

The Impact of Artificial Intelligence on Financial Decision-Making in Project Management Evidence from Large Infrastructure Projects

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ABSTRACT: Large-scale projects involve numerous decisions under uncertainty, including cost estimation, contingency planning, vendor selection, cash flow planning, and managing emerging cost risks. By analysing project data, artificial intelligence (AI) can identify trends and provide predictions and recommendations. This quantitative study investigates relationships among AI utilization, data quality, data integration, AI capability, trust and transparency, financial decision quality, and project financial performance. A 27-item questionnaire and a synthetic cross-sectional dataset of 320 project professionals were developed to demonstrate an analytical workflow using SPSS. Reliability analysis, exploratory factor analysis, Pearson correlation, hierarchical multiple regression, one-way analysis of variance, and bootstrapping mediation analysis were conducted. All six scales demonstrated good internal consistency ($\alpha = .849-.899$). The KMO value was .927, and Bartlett's test was significant, $\chi^2(351) = 4,986.53$, $p < .001$. Six factors explained 70.1% of the total variance. Data quality ($\beta = .287$), trust and transparency ($\beta = .266$), AI utilization ($\beta = .254$), and AI capability ($\beta = .204$) significantly predicted financial decision quality. The relevant dimensions explained 53.1% of its variance. Financial decision quality strongly predicted project financial performance ($\beta = .434$) and partially mediated the relationship between AI adoption and financial performance. These simulated findings suggest that AI's financial value depends not only on tool utilization but also on data integration, competent application, explainability, governance, and human accountability. Since the dataset is synthetic, the results illustrate a research design and do not constitute empirical evidence or support generalizable claims.

KEYWORDS: Artificial Intelligence, Financial Decision-making, Project Management, Infrastructure Projects, Data Quality, Cost Management, AI Governance, Quantitative Research

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Introduction

One type of organized work that has great economic impact is large construction projects. Round-the-clock, around-the-year systems like transport corridors, power plants, water systems, airports, telecommunications systems, and large-scale urban development tend to be of high capital intensity, high levels of inflation, design change, delay, political and environmental risk, and have long delivery times and numerous contractors, as well as uncertain demand levels. Financial decisions in such settings thus cannot be restricted to the approval of the initial budget. They are present from the inception of the project, during the planning of costs, and when financing is secured, during the switchover process, as part of contingency management, while cash flow forecasting, claims assessment, and determining corrective action are carried out, as well as during the utilization of resources. Commonly used tools in traditional project financial management involve the use of historical cost databases, expert judgement, and the creation of a spreadsheet model, as well as regular reporting on earned value indicators and risk registers. While important, such methods are potentially limited by a lack of integrated information systems, reporting lags, reporting inconsistencies, and the complexity of estimating multiple variables with nonlinear relationships. The lack of information or receiving it late may cause managers to discover symptoms of financial difficulty upon making cost commitments. This is especially important for megaprojects or any other big-scale infrastructure project where percentage error measurement can result in a very significant dollar cost (Flyvbjerg et al., 2002).

AI can offer an alternative decision-making process. Anomalies, cost and duration estimation, risk classification and procurement/change order pattern recognition can be done using machine learning models, and these models can be improved as changes happen; AI-based risk assessment can also capture complexity–risk interdependencies in construction projects (Afzal et al., 2021). NLP technology can structure data within contracts, reports, meeting minutes and claims. Optimisation could be used to assess alternatives for resources and scheduling, and generative AI could help in supporting the development of scenarios, explanations, and preparation of decision materials. Although adoption is not widespread, and many applications of AI are still in their infancy (Shang et al., 2023), recent reviews have identified that there is a developing body of work in the area of project planning, building, tracking, risk management and cost management (Datta et al., 2024; Taboada et al., 2023).

However, having an AI tool available doesn't equate to creating a better financial decision. Modelling results can show erroneous results when the information sources are incomplete, biased, poorly integrated, or not reflective of actual market conditions. The understanding of the automated recommendations and lack of sensitivity to potentially useful outputs can lead to project staff either over-trusting the automated recommendations or rejecting them as outputs. Moreover, if the responsibility for the money is assigned to a variety of different people such as the software vendor, data team, project manager, finances, and even sponsor, it can become murky. Therefore, the socio-technical value of AI is likely to be socially dependent and associated with the quality of information, capabilities of organisations, governance, transparency, and informed supervision of technology use by humans. Although numerous studies have been conducted on the empirical research of AI in project management, there are still a few gaps. Firstly, there is a substantial amount of literature that is conceptual, review, or technical in accuracy of one prediction model.

