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SEM-Based Decision Support Model for Cost-Quality Impact Analysis on a Fast-Track Project's Duration

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Abstract

The fast-track technique was introduced to mitigate time overruns and meet project deadlines; however, limited understanding exists regarding how cost and quality-related decisions influence the duration of such projects. This study aims to analyze the impact of cost and quality variances on project duration, ultimately proposing a decision support model tailored for fast-track high-rise building projects. Data were collected from 159 respondents and analyzed using Structural Equation Modeling (SEM), through which four hypotheses were formulated. The findings reveal that both cost and quality variances significantly affect project duration, with quality variance also exerting a notable influence on project cost. Mediation analysis further demonstrated that cost variance serves as a statistically significant mediator between quality variation and project duration. The R^2 values of the proposed model indicate that 78.4% of the variation in project duration can be attributed to changes in cost and quality, while 72.9% of the variation in project cost is linked to quality changes. The Importance–Performance Map Analysis (IPMA) identified the early procurement of long-lead-time items, the adoption of a scope-freeze approach during the early design phase, and the over-design of facilities as the most critical and best-performing decisions. The model introduces novel β-values and confirms the statistically significant relationships among cost, quality, and time. Additionally, model validation metrics—including Q^2, RMSE, MAE, and CVPAT—demonstrated strong out-of-sample predictive power of the proposed framework.

Keywords: Cost and Quality Impact; Decision Support Model; SEM; Fast-Tracking.

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1. Introduction

The construction industry plays a pivotal role in driving economic growth, acting as a catalyst for development in both developed and developing countries [1]. However, the global construction industry is faced with a trinity of challenges that are time-, cost-, and quality-related, which collectively pose hurdles in achieving successful project outcomes [2]. The success of construction projects depends on the complex balance among time, cost, and quality constraints. Time constraints are pivotal, as meeting deadlines is crucial for project completion and subsequent occupancy. Delays can result in financial losses and stakeholder dissatisfaction. Despite substantial progress in construction planning and scheduling, 98% of megaprojects suffer from cost overruns exceeding 30% of the project's planned budget, and 77% are delayed by over 40% of the project's planned duration [3]. Similarly, ensuring high-quality standards becomes a delicate aspect, as pressures to expedite timelines or adhere strictly to budget constraints may jeopardize the final product. Among time, cost, and quality, timely completion is the most crucial aspect for all stakeholders, whether it's the client, contractor, or consultant. Meeting deadlines is not merely a logistical consideration

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but a fundamental prerequisite for project completion, stakeholder satisfaction, and the realization of anticipated benefits. Delays can have cascading effects, resulting in increased costs, contractual disputes, and a diminished return on investment. A project not delivered on time not only reflects inefficiency in planning and execution but also spoils the reputation of project stakeholders. Hence, recognizing and meticulously managing time constraints is paramount, as it is the key to ensuring the success and viability of construction endeavors.

The Project Management Institute (PMI) identifies schedule compression as an effective strategy for reducing project timelines, highlighting fast-tracking and crashing as the two most commonly used techniques. Crashing is defined as a method for shortening the schedule by adding additional resources at the lowest possible incremental cost. In contrast, fast-tracking involves executing project phases in parallel that would typically be performed sequentially, as illustrated in Figure 1. The primary issue with crashing is its cost inefficiency, as adding resources to accelerate progress often leads to increased expenses. Fast-tracking addresses this challenge by achieving shorter durations without significantly increasing resource input. While both techniques aim to reduce project timelines, it is essential to distinguish between them due to their differing mechanisms [4]. Some researchers, such as El-Far et al. [5], have conflated the two methods by suggesting that fast-tracking involves additional resource allocation. However, in fast-tracking, reduced durations are achieved by overlapping dependent activities—originally planned in sequence—using the same resource levels as in conventional scheduling. Based on this distinction, Prawirawati et al. [6] concluded that fast-track projects are generally more cost-effective than those employing crashing. The fast-track method was first introduced in the 1960s [7, 8].

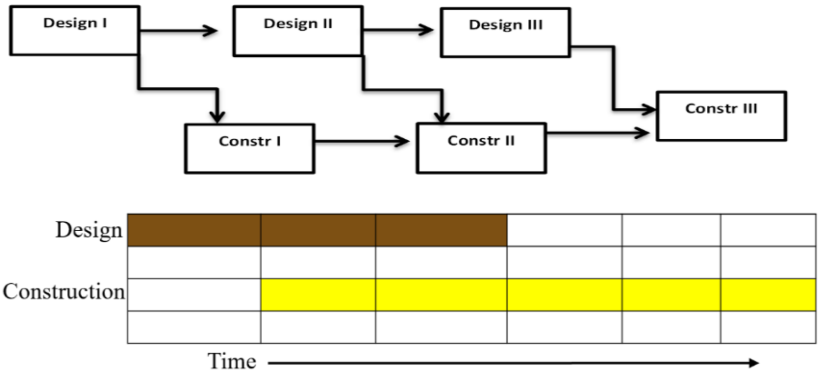


Figure 1. Overlapping Mechanism [9]

Decision-making is the most important aspect of time-saving on fast-track projects. According to Austin et al. [10], fast-track projects are successful because of the timely and well-informed decisions. Timely decisions can lead to significant success in construction projects, while delays can have disastrous consequences. On fast-track projects, where time is a major constraint, the objectivity of the decision-making process becomes crucial [11]. As of now, no comprehensive decision support model exists that not only identifies and ranks the decision-making aspects but also correlates them with the globally accepted project success indicators, i.e., time, cost, and quality. The lack of such a comprehensive decision support model leads to reluctance of construction industry professionals in adopting the fast-track approach. In the research conducted by El-Far et al. [5], 63% of the respondents recommended using a fast-track approach on construction projects, whereas 28% were neutral and only 9% opposed it.

2. Research Motivation

This research was inspired by the work done by El-Far et al. [5], Cho & Hastak [12], & Alhomadi et al. [13] in the domain of fast-track construction. Cho & Hastak [12] proposed a time- and cost-optimized model using a genetic algorithm, which lacked the quality-related aspects of fast-track construction. Moreover, they reported that their model could not ensure the success of fast-track projects and further stated that a computer-based application using several decision criteria is required for the successful implementation of fast-track projects. Alhomadi et al. [13] mentioned that to enhance the predictability of fast-track projects, further research is needed on the relationship between predictability indices and fast tracking. According to El-Far et al. [5], further study is necessary, which analyzes predictability indices using data from finished fast-track projects. Incorporating actual data will enhance the accuracy of predictability ratings. Alhomadi et al. [13] concluded that it is crucial to examine the factors that impact real-world project predictability. Additional research is needed to gain a better understanding of the relationship between fast-track projects and their predictability indices, which would enhance project success. This research not only addresses the shortcomings of previous models but also accounts for the future directions suggested by various researchers.

3. Research Questions

Research questions define the specific areas of inquiry and determine the scope of the study. These questions are formulated based on the research problem and are designed to address the key issues, gaps, or areas of interest within that topic. Figure 2 shows the basic framework of this research. The present study focuses on finding answers to the following research questions:

- What is the impact of variations in cost and quality on the duration of fast-track projects?
- How does the variation in project quality influence the variations in project cost for projects on fast-track schedule?
- How do the time, cost, and quality-related decisions on fast-track projects impact the relevant KPIs?
- What is the impact of cost- and quality-related decisions on variations in project duration on fast-track projects?

