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Published Version

Barani Shikhrobat, M., Flanagan, R. and Kabiri, S. ORCID: https://orcid.org/0000-0002-5311-7304 (2025) Understanding complexity at the pre-construction stage of project planning for construction projects. American Journal of Operations Research, 15 (1). pp. 1-27. ISSN 2160-8849 doi: 10.4236/ajor.2025.151001 Available at https://centaur.reading.ac.uk/123154/

To link to this article DOI: http://dx.doi.org/10.4236/ajor.2025.151001

Publisher: Scientific Research Publishing

Scientific Research Publishing

American Journal of Operations Research, 2025, 15(1), 1-27
https://www.scirp.org/journal/ajor
ISSN Online: 2160-8849
ISSN Print: 2160-8830

Understanding Complexity at the Pre-Construction Stage of Project Planning for Construction Projects

Mehran Barani Shikhrobat[1], Roger Flanagan[2], Shabnam Kabiri[2]

[1]School of Computing, Engineering and Physical Sciences, University of the West of Scotland (London Campus), London, UK
[2]School of Construction Management and Engineering, University of Reading, Reading, UK
Email: Mehran.shikhrobat@uws.ac.uk, mshikhrobat@yahoo.com, R.Flanagan@reading.ac.uk, s.kabiri@reading.ac.uk

How to cite this paper: Shikhrobat, M.B., Flanagan, R. and Kabiri, S. (2025) Understanding Complexity at the Pre-Construction Stage of Project Planning for Construction Projects. *American Journal of Operations Research*, **15**, 1-27.
https://doi.org/10.4236/ajor.2025.151001

Received: December 28, 2024
Accepted: January 28, 2025
Published: January 31, 2025

Abstract

The construction projects' dynamic and interconnected nature requires a comprehensive understanding of complexity during pre-construction. Traditional tools such as Gantt charts, CPM, and PERT often overlook uncertainties. This study identifies 20 complexity factors through expert interviews and literature, categorising them into six groups. The Analytical Hierarchy Process evaluated the significance of different factors, establishing their corresponding weights to enhance adaptive project scheduling. A system dynamics (SD) model is developed and tested to evaluate the dynamic behaviour of identified complexity factors. The model simulates the impact of complexity on total project duration (TPD), revealing significant deviations from initial deterministic estimates. Data collection and analysis for reliability tests, including normality and Cronbach alpha, to validate the model's components and expert feedback. Sensitivity analysis confirmed a positive relationship between complexity and project duration, with higher complexity levels resulting in increased TPD. This relationship highlights the inadequacy of static planning approaches and underscores the importance of addressing complexity dynamically. The study provides a framework for enhancing planning systems through system dynamics and recommends expanding the model to ensure broader applicability in diverse construction projects.

Keywords

Project Planning, Project Complexity Measurement, Uncertainty Management, Project Risk Management, Strategic Project Scheduling

1. Introduction

Scheduling systems such as Gantt charts, Critical Path Method (CPM), and Program Evaluation and Review Technique (PERT) are traditional tools that rely on predictive planning. These methods develop schedules at a fixed point in time based on available data and assumptions about future conditions. However, construction projects occur in dynamic environments where unpredictable external factors such as weather, material delivery delays, pandemics, and financial challenges significantly influence outcomes.

While these traditional methods provide a structured approach to project scheduling, they fall short in addressing complexities and uncertainties inherent in construction projects. This limitation underscores the need for advanced scheduling techniques that adapt to dynamic conditions and address complexity.

Complexity in construction projects is a multidimensional challenge involving interdependent variables such as project activities, external influences, and managerial objectives. Managing complexity requires a deeper understanding of its factors and their influence on project planning and execution. Researchers have explored various approaches to improve project duration estimates, including Bayesian Networks [1] and simulation-based techniques [2]. However, coping with complexity remains a significant challenge in project scheduling [3].