In rare cases, research is conducted to explore how the organizational and governance setting affects the quality of AI-generated financial decisions. In rare instances, research is done to assess the effect of the organisational and governance context on the quality of financial decision-making through AI. Second, it is generally assumed that project success is a generic end-goal, and less attention is given to the process in between (financial decision quality). Third, the characteristics of a large infrastructure project (being capital intensive, complex, having long time horizons, and being publicly accountable) warrant a focused model. This article aims to fill these gaps by presenting and testing a quantitative survey framework. The research aims to gain an understanding of the impact of AI adoption on financial decision-making within managing large-scale infrastructure projects and validate the importance of data quality and integration, AI capability and trust, as well as transparency. One of the other objectives is to investigate

the relationship between the perceived financial performance on projects and the quality of the financial decisions. There is a complete questionnaire, a synthetic data set, as well as syntax for SPSS and a replicable analysis structure. The numerical results are presented in the form of a simulation; in an applied study, the numerical data should be replaced by data from the survey.

Research Objectives

1. To establish a relationship between the use of AI and quality financial decisions in major infrastructure projects.
2. To measure the effect of data quality/data integration, AI capability, and trust and transparency on financial decision quality.
3. To study the relationship between financial decision quality and perceived financial performance of the project.
4. To assess financial decision quality and how financial projects perform throughout the spectrum of AI maturity. To examine the mediation of quality of financial decision making between AI utilization and project financial performance.

Research Questions

RQ1: What difference does the application of AI make in the quality of the financial decisions made in large infrastructure projects?

RQ2: How do data quality and integration, AI capability, trust, and transparency affect financial decisions powered by AI?

RQ3: Is the quality of financial decisions being taken improved, and does it increase a sense of financial performance for the project?

RQ4: Is financial decision quality and financial performance higher at higher levels of project maturity in terms of their AI?

RQ5: Do financial decision quality partially mediate the impact of AI uses on project financial performance? Conducting a literature review and hypothesis formation.

Literature Review and Hypothesis Development

The Use of AI in Project and Infrastructure Management

The types of AI used in project management include natural-language processing, generative AI, computer vision, machine learning, and predictive analytics, as well as expert systems and optimization. These technologies can automate mundane information processing as well as provide information support in decision-making in knowledge-intensive work. Taboada et al. (2023), Darko et al. (2020), and Niederman (2021) documented the expanding use and study of AI in project and construction management, while Datta et al. (2024) recognized that the application of AI in PM has been high in the Planning/Construction stages but is now reaching the other stages of the project life cycle. Another important factor for the appropriateness of the AI tool will depend on the type of knowledge that is required; formal and data-driven tasks are more likely to be supported by AI tools than decisions for which tacit and/or politicking knowledge is required,” said Almeida et al. (2025). There are many ways in which AI directly impacts infrastructure projects, including cost estimation, delay prediction, risk assessment, resource optimization, tracking project progress, quality management, and safety (Fridgeirsson et al., 2021; Hughes et al., 2025; Sultan, 2023; Zhu et al., 2022). There are complicated nonlinear relationships that are not accounted for in conventional estimation techniques but can be modeled using deep learning and machine learning techniques (Akinosho et al., 2020; Pan & Zhang, 2021). A variety of hybrid mathematical and machine-learning methods have also been employed to improve the cost prediction of green buildings (Alshboul et al., 2022).

One can see from these applications a trajectory that connects the use of AI and the decisions that evolve from it to financial decisions and, in turn, that the faster data is processed, the more accurate the prediction, the earlier detection of unfavorable information, and systematic comparison of alternatives results in better financial decisions. But the usefulness of managerial forecasting is more than just the technical correctness. Prediction must occur at the proper time, location, and level of understanding for the persons familiar with the specific model and project context for a particular situation. It should then be considered as a part of a decision system, not a replacement for project governance. Evaluations of the financial quality of projects are considered in addition to indicators of quality. Financial decision quality is a voice of making crucial decisions at the right time, based on accurate data, with evidence, being sensitive to risk, consistent and auditable. In a project context, it may involve having to manage the quality of cost forecasting, contingency selections, funding choice, procurement choices, change approval, and reacting to new cost risks identified. Although a decision is made with high quality, it is not guaranteed that all the forecasts will be correct and that there are not uncertainties in the appropriation of funds for infrastructure projects. Rather, it is about treating evidence available for processing in a rigorous way, comparing the alternatives explicitly, assuming visible, and decisions to be reviewed and changed. This build is particularly important as this completes an essential link in the chain between the use of AI and project outcomes. Financial decision quality is thus envisioned as an outcome and a mediator of the impact of AI on financial performance. The quality and utilization of AI to make financial decisions. AI utilization focuses on the degree of true use of AI in cost forecasting, earned value analysis of work, vendor risk assessment, simulation of financial risks, and resource allocation decisions. This is not a matter of the interest of organisations in AI, or whether they have a software license. Decision makers should see more up-to-date scenarios, warnings of anomalies, and forecasts from utilization. The technology-acceptance tradition suggests that systems may be of value when users believe that they are useful, and when they become part of the work practice (Davis, 1989). In project management, AI can help minimize information collection and analysis time, and can aid in risk/ resource/ schedule decisions (Project Management Institute, 2024). However, there is also the danger of automation bias and reliance on AI models trained in different contexts, as well as false precision in AI use. Its net effect is anticipated to be positive if the outputs are not considered to be "authoritative" but instead are utilized as "decision support."