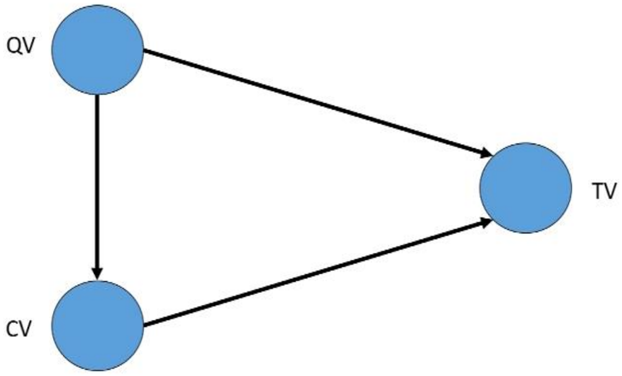


Figure 2. Relationship between the latent constructs (time, cost and quality variance)

4. Literature Review

4.1. Fast-Track and its Impact on Key Performance Indicators (KPI)

The fast-track technique has been defined in various ways by the research community; however, the core concept remains consistent with the PMI’s definition. Fast-tracking is a schedule compression method where activities or phases that are typically performed sequentially are executed in parallel for at least part of their duration [14, 15]. In other words, project activities are overlapped (see Figure 1) [16, 17]. The primary objective is to shorten the overall construction timeline by initiating portions of the work as soon as their designs are completed, even if the rest of the project is still under design [18]. The fast-track approach aims to save time by bypassing the traditional sequence of documentation, tendering, and construction processes [19]. Several terms in the literature are used interchangeably with fast-tracking, including concurrent engineering, parallel engineering, phased construction, flash-tracking, and agile project management [10, 14, 15, 19, 20]. Existing literature thoroughly explores the universally accepted project key performance indicators (KPIs)—namely quality, cost, and time—within the context of fast-track project delivery [13, 19, 21]. One of the most persistent challenges in project management is determining the criteria for project success. Traditionally, time, cost, and quality have been considered the most critical metrics. However, many researchers argue that fast-track projects tend to be less predictable in terms of these key parameters [14].

4.2. Fast-Track’s Impact on Time

The difference between the actual and planned project duration is referred to as time variance, which serves as a key indicator of a fast-track project's predictability [5]. Kasim et al. [22] reported that fast-tracked projects can be completed in less than 70% of the originally planned duration. Similarly, Alhomadi et al. [13] found that project durations under fast-track delivery are typically 50–75% shorter compared to traditional project timelines. There is broad consensus that the fast-track approach offers significant time savings over conventional delivery methods [8, 23]. Attar et al. [24] and Khoueiry et al. [25] demonstrated in their respective studies that fast-tracking reduced project durations by 25% and 30% when compared to traditional construction practices [26]. However, Pena-Mora and Li [27] cautioned that excessive overlapping of design and construction phases may introduce additional design changes, potentially leading to delays that offset the time gains achieved through fast-tracking. Table 1 outlines the time-related decision criteria identified in the literature that influence overall project timelines.

Table 1. Time related decision criteria for Fast-track Projects

Time Related Decision Criteria (Indicators)	References
Adopt Pre-fabrication and Modularization	[2, 10, 11, 20, 22]
Secure Early Permits/ Approvals	[7, 8, 10]
Imposing penalties for delays	[10, 11]
Awarding Early contract for enabling works	[8, 28]
Implement design-construction interface management plan	[7, 29]
Adopt an effective dispute resolution technique	[22]
Client to retain design-construction interface management responsibilities	[18]
Limit the design optimization process	[11, 30]
Fast-track application to industrial/ commercial buildings that are high profit & time critical) else than residential buildings	[7, 12, 16]
Decision regarding optimal level of overlap among phases	[13-15, 17, 31]
Prefer critical path over non-critical for fast-tracking	[6, 7, 10, 32]
Announce incentives/ bonus for early completion	[9, 11, 33]
Select the most suited project delivery method and contractual Strategy	[1, 2, 29, 34]

4.3. Fast-Track's Impact on Project Cost

El-far et al. [5] regarded cost variance as a vital success indicator on fast-track projects. With regard to fast-track's impact on project cost, the research community seems divided. Moazzami et al. [34] reported that although site modification issues and reworks are not specifically related to the fast-track approach, their occurrence is comparatively higher, which results in project cost increase [14]. Fast-tracking gives the owner a less than optimal design and a costly construction [35]. Fast-tracking leads to higher construction costs due to shortened duration, due to which project owners can be reluctant in its adoption [7]. On the other hand, Russell & Ranasinghe [36] reported that the fast-track method may offer an advantage over sequential construction with regard to life cycle costs, due to earlier occupancy and reduced overhead expenses. Pena-Mora & Li [27] concluded that fast-track may result in cheaper construction and there are no additional project costs. According to Lalu et al. [32], considerable time saving (9.09%) and cost saving (0.41%, or Rp. 49.8 million) of the contract amount were achieved when Muhamadiyah General Hospital, Ponorogo, Indonesia, was fast-tracked with no project acceleration cost. Egbelakin et al. [37] reported that fast-track construction provides opportunities to counter the risks of inflation and cost escalation that are presently plaguing the construction industry. According to Elvin [38], once project phases are executed simultaneously, uncommitted resources on one phase are shifted to another, which will decrease the project budget and enhance payback period, organizational performance, and cash flow. Table 2 shows the project cost-related decision criteria identified from the literature.

Table 2. Cost related decision criteria for fast-track projects

Cost Related Decision Criteria (Indicators)	References
Client Authorizing "Extras"	[31]
Over-designing the facility	[5, 30, 35, 39]
Limit cost increase to 120% of the conventional projects	[5, 40]
Implement an effective Change Management Plan	[28, 37, 41, 42]
Contingency allocations by the owner	[11, 37]
Early Procurement of Long-Lead-Time Items	[7, 10, 11]
During early design stage implement scope freeze approach	[10, 26, 30, 37]
Value Engineering Implementation	[18]
Resource management plan Implementation	[3]
Evaluate client's financial strength	[7, 33, 43]
Compliance with site safety regulations	[1, 10, 37]

4.4. Fast-Track's Impact on Quality

Besides time and cost, quality is also a measure of fast-track project predictability [13]. Quality variation can be measured by reworks, change orders, defects, deviations, or omissions. As fast-track projects have less time for optimization, chances of quality variation increase [11]. Speed is a requisite for a fast-track approach, and quality management practices function against speed. The construction phase commences before design completion; therefore, maintaining quality on fast-track projects is very difficult [2]. In fast-track, the facility is designed to meet certain criteria, after which no further work is done. Project quality may be adversely affected by the accelerated nature of the fast-track approach [13]. Since fast-track focuses on finishing the project as early as possible and handling multiple tasks simultaneously, it often overlooks quality standards [5]. El-Far et al. [5] further reported that for an owner the priority is to complete the project with possibly the best quality with minimum costs. Table 3 shows the quality-related decision criteria identified from the literature.

Table 3. Quality related decision criteria for fast-track projects

Quality Related Decisions Criteria (Indicators)	References
Implement effective communication mechanism	[7, 11, 29, 40]
Constructability review during design stage (BIM)	[41, 44-46]
Delegate authority to project level	[10]
Prototyping the facility	[30]
Lean Construction implementation	[10, 47]
Contractor pre-qualification Strategy implementation	[1, 7, 10]
Implement Front End Planning (FEP)	[10, 17, 28, 41]
Fast-track application to complex high-rise	[8, 26, 29, 48]
Submit Quality Management Plan during pre-design phase	[2]
Limiting the quality compromise to 90%	[5]
Early contractor involvement during design stage	[2, 7, 10, 22]
Involving O&M personnel early in the design stage	[49]
Organizational restructuring (Experienced Team)	[2, 10, 11, 33, 50]

4.5. Decision-Making on Fast-track Projects

Fast-track requires project owners to take complex decisions and exhibit firm discipline [23]. Fazio et al. [29] concluded that accelerating a project through fast-tracking is a major decision, and construction professionals are often not aware of its implications. On a fast-track project, the overlapping decision is basically a trade-off between time savings and increased cost [30]. Tengler [20] reported that within the next few years, the only restraint on fast-track projects may well be the prospective owner's decision-making capability. Srour et al. [26] emphasized that the construction sector lacked a computer-aided model for decision-making pertaining to activity overlap.

