International Journal of Innovation and Industrial Revolution
IJIREV
EISSN: 2637-0972

Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050

INTERNATIONAL JOURNAL OF INNOVATION AND INDUSTRIAL REVOLUTION (IJIREV)
www.ijirev.com

GLOBAL ACADEMIC EXCELLENCE

DELAYS IN RAILWAY CONSTRUCTION: INSIGHTS FROM THE CONTRACTOR'S PERSPECTIVE

Mohd Rafe Abdul Majid[1*], Hariez Izhan Abdul Rani[2], Raja Nor Husna Raja Mohd Noor[3], Juzailah Nur Yunus[4]

[1] Fakulti Kejuruteraan Awam, Universiti Teknologi Mara Cawangan Pulau Pinang, Malaysia
Email: rafebanu@uitm.edu.my
[2] Fakulti Kejuruteraan Awam, Universiti Teknologi Mara Cawangan Pulau Pinang, Malaysia
Email: Hariezizhan03@gmail.com.my
[3] Fakulti Kejuruteraan Awam, Universiti Teknologi Mara Cawangan Pulau Pinang, Malaysia
Email: rajanorhusna@uitm.edu.my
[4] Fakulti Kejuruteraan Awam, Universiti Teknologi Mara Cawangan Pulau Pinang, Malaysia
Email: juzailah.nur@uitm.edu.my
[*] Corresponding Author

Article Info:

Article history:
Received date: 20.07.2025
Revised date: 18.08.2025
Accepted date: 15.09.2025
Published date: 30.09.2025

To cite this document:

Majid, M. R. A., Rani, H. I. A., Noor,R. N. H. R. M., & Yunus, J. N. (2025). Delays In Railway Construction: Insights from The Contractor's Perspective. *International Journal of Innovation and Industrial Revolution, 7* (22), 865-879.

DOI: 10.35631/IJIREV.722050

This work is licensed under CC BY 4.0

Abstract:

The construction sector in Malaysia has undergone rapid expansion, significantly contributing to the nation's GDP and supporting various other industries. However, this rapid development—particularly in infrastructure projects within Selangor—has faced notable challenges. One such challenge is the persistent delay in railway construction projects, including the Mass Rapid Transit (MRT) system. This study investigates the primary causes of these delays from the contractor's perspective, evaluates their impacts, and proposes mitigation strategies. Employing Structural Equation Modelling (SEM) for analysis, the research identifies key delay factors such as material procurement difficulties, regulatory constraints, and environmental issues. The findings offer valuable insights into enhancing project timelines and improving overall productivity in railway infrastructure development, ultimately contributing to more effective project management practices.

Keywords:

Delay Factors, Railway Construction, Contractor, Structural Equation Modelling

International Journal of Innovation and Industrial Revolution
IJIREV
EISSN: 2637-0972
Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050

Introduction

The construction sector is a vital component of Malaysia's economy, experiencing rapid expansion and contributing significantly to national economic growth. According to the Department of Statistics Malaysia, the value of construction work completed in the fourth quarter of 2022 increased by 15.7%, culminating in an overall recovery of 8.8% for the year. Notable growth was recorded in subsectors such as civil engineering and residential construction. Prominent infrastructure projects such as the Pan Borneo Highway, the Kuala Lumpur-Singapore High-Speed Rail, and the Kuala Lumpur Mass Rapid Transit (MRT) serve as key examples of this expansion. These initiatives not only enhance domestic connectivity but also strengthen regional integration and transit networks, thereby stimulating broader economic development across the country (Ambashi et al., 2022).

With the surge of rapid development projects in Selangor a central state in Peninsular Malaysia and one of the country's most developed and densely populated regions delays in infrastructure projects have become a significant and recurring issue. Major urban centres such as Shah Alam, Petaling Jaya, and Subang Jaya are witnessing extensive construction activity, especially in transport and urban infrastructure. These delays not only affect project delivery but also disrupt economic efficiency, public mobility, and regional development. Given Selangor's pivotal role in Malaysia's national development agenda, there is an urgent need to address the root causes of these delays, particularly in railway infrastructure projects. The railway system, being the earliest form of organized transportation in Malaysia, remains a critical component of the country's public transport network and continues to face challenges in timely execution (Abd Aziz et al., 2018).

Malaysian railway development faces a range of persistent challenges that significantly affect project budgets, timelines, operational efficiency, and safety outcomes. One of the most critical issues is the complex and often protracted process of land acquisition and securing rights-of-way. Acquiring land for rail alignments, stations, and maintenance depots is frequently hindered by legal disputes, objections from local communities or landowners, and environmental considerations. These issues can result in substantial project delays and cost overruns. In addition to land-related complications, financing and funding present major obstacles to railway infrastructure delivery. High capital requirements often necessitate external borrowing, which can lead to financial strain. For instance, the East Coast Rail Link (ECRL) project has drawn criticism for its reliance on large-scale loans, raising concerns over long-term national debt and fiscal sustainability (Wang et al., 2020). These factors underscore the importance of addressing governance, stakeholder engagement, and financial planning in the successful implementation of large-scale railway initiatives in Malaysia.

