692
EF3	**0.88**	0.84	0.867	0.713
EF4	**0.884**	0.883	0.883	0.69
EF5	**0.869**	0.863	0.833	0.657
EF6	**0.871**	0.873	0.88	0.648
EF7	**0.848**	0.793	0.812	0.634
MF1	0.772	**0.818**	0.808	0.601
MF2	0.868	**0.874**	0.813	0.801
MF3	0.878	**0.879**	0.872	0.687
MF4	0.842	**0.856**	0.812	0.649
MF5	0.785	**0.849**	0.807	0.61
MF6	0.81	**0.838**	0.821	0.606
MF7	0.701	**0.798**	0.746	0.607
TF1	0.86	0.898	**0.908**	0.776
TF2	0.834	0.789	**0.823**	0.614
TF3	0.857	0.867	**0.877**	0.672
TF4	0.883	0.879	**0.897**	0.713
TA 1	0.652	0.669	0.669	**0.795**
TA 2	0.626	0.63	0.641	**0.882**
TA 3	0.665	0.683	0.701	**0.829**
TA 4	0.662	0.682	0.686	**0.844**
TA 5	0.574	0.589	0.601	**0.806**

The result obtained from Table 4 shows for the Environmental Factor in the structural equation model is deemed good, with loading values ranging from 0.823 to 0.848. A comparison with other factors, such as the, Management Factor, Technical Factor, and Falsework Accident, shows that the Environmental Factor indicators have significantly higher values. This observation implies a strong link between the indicators and their latent construct, emphasizing the model's effective description and measurement of the Environmental Factor. The result also show the Management Factor is deemed satisfactory, with loading values ranging from 0.701 to 0.878. These values are much higher when compared to other components, indicating a significant and distinct link with the latent construct. The data's acceptance demonstrates the effectiveness of the chosen indicators in effectively expressing the Management Factor within the structural equation model. Similarly, the result also show the Technical Factor is accepted, with loading values ranging from 0.857 to 0.908. These values outperform those of other variables on a constant basis, demonstrating a strong and distinct link with the Technical Factor. The data's acceptance demonstrates the usefulness of the selected indicators in accurately capturing the underlying notion within the model. Finally, the result is declared acceptable for the Falsework Accident Factor, with loading values ranging from 0.795 to 0.882. These values are much higher when compared to other components, indicating a strong and distinct link with the latent construct. The data's acceptance highlights the efficiency of the selected indicators in effectively capturing the Falsework Accident Factor within the structural equation model. Overall, these findings contribute to the measurement model's reliability and validity.

Stage 2: Structure Model Test Result

The Table 5 shows the data's acceptance is justified since it meets established hypothesis testing standards. In the context of statistical significance, where a p-value of less than 0.05 is typically used, the stated P values of 0 in all comparisons closely correspond to this requirement. This emphasizes the high degree of statistical significance and provides strong evidence against the null hypothesis. Furthermore, the criteria for a T value greater than 1.96, equivalent to a two-tailed significance threshold of 0.05, is consistently satisfied throughout the numerous comparisons. The T statistics, which range from 6.948 to 16.635, far exceed this criterion, strengthening the data's acceptability.

By meeting these criteria—achieving a p-value less than 0.05 and a T-value more than 1.96—the data not only exhibits statistical significance but also emphasizes the size of the observed changes in averages relative to standard deviations. The consistency of these results across many conditions and comparisons adds to the findings' dependability and validity. As a result, the data is widely accepted, suggesting strong evidence that the factors investigated, particularly those connected to falsework and technical issues, have a considerable impact on the frequency of infrastructure building accidents.

Furthermore, the Significance of Relationships investigation digs into the statistical significance of connections between variables inside the model. The structural model emphasizes the importance of the independent variable-dependent variable link. Hypothesis 1: Technical considerations have a substantial effect on the sorts of infrastructure building that lead to falsework failure. Based on the findings, TA2 had the greatest factor loading of 0.882 in influencing the types of infrastructure development associated with falsework failure. TA1 has the lowest effect of delay on infrastructure building activity, with a factor loading of 0.794.