4.6. Structural Equation Modeling-SEM

SEM is a 2nd -generation multivariate statistical technique used for experimental and non-experimental research with cross-sectional and longitudinal data [51], risk analysis, model predictions, and decision support. SEM describes and tests relationships between the latent variables and the observed variables [52]. Variance-based SEM (PLS-SEM) and covariance-based SEM (CB-SEM) are the two main methods [53]. SEM analysis comprises two models: measurement and structural. The measurement model studies the relationships among the constructs and their indicators, whereas the structural model enables the analysis of interrelationships among the constructs [54]. In the measurement model, we assess the convergent and discriminant validity. The degree of agreement among two or more manifest variables used to define a construct is called convergent validity [55]. Discriminant validity is the measure of a construct that clearly differs from other constructs [56]. Collinearity means that two or more indicators in a model are highly correlated, triggering type II errors (i.e., false negatives) [57]. Xiong et al. [58] used chi-square/df (degrees of freedom), goodness-of-fit index (GFI), normed fit index (NFI), and standardized root-mean squared residual (SRMR) to assess the model fit in their study. For endogenous variables, the R^2 value is the most essential evaluation in PLS-SEM [59]. R^2 represents the variance in endogenous variables that can be attributed to the exogenous variables attached to them [60]. f^2 is used to ascertain the impact of the removed exogenous construct on the endogenous constructs [61]. Predictive validity assessment is an essential part of any structural model [62]. Al-Khatib & Ramayah [63] assessed the out-of-sample prediction of their model with the PLSpredict algorithm (cross-validation procedure) using Q2, RMSE, and MAE.

4.7. Conceptual Model Development

The literature review resulted in the identification of the cost, quality, and time-related decisions, which were further used to develop a conceptual model. The conceptual model consists of a network of constructs and indicators that provides a detailed understanding of how the exogenous constructs could influence the endogenous constructs. The conceptual model in Figure 3 consists of the 37 decisions as indicators and cost, quality, and time variances as the latent constructs.

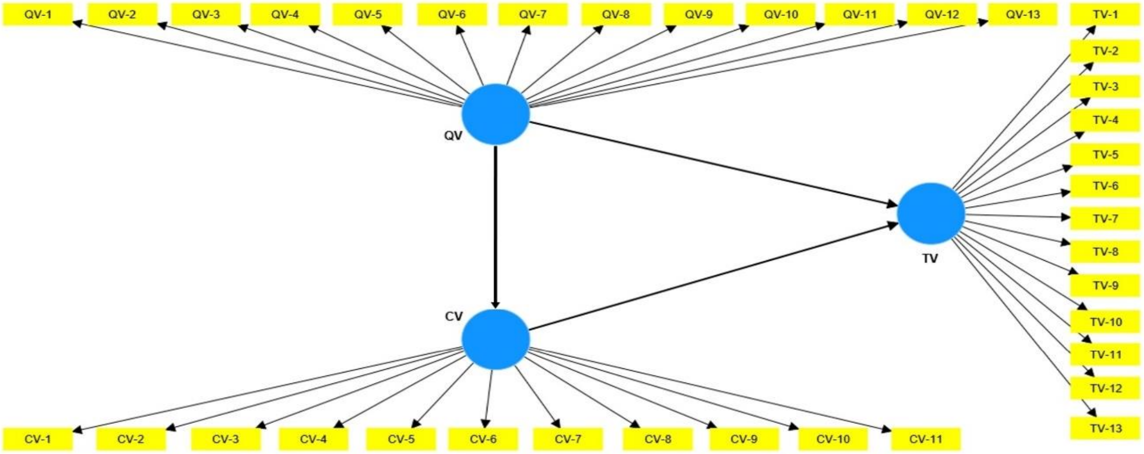


Figure 3. Conceptual Model

5. Research Methodology

Figure 4 outlines the research methodology adopted. An extensive literature review was conducted in which 157 research papers from Google Scholar and internet sources were reviewed, and 71 have been included in this research. The 41 decisions initially identified from the literature were reduced to 37 after the Delphi process and pilot surveys. Data was collected through a 5-point Likert scale-based questionnaire survey and analyzed in smart PLS-4 SEM. Four research hypotheses, including a mediation analysis (mentioned below), were developed from the conceptual model.

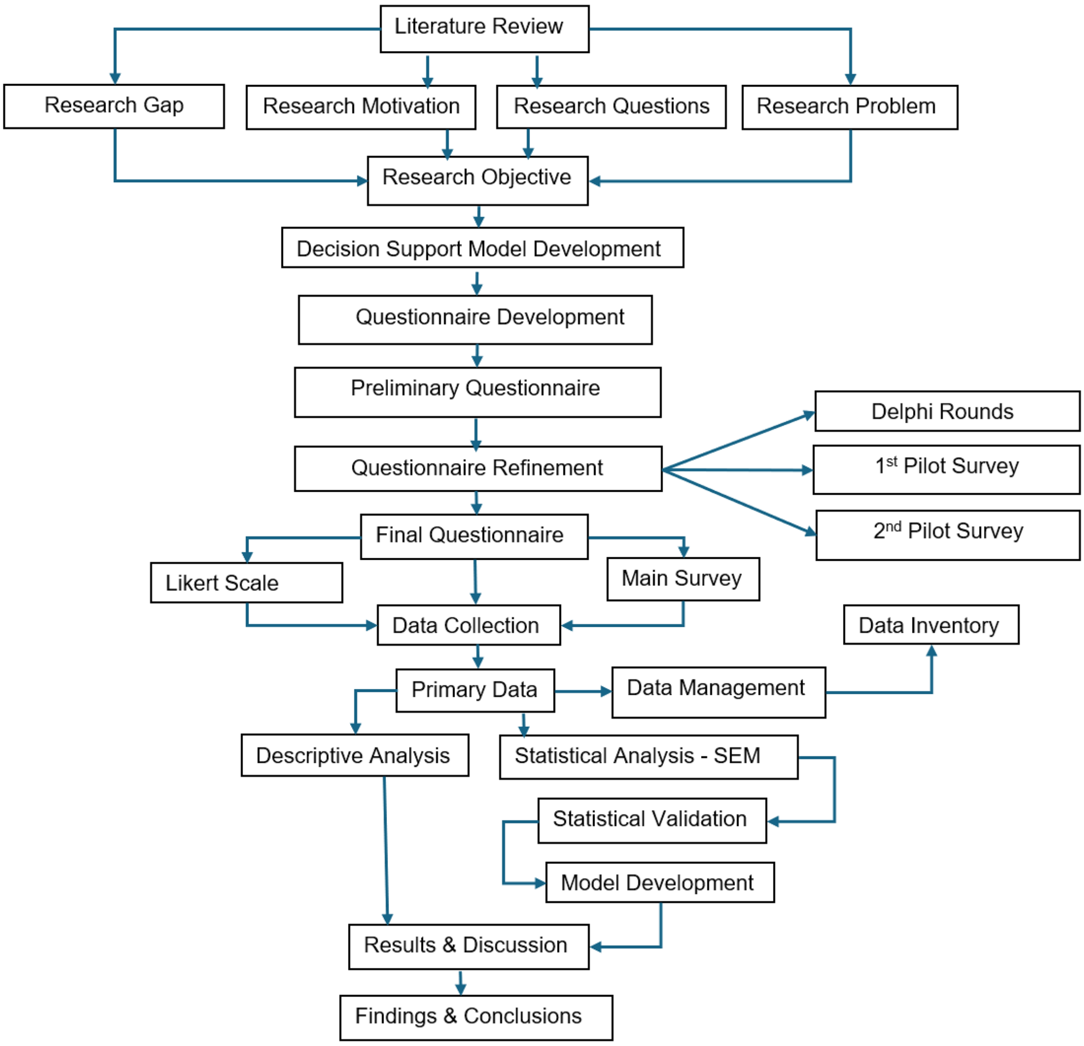
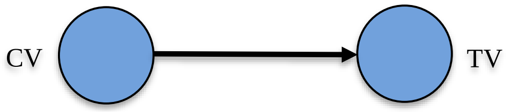
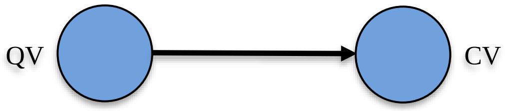


Figure 4. Research Methodology



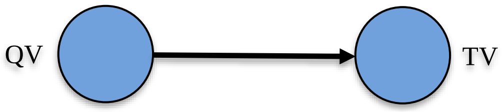
H_0: The variation in project cost does not have significant impact on project time variation

H_1: The variation in project cost has significant impact on project time variation



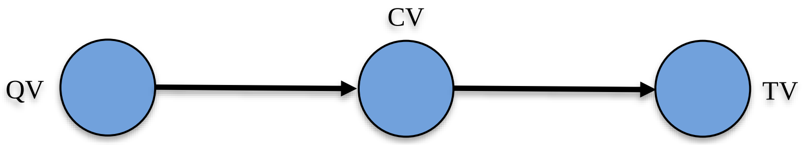
H_0: The variation in project quality does not have significant impact on variation in project cost.