Empirical evidence from previous studies highlights that delays and budget overruns are a pervasive issue in Malaysia's public infrastructure projects. According to Yusof et al. (2021a), approximately 65% of public projects experience cost and schedule overruns, often resulting in stakeholder conflicts and diminished project performance. From the contractor's perspective, our research reveals that 72.7% of the most critical delay factors directly contribute to project delays in Malaysia's construction sector. These findings emphasize the urgency of addressing inefficiencies in project planning and execution. Furthermore, Selangor recognized as one of Malaysia's most rapidly developing states and a major contributor to national GDP is at the forefront of this infrastructure expansion. As a key urban and economic hub, Selangor's

International Journal of Innovation and Industrial Revolution
EISSN: 2637-0972
IJIREV
Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050
performance in infrastructure delivery has substantial implications for national growth and urban development (Okpala et al., 2019).

The primary objective of this research is to comprehensively identify the factors contributing to delays in railway construction projects in Malaysia. The study aims to apply the Relative Importance Index (RII) method to rank and determine the most critical delay factors from the contractor's perspective. In addition, it seeks to examine the impacts of these delays and propose practical solutions to mitigate them. The findings will contribute to a clearer understanding of delay dynamics in railway infrastructure projects and support the development of targeted strategies to address them.

By leveraging this information, contractors and project stakeholders can improve the planning and execution of future infrastructure projects, ultimately reducing the likelihood of delays. Enhancing project scheduling, strengthening communication channels, and fostering collaborative engagement with stakeholders are essential steps toward improving delivery timelines. Furthermore, the adoption of innovative technologies and construction methods such as off-site prefabrication and Building Information Modelling (BIM) is recommended to enhance overall project efficiency and performance.

Research Method

This study investigates the causes of delays in railway infrastructure projects in Selangor, Malaysia, from the contractor's perspective by quantitative techniques. 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 previous research were adopted and adjusted to construct the questionnaire items to make sure that all the important points are covered during measurement. The total number of 55 copies of questionnaire was distributed personally and others via google form. The sample size for this research was 200 companies in Selangor. The Quantitative data were collected through a structured questionnaire distributed to contractors involved in railway infrastructure projects in Selangor. The survey was designed to assess the frequency, severity, and impact of various delay factors. 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 analysing the data, SPSS software version 28.0 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 4. 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 & Discussion

Demographic Respondents

A total of 133 questionnaires were distributed using a Google Form, with the link shared through email and WhatsApp. The objective of this survey was to collect data from selected railway construction projects in Selangor, focusing on perspectives from various project stakeholders including clients, consultants, contractors, and skilled workers. The survey

International Journal of Innovation and Industrial Revolution
IJIREV
EISSN: 2637-0972
Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050

specifically targeted respondents involved in contractor and consultant roles, such as Project Managers, Quantity Surveyors, Project Engineers, Design Engineers, and Site Supervisors. By engaging a diverse set of professionals, the study aimed to capture a wide range of viewpoints regarding factors contributing to delays in railway construction projects. As illustrated in Table 1, most respondents occupy core contractor-side roles. Notably, Site Supervisors (50%) and Project Engineers (27.4%) offer direct, on the ground experience with construction processes, allowing them to provide relevant insights into operational delay factors such as labour management, material supply, site coordination, and subcontractor issues. Additionally, Project Managers (16.1%) offer upper-level strategic perspectives related to project planning, budgeting, and scheduling. This distribution of roles ensures a well-rounded understanding of project delivery from the contractor's operational standpoint. In terms of experience, 83.9% of respondents have between 3 and 10 years of working experience, representing early to mid-career professionals who are likely to have been involved in multiple projects. Although only 16.1% of respondents have more than 10 years of experience, the current sample is still suitable for analysing recurring patterns of delays, particularly those encountered during the construction phase. Regarding project duration, most respondents have handled short- to medium-term projects lasting less than 24 months. This equips them to identify challenges that arise during active execution phases. However, only a small percentage have experience with long-duration projects (over 24 months), which may limit the study's ability to fully explore delays related to long-term issues such as land acquisition, stakeholder coordination, and regulatory processes. The age profile shows a predominantly young workforce, with 83.9% under the age of 40. This suggests a high level of field engagement and day-to-day involvement in project activities, although it may reflect a lesser representation of senior strategic decision-makers. The gender distribution is male-dominated (66.1%), consistent with industry norms in construction-related sectors, although the presence of female respondents (33.9%) is notable and indicative of increasing gender diversity.

In summary, the respondents are highly appropriate for research on railway construction delays from the contractor's perspective. Their practical roles, relevant experience, and involvement in ongoing projects provide valuable ground-level insights into delay factors. To enhance the depth of analysis in future research phases, the inclusion of senior managers or contract specialists is recommended to capture perspectives on external and systemic delays, including procurement challenges, legal issues, and inter-agency coordination.

