

From Explanation to Prediction in Bridge Construction Efficiency: A PLS-SEM, PLSpredict, CVPAT and IPMA Study

Moustafa Metwally*, Intan Rohani Endut

Graduate School of Management (GSM), Management and Science University, Shah Alam, Malaysia

Email: 012024021443@gsm.msu.edu.my, Intan_rohani@msu.edu.my

*Corresponding author

Abstract:

Construction-management models are often judged by in-sample explanatory statistics, although high explained variance does not guarantee equally strong performance on held-out observations. This study evaluates the predictive and managerial usefulness of a bridge-construction efficiency model estimated from 348 respondents with direct bridge-construction experience in Saudi Arabia. The explanatory model was first assessed using PLS-SEM and then examined using PLSpredict, the cross-validated predictive ability test (CVPAT) and importance-performance map analysis (IPMA). The structural model explained 85.5% of Bridge Construction Efficiency, 25.1% of Stakeholder Collaboration and 24.8% of Stakeholder Communication. Q^2_{predict} was 0.220 for collaboration, 0.217 for communication and 0.066 for efficiency. CVPAT showed lower overall PLS loss than both the indicator-average and linear-model benchmarks; for Bridge Construction Efficiency, PLS loss was lower than the linear-model benchmark ($p < 0.001$) but not statistically lower than the indicator-average benchmark ($p = 0.072$). IPMA identified Stakeholder Communication (0.556) and Stakeholder Collaboration (0.454) as the highest nominal importance values for efficiency, with similar performance scores near 44. Sample-sensitivity analysis using 432 responses produced stable explained variance and stakeholder paths. The findings show that explanation, prediction and managerial priority provide different information. The model has high in-sample explanatory power, positive but uneven out-of-sample relevance, and a clear stakeholder-process priority domain. The paper illustrates how construction-management studies can separate explanatory inference from predictive and decision-oriented assessment.

Keywords — Bridge construction, prediction, PLSpredict, CVPAT, IPMA, PLS-SEM, Saudi Arabia.

I. INTRODUCTION

Construction-management research often reports model fit, explained variance and statistical significance, then moves directly to managerial recommendations. That sequence can blur three different questions: how well a model explains the observed sample, how well it predicts held-out observations, and where management attention may have the greatest practical value. Predictive research has long argued that explanatory adequacy and predictive usefulness should be evaluated separately [1]. PLS-SEM now provides procedures designed specifically for this distinction, including PLSpredict and CVPAT [2], [3].

The distinction is relevant to bridge construction because project delivery involves interacting technical, managerial, stakeholder and institutional conditions. A model may explain a large share of perceived bridge efficiency because the constructs are strongly related within the sample, while still showing more modest performance when asked to predict new cases. This paper therefore treats prediction as a separate empirical question rather than as a restatement of R^2 .

The empirical setting is Saudi bridge construction. The underlying model includes five antecedent conditions, Level of Innovation Adoption (LIA), Project Planning (PP), Risk Management Effectiveness (RME), Design Quality and Constructability (DQC), and the Regulatory and Funding

Environment (RFE), with Stakeholder Collaboration (SCOL) and Stakeholder Communication (SCOM) as stakeholder-process variables and Bridge Construction Efficiency (BCE) as the outcome. The model was developed in response to Saudi evidence on delay, planning, client decisions, payment, digital adoption and information flow [4]–[7].

Three research questions guide this paper. First, does the model show positive out-of-sample predictive relevance for the three endogenous constructs? Second, does PLS produce lower prediction loss than simple benchmarks? Third, which constructs combine high total importance with lower performance and therefore merit managerial attention? These questions are intentionally distinct from the mediation hypotheses examined in the theory-led paper from the same thesis dataset.