H_1: The variations in project quality have significant impact on variation in project cost.



H_0: The variation in project quality do not have significant impact on project time variation.

H_1: The variation in project quality have significant impact on project time variation.



H_0: The variation in project cost do not mediate a significant impact between the variation in project quality and project duration.

H_1: The variation in project cost mediates a significant impact between the variation in project quality and project duration.

5.1. Delphi Process

The preliminary questionnaire comprising of the indicators and constructs identified from the literature, The preliminary questionnaire comprising of 3 parts i.e., demographic information, respondent's familiarity with fast-track and a 5-point Likert's scale (1 for very low impact and 5 for very high impact) was refined using the Delphi technique. Delphi technique is a structured communication method used to gather opinions and achieve consensus among a group of experts on a particular topic. In this regard, 10 construction industry experts (Table 4) participated and 70% consensus among the experts was achieved in the 3rd round (Figure 5). The questionnaire was refined and used for the pilot survey.

Table 4. Frequency Analysis of Delphi Experts with Experience in Fast-tracking

Respondents	Qualification	Experience
Project Manager	BE (Civ)	16 Yrs
Project Manager	MS (PM)	13 Yrs
Construction Manager	BE (Civ)	27 Yrs
Structural Engineer	MS (Structure)	19 Yrs
Construction Manager	MS (CE&M)	16 Yrs
Project Manager	MS (PM)	14 Yrs
Architect	MS (Arch)	15 Yrs
Project Planner	BE (Civ)	25 yrs
Construction Manager	MS (CE&M)	18 Yrs
Structural Engineer	MS (Structure)	19 Yrs

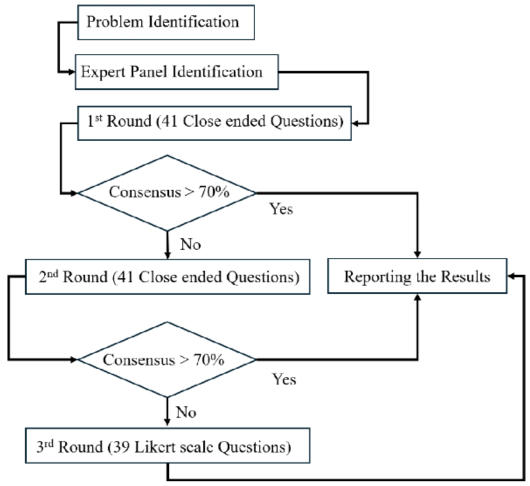


Figure 5. Delphi Process

5.2. Pilot Survey

A pilot study is a small-scale preliminary investigation conducted before the main research study. It serves as a trial run to test and refine the research methods, procedures, instruments, and data analysis techniques that will be used in the full-scale study. Two pilot surveys were conducted in which the preliminary questionnaire was sent to 31 professionals from Pakistan's construction industry and 3 professors of SEM in the US and Pakistan. The contents of the questionnaire were highly appreciated by the respondents; however, they suggested removing two decision criteria. Based on suggestions, the preliminary questionnaire was refined into a final questionnaire, which was used for the main survey.

5.3. Coding Scheme

A coding scheme is required for feeding the latent and the manifest variables to the SEM software. Table 5 shows the coding used for representing the latent and the manifest variables.

Table 5. Coding Scheme of the Latent variables and the indicators

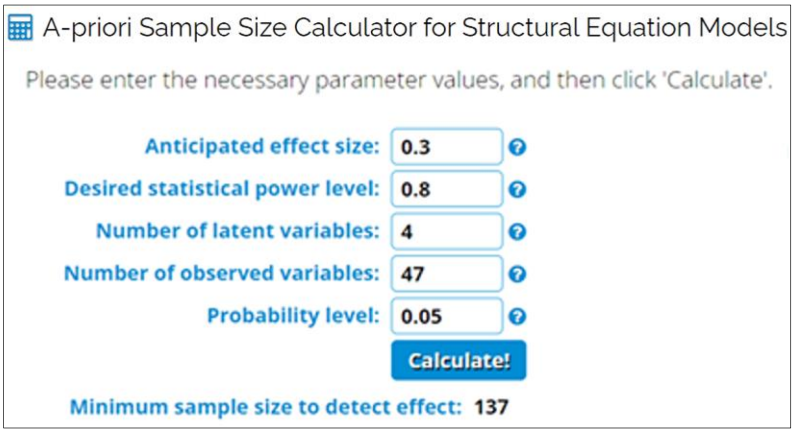
Latent Variable	Decision Criteria (Indicators)	Code
Cost Variance (CV)	Client Authorizing "Extras"	CV-1
	Over-designing the facility	CV-2
	Limit cost increase to 120% of the conventional projects	CV-3
	Implement an effective Change Management Plan	CV-4
	Contingency allocations by the owner	CV-5
	Early Procurement of Long-Lead-Time Items	CV-6
	Implement scope freeze approach during early design stage	CV-7
	Value Engineering Implementation	CV-8
	Resource management plan Implementation	CV-9
	Evaluate client's financial strength	CV-10
	Compliance with site safety regulations	CV-11
Quality Variance (QV)	Implement effective communication mechanism	QV-1
	Early contractor involvement during design stage	QV-2
	Delegate authority to project level	QV-3
	Prototyping the facility	QV-4
	Implement Lean Construction	QV-5
	Adopt contractor pre-qualification Strategy	QV-6
	Implement Front End Planning (FEP)	QV-7
	Fast-track application to complex high-rise	QV-8
	Submit Quality Management Plan during pre-design phase	QV-9
	Limiting the quality compromise to 90%	QV-10
	Constructability review during design stage (BIM)	QV-11
	Involving O&M personnel early in the design stage	QV-12
	Organizational restructuring (Experienced Team)	QV-13

Time Variance (TV)	Adopt Pre-fabrication and Modularization	TV-1
	Secure Early Permits/ Approvals	TV-2
	Imposing penalties for delays	TV-3
	Awarding Early contract for enabling works	TV-4
	Implement design-construction interface management plan	TV-5
	Adopt an effective dispute resolution technique	TV-6
	Client to retain design-construction interface management responsibilities	TV-7
	Limit the design optimization process	TV-8
	Fast-track application to industrial/commercial buildings else than residential buildings	TV-9
	Decision regarding optimal level of overlap among phases	TV-10
	Prefer critical path over non-critical for fast-tracking	TV-11
	Announce incentives/ bonus for early completion	TV-12
	Select the most suited project delivery method and contractual Strategy	TV-13

6. Data Collection

6.1. Sample Size

The sample size for SEM lacks consensus among the researchers. Some researchers suggest that the sample size should be between 100 to 400 whereas studies in construction management have used smaller sample sizes [54]. Al-Mekhlafi et al. [56] suggested that the sample size for SEM must not exceed 100. This study used Daniels Priori online calculator [64] to find the minimum sample size required against a 95% confidence interval, a 0.3 effect size, and 80% statistical power. The minimum sample size calculated by the calculator was 137 (see Figure 6). Refined questionnaires comprising 37 decision criteria and 3 latent variables were self-administered to 217 construction industry professionals in Lahore, Karachi, Islamabad, and Rawalpindi (being hubs of high-rise construction); 176 were received, indicating a response rate of 81.1%. Keeping in view the respondent's familiarity with the fast-track concept (identified in part 2 of the questionnaire), only 159 questionnaires were made part of this research.