Table 1: Respondents Demographic Profile

Type	Items	Percentage (%)
Gender	Female	33.9
	Male	66.1
Age	20 29 Years	50
	30- 39 Years	33.9
	40-49 Years	9.7
	>50 Years	6.5
Position	Project Manager	16.1
	Design Engineer	6.5
	Project Engineer	27.4
	Site Supervisor	50

International Journal of Innovation and Industrial Revolution
IJIREV
EISSN: 2637-0972
Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050

Working Experience	3-5 years	50
	5-10 years	33.9
	Above 10 years	16.1
Duration of Handle Project	6 to 12 months	50
	12 to 24 months	33.9
	24 to 36 months	9.7
	Above 36 months	6.5

Developing a Framework Model

Smart PLS 4 visions validated the model, and the Tenenhaus et al (2005), criteria were used to assess the model's overall quality. The framework consists of three stages: a first-stage measurement model test, a second-stage structural model test, and a third-stage quality test model.

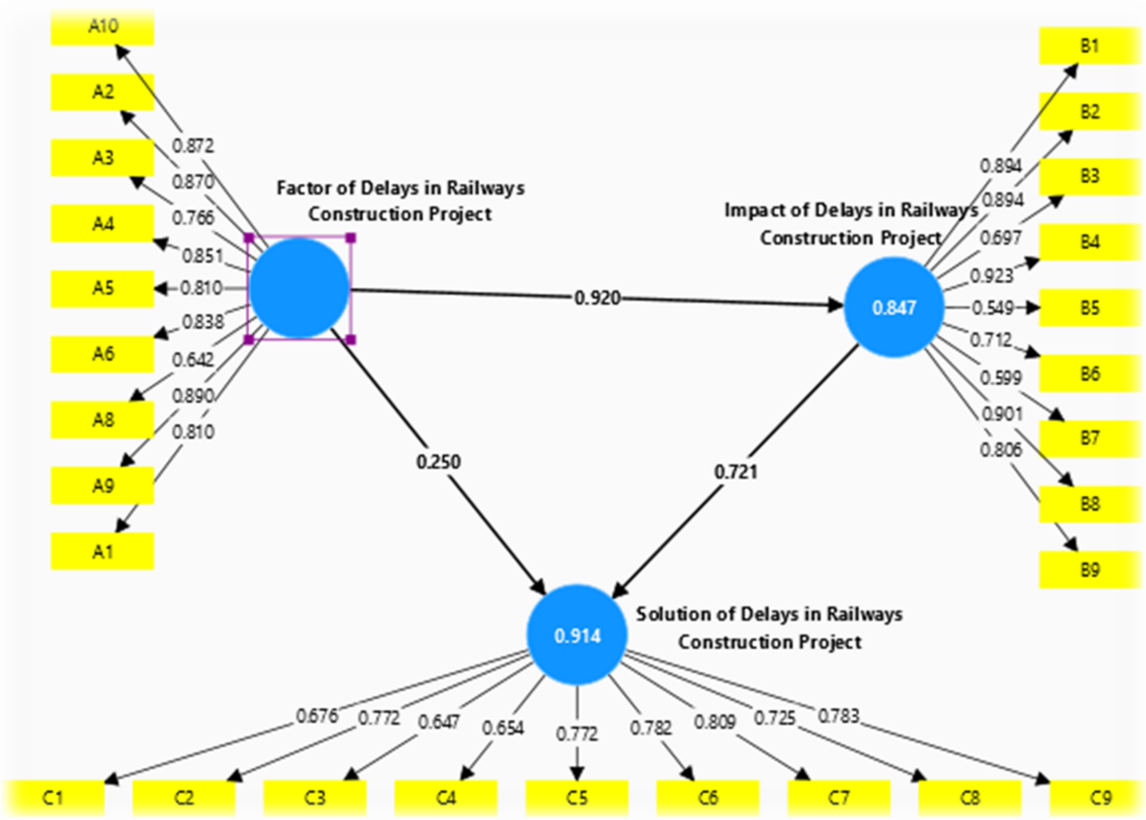

Figure 1: Measurement Model

Loading Variable

Loading data into Smart-PLS and applying Structural Equation Modelling (SEM) is a crucial process for assessing the quality of indicators, the relationships between constructs and their indicators, and the validity and reliability of the measurement model. This evaluation ensures the accuracy and robustness of the study's findings, as well as the empirical soundness of the proposed theoretical framework. To assess a reflective measurement model, the key criteria

International Journal of Innovation and Industrial Revolution
EISSN: 2637-0972
IJIREV
Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050

include indicator loadings, Average Variance Extracted (AVE), and Composite Reliability (CR). According to standard thresholds, indicator loadings should ideally exceed 0.708, as this indicates that more than 50% of the variance in the observed variable is explained by the latent construct (Hair et al., 2021). Loadings below this value, specifically those between 0.40 and 0.70, may still be retained based on specific conditions such as whether their removal significantly improves composite reliability without reducing AVE below acceptable limits. In this study, items with loading values below 0.40 were excluded to maintain the model's quality. For items with loading values between 0.40 and 0.70, a careful analysis was performed. If their removal did not improve the model significantly, they were retained. Table 2 presents the final item loadings and confirms that all retained items maintained an AVE value above 0.50, meeting the recommended threshold for convergent validity. Furthermore, Table 3 highlights the indicators that contributed most significantly to the AVE scores, identifying which items had the strongest influence on the construct's variance. These results demonstrate the robustness and validity of the measurement model and confirm that the retained indicators appropriately reflect their respective constructs.