II. THEORETICAL BACKGROUND: EXPLANATION, PREDICTION AND MANAGERIAL PRIORITY

A. Why Explained Variance Is Not Enough

R^2 is an in-sample measure. It indicates how much variance in an endogenous construct is accounted for by the model in the data used for estimation. It does not test how accurately the same model predicts observations withheld from estimation. Shmueli and Koppius [1] frame this as a difference between explanatory modelling and predictive modelling. In PLS-SEM,

PLSpredict extends this logic through cross-validated prediction, while CVPAT allows prediction loss to be compared statistically with benchmark models [2], [3].

B. From Prediction to Managerial Priority

Prediction still does not answer where managers should focus. IPMA combines a construct's total importance for a target with its performance score. This paper uses IPMA as a decision-support layer rather than as a hypothesis test. The resulting map is interpreted together with measurement evidence because managerial ranking can be misleading when constructs are not well separated.

III. METHOD

The analysis uses the primary $N = 348$ sample of respondents with direct bridge-construction experience. The final model contains 69 substantive indicators across eight reflective first-order constructs. PLS-SEM was estimated in SmartPLS 4 [8], with standard measurement and structural assessment following established guidance [9], [10]. The primary explanatory model is not re-tested here as a separate theory contribution; it provides the baseline against which predictive and priority evidence are interpreted.

PLSpredict was used to assess out-of-sample relevance. The reported target-level statistics are Q^2_{predict} , RMSE and MAE for SCOL, SCOM and BCE. CVPAT compared PLS loss with an indicator-average benchmark and a linear-model benchmark. IPMA reported construct-level total importance and performance for BCE, and antecedent importance for SCOL and SCOM. The full $N = 432$ sample was used as a sensitivity check. The analysis therefore separates explanation, prediction, benchmark comparison and managerial prioritisation.

IV. RESULTS

A. Explanatory Baseline

The explanatory baseline (Table I) is asymmetric. The model explains roughly one quarter of each stakeholder process but 85.5% of BCE. This high BCE value makes an explicit predictive check especially useful because strong in-sample explanation may reflect relations that do not translate proportionally into held-out prediction.

TABLE I
EXPLANATORY BASELINE: EXPLAINED VARIANCE FOR THE THREE
ENDOGENOUS CONSTRUCTS

Endogenous construct	R ²	Adjusted R ²	Reading
SCOL	0.251	0.240	About one quarter of collaboration variance explained
SCOM	0.248	0.237	About one quarter of communication variance explained
BCE	0.855	0.852	High in-sample explained variance; interpret with mediator-overlap caution

B. PLSpredict

All Q^2_{predict} values are positive (Table II). The stakeholder constructs show the stronger predictive values, while BCE remains positive but much smaller. The contrast between BCE R^2 of 0.855 and Q^2_{predict} of 0.066 is the central result of this paper. The model explains the observed BCE data very well, but its held-out predictive relevance is more modest.

TABLE II
OUT-OF-SAMPLE PREDICTIVE RELEVANCE (PLSPREDICT)

Target	Q^2_{predict}	RMSE	MAE	Assessment
SCOL	0.220	0.889	0.697	Positive predictive relevance
SCOM	0.217	0.890	0.696	Positive predictive relevance
BCE	0.066	0.972	0.764	Positive but modest predictive relevance

C. CVPAT Benchmark Comparisons

PLS produced lower overall loss than both benchmarks (Table III). At the target level, the BCE comparison with the linear model favoured PLS, while the BCE difference from the indicator-average benchmark did not reach 0.05. This result avoids an overly simple claim that the model is uniformly superior across every target and benchmark.

TABLE III
CROSS-VALIDATED PREDICTIVE ABILITY TEST (CVPAT) BENCHMARK
COMPARISONS

Comparison	Target	PLS loss	Benchmark loss	Difference	p
PLS vs indicator average	SCOL	0.257	0.301	-0.044	<0.001
PLS vs indicator average	SCOM	0.256	0.299	-0.044	<0.001
PLS vs indicator average	BCE	0.601	0.631	-0.030	0.072
PLS vs indicator average	Overall	0.415	0.453	-0.038	0.006
PLS vs linear model	SCOL	0.257	0.282	-0.025	<0.001
PLS vs linear model	SCOM	0.256	0.281	-0.025	<0.001
PLS vs linear model	BCE	0.601	0.661	-0.060	<0.001
PLS vs linear model	Overall	0.415	0.456	-0.041	<0.001