A-priori Sample Size Calculator for Structural Equation Models

Please enter the necessary parameter values, and then click 'Calculate'.

Anticipated effect size: 0.3

Desired statistical power level: 0.8

Number of latent variables: 4

Number of observed variables: 47

Probability level: 0.05

Minimum sample size to detect effect: 137

Figure 6. Sample size calculator for SEM

7. Statistical Analysis-SEM

Techniques such as regression, SEM, neural networks, fuzzy logic, and system dynamics were considered for data analysis. However, SEM was selected because SEM assists in studying the relationships among latent variables and their manifest variables, focusing on hypothesis testing and model predictability as outlined in Figure 7. First, the data was screened for outliers, missing values, and data distribution. The data is normally distributed if the skewness and kurtosis values are between -2 and +2 [65]. Then the data was checked for common method bias (CMB), using Harman's one-factor test in SPSS [66]. First, we assessed the measurement model and then the structural model. In the measurement model, internal consistency was assessed using Cronbach's Alpha and composite reliability, for which the values should be ≥ 0.7, and convergent validity using AVE, which should be ≥ 0.5 [51]. To establish discriminant validity, the Fornell & Larcker Criterion and Heterotrait-Monotrait ratio (HTMT) were used. The HTMT value should be < 0.85, and the Fornell & Larcker criterion requires that the square root of the average variance extracted by a construct must be greater with itself than any other construct [62]. Moreover, indicators with outer loading < 0.7 were eliminated from the model as suggested by Permana et al. [67]. Before conducting the path analysis, multi-collinearity was ruled out using the VIF values, which should be < 3.5 [62]. Then model fit was assessed using squared root mean residual (SRMR) with a cut-off of 0.08 [68], normed fit index (NFI) ≥ 0.8 [69], Chi-square/$df \leq 3$ [51], and goodness of fit index (GFI) ≥ 0.90 [70]. Degrees of freedom *(df)* and GFI for this model were calculated using equation 1 [58] and equation 2 [69], respectively, where "*p*" represents the number of manifest variables and "*q*" represents the number of latent variables in Equation 1.

$$df = p\,(p+1)/2 - q \tag{1}$$

$$GFI = \sqrt{Avg.AVE \times R^2} \tag{2}$$

Then the structural model was evaluated using path analysis through a bootstrapping procedure. Path coefficients (β) and p-values for hypothesis testing were attained [70]. $\beta > 0$ indicates a direct and positive relationship, whereas $\beta < 0$ indicates an inverse relationship; zero indicates no relationship [61]. Moreover, β-value between 0.1- 0.3 show weak impact, between 0.3-0.5 moderate impact and 0.5-1.0 strong influence [71], while the p-value for 95% confidence level should be < 0.05 for establishing statistical significance. Explanatory power of the model was assessed using R^2 and f^2 [55]. f2 ≥ 0.02, ≥ 0.15, and ≥ 0.35 indicate small, medium, and enormous impact of the exogenous constructs on the endogenous construct [71]. The out-of-sample predictability of the model was assessed with the PLSpredict algorithm (cross-validation procedure) using Q2, RMSE, and MAE [63]. The key criterion for assessing the predictive relevance of the model is Q2>0 [53]. Moreover, PLSpredict compares PLS-SEM_RMSE values with LM_RMSE and PLS-SEM_MAE values with LM_MAE values. Cross validation predictive ability test (CVPAT) is an alternative to PLSpredict for prediction-oriented assessment of the PLS-SEM model. CVPAT uses indicator average (IA) and linear model (LM) as a benchmark for comparing the average loss values of PLS-SEM (see Figure 7). The difference of average loss values should be significantly less than zero to substantiate better predictive capabilities of the model and p-value < 0.05 to the support the hypothesis that predictive ability of PLS-SEM is better than IA and LM. Importance Performance Map Analysis (IPMA) was used to rank and assess importance against performance for each decision related to cost variance (CV) and quality variance (QV) on the target variable (TV) [61].

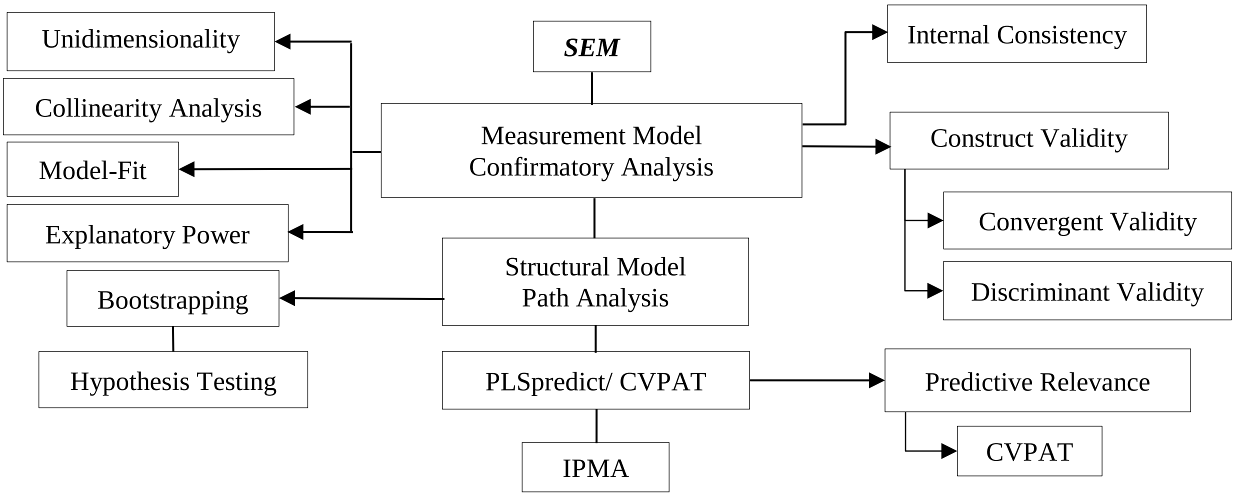


Figure 7. SEM Flowchart

8. Results and Discussion

8.1. Demographic Analysis

The respondents consist of professionals working for clients (43), contractors (75), and consultants (41). These respondents vary in experience and qualification; however, all of them have the experience of working on fast-track projects in Dubai, Qatar, Saudi Arabia, or Pakistan. Demographic analysis shows that most of the respondents have a bachelor's degree, 37% of the respondents hold a master's degree, 16% of the respondents have a diploma of associate engineer, 6 respondents have a PhD in civil engineering, and 2 respondents were chartered accountants.

42 respondents had more than 20 years of experience, and they provided valuable insight into the decision support aspects of fast-track projects and also highlighted the need for evaluating the impact of quality and cost on project duration on fast-track projects. The distribution of respondents as per their role in the industry is also shown in the demographic analysis (see Figure 8).