H1: AI's ability to enhance the quality of financial decisions is definitely positive and significant.

Together with data mapping, data quality and integration come into play. AI systems learn from and from data. In the case of large projects, financial information is distributed across a variety of contracting reports, BIM, risk registers, contractor scheduling systems, procurement databases and enterprise resource planning systems. Issues with the data code, data duplication, missing prior data, and updates too late can negatively impact the performance of the data model. Information quality is in the middle of DeLone and McLean's (2003) information-systems success model, and modern AI advice highlights that information governance is a prerequisite for trustworthy information systems for decision-making. Of course, integration is a critical aspect, and there are financial implications in working with the interactions of schedule, scope, risk, and procurement. There are quite a number of factors in that isolated cost database that will NOT show the schedule delay that will cause escalation, the rework that may be caused by a design change, or the dependency that could change the cash flow associated with procurement. Hence, Data quality and Data connectivity will enhance the accuracy, relevance, and timeliness of AI-based financial decisions.

H2: Data quality and integration create a positive and significant impact on the accuracy of financial decisions.

AI capability refers to the organization's technical ability, training, interpretive skill, validation ability, and capacity to work in conjunction with human validation. Project and finance professionals need to be much more "AI-literate" to comprehend the prediction, the data it was developed from, and the degree of uncertainty regarding that prediction, and whether there is enough contextual information to defy the prediction. Research on project managers' expectations from AI similarly emphasizes augmented professional roles and human judgment (Holzmann

et al., 2022). The technology readiness research reinforces the idea that AI adoption and use within an organisation is a journey, rather than a purchase and use, and it requires existing skills, technology and governance within the organisation to do so (Uren & Edwards, 2023). Productive challenge is what Capability means too. They have a good crew who can test model sensitivity and compare results with the reference models; they can identify inconsistencies in the data and note deviations from the recommendations. In the absence of such understanding, the organisation can either outright refuse to use AI, or it can blindly accept it. A dampening effect on decisions in both reactions. PMI likewise emphasizes systematic capability development and human intervention as task complexity increases (Project Management Institute, 2023).

H3: The ability to utilize AI greatly enhances the quality of financial decisions. Basing your trust: Transparency and Governance

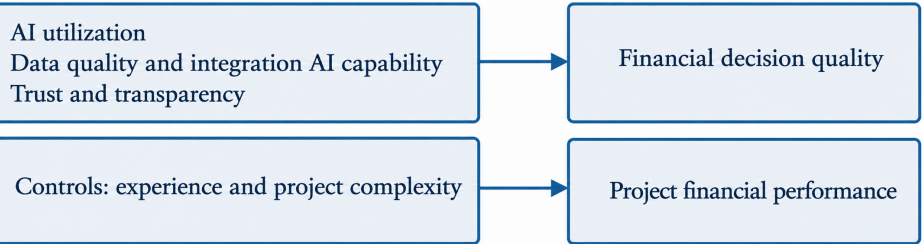
There's a trust factor involved in technology use, and there are degrees of trust; it's better to have appropriate trust than maximal trust. From this, Lee and See (2004) suggested the use of appropriate automation based on the capabilities of the automation and the context. Managers—of financial decisions—need explanations, confidence estimates, audit trails, clear accountability and controls over bias, and privacy, and with regard to cybersecurity and with respect to modelling risk. Project stakeholders are less likely to take consequential recommendations seriously if they are unable to see why it was developed and what parts are still the project stakeholders' responsibilities. Governance sets guidelines for data access; model approval; human oversight; escalation; monitoring; and accountability. PMI guidance also reminds us that governance around AI should establish a clear process for oversight and that governance must remain accountable for AI-supported decision-making (Project Management Institute, 2024). Transparency is likewise linked to contracting habits, assessment by the regulators, and legitimacy with the public in the case of public and PPP infrastructure.

H4: Trust and transparency have a positive contribution and a significant effect on the quality of financial decisions.

The ability to make a good financial decision and the performance of the project in terms of finances. The financial performance of the project is expressed in terms of project budget adherence, project budget contingencies, project budget overruns, and planned financial value in this study. These outcomes can be affected by a myriad of external factors, and managers have to make decisions with uncertainty. Finding out about price pressure can provide time to renegotiate, scope change, transfer risk, or take contingency actions before it becomes irreversible. Comparisons can be enhanced, as well, when there is a focus on creating greater resource efficiency and reducing waste. Therefore, it is expected that financial decision with financial performance is directly positively correlated. The use of AI could also have a direct effect as automated monitoring and detection of anomalies have an impact on performance beyond individual decision events.