D. Importance-Performance Map Analysis (IPMA)

The IPMA (Table IV) identifies the stakeholder-process domain as the main priority area. SCOM and SCOL have the highest nominal importance values, while both have performance scores around 44, below the antecedent constructs. The two rankings should not be treated as a precise contest because SCOL and SCOM have a correlation of 0.978 and HTMT of 1.030. The defensible managerial conclusion is that stakeholder coordination, taken as a domain, has high importance and comparatively lower performance.

TABLE IV
IMPORTANCE-PERFORMANCE MAP ANALYSIS FOR BRIDGE CONSTRUCTION
EFFICIENCY

Construct	Importance for BCE	Performance	Managerial reading
SCOM	0.556	43.96	Highest nominal importance; relatively low stakeholder performance
SCOL	0.454	44.19	High nominal importance; very similar performance
LIA	0.199	49.57	Secondary importance
PP	0.149	50.01	Secondary importance
DQC	0.106	50.85	Lower total importance

Construct	Importance for BCE	Performance	Managerial reading
RFE	0.106	49.02	Lower importance and relatively low antecedent performance
RME	0.076	49.87	Lowest total importance in the BCE IPMA

E. Sensitivity Evidence

The broader sample reproduces the same pattern (Table V). Explained variance changes very little, and both stakeholder paths remain positive. The prediction and priority interpretation is therefore not dependent on excluding respondents without direct bridge experience, although the $N = 348$ sample remains the inferential source of truth for the thesis.

TABLE V
SAMPLE-SENSITIVITY ANALYSIS ($N = 348$ VERSUS $N = 432$)

Metric	$N = 348$	$N = 432$	Conclusion
BCE R^2	0.855	0.857	Stable
SCOL R^2	0.251	0.249	Stable
SCOM R^2	0.248	0.242	Stable
SCOL $\rightarrow$ BCE	0.454	0.509	Positive in both
SCOM $\rightarrow$ BCE	0.556	0.497	Positive in both

V. DISCUSSION

The results show why explanation and prediction should be kept separate. A BCE R^2 of 0.855 could encourage a strong claim about model performance if reported alone. PLSpredict places that result in context: BCE has positive predictive relevance, but the magnitude is modest compared with SCOL and SCOM. CVPAT adds another layer by showing that the PLS specification improves prediction loss overall and against the linear benchmark for BCE, but not against every benchmark at every target. The model therefore has useful predictive content without warranting a claim of uniformly high out-of-sample accuracy.

The IPMA results also change the practical interpretation. The antecedent constructs are not the highest priority domain for BCE. Stakeholder processes carry the largest total importance, and their performance scores are lower than those of the antecedents. This directs attention towards the way project organisations exchange information and coordinate decisions. Recent construction evidence on information management, logistics coordination and inter-organisational collaboration provides a substantive basis for that interpretation [7], [11]–[13].

The measurement overlap between SCOL and SCOM is central to responsible use of IPMA. An importance difference of 0.102 between the two constructs cannot be read as a clean estimate of the superiority of communication over collaboration because the constructs are not empirically distinct in this sample. A future decision model should either improve their measurement separation or use a broader stakeholder-process construct when the managerial objective is prioritisation rather than hypothesis-specific decomposition.

VI. IMPLICATIONS FOR CONSTRUCTION-MANAGEMENT RESEARCH AND PRACTICE

For research, the paper supports a reporting sequence in which explanatory fit, out-of-sample prediction and managerial priority are treated as separate forms of evidence. PLS-SEM can estimate structural relations; PLSpredict and CVPAT can assess whether those relations improve prediction beyond simple benchmarks; and IPMA can translate total effects into a prioritisation view. None of these layers substitutes for the others [1]–[3].