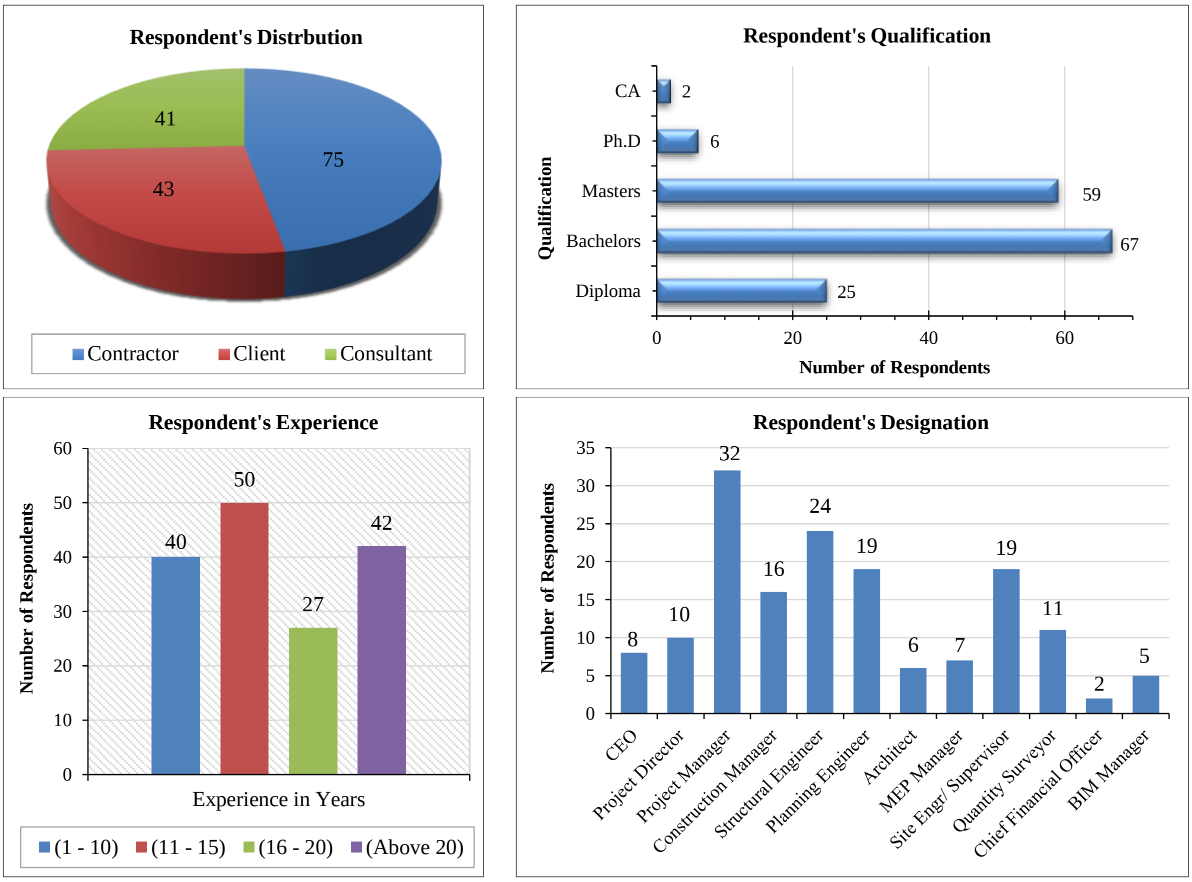


Figure 8. Demographic Analysis of the Respondents

9. Statistical Analysis

9.1. Data Screening

Table 6 shows that all the observed values were as per the range of the Likert scale; no outliers and missing values were observed. Skewness and kurtosis values were between -2 and +2; hence, data was normally distributed. Harman's one-factor test showed that the first indicator accounted for 38.43% of the variance, which is < 50%; thus, CMB is not influencing the outcome of the study [55].

Table 6. Descriptive Statistics and Normality Test Results

Name	No	Type	Missing Value	Mean	Median	Scale min	Scale max	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
SV-1	0	MET	0	3.61	4	1	5	1	5	1.288	-0.942	-0.523	0.00
SV-2	1	MET	0	3.465	4	1	5	1	5	1.368	-1.134	-0.41	0.00
SV-5	2	MET	0	3.352	4	1	5	1	5	1.313	-1.238	-0.221	0.00
SV-9	3	MET	0	2.925	3	1	5	1	5	1.376	-1.322	-0.038	0.00
SV-10	4	MET	0	3.314	4	1	5	1	5	1.388	-1.154	-0.365	0.00
TV-7	5	MET	0	2.792	3	1	5	1	5	1.269	-1.169	0.025	0.00
TV-8	6	MET	0	2.673	2	1	5	1	5	1.325	-1.069	0.326	0.00
TV-10	7	MET	0	2.635	2	1	5	1	5	1.425	-1.216	0.388	0.00
TV-11	8	MET	0	3.025	3	1	5	1	5	1.453	-1.418	-0.019	0.00
TV-12	9	MET	0	2.893	3	1	5	1	5	1.421	-1.361	0.111	0.00
TV-13	10	MET	0	2.579	2	1	5	1	5	1.56	-1.477	0.385	0.00
QV-1	11	MET	0	3.447	4	1	5	1	5	1.528	-1.33	-0.453	0.00
QV-2	12	MET	0	2.484	2	1	5	1	5	1.391	-1.236	0.429	0.00
QV-9	13	MET	0	2.906	3	1	5	1	5	1.453	-1.344	0.091	0.00

QV-10	14	MET	0	3.321	3	1	5	1	5	1.338	-1.17	-0.207	0.00
QV-11	15	MET	0	3.182	3	1	5	1	5	1.378	-1.198	-0.216	0.00
QV-12	16	MET	0	2.899	3	1	5	1	5	1.433	-1.393	-0.042	0.00
QV-13	17	MET	0	3.39	4	1	5	1	5	1.336	-1.025	-0.377	0.00
CV-1	18	MET	0	2.491	2	1	5	1	5	1.228	-0.553	0.68	0.00
CV-2	19	MET	0	3.182	3	1	5	1	5	1.364	-1.244	-0.14	0.00
CV-3	20	MET	0	2.346	2	1	5	1	5	1.317	-0.377	0.872	0.00
CV-6	21	MET	0	2.931	3	1	5	1	5	1.406	-1.293	0.097	0.00
CV-7	22	MET	0	3.409	4	1	5	1	5	1.45	-1.327	-0.329	0.00

9.2. Measurement Model (CFA)

Table 7 shows that values for composite reliability and Cronbach's alpha were > 0.7, thus establishing internal consistency and reliability. AVE values of all the constructs were > 0.5 less QV, which also improved after eliminating the indicators with factor loadings less than 0.7 (Figure 9) thus establishing convergent validity for the constructs. Table 8 shows that the Fornell & Larcker criterion is satisfied and HTMT values are > 0.85 thus establishing discriminant validity. Table 9 shows that the VIF values for all the constructs are < 3.5 thus verifying that multicollinearity does not exist in the model.

Table 7. Internal consistency and convergent validity statistics

Constructs	Code	Cronbach's Alpha (α)	Composite Reliability (ρ_c)	(AVE)	
				Initial	Modified
Cost Variance	CV	0.864	0.902	0.581	0.648
Quality Variance	QV	0.928	0.939	0.493	0.690
Time Variance	TV	0.891	0.917	0.534	0.650

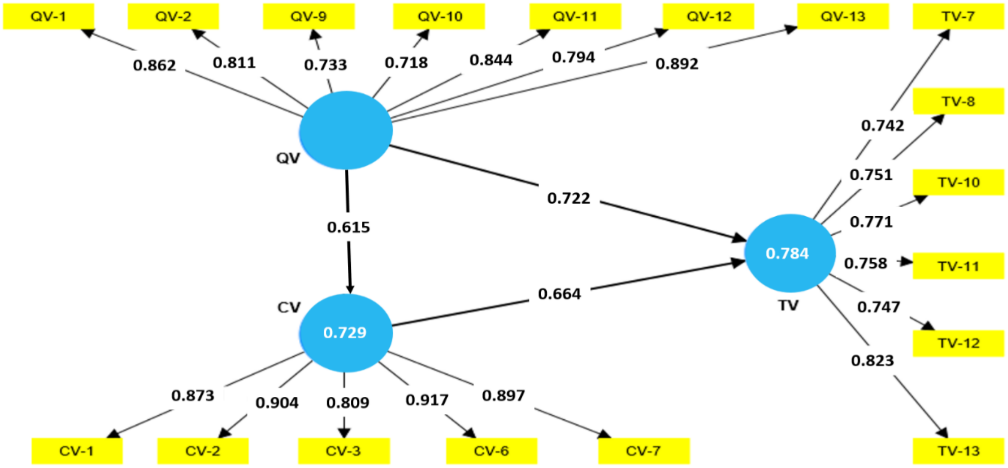


Figure 9. Final Modified model showing outer Loadings, path coefficients and R^2 values

Table 8. Discriminant Validity

	CV	QV	TV		HTMT
CV	0.805			QV ↔ CV	0.113
QV	0.115	0.831		TV ↔ CV	0.771
TV	0.684	0.003	0.806	TV ↔ QV	0.074

Table 9. Multicollinearity and f-square values

	VIF	f-square (f^2)
CV → TV	1.013	0.604
QV→ CV	1.000	0.362
QV → TV	1.013	0.213

9.3. Model Fit

The SRMR and NFI values of the model were $0.05 < 0.08$ and $0.911 \geq 0.90$, respectively, and those of the GFI and chi-square/df were $0.96 > 0.9$ and $2.16 < 3.0$, respectively, thus verifying a good model fit and establishing that the conceptual model aligns well with the observed data. Hence, the model is appropriate for the next phase of statistical analysis, i.e., path analysis.