H5: The financial decision can positively and significantly impact project financial performance. **H6:** AI's usage has a positive impact on project financial performance but via financial decision quality.

Figure 1
Conceptual model



Methodology

Research Design

This study is cross sectional, quantitative and positivist-explanatory study. The proposed field version would be a survey of financial and/or project control participants in very large scale infrastructure projects. Project managers, cost and finance, risk, procurement, engineers or design managers, programme or portfolio executives would all be considered as eligible respondents. A large project is defined as one that requires a US\$100 million or more, and has been approved or is anticipated to be approved as an infrastructure project. The methodological demonstration did not involve human subjects. Instead, an Artificial data set was created that contained 320 cases. The data set is well suited for checking the structure of questionnaires and SPSS syntax, as well as formatting of tables and interpretation of statistical procedures, but not to make claims regarding real life organisations or projects. Before collecting actual responses ethical approval and informed consent would have to be obtained.

Instrument Development

The questionnaire has demographic questions, project-profile questions as well as 27 items of Likert. The items were selected from the literature on the subject of AI support for project management, Information- System Quality, trust in automation, AI governance and project performance. The instrument has six constructs, namely: AI utilization (5 items), data quality (4 items), data integration (4 items), AI capability (4 items), trust and transparency (4 items), financial decision quality (6 items), and project financial performance (4 items). Responses options are given on a response scale of 1 (strongly disagree) to 5 (strongly agree). To establish content validity for applied research you'll want a panel of the industry's experts in project management, financial, infrastructure, and artificial intelligence. About 30-50 respondents who meet the eligibility criteria should then undergo preliminary reliability tests including: clarity and item-total correlation, completion time and number of respondents. If more than one language is used for the questionnaire, then translation and back-translation would be required.

Table 1

Constructs and Operational Definitions

Construct	Items	Operational definition	Role in model
AI Utilization	5	Use of AI in forecasting, cost control, vendor evaluation, risk simulation, and allocation decisions	H1
Data Quality and Integration	4	Accuracy, standardization, timeliness, and integration of project data	H2
AI Capability	4	Skills, training, validation ability, and human-review capacity	H3
Trust and Transparency	4	Explainability, confidence, accountability, and governance controls	H4
Financial Decision Quality	6	Timeliness, accuracy, risk awareness, consistency, and auditability	H1-H4; mediator
Project Financial Performance	4	Budget adherence, contingency control, reduced escalation, and value realization	H5-H6

Synthetic data Generation

These synthetic data have been generated by the use of correlated latent variables to produce data with realistic but fully artificial response patterns. Moderate positive correlations were seen in AI utilization, data quality & integration,

AI capability & trust & transparency. The model for financial decision quality is a multiplicative function of the four predictors, small control effects and random error. The financial performance of the project was computed as financial decision quality, AI usage, data quality, and professional experience, and random error. Common thresholds were applied to continuous scores at the item level to convert these scores to five Likert categories. The generation process was tuned to not make the result to look too perfect. Construct: ranged from 3.40 to 3.67, with near one point standard deviations, moderate correlations, and regression residuals near normal. Significance tests test mechanics of analysis and are NOT used to make a sampling inference about a population since these properties are not designed to be observed.

Data Analysis

Analysis plan is based upon SPSS procedures (IBM SPSS Statistics). The frequencies are the ones of the synthetic sample. Distributions are evaluated by three different types of measurement: means, standard deviations, skewness and kurtosis. Cronbach's alpha is used to determine internal consistency and a score of .70 is the minimum guideline. The Exploratory Factor Analysis is conducted using the Principal axis factoring method with varimax rotation. Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's test of sphericity are used to test sampling adequacy. Bivariate Associations can be analyzed using Pearson correlations. Predictors of financial decision quality are Experience and Project Complexity (in the first block); AI utilization, Data Quality and Integration, AI capability, and Trust and transparency (in the second). Another regression is conducted to predict Financial Performance of the project. The variance inflation factors are the measures for multicollinearity, following established multivariate-analysis guidance (Hair et al., 2019). One-way ANOVA is used to compare AI-maturity groups. A 5,000-resample percentile bootstrap is used in the indirect effect of AI utilization on financial performance through financial decision quality. The calculations have been repeated on a programming level and an SPSS syntax file is included.

Results

Sample profile

A synthetic sample of 320 professionals was used. Most were in the public/ public/private sector and all projects had a project value of \$100,000 or more. The biggest sector segments were transport and energy projects. Both operational and technical and financial occupations were included in the sample, 51.9 percent of whom said they use operational or advanced AI.