Table 2: Tabulation of Loading Factor Result

	Factor of Delays	Impact of Delays	Solution of Delays
A1	0.858		
A2	0.903		
A3	0.799		
A5	0.860		
A6	0.721		
A8	0.721		
A9	0.920		
B2		0.908	
B3		0.666	
B4		0.922	
B9		0.849	
C1			0.652
C3			0.751
C4			0.754
C7			0.840
C8			0.798
C9			0.820

Composite Reliability

Internal consistency reliability was assessed using Jöreskog's composite reliability (Jöreskog, 1971), which is widely recognized as a more accurate estimate than Cronbach's alpha in structural equation modeling. Composite reliability values in this study ranged between 0.877 and 0.939, all of which fall within the acceptable range of 0.70 to 0.90, indicating satisfactory to good reliability. According to Hair et al. (2019), reliability scores within this range suggest that the items consistently represent their associated latent constructs. Notably, none of the values exceeded 0.95, thereby avoiding concerns of item redundancy or duplication, which could compromise construct validity.

International Journal of Innovation and Industrial Revolution
IJIREV
EISSN: 2637-0972
Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050

In addition, convergent validity was evaluated using Average Variance Extracted (AVE). AVE values for all constructs exceeded the recommended threshold of 0.50, confirming that a significant proportion of variance in the observed indicators is accounted for by the latent variables. This demonstrates that the items collectively have a strong ability to capture the underlying concept they are intended to measure, thereby affirming the construct validity of the measurement model.

Table 3: Composite Reliability and Average Variance Extracted Result

	Cronbach's alpha	Composite reliability (rho'a)	Composite reliability (rho'c)	Average variance extracted (AVE)
Factor of Delays	0.923	0.929	0.939	0.688
Impact of Delays	0.860	0.893	0.906	0.710
Solution of Delays	0.865	0.877	0.898	0.595

Table 3 presents the reliability and validity results for the three constructs: Delays in Railway Construction Project, Impact of Delays in Railway Construction Project, and Solution of Delays in Railway Construction Project. Cronbach's Alpha values for all constructs exceed the threshold of 0.70 (Hair et al., 2022), indicating strong internal consistency. Specifically, Factors of Delays (0.923), Impact of Delays (0.860), and Construction Project Solution (0.865) demonstrate high levels of reliability. Both rho'a and rho'c values are well above the recommended cut-off of 0.70, confirming satisfactory construct reliability. Factor of Delays (rho'a = 0.929; rho'c = 0.939), Impact of Delays (rho'a = 0.893; rho'c = 0.906), and Construction Project Solution (rho'a = 0.877; rho'c = 0.898) show strong reliability. The AVE values for all constructs are greater than 0.50, supporting convergent validity. Factor of Delays (0.688), Impact of Delays (0.710), and Solution of Delays (0.595) all meet the recommended threshold (Hair et al., 2022). The findings confirm that all three constructs demonstrate adequate reliability and convergent validity, fulfilling the measurement model assessment criteria.

Discriminant Validity

Shared variances below AVE should be present for all model constructs. However, a recent study reveals that the discriminant validity of this measure remains unevaluated. According to Henseler et al. (2015), the Fornell-Larcker criterion performs badly, particularly when there is a slight shift in the indicator loadings on a construct (e.g., all indicator loadings fall between 0.65 and 0.85). Table 4 shows the data of cross loading that has been analysis by using smart PLS.

Table 4: Discriminant Validity-Cross Loading Result

	Factor of Delays	Impact of Delays	Solution of Delays
A1	0.858	0.641	0.798
A2	0.903	0.827	0.802
A3	0.799	0.639	0.686
A5	0.860	0.638	0.795
A6	0.721	0.883	0.809

International Journal of Innovation and Industrial Revolution
IJIREV
EISSN: 2637-0972
Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050

A8	0.721	0.532	0.652
A9	0.920	0.849	0.830
B2	0.705	0.908	0.778
B3	0.509	0.666	0.498
B4	0.756	0.922	0.840
B9	0.920	0.849	0.830
C1	0.721	0.532	0.652
C3	0.608	0.508	0.751
C4	0.612	0.515	0.754
C7	0.756	0.922	0.840
C8	0.858	0.641	0.798
C9	0.729	0.889	0.820

According to Table 4, the indicators are most heavily loaded on their respective constructs compared to cross-loading on the other construct. This shows that the indicators are more strongly connected with their target constructs than with unrelated constructs, hence establishing discriminant validity. The results indicate that all indicators exhibit high loadings on their respective constructs. For the construct Delays in Railway Construction Project, the factor loadings range from 0.721 to 0.920, exceeding the minimum recommended threshold of 0.70 (Hair et al., 2022). Similarly, the construct Impact of Delays in Railway Construction Project demonstrates loadings between 0.660 and 0.922, while the construct Solution of Delays in Railway Construction Project shows loadings ranging from 0.652 to 0.840. Each indicator loads most strongly on its designated construct, thereby supporting convergent validity of the measurement model.