9.4. Structural Model (Path Analysis)

The results of hypotheses testing, p-values (Figure 10) and β-values (path coefficient) in Tables 10 and 11 provide a useful insight into the cost-quality impact on project duration, which is discussed as follows.

Table 10. Direct Effects

		β	Sample Mean (M)	Standard Deviation	T Statistics (β /STDEV)	p-values	Decision
H1	CV→TV	0.664	0.665	0.045	14.311	0.000 < 0.05	Accepted
H2	QV→CV	0.615	0.616	0.121	5.082	0.002 < 0.05	Accepted
H3	QV→TV	0.722	0.723	0.080	9.025	0.000 < 0.05	Accepted

Table 11. Indirect Effects (Mediation Analysis)

		β	Sample Mean	Standard Deviation	T Statistics	p-value	Decision
H4	QV→CV→TV	0.561	0.563	0.151	3.715	0.004 <0.05	Accepted

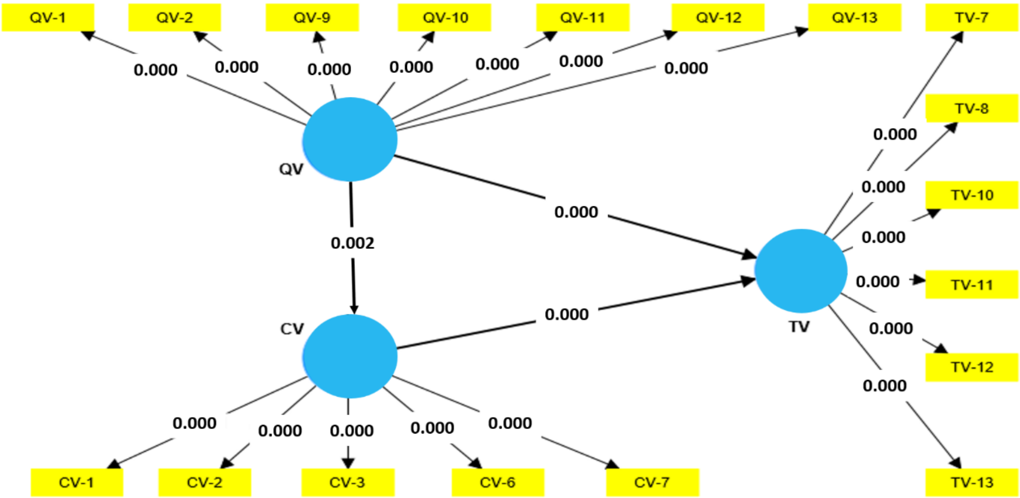


Figure 10. Modified Model showing the p-values

9.5. Hypothesis 1

With β = 0.664 and p-value < 0.05, the variation in project cost has a large positive effect on changes in project duration, and the relationship between both is statistically significant; therefore, H1 is accepted. The β-value also revealed that a 1-standard-deviation increase in project cost will result in a 0.664-standard-deviation increase in project duration.

9.6. Hypothesis 2

With β = 0.615 and p-value < 0.05, variance in project quality has a large positive effect on variation in project cost, and the relation is statistically significant; hence, the null hypothesis (Ho) is rejected, and the alternate hypothesis (H1) is accepted. The β-value suggests that a 1-standard-deviation variation in project quality will vary the project cost by 0.615 standard deviations.

9.7. Hypothesis 3

With β = 0.722 and a p-value < 0.05, quality variations have a strong positive impact and a significant relation with project time variation; therefore, the null hypothesis is rejected and the alternate hypothesis (H1) is accepted. The β-value indicates that if project quality changes by 1 standard deviation, then the project duration will change by 0.722 standard deviations.

9.8. Hypothesis 4 (Mediation Analysis)

A β-value of 0.561 and a p-value > 0.05 indicate that variation in project cost mediates a strong positive and statistically significant relation between variations in project quality and duration; thus, the null hypothesis is rejected and the alternate hypothesis (H1) is accepted. The β-value suggests that a 1-standard-deviation change in project quality will result in a 0.561-standard-deviation change in project duration through variations in project cost.

9.9. Explanatory Power of the Model

The coefficient of determination (R^2) and f^2 are used to assess the explanatory power of the model. In the final modified decision support model (Figure 9), the R^2 for TV is 0.784, which suggests that 78.4% of the variation in project duration is attributable to variations in project cost and quality. Similarly, R^2 for CV is 0.729, indicating that 72.9% of the variation in project cost is attributable to variation in project quality. f2 is the extension of R^2 that indicates the proportion of variance in an endogenous variable that is uniquely explained by a specific exogenous variable. f^2 values in Table 9 indicate that cost variance has an enormous effect on project duration (0.604) and quality variance also has an enormous impact on project cost (0.362), whereas quality variance has a medium impact on variation in project duration (0.213).

9.10. Predictive Relevance of the Structural Model

Table 12 shows that all the values of Q^2 are > 0; thus, the predictive relevance of the model is established. Similarly, all the PLS_RMSE and PLS_MAE values are less than the LM_RMSE and LM_MAE values, indicating lesser error in the SEM than the linear model (LM); hence, the final decision support model has high out-of-sample predictability.

Table 12. Manifest Variable (MV) Prediction Summary

	Q^2-predict	PLS-SEM_RMSE	LM_RMSE	PLS-SEM_MAE	LM_MAE
QV-1	0.403	0.948	0.953	0.751	0.772
QV-10	0.572	0.898	0.916	0.712	0.731
QV-11	0.270	1.133	1.180	0.881	0.923
QV-12	0.372	1.121	1.144	0.898	0.915
QV-13	0.377	1.151	1.172	0.927	0.952
QV-2	0.566	0.978	0.983	0.732	0.743
QV-9	0.275	1.122	1.132	0.817	0.878
TV-10	0.341	1.064	1.118	0.903	0.916
TV-11	0.505	1.030	1.061	0.819	0.831
TV-12	0.475	1.038	1.065	0.807	0.815
TV-13	0.271	1.340	1.381	1.107	1.136
TV-7	0.335	1.043	1.071	0.838	0.857
TV-8	0.382	1.049	1.104	0.845	0.862

Another predictive relevance method is the CVPAT, in which the dataset is divided into training and testing sets. The model is estimated on the training set, and its predictive performance is evaluated on the testing set. This helps estimate how well the model would perform on new data. The CVPAT results in Table 13 show that all the values of average loss difference are negative for both IA and LM. Moreover, the p-values are < 0.05, which supports the hypothesis that the predictive ability of the PLS model is better than IA and LM, thus indicating high out-of-sample predictive power of this final decision support model.