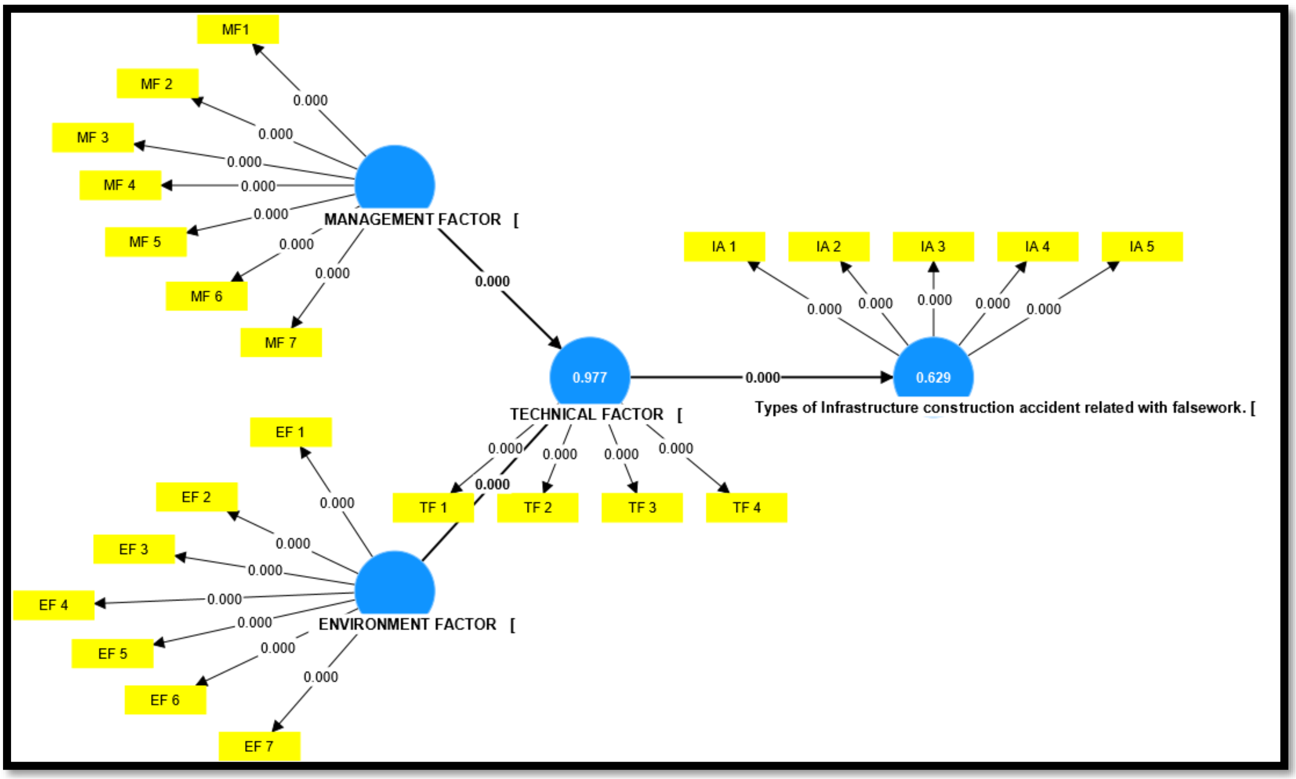


Figure 2. Structure Framework Model

Table 5
Hypothesis Testing

Hypothesis Testing

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ENVIRONMENT FACTOR [-> TECHNICAL FACTOR [	0.489	0.484	0.063	7.731	0
MANAGEMENT FACTOR [-> TECHNICAL FACTOR [	0.508	0.513	0.063	8.068	0
TECHNICAL FACTOR [-> Types of Infrastructure construction accident related with falsework. [	0.793	0.79	0.048	16.635	0

Stage 3: Quality Model Test Result

Smart PLS is a statistical approach within structural equation modelling (SEM) that is extensively used in social sciences and business research to analyze variable interactions. A quality model in the context of Smart PLS refers to the set of criteria and standards used to assess both the structural equation model and its outputs. This includes features such as dependability, which focuses on the consistency and stability of the measuring devices used in the model. The precision with which the model captures the underlying theoretical ideas is addressed by validity. Model Fit measures how well the structural model matches the observed data, whereas Predictive Power measures the model's ability to predict outcomes or behaviors.

i. R^2 Explained Variance

In the absence of collinearity problems, it is prudent to investigate the R^2 value(s) of the intrinsic construct. R^2 is a statistic used to evaluate the model's explanatory power, measuring the amount of variance explained by each endogenous component (Shmueli and Koppius, 2011). According to Rigdon (2012), R^2 also represents the model's in-sample predictive performance. The model's explanatory power improves as the R^2 values grow. R^2 values of 0.75, 0.50, and 0.25 are classified as substantial, moderate, and weak, respectively (Henseler et al., 2009), with R^2 values of 0.10 being adequate for stock return forecasts (Raithel et al., 2012). Importantly, R^2 should be interpreted within the context of the study framework and compared to other studies and models, since overfitting can falsely inflate R^2 values. Sharma et al. (2023) warn against overfitting, pointing out that overly high R^2 values may be caused by the advanced partial regression model fitting noise rather than properly reflecting the population. R^2 values of 0.90 are regarded appropriate for physical processes. It is worth noting that overfit models can predict attitudes, perceptions, and intentions with identical R^2 values, highlighting the importance of this criterion in elucidating how an independent variable influences a dependent variable and establishing links between structural equation modelling measurement and structural components.