Table 2

Synthetic Sample Characteristics (N = 320)

Characteristic	Category	n	%
Gender	Male	226	70.6
	Female	88	27.5
	Prefer not to say	6	1.9
Age group	25-34	74	23.1
	35-44	128	40.0
	45-54	97	30.3
	55+	21	6.6
Professional role	Project manager	69	21.6
	Finance/cost professional	95	29.7
	Engineer/design manager	78	24.4
	Risk/procurement professional	43	13.4
	Programme/portfolio executive	35	10.9

Characteristic	Category	n	%
Infrastructure sector	Transport	105	32.8
	Energy	83	25.9
	Water and sanitation	63	19.7
	Urban development	46	14.4
	Digital/telecom infrastructure	23	7.2
Ownership/delivery model	Public	145	45.3
	Public-private partnership	102	31.9
	Private/regulated utility	73	22.8
Project value	US\$100-249m	100	31.2
	US\$250-499m	88	27.5
	US\$500m-999m	66	20.6
	US\$1bn+	66	20.6
AI maturity	No formal use	58	18.1
	Pilot use	96	30.0
	Operational use	108	33.8
	Advanced/embedded use	58	18.1

Measurement Quality

Reliability for all six scales was greater than the recommended .70. Cronbach's alpha ranged from 0.849 to 0.899. The KMO statistic was 0.927, and Bartlett's test was significant, $\chi^2(351) = 4,986.53$, $p < .001$. The results of the six factor solution accounted for 60% of the total variance. Primary rotated loadings were between .474 and .822 while nearly all cross-loadings were less than .35. The single factor contributed by Harman had 37.1% of the variance, which is less than the standard diagnostic cut-off point of 50%. These results confirm the measurement structure a priori expected with the simulated data.

Table 3

Descriptive Statistics and Reliability

Construct	Items	Mean	SD	Cronbach alpha
AI Utilization	5	3.417	0.956	0.876
Data Quality and Integration	4	3.541	0.976	0.849
AI Capability	4	3.673	0.968	0.854
Trust and Transparency	4	3.450	1.043	0.883
Financial Decision Quality	6	3.517	0.964	0.899
Project Financial Performance	4	3.402	1.026	0.867

Table 4

Pearson Correlations among Study Variables

Variable	1	2	3	4	5	6
1. AI utilization	—					
2. Data quality and integration	0.342***	—				
3. AI capability	0.335***	0.371***	—			
4. Trust and transparency	0.353***	0.344***	0.394***	—		
5. Financial decision quality	0.512***	0.542***	0.498***	0.535***	—	
6. Project financial performance	0.425***	0.397***	0.332***	0.351***	0.574***	—

Note. *** $p < .001$. Two-tailed significance. This is because the syntax that is provided produces the exact p-values. Scatter graph of the variables. Scatter of the variables is done. The control-only model was not significant, $R^2 = 0.007$, $F = 1.19$, $p = 0.305$. The four AI-related predictors explained an additional 0.523 of the variance. The full model was significant, $F(6, 313) = 59.03$, $p < .001$, with $R^2 = 0.531$ and adjusted $R^2 = 0.522$. The four focal predictors had a significant effect. The standardized impacts of the biggest and most significant were data quality and integration, trust and transparency, AI utilization, and AI capability. Once the focal predictors were included in the model, experience and project complexity were not significant predictors. Multicollinearity was not a problem (VIF values ranging from 1.003 to 1.326). Both types of support were used in the synthetic analysis of H1, H2, H3 and H4.

Table 5

Hierarchical Regression Predicting Financial Decision Quality

Predictor	B	SE	Beta	t	p	95% CI	VIF
AI utilization	0.256	0.044	0.254	5.81	<.001	[0.169, 0.343]	1.273
Data quality and integration	0.284	0.043	0.287	6.56	<.001	[0.199, 0.369]	1.282
AI capability	0.203	0.044	0.204	4.58	<.001	[0.116, 0.291]	1.326
Trust and transparency	0.246	0.041	0.266	6.01	<.001	[0.165, 0.326]	1.309
Experience (years)	-0.003	0.006	-0.020	-0.50	0.616	[-0.016, 0.010]	1.028
Project complexity	0.037	0.037	0.038	0.99	0.324	[-0.036, 0.109]	1.003

Financial Viability of Projects and Mediation

The $F(5, 314) = 39.29$ with an R-squared value of the model of 0.385 was significant for the financial-performance model, $p < 0.001$. The standardized beta coefficient of financial decision quality was the highest at .434 ($p < .001$). Smaller positive effects continued for AI, data quality, as well as experience, and no effect was found for project complexity. H5 was supported.