Table 13. CVPAT-Difference of Average Loss values for PLS-SEM vs IA and LM

	Indicator Average (IA)			Linear Model (LM)		
	Average loss difference	t value	p-value	Average loss difference	t value	p-value
QV	-0.742	7.963	0.000	-0.048	1.989	0.047
TV	-0.776	7.277	0.000	-0.052	2.023	0.029
Overall	-0.761	8.932	0.000	-0.050	2.148	0.033

9.11. Importance-Performance Map Analysis – IPMA

Figure 11 and Table 14 suggest that the project cost-related decisions, i.e., CV-6, CV-7, CV-2, CV-3, and CV-1, are the most important and highly performing variables with regards to the target variable, i.e., project duration. The quality-related decisions, i.e., QV-10, QV-11, QV-12, and QV-9, are also highly performing but have low importance, indicating that resources allocated to these indicators might be better redirected to more important but lower-performing indicators for greater impact. Which is also supported in literature that over-extending the resources to achieve quality on the fast track is the least desired aspect.

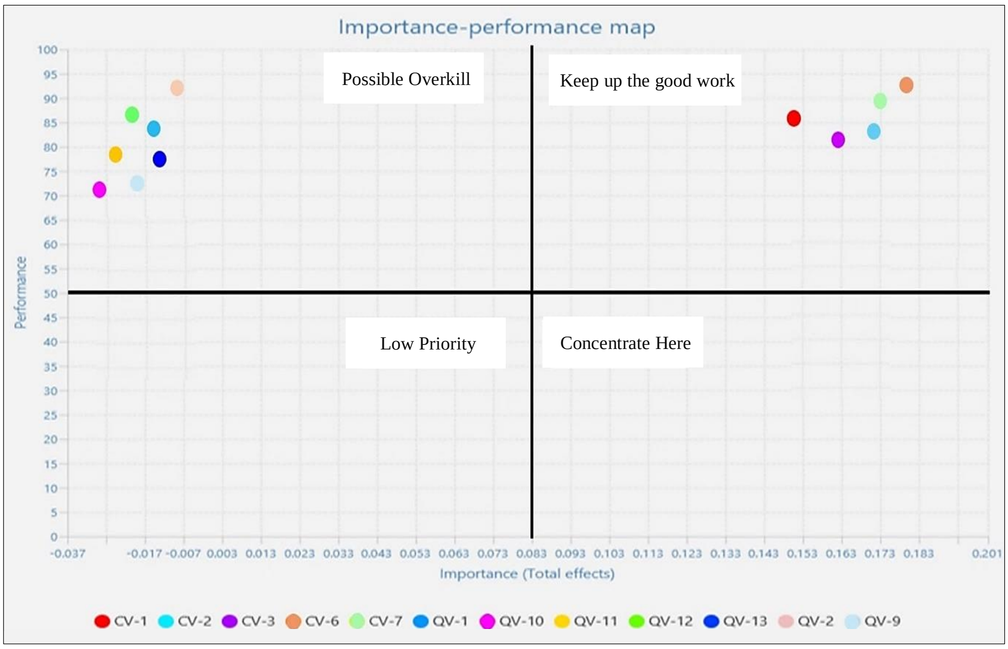


Figure 11. Importance-Performance Map Analysis – Indicators

Table 14. Importance-Performance Map Analysis values - Indicators

Indicators	Importance for TV	MV Performance
CV-1	0.149	86.441
CV-2	0.169	84.258
CV-3	0.160	81.659
CV-6	0.180	94.662
CV-7	0.171	89.428
QV-1	-0.015	84.279
QV-10	-0.029	71.237
QV-11	-0.024	88.756
QV-12	-0.021	87.466
QV-13	-0.011	77.287
QV-2	-0.009	92.210
QV-9	-0.019	72.851

10. Novelty and Comparison with Existing Research

A few decision support tools for fast-track projects were found in the literature, but they only focused on a specific aspect of the fast-track approach and lacked comprehensiveness. The decision-making model proposed by Cho & Hastak [12] is only a time and cost optimization model and neglects the quality-related aspects of fast-track projects. As concluded by the authors, their model cannot ensure the success of fast-track applications. Moreover, it also fails to provide an insight into the actual decisions encountered on such projects. The model focuses only on work packages related to design and construction, neglecting the decision-making aspects such as procurement, finance and economics, contracting, management, etc. Furthermore, the proposed model does not explicitly identify work packages and randomly terms them as DWPk and CWPnm, which fails to provide an in-depth understanding of the decision-making scenarios encountered by the stakeholders. Bogus et al. [30] proposed a framework for overlapping dependent design activities on fast-track projects that can assist the project managers in making better decisions on when and how much to overlap the sequential activities. Khoueiry et al. [25] presented a decision support tool that was based on activity schedule optimization for fast-track projects. Russell & Ranasinghe [36] presented a deterministic analysis framework that permits the computation of an upper bound on the constant dollar expenditure that should be made to fast-track a project to achieve a specified duration.

All these decision frameworks lack comprehensiveness and focus only on one aspect of fast-tracking, either its information flow, overlapping design activities, reducing reworks, or financial considerations. The model proposed in this research overcomes the shortfalls of existing models for fast-track projects by incorporating the KPIs, i.e., time, cost, and quality variances. Moreover, this model uses real-life decisions to ensure the successful application of fast-track methodology on high-rise buildings and highlights the impact of each decision on the relevant KPI. The novelty of this research lies in the final model that empirically proves the significance of the relationship between the universally accepted KPIs. The model also presents the novel β-values, which highlight the interplay between the KPIs. IPMA results assist the decision-makers in allocating and redirecting the resources for optimal outcome of the target variable. The model also accurately accounts for the amount of variance in the endogenous variable attributable to the exogenous variables through the novel R^2 and f^2 values.

11. Conclusion

This research was initiated to analyze the impact of cost and quality variances on project duration in fast-track high-rise buildings, with the ultimate goal of supporting informed decision-making. The proposed model addresses this objective by identifying and evaluating key decisions based on their influence on the latent variables—time, cost, and quality—through factor loadings. In the final modified model, factor loadings reveal that individual decisions account for between 51.5% (0.7182) and 84% (0.9172) of the variance in their respective KPIs.

Path analysis provided statistical confirmation of significant relationships among time, cost, and quality, as well as the mediating role of cost variance between quality and time. The model introduces novel β-values, which indicate the effect of a one standard deviation change in an exogenous variable on an endogenous variable. These values (0.664, 0.615, 0.722, 0.561) significantly contribute to the body of knowledge, equipping decision-makers with predictive insights about the potential impact of each decision before implementation.

The R^2 values suggest that 78.4% of the variance in project duration is attributable to variations in cost and quality, while 72.9% of the variance in project cost can be explained by changes in quality. Additionally, the f^2 values (0.604, 0.362, 0.213) highlight the critical role of each exogenous variable, indicating that removing either cost or quality variance would substantially affect project duration—thus underscoring the importance of applying the model holistically.

The Importance–Performance Map Analysis (IPMA) emerges as a key decision-support tool, enabling effective prioritization and resource allocation. The IPMA results indicate that cost-related decisions—such as early procurement of long lead-time items, scope freeze during early design, and over-designing the facility—exhibit both high importance and performance, signaling their strategic significance. On the other hand, quality-related decisions—such as early involvement of contractors and O&M teams during the design phase—demonstrate high performance but relatively low importance, suggesting that resources in these areas might be better allocated elsewhere.

Model validation through Q^2, RMSE, MAE, and CVPAT metrics confirms strong out-of-sample predictive power, ensuring the model's applicability across varying project contexts. This enhances decision-makers' confidence in its reliability for forecasting outcomes under different conditions.

In summary, the proposed decision support model offers a robust framework for improving project predictability, minimizing uncertainties, and optimizing performance by effectively balancing the fundamental trade-offs between cost, time, and quality in fast-track high-rise construction projects.

12. Declarations

12.1. Author Contributions

Conceptualization, M.S.; methodology, S.S.; software, M.S.; validation, I.H. and S.S.; formal analysis, M.S.; data curation, M.S.; writing—original draft preparation, I.H. and M.S.; writing—review and editing, M.S.; supervision, I.H. All authors agree to the published version of the manuscript.

12.2. Data Availability Statement

The data presented in this study are available in the article.

12.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

12.4. Conflicts of Interest

The authors declare no conflict of interest.

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