Table 6
Explained Variance, R^2

	R^2	R^2 adjusted
Technical Factor [	0.977	0.977
Types of Infrastructure construction accident related with falsework. [	0.629	0.628

The table 6 shows data's acceptability is assessed by comparing the R^2 and modified R^2 values for the "Types of Infrastructure Construction Accident Related with Falsework." The R^2 value of 0.629 indicates that the model accounts for about 62.9% of the variance in the dependent variable. Meanwhile, the corrected R^2, which accounts for the number of predictors, falls marginally to 0.628. When compared to the adjusted R^2, the larger R^2 value indicates that the model has a substantially greater explanatory potential.
Moreover, comparing the R^2 and modified R^2 values for the technical factor. The value for both data is similar.

ii. Predictive Relevance, Q^2

In the context of predictive relevance, especially Q^2, the model's efficacy may be tested using two independent approaches: cross-validated redundancy and communality. The model is predictively significant and effectively rebuilt, as indicated by the Q^2 values in Table, which all surpass zero.

Table 7
Predictive Relevance, Q^2

	Q^2predict
TF 1	0.675
TF 2	0.778
TF 3	0.786
TF 4	0.758
TA 1	0.438
TA 2	0.388
TA 3	0.453
TA 4	0.452
TA 5	0.332

The Table 7 provided result includes Q^2predict values for different factors, specifically "TF" (Technical Factor) and "TA" (Infrastructure Accident). These values indicate the predictive relevance of the models for each factor.

For "TF," the Q^2predict values are 0.675, 0.778, 0.786, and 0.758 across four instances. These values, all greater than zero, suggest positive predictive significance for each TF model. Higher Q^2predict values generally indicate a stronger ability to predict outcomes consistently.

For "TA," the Q^2predict values range from 0.438 to 0.332 across five instances. While these values are positive, they are somewhat lower compared to the "TF" values. Nevertheless, positive Q^2predict values indicate that the TA models have predictive importance and can consistently predict events.

In summary, the data's acceptability is supported by positive Q^2predict values for both "TF" and "TA," indicating predictive relevance and the ability of the models to consistently predict outcomes. The higher Q^2predict values for "TF" suggest a relatively stronger predictive ability compared to the "TA" models.

iii. PLS Predict

Stone Geiser's criteria are useful in establishing the model's endogenous structure. Q grades are used to evaluate well-structured models, with values of 0.02, 0.15, and 0.25 indicating low, moderate, and good prediction, respectively. The majority of Q values for each dependent variable exceed 0.25, indicating that the structural model is both acceptable and predictive. The predictive power of independent variables is emphasized in the evaluation of relevant predictions, with PLS predicting Q scores for exact suggestions. Route coefficients must be statistically significant and advantageous after the model explains and predictions to ensure their relevance and utility. These coefficients, which serve as formative indicator weights, are evaluated via bootstrapping and range from -1 to +1. Understanding the influence of intervening constructs on a target construct is critical, especially in the context of moderation, which necessitates understanding the sort of impact. According to Shmueli et al., (2019), PLS prediction entails separating training samples from holdout data to estimate model parameters and assess the model's ability to predict future events. The paper investigates the Root Mean Squared Error (RMSE) benchmark in PLS- SEM and the linear regression model. When all indicators have higher RMSE (or MAE) values than the naive LM benchmark, PLS-SEM analysis becomes inaccurate. The model's strong predictability is validated when no PLS-SEM indicators have RMSE (or MAE) values greater than the naive LM's benchmark value. Table 8 shows that there are significant differences between RMSE(PLS) and RMSE(LM), indicating that the structural model has predictive power. Negative values are required for predictability. Notably, the PLS-RMSE SEM outperforms the naïve LM when many indicators have RMSE values greater than the benchmark value. Figure depicts the important factors between the delay factor and the effect of delay on infrastructure development works, with the management factor and the resource allocation factor recognized as relevant variables.

Table 8
PLS Predict

	PLS- SEM_RMSE	LM_RMSE	Differences
TF 1	0.541	0.352	-0.189
TF 2	0.447	0.316	-0.131
TF 3	0.437	0.466	0.029
TF 4	0.46	0.414	-0.046
TA 1	0.708	0.706	-0.002
TA 2	0.805	0.795	-0.01
TA 3	0.736	0.812	0.076
TA 4	0.775	0.763	-0.012
TA 5	0.816	0.839	0.023

The data presented here shows the Root Mean Square Error (RMSE) values for frameworks, PLS-SEM and LM, spanning tasks labelled TF and TA. The "Differences" column shows the variation in the RMSE values of PLS-SEM and LM. PLS-SEM has a much lower RMSE than LM, indicating higher performance. The quality of the framework is medium predictive power, since the data gathered show more negative values than positive values.

Conclusion

This study focuses on investigating the significant differences between the types of factors contributing to falsework failure and the types of falsework failure accidents at building construction sites. The results show that the technical factor, combined with either the environmental factor or the management factor, contributes to the type of falsework failure accident during construction projects. Also, information on the possible cause of a falsework accident during the building construction in Seberang Perai Tengah Penang has been revealed. This model will be able to help construction management plan to avoid fatal accidents during construction.

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