Table 6

Regression Predicting Project Financial Performance

Predictor	B	SE	Beta	t	p	95% CI
Financial decision quality	0.461	0.062	0.434	7.49	<.001	[0.340, 0.582]
AI utilization	0.156	0.056	0.145	2.78	0.006	[0.046, 0.266]
Data quality and integration	0.115	0.056	0.109	2.07	0.040	[0.005, 0.224]
Experience (years)	0.026	0.008	0.150	3.34	<.001	[0.011, 0.042]
Project complexity	-0.044	0.045	-0.043	-0.98	0.329	[-0.133, 0.045]

The indirect effect obtained by using the bootstrap mediation analysis was: $c' = 0.114$, with a 95% confidence interval of (0.067, 0.169). The indirect effect was statistically significant as the interval did not contain zero. This was a partial mediation as the direct effect of the use of AI remained positive at 0.152. Concentrated H6 was used in synthetic model. There are four primary distinctions based on the degree of AI maturity. AI maturity has four major differences. The one-way ANOVA between groups showed that there was a significant difference between the financial decision quality sub-groups ($F(3, 316) = 31.59$, $p < .001$, $\eta^2 = 0.231$). Project financial performance also differed, $F(3, 316) = 24.27$, $p < .001$, $\eta^2 = 0.187$. The percentage of students achieving each of the outcomes increased steadily from 'No formal AI use' up to 'Advanced / Embedded AI use'. The pattern is similar to that observed in the regression, but cannot be interpreted causally because it is cross-sectional and synthetic.

Differences by Degree of AI Maturation

The one-way between-group analysis of variance indicated that financial decision quality significantly varied between AI-maturity sub-groups ($F(3, 316) = 31.59, p < .001, \eta^2 = 0.231$). Project financial performance also differed, $F(3, 316) = 24.27, p < .001, \eta^2 = 0.187$. The levels of attainment for both outcomes rose gradually from 'No formal AI use' to 'Advanced / Embedded AI use'. The pattern is similar to that found in the regression, but it should not be interpreted causally, as the design is cross-sectional and synthetic.

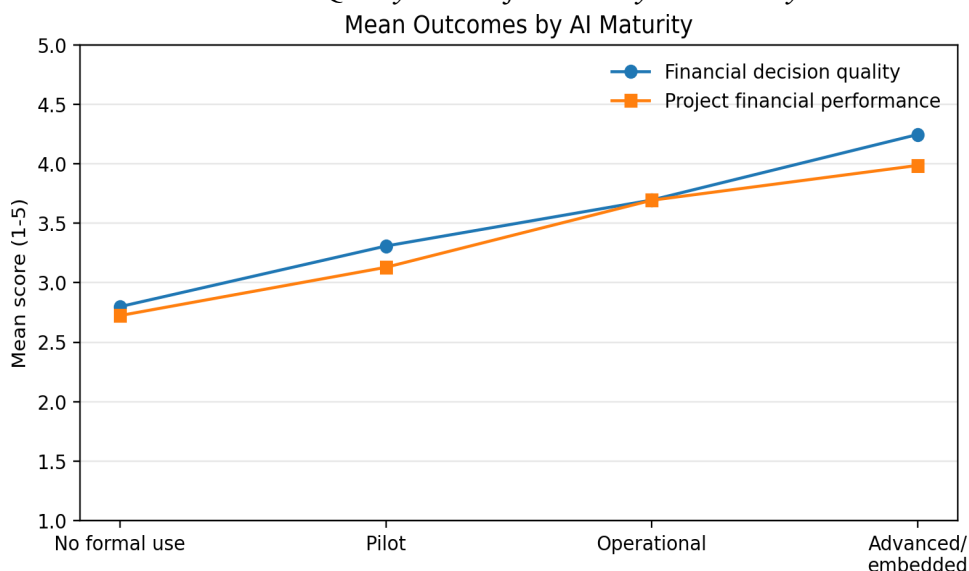
Table 7

Outcomes by AI maturity level

AI maturity	n	FDQ mean	FDQ SD	PFP mean	PFP SD
No formal use	58	2.799	0.930	2.724	1.030
Pilot use	96	3.309	0.911	3.130	0.977
Operational use	108	3.696	0.823	3.694	0.887
Advanced/embedded use	58	4.247	0.696	3.987	0.810