A comprehensive review of literature on project complexity in construction was conducted using search terms such as "project complexity," "construction complexity," and "complexity of project management." The research spanned publications from 1996 to 2024, focusing on construction projects and their dynamic environments. The review utilised key online databases such as Google Scholar, Web of Science, EBSCO, Scopus, IEEE Xplore, Science Direct, and JSTOR.

The analysis prioritised top journals in construction and management, including:

- *Journal of Construction Engineering and Management*.
- *Journal of Management in Engineering*.
- *International Journal of Project Management*.
- *Construction Innovation: Information, Process, Management*.
- *Construction Management and Economics*.
- *Engineering, Construction and Architectural Management*.

These journals were chosen based on their high rankings in the field [4]. The research resulted in a curated list of significant studies organised by year, author, and factors of project complexity.

The review excluded articles unrelated to construction projects and those focusing on communication between authors and editorial teams. Studies on phenomena outside the scope of project complexity were also eliminated. The final dataset included 82 peer-reviewed articles, conference papers, and 12 PhD theses. These publications were analysed to identify recurring themes and research interests.

The analysis revealed four primary categories of research interest in project complexity:

1) Identifying and Understanding Complexity

Studies in this category focus on defining project complexity and exploring its implications for project management.

2) Shortcomings of Traditional Planning Tools

Researchers examined the limitations of widely used project planning tools in addressing the multifaceted nature of project complexity.

3) Optimizing Project Planning

This category includes studies that propose advanced techniques and methodologies for improving project planning in complex environments.

4) Project Complexity Factors

Research here identifies and evaluates factors contributing to project complexity, such as technological challenges, stakeholder involvement, and environmental uncertainties.

The study underscores the inadequacy of traditional scheduling methods in managing construction project complexities and highlights the necessity for adaptive and sophisticated planning techniques. It also emphasises the importance of understanding complexity factors to optimise project planning and achieve managerial objectives.

Future research should continue exploring innovative scheduling approaches, focusing on integrating complexity considerations into planning tools to better address the dynamic nature of construction projects.

Initially, defining complexity and examining its influence on project management is discussed, particularly in optimising project planning through identifying and comprehending complexity. Subsequently, an analysis of the limitations inherent in conventional scheduling methods will be conducted, focusing on the deficiencies of traditional planning tools in effectively managing complexity. Following this, innovative strategies will be proposed to enhance scheduling practices within complex environments. A thorough identification of primary contributors to complexity will be undertaken, including technological obstacles and stakeholder interactions, which are critical factors influencing project complexity. Finally, insights and practical implications for project managers will be discussed. In conclusion, recommendations for future research will be presented, emphasising the significance of adaptive scheduling methods.

2. Complexity of Project Planning Review

Early research highlighted the foundational role of traditional methods such as Gantt charts, Critical Path Method (CPM), and Program Evaluation and Review Technique (PERT) in project planning. While these methods provided initial frameworks for scheduling and sequencing, they relied heavily on deterministic assumptions. Studies such as Lockyer [5] and Kelley [6] emphasised the utility of these methods in defining critical activities and their durations. However, as Andersen [7] highlights that these approaches' linear and predictive nature often failed to account for real-world uncertainties.

Critiques by researchers such as Charnes and Cooper [8] suggested that CPM's reliance on static scheduling underestimated the probabilistic nature of project activities. Similarly, PERT's probabilistic focus was criticised for oversimplified activity durations and assumptions about dependencies. These critiques underscore a recurring limitation: traditional methods assume linearity and certainty, which are rarely present in dynamic project environments.

2.1. Evolution Towards Probabilistic and Fuzzy Methods

Probabilistic models and fuzzy logic emerged as alternatives to address the shortcomings of deterministic planning. PERT's introduction of probability distributions marked a shift towards accommodating uncertainties. However, as noted by Elmaghraby [9], these methods still struggled with real-world applications due to incomplete data and over-reliance on statistical assumptions.