For practice, the results point towards stakeholder coordination as the main improvement domain. Project controls should connect planning, risk, design, digital information and regulatory decisions with clear communication routes, joint decision rights and traceable feedback. The aim is not to maximise an isolated survey score but to improve the interfaces through which multiple organisations act on project information.

VII. LIMITATIONS AND CONCLUSION

Prediction is evaluated within one cross-sectional survey dataset and should be tested on an independent external sample in future research. The outcome is perceptual rather than based on verified project records. The SCOL-SCOM overlap also limits fine-grained IPMA ranking. Within these boundaries, the study shows a useful contrast: the model has very high in-sample explanatory power for BCE, positive but more modest out-of-sample relevance for BCE, and a clear stakeholder-process priority domain. Construction-management models therefore benefit from reporting prediction and priority separately from statistical explanation.

REFERENCES

- [1] G. Shmueli and O. R. Koppius, "Predictive analytics in information systems research," *MIS Quarterly*, vol. 35, no. 3, pp. 553–572, 2011, doi: 10.2307/23042796.
- [2] G. Shmueli, M. Sarstedt, J. F. Hair, J.-H. Cheah, H. Ting, S. Vaithilingam, and C. M. Ringle, "Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict," *European Journal of Marketing*, vol. 53, no. 11, pp. 2322–2347, 2019, doi: 10.1108/EJM-02-2019-0189.
- [3] P. N. Sharma, B. D. Liengard, J. F. Hair, M. Sarstedt, and C. M. Ringle, "Predictive model assessment and selection in composite-based modeling using PLS-SEM: Extensions and guidelines for using CVPAT," *European Journal of Marketing*, vol. 57, no. 6, pp. 1662–1677, 2023, doi: 10.1108/EJM-08-2020-0636.
- [4] E. Alenazi, Z. Adamu, and A. Al-Otaibi, "Exploring the nature and impact of client-related delays on contemporary Saudi construction projects," *Buildings*, vol. 12, no. 7, Art. no. 880, 2022, doi: 10.3390/buildings12070880.
- [5] A. M. Alajmi and Z. A. Memon, "A review on significant factors causing delays in Saudi Arabia construction projects," *Smart Cities*, vol. 5, no. 4, pp. 1465–1487, 2022, doi: 10.3390/smartcities5040075.
- [6] A. S. Bageis, "An investigation into the causes of payment delays and deliberate delay tactics in public construction projects in Saudi Arabia," *Buildings*, vol. 14, no. 6, Art. no. 1792, 2024, doi: 10.3390/buildings14061792.
- [7] R. BinSaddig, A. S. Ruzieh, B. S. Razia, R. Khamis, and B. S. Awwad, "Information flow and logistics coordination challenges in Saudi Arabian construction projects: A SCOR-based qualitative investigation," *Logistics*, vol. 10, no. 8, Art. no. 185, 2026, doi: 10.3390/logistics10080185.
- [8] C. M. Ringle, S. Wende, and J.-M. Becker, *SmartPLS 4*. SmartPLS GmbH, 2024. [Online]. Available: <https://www.smartpls.com>
- [9] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *European Business Review*, vol. 31, no. 1, pp. 2–24, 2019, doi: 10.1108/EBR-11-2018-0203.

- [10] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed. SAGE Publications, 2022.
- [11] F. H. Abanda, B. Balu, S. E. Adukpo, and A. Akintola, "Decoding ISO 19650 through process modelling for information management and stakeholder communication in BIM," *Buildings*, vol. 15, no. 3, Art. no. 431, 2025, doi: 10.3390/buildings15030431.
- [12] J. Lehtinen and K. Aaltonen, "Organizing external stakeholder engagement in inter-organizational projects," *International Journal of Project Management*, vol. 38, no. 2, pp. 84–95, 2020.
- [13] A. T. Shiferaw, M. Azarian, and T. K. Stevik, "Implementing collaboration in construction projects: A dual-layered framework for practice," *Journal of Management in Engineering*, vol. 42, no. 6, 2026, doi: 10.1061/JMENEA.MEENG-7667.