Heterotrait-Monotrait Ratio (HTMT)
The HTMT is defined as the mean value of the item correlations across constructs, and it is derived from the (geometric) mean of the average correlations for the items measuring the same construct. When HTMT readings are high, discriminant validity issues arise. Henseler et al. (2015) suggest a threshold value of 0.90 for structural models containing dimensions like cognitive satisfaction, affective satisfaction, and loyalty that are conceptually quite comparable. In this scenario, an HTMT score less than 0.90 indicates the validity of discriminant validity.

However, Henseler et al. (2015) advise a lower, more conservative threshold value, such as 0.85, when concepts are conceptually more distinct. Franke and Sarstedt (2019) suggest using bootstrapping to determine if the HTMT value significantly deviates from 1.00 or a lower threshold value like 0.85 or 0.90. Based on the data analysis below, the Value HTMT has been analysis in Table 5.

International Journal of Innovation and Industrial Revolution
IJIREV
EISSN: 2637-0972
Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050

Table 5: Discriminant Validity-Heterotrait-Monotrait Ratio (HTMT) Result

	Factor of Delays	Impact of Delays	Solution of Delays
Factor of Delays			
Impact of Delays	0.952		
Solution of Delays	1.031	0.983	

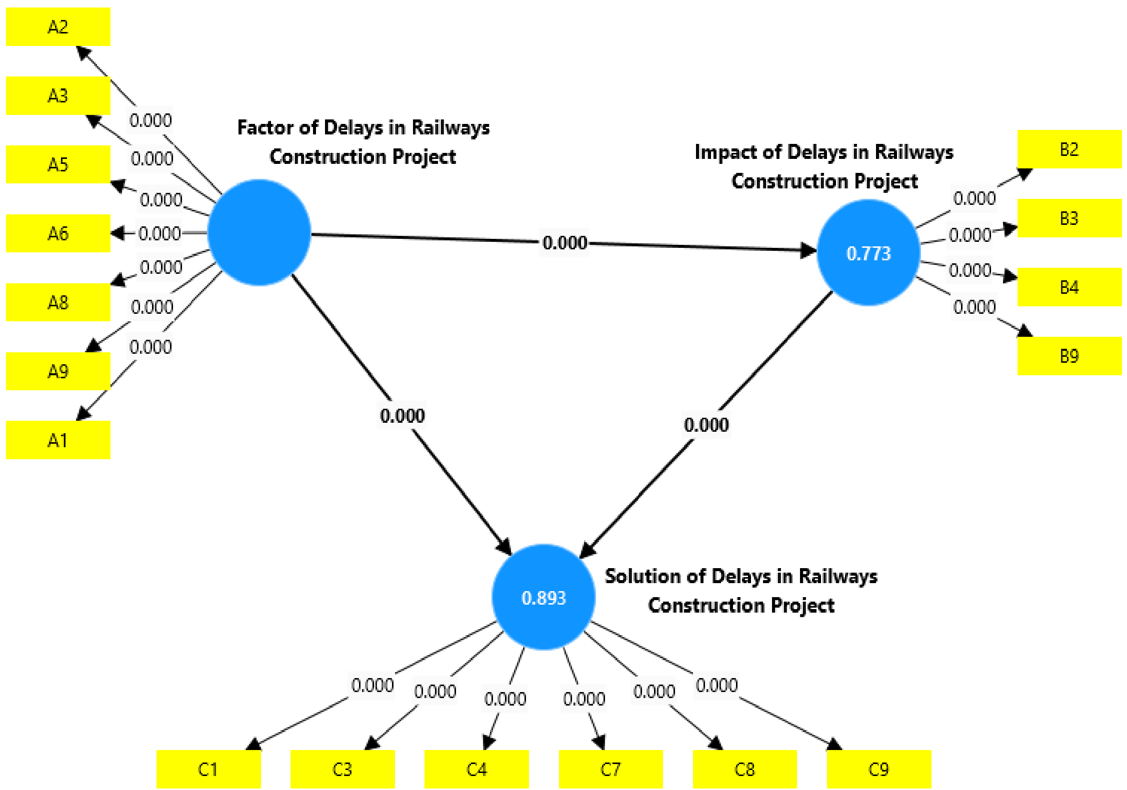

Figure 2: Structural Model

Variance Test Inflation Factor (VIF)

The study previously mentioned that multiple regression in Smart PLS can obtain VIF and tolerance values for collinearity checks. With the use of the Variance Test Inflation Factor (VIF), the existence or lack of collinearity between the variables was evaluated. If the VIF score is less than 5.0, it indicates that there are no severe collinearity issues when research data are gathered utilizing the PLS algorithm technique. Ideally, the VIF values should be near or less than 3. When collinearity is a problem, one common approach is to create theoretically justified higher-order models (Hair et al., 2017a). The VIF test between the independent and dependent variables has a value less than 5.0.