Figure 2

Mean Financial Decision Quality and Performance by AI Maturity



Discussion

The objective of the research was to develop and develop an AI-supported Financial Decision Making model for Large Infrastructure Projects based on quantitative modelling. In general, the synthetic results confirm that the contribution of AI is not measurable by means of utilization indicators. AI utilization, data quality and integration, AI capability, and trust and transparency all independently and strongly predicted financial decision quality, and decision quality was strongly linked to financial performance. This is in line with a socio-technical perspective on the adoption of AI. The data quality and data integration standardized effects were largest. In theory, this is possible because if the cost, schedule, procurement, risk, and contract information is disjointed or inconsistent, AI can't provide the right financial insight. Developing analytical tools before working out data definitions, owners, and integration is common in infrastructure organizations. The model indicates there is likely to be a reduced gain from the decisions if such an implementation sequence was used. So, the first step in a realistic approach to AI implementation is to begin with the architecture of the data, structure of the coding, rules for data validation, and interfaces between the project-control systems. Trust and transparency nearly took the place of data quality as a factor. The outcome highlights this disparity between the statistics and management. Project sponsors and finance

committees must understand why a model is proposing a change in contingency or rejecting a supplier or why a model is forecasting a cost escalation. Explainability also applies when auditing, subject to regulatory review, or in the context of fair procurement and/or dispute resolution. The most crucial elements of an appropriate level of trust are evidence of performance, expressed uncertainty, documented data, and expressed responsibility. This positive effect of the use of AI remained even after taking into account data, capability, and trust. This implies that there should be no replacement for governance and preparedness with 'use'—organisations must embed AI into their actual decision-making. Pilot projects which may not affect the forecasting/ resource allocation/ response to risk activities may create activity of no value. The maturity of a decision should be gauged in terms of integration of the decisions rather than simply buying tools. The smallest of the four focal effects, but most important, was the AI capability. This does not imply that 'capability' is not essential. Partly, Capability can be achieved by improvements in enhanced utilization, data practices, and trust. An experienced team knows how to set up the decision problem properly, select the appropriate data, 'check the answer' to confirm outputs, and question outputs. They also identify when there are elements of the decision which cannot be expressed in a model (political, contractual, ethical or contextual). In the future, it might be worth it to do field-based research in which to test whether or not it is a moderator or a higher-order organizational readiness construct. The proposed mechanism is supported by a high correlation between the quality of financial decisions and the financial results of the project. AI's promise to make budgets better is not going to come about automatically because there is an algorithm. It enhances performance when it alters the timing, accuracy, consistency, and risk awareness in managerial decisions. The partial mediation result also suggests that there are two pathways through which AI influences the results – direct, through automated monitoring, anomaly detection, availability monitoring, and/or accelerated workflows, and indirect, through better decisions. The maturity analysis identified not only that the difference is between adopters and non-adopters but also a graded difference. Operational and embedded projects rated more highly for decision quality and performance than did the pilot and non-user groups. A real study should have a longitudinal study of this pattern; projects that had a positive impact on the implementation of AI systems could have more reason to invest in AI systems, which could lead to reverse causality. Organizational size, digital capability, sector, or procurement model may also be used to characterize the maturity.

Theoretical and Practical Implications

The model provides an addition to the literature on technology-adoption studies by using a dependent variable other than intention to use, but instead one focused on the quality of financial decisions that are a result of the use of the technology. It captures a range of information quality, organizational capability, trust in automation, and project performance items, all in one. Financial decision quality can serve as a more fine-grained explanation, a process-level solution, between AI usage and project outcome than a direct link from AI to project outcome. The other theme that is emphasised in the framework is complementarity. The uses and the explanations of AI are not exclusive, but there are two modes of failure: one is using it, the other one is explaining it. Even highly technically sophisticated models can fail due to poorly developed data, unready users, or poorly accepted recommendations. AI-driven decision-making, on the other hand, is essential for effective governance; otherwise, it is powerless.

Managerial Implications

Infrastructure and delivery companies should think about the contexts in which financial decisions can be made using fine-grained data that have an economic impact on their business. The following are possible initial applications: Estimate at completion forecasting; Change Order risk screening; Cash flow forecasting; Anomalous

commitments/invoices detection; Evaluation of tenders. Implementation shall be done in a deliberate decision design cycle. For every use case, think about the decision owner, the input data for the use case, the purpose of the model, acceptable error, what needs to be explained, the validation procedure, who can override it, how frequently it needs to be monitored, and who will keep a record of it. Human review should be most robust in areas where decisions impact the fairness of the procurement, public funds, contract rights, safety, or long-term service commitments. Common identifiers for Work packages, contracts, risks, changes, schedule activities and financial accounts should comprise a project-data environment, which is integrated by organisations. Model performance should be monitored for drift due to inflation, supply chain disruption, design evolution and/or change in the delivery strategy. Training should not only draw attention to the promptness of use and software operation, but it is important to emphasize statistical uncertainty, bias, model limits as well as accountable judgement. Last but not least, assess benefits by decision criteria, not by productivity statements. These measures apply, such as Forecast Error, Time to Decision, Lead Time until an Overrun is Detected, Quality of causal explanations provided, frequency of last minute Financial Surprises and percentage of AI recommendations validated/overridden/escalated.