Table 6 indicates VIF values of 1.000 are far lower than the recommended limits, showing that the model lacks collinearity problems. This maintains the validity of the path coefficients computed in the structural model, allowing for interpretation without the risk of multicollinearity bias. The lack of collinearity difficulties, as indicated by VIF values of 1.000,

International Journal of Innovation and Industrial Revolution
IJIREV
EISSN: 2637-0972
Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050

implies that the model's constructs are different and measure distinct parts of the phenomenon under inquiry. This verifies the overall validity and dependability of the PLS-SEM analysis, as well as the structural relationship-based results.

Table 6: Tabulation of Variance Test Inflation (VIF) Result

	VIF
Factor of Delays -> Impact of Delays	1.000
Factor of Delays -> Solution of Delays	4.420
Impact of Delays -> Solution of Delays	4.420

Hypothesis Testing

This analysis, based on a bootstrapping discussion on the factor of delays in railway construction works, the impact of delays, and solutions to improve our problem, leads to the following conclusions: The following conclusions can be drawn based on result from Table 7: The first hypothesis, which tests the relationship between the impact of delays and factors that cause delays in railway construction projects, shows the original sample (O) value is 0.879 and the T-statistic is 53.748. The measurement results confirm the acceptance of the first hypothesis in this study, with a P-value of 0.000. According to the results of the second hypothesis, which examines the connection between factor and solution due to delays in railway construction projects, the original sample value (O) is 0.935 and the t-statistic is 75.563. The second hypothesis is also accepted because the measurement results indicate that the P-value is 0.000. The original sample (O) is 0.289, and the T-statistic is 4.093 for the third hypothesis, which examines the relationship between delays and the solution to delays in railway construction projects. In this research, Table 7 shows the analysis of hypotheses between two variables.

Table 7: Hypothesis Testing Result

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Factor of Delays -> Impact of Delays	0.879	0.880	0.016	53.748	0.000
Factor of Delays -> Solution of Delays	0.935	0.935	0.012	75.563	0.000
Impact of Delays -> Solution of Delays	0.289	0.294	0.071	4.093	0.000

Quality Model

R-Square (R^2)

The next step is to examine the endogenous construct's R^2 value (s) if collinearity is not an issue. The R^2, which quantifies the variation explained by each of the endogenous constructs,

International Journal of Innovation and Industrial Revolution
EISSN: 2637-0972
IJIREV
Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050

indicates the explanatory ability of the model (Shmueli and Koppius, 2011). More importantly, the number of predictor constructs influences the R^2 which the more constructions, the higher the R^2. Therefore, one should always evaluate the R^2, considering the study's context and the R^2 outcomes of similar studies and models. R^2 scores might also be too high if the model overfits the data. In other words, rather than accurately representing the population, the too-complex partial regression model matches the random noise seen in the sample. It is unlikely that a different sample drawn from the same population would fit the same model (Sharma et al., 2019a). When assessing something that is fundamentally predictable, such as physical processes, R^2 values of 0.90 could make sense.

Overfit models with the same R^2 values predict attitudes, perceptions, and intentions. This criterion connects the measurement and structural components of structural equation modelling by demonstrating how an independent variable influences a dependent variable.

Table 8: Tabulation of R-Squared (R^2)

	R-square	**R-square adjusted**
Impact of Delays	0.774	0.772
Solution of Delays	0.895	0.893

Table 8 presents the coefficient of determination (R^2) for the latent constructs within the structural model. The Impact of Delays in Railway Construction Project construct has an R^2 value of 0.774, indicating that approximately 77.4% of the variance in this construct is explained by its predictor variables. The adjusted R^2 value of 0.772, which accounts for the number of predictors in the model, offers a slightly more conservative yet still robust estimate of explanatory power. These values suggest that the model provides a moderate level of predictive accuracy for this construct. In comparison, the Solution to Delays in Railway Construction Project construct has a substantially higher R^2 value of 0.895, meaning that 89.5% of its variance is explained by the other constructs in the model. The adjusted R^2 for this construct is 0.893, which confirms that the model possesses strong explanatory power. These findings indicate that the hypothesized model is effective in capturing the relationships among variables and explaining the outcomes associated with railway construction delays and potential mitigation strategies.

Predictive Relevance (Q^2)

The Q^2 value is used to assess the predictive relevance of the structural model, particularly in evaluating how well the model can predict the observed values of the endogenous constructs. This value was determined using the blindfolding technique, a resampling-based procedure that omits part of the data matrix and then estimates the omitted part using the model parameters. In this context, the Q^2 value reflects the model's out-of-sample prediction capability. Specifically, it assesses how accurately the structural model predicts the data points of the indicators associated with reflective measurement models and the endogenous constructs. A Q^2 value greater than zero indicates that the model has predictive relevance for a given endogenous construct. The higher the Q^2 value, the stronger the model's predictive power. Therefore, a $Q^2 > 0$ supports the model's usefulness in making reliable predictions about the relationships between delay factors, their impacts, and potential solutions in railway construction projects. The internal predictive power of the structural model is evaluated using Stone-Geisser's Q^2 statistic, which assesses the model's predictive relevance. According to Geisser (1975) and Stone (1974), Q^2 values of 0.02, 0.15, and 0.35 are indicative of small,

International Journal of Innovation and Industrial Revolution
IJIREV
EISSN: 2637-0972
Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050
medium, and large predictive relevance, respectively. In the context of this study, Q^2 values greater than 0.25 for each dependent variable suggest that the structural model has strong predictive relevance and is well-structured. Q^2 values were computed using the blindfolding technique, and two common types of Q^2 indicators were considered: cross-validated communality and cross-validated redundancy. Cross-validated communality assesses the quality of the measurement model, while cross-validated redundancy evaluates the quality of both the measurement and the structural models simultaneously. As shown in Table 9, all endogenous constructs demonstrate Q^2 values greater than zero, with the majority exceeding the 0.25 threshold. This confirms that the model is not only statistically significant but also possesses practical predictive power, reinforcing its reliability and usefulness in predicting the impact and mitigation of delays in railway construction projects in Selangor.

Table 9: Tabulation of Q^2

Item	Q^2 predict
B2	0.485
B3	0.245
B4	0.566
B9	0.812
C1	0.503
C3	0.353
C4	0.359
C7	0.568
C8	0.721
C9	0.525

Table 9 shows most of the Q^2 predict values are positive, ranging from 0.245 to 0.812. This shows that the model has predictive value for most endogenous constructs. The model's predictive relevance is greatest for constructs B9 (0.812), C8 (0.721), and C7 (0.568). Overall, Q^2 predict values reveal the model's capacity to foresee the original values of indicators in reflective measurement models and endogenous constructs in structural models.

Effect Size (f^2)

The effect size (f^2) quantifies the extent to which an independent variable (predictor construct) contributes to explaining a dependent variable (endogenous construct) in a Partial Least Squares Structural Equation Modelling (PLS-SEM) framework. It provides additional insight beyond the R^2 value by indicating the individual contribution of a predictor to the variance explained in a dependent construct. Researchers can evaluate the f^2 value by examining the difference in R^2 values with and without the inclusion of a specific predictor construct. Alongside path coefficients, the f^2 effect size offers a comprehensive view of the relative importance of predictor variables within the model. Both measures typically rank the predictor constructs similarly in terms of influence, but f^2 adds clarity regarding magnitude and mediating effects. According to Cohen's (1988) guidelines, f^2 values are interpreted as follows: 0.02 = small effect, 0.15 = medium effect, 0.35 = large effect. As reported in the findings (Table 10), only one construct Factor of Delays in Railway Construction Projects demonstrated a high f^2 value, suggesting a strong effect on the dependent construct. This high f^2 value also indicates total mediation, meaning the construct significantly mediates the relationship within the structural model. In contrast, constructs with non-significant or low f^2 values may indicate

International Journal of Innovation and Industrial Revolution
IJIREV
EISSN: 2637-0972
Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050
partial or no mediation. As emphasized by Nitzl et al. (2016), the interpretation of f^2 alongside path coefficients is essential for assessing mediation effects and understanding the model's internal dynamics.

Table 10: Tabulation of Effect Size (f^2)

	Factor of Delays	Impact of Delays	Solution of Delays
Factor of Delays		3.420	0.898
Impact of Delays			0.227
Solution of Delays			

PLS Predict
Weights for formative indicators are called route coefficients. To evaluate route coefficients, which range from -1 to +1, researchers must employ bootstrapping. They might be aware of the effects that intervening constructs have on target construct. Moderating calls for this kind of impact. According to Shmueli et al., 2019, PLS prediction isolates training samples from holdout data to estimate model parameters and evaluate a model's ability to predict future events. This study looked at the linear regression model and the benchmark RMSE of PLS-SEM. PLS-SEM analysis is improper if all indicators have a bigger RMSE (or MAE) than the naïve LM benchmark, as Shmueli et al., 2019 found. If there are no PLS-SEM indicators with RMSE (or MAE) values greater than the benchmark value for the naïve LM, the model is considered highly predictive. Positive differences between RMSE (PLS) and RMSE (LM) are shown in Table 11, indicating the predictive power of the structural model. A predictable outcome requires negative values. Because some indicators have higher RMSE values than the benchmark value, the PLS-RMSE SEM performs worse than the naive LM.