Limitations and Future Research

The major issue is that it is a synthetic dataset. Correlations, significance levels, and effect sizes were generated by a controlled process and not observed in infrastructure projects. This is not an empirical article, but a research format. An actual study should include ethics approval, purposive and stratified sampling, and provide details of the response rate; the non-response bias and the range of countries and contexts within the project should be checked. The design of the field is cross-sectional, with the basis of self-reported perceptions. Actual data does not rule out common method bias or social desirability and reverse causality. The next step is to incorporate the information from the surveys with other objective measures like the estimate-at-completion error, cost growth, contingency utilization, decision-cycle time, and time of risk detection. It may be possible to do longitudinal designs that involve comparisons between projects before and after the AI is inserted. The term "utilization of AI" is a general term in the model. Future research is needed to distinguish between some of these terms, as they have varying risks and benefits, and are essentially different concepts, e.g., predictive machine learning, optimization, computer vision, natural-language processing, and generative AI. Multi-group analysis might be carried out for transport, energy, water and digital infrastructure, public versus private delivery, and PPP delivery. Structural equation modeling can be used to test higher-order relations, moderation, and reciprocal relations. Qualitative interviews would also be conducted to understand when project professionals accept, challenge, or override the AI recommendations.

Conclusion

The study has introduced a quantitative method to analyze the impact of AI in the financial decision-making of a large infrastructure. The synthetic analysis shows a relationship between the use of AI and improved financial decision-making quality, but this relationship is closely linked to several key elements: data quality and data integration, competent users, transparency, trust, governance, and human accountability. Budget control and financial value realization are in turn correlated with financial decision quality. But these AI tools are not a substitute for accountability in decision making – they are to be used in conjunction with it. The questionnaire, the dataset, the workbook, and the SPSS syntax provide an idea of what should be used for an empirical research of your own, but only to support a claim that you would want to use for academic/managerial purposes can be done by field data that is collected in an ethical manner. The resources provided include synthetic data, a codebook, a questionnaire, an analysis workbook, and SPSS syntax. No real personal or organisational information was gathered. There was no issue of ethics of use of humans in the simulation context. If researchers are to use the questionnaire with real persons, they have to get the proper institutional approval, informed consent, and data-protection measures.

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Appendix A. Questionnaire

Directions: For the major infrastructure project you know best, please state the degree to which you agree or disagree with the statement. Scale: 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree.

Code	Construct	Statement
AIU1	AI utilization	Total Project cost and Project Cash Flow are predicted using AI tool.
AIU2	AI utilization	Cost variance, earned value and budget performance data are analysed via AI tools.
AIU3	AI utilization	AI facilitates tender evaluation, supplier assessment and making supplier decisions based on financial information.
AIU4	AI utilization	Financial Risk simulations and scenario analysis are done using AI.
AIU5	AI utilization	Funding, contingency and reallocation of resources decisions are based on AI generated recommendations.
DQI1	Data quality and integration	Project cost, schedule, procurement and risk data is readily available for AI analysis.
DQI2	Data quality and integration	Financial and operational information systems are connected and delivered timely information.
DQI3	Data quality and integration	Historical project data is always well defined, standardized and reusable.
DQI4	Data quality and integration	AI financial outputs are updated in a timely manner that aligns with ongoing decision-making processes.
AIC1	AI capability	Both the project and finance departments know what to do with the financial outputs from the AI.
AIC2	AI capability	The organisation has the necessary AI expertise, training and technical support.
AIC3	AI capability	Project team has the ability to question, verify and amend AI suggestions.
AIC4	AI capability	Financial workflows with AI human checks and escalations.
TRT1	Trust and transparency	Financial recommendations generated with an AI can be easily understood and explained.
TRT2	Trust and transparency	Decision makers trust and accept output of AI which are accurate and consistent.
TRT3	Trust and transparency	There is an understanding of who is responsible/ accountable for AI-assisted decision making.
TRT4	Trust and transparency	Control frameworks are in place to address data privacy, bias, security and model risk.
FDQ1	Financial decision quality	AI can aid in making financial decisions faster.
FDQ2	Financial decision quality	AI makes project cost and cash-flow estimates more accurate.
FDQ3	Financial decision quality	AI enhances the analysis of financial options, taking risk into account.
FDQ4	Financial decision quality	AI helps detect potential cost overruns earlier.
FDQ5	Financial decision quality	AI Optimizes distribution of budget, contingencies, and financial resources.
FDQ6	Financial decision quality	AI facilitates more consistent, evidence-based, and auditable financial decisions.
PFP1	Project financial performance	The project is on track to deliver what it requested for in its approved budget.
PFP2	Project financial performance	There is a controlled and justified use of contingency funds.
PFP3	Project financial performance	There were less of any unforeseen cost increases for the project.
PFP4	Project financial performance	The project is progressing towards the target amount of funding.