Table 11: Tabulation of Data for PLS Predict

	PLS-SEM_RMSE	LM_RMSE	PLS Predict
B2	0.889	0.515	0.374
B3	0.904	0.939	-0.035
B4	0.799	0.296	0.503
B9	0.552	0.000	0.552
C1	0.979	0.000	0.979
C3	0.859	0.929	-0.090
C4	0.877	0.967	-0.090
C7	0.796	0.296	0.500
C8	0.557	0.000	0.557
C9	0.831	0.374	0.457

Conclusion
This study investigates the fundamental causes of railway construction delays in Selangor, their impact on contractors, and potential solutions from the contractors' perspective. By gathering empirical data from 150 G7-class contractors involved in monorail or railway line projects in Selangor, the study provides grounded insights into real-world challenges faced by industry stakeholders. Data was collected through a structured questionnaire survey and analyzed using

Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050

Partial Least Squares Structural Equation Modelling (PLS-SEM). The structural model was evaluated through key statistical measures including R-squared (R^2), effect size (f^2), Average Variance Extracted (AVE), and Heterotrait-Monotrait Ratio (HTMT). A high R^2 value for the "Delay Factors" construct indicates strong explanatory power within the model, suggesting that the identified variables significantly account for the variance in delay-related outcomes in railway construction projects. Furthermore, all AVE values exceeded the recommended threshold of 0.50, confirming convergent validity of the constructs. However, HTMT values above 0.90 were flagged as potential indicators of a lack of discriminant validity and were addressed carefully during model evaluation to ensure construct distinctiveness. To test the significance of the hypothesized relationships, the bootstrapping method was employed. Results from this analysis identified three statistically significant relationships: Between delay factors and their impact on contractors, between delay factors and mitigation strategies, and between the impact on contractors and the proposed solutions. These findings provide strong support for the research model and highlight the need for targeted strategies to manage delays effectively such as improved planning, stakeholder collaboration, and adoption of technological tools like Building Information Modelling (BIM) and off-site prefabrication to minimize disruptions in future infrastructure projects.

Acknowledgements
The authors wish to express their sincere gratitude to Universiti Teknologi MARA Cawangan Pulau Pinang.

“Artificial intelligence tools (e.g., ChatGPT, OpenAI) were used to improve the language clarity and grammar of this manuscript. The authors confirm that the study’s conception, design, analysis, interpretation, and conclusions are entirely their own.”

References

Abd Aziz, S., Kassim, R., & Mohd Masirin, M. I. (2018). Railway Development and the Impact to Malaysian Economy. In *Jour of Adv Research in Dynamical & Control Systems* (Vol.10, Issue 6).

Ambashi, M., Fujita, T., & Suzuki, H. (2022). CADP 3.0: Towards an Integrated, Innovative, Sustainable Economy. In *ERIA*.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences Second Edition*.

Geisser, S. (1975). The predictive sample reuse method with applications. *Journal of the American Statistical Association, 70*(350), 320–328. https://doi.org/10.1080/01621459.1975.10479865

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017a). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Thousand Oaks, CA: Sage.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Cham, Switzerland: Springer.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (3rd ed.). Sage. https://doi.org/10.1007/978-3-030-80519-7

Volume 7 Issue 22 (September 2025) PP. 865-879
DOI 10.35631/IJIREV.722050
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Jöreskog, K. G. (1971). Simultaneous factor analysis in several populations. *Psychometrika, 36*(4), 409–426. https://doi.org/10.1007/BF02291366

Nitzl, C., Roldán, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management & Data Systems, 116*(9), 1849–1864. https://doi.org/10.1108/IMDS-07-2015-0302

Okpala, P. U., Okoye, C. L., Adeyemo, F. O., Iheanacho, P. N., Emesonwu, A. C., Osuala, E. O., & Okpala, I. G. (2019). Utilization of maternal and child health services in Enugu, South East, Nigeria. *International Journal of Community Medicine and Public Health, 6*(8), 3228-3233. https://doi.org/10.18203/2394-6040.ijcmph20193124

Sekaran, U. (2006). *Research methods for business: A skill building approach* (4th ed.). Hoboken, NJ: John Wiley & Sons.

Sharma, A., Kumar, V., Shahzad, B. and Tanveer, M. (2019) Worldwide Pesticide Usage and Its Impacts on Ecosystem. SN Applied Sciences, 1, 1446. https://doi.org/10.1007/s42452-019-1485-1

Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. *MIS Quarterly, 35*(3), 553–572. Retrieved from http://hdl.handle.net/1765/87835

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing, 53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society: Series B (Methodological), 36*(2), 111–147.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y.-M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis, 48*(1), 159–205. https://doi.org/10.1016/j.csda.2004.03.005

Wang, H. K., Khoo, C. M., & Ooi, T. A. (2020, May). *Mega transport projects and politics: East Coast Rail Link, Malaysia* [Conference paper]. World Tunnel Congress (WTC) 2020 & 46th General Assembly, Kuala Lumpur, Malaysia.

Yusof, A. M., Khoso, A. R., Sohu, S., Khahro, S. H., & Chai, C. S. (2021a). Improving performance in construction projects: A case study of Malaysian public projects. *Pertanika Journal of Science & Technology, 29*(4), 2579-2604. https://doi.org/10.47836/PJST.29.4.19