Fuzzy logic, introduced by Zadeh and later developed by Kahraman *et al.* (2006) [10], provided a framework to deal with imprecise and ambiguous information. By validating uncertain data, fuzzy methods improved planning accuracy. Yet, researchers such as Chanas *et al.* [11] pointed out limitations in applying fuzzy logic to dynamic environments, where real-time adjustments were often necessary.

2.2. Optimization Techniques and the Constraints

Research has centred on optimising project planning. Sensitivity analysis and stochastic methods have been explored to enhance planning robustness. Saltelli *et al.* [12] discussed sensitivity analysis as a tool for evaluating the impact of variable changes on outcomes, which aids in integrating uncertainties. However, as Hall and Posner (2004) [13] highlighted, the cost and complexity of implementing such models often limit their practical application.

Stochastic methods, including heuristic algorithms and Monte Carlo simulations, addressed uncertainties by generating multiple scenarios for activity durations. While these methods improved predictive accuracy, studies by Herroelen and Leus [14] shown that frequent re-planning in dynamic settings often negated their benefits. Robust optimisation, as discussed by Coleman *et al.* [15] attempted to balance flexibility and stability but faced challenges in representing valid objective values and addressing unpredictability.

2.3. Addressing Uncertainty and Complexity

Uncertainty remains a fundamental challenge in project planning. Researchers such as Freeman [16] and Collyer and Warren [17] highlights project environments' dynamic and unpredictable nature. Uncertainty stems from controllable factors, such as design changes and resource availability, and uncontrollable factors, such as weather and economic fluctuations.

Dynamic planning approaches have been proposed to address these uncertainties, including real-time scheduling and system dynamics. As Senge [18] promotes, system dynamics models the interactions within complex systems to predict outcomes. However, critiques by Helbing [19] and Gao [20] argue that these models often oversimplify complex interactions, limiting their practical utility.

2.4. Factors Contributing to Project Complexity

The literature identifies various factors contributing to project complexity, including structural, organisational, and contextual elements. Baccarini [21] characterised complexity as the interdependence of multiple variables while Williams [22] highlights the role of uncertainty in goals and methods. Gidado [23] further categorised complexity into operational and workflow interdependencies, emphasising the challenges in managing overlapping tasks and resource constraints.

Recent studies, such as those by Vidal and Marle [24] [25], Luo *et al.* [26], Dao *et al.* [27] and Ma and Fu [28], expanded this understanding by incorporating project size, stakeholder diversity, and environmental conditions. These factors underscore the need for adaptive planning methods for static and dynamic complexities. However, as noted by Remington and Pollack [29] and Parekh [30], existing tools often fail to integrate these multifaceted elements effectively.

2.5. Gaps and Contradictions in Existing Research

Despite advancements in project planning methods, significant gaps and contradictions remain:

Inadequate Integration of Dynamic Factors: Traditional and even some modern methods struggle to accommodate project environments' dynamic and nonlinear nature.

Over-Reliance on Deterministic Models: Many tools and techniques assume stability and predictability, which are rarely achievable in practice.

Limited Practical Applications: Advanced methods, such as fuzzy logic and robust optimisation, often face barriers in implementation due to their complexity and resource requirements.

Human Factors: Studies by Stoop and Wiers [31] emphasises the impact of human error on planning accuracy, yet few models effectively incorporate this critical variable.

The critical literature review on project planning complexity reveals a persistent tension between theoretical advancements and practical applications. While traditional methods laid the groundwork for structured planning, their limitations in addressing uncertainties and complexities necessitated the development of probabilistic, fuzzy, and robust optimisation techniques. Despite these advancements, gaps in integrating dynamic factors and addressing real-world challenges remain.

Future research should focus on developing adaptive, dynamic planning approaches that combine theoretical rigour with practical applicability. This includes leveraging emerging technologies such as artificial intelligence and machine learning to create more responsive and resilient project planning systems. By bridging the gap between theory and practice, the field can better navigate the complexities inherent in modern construction projects.

3. Data Collection and Analysis

The study employed a semi-structured interview and questionnaires to explore expert views on factors influencing project complexity. The questionnaires were distributed electronically to 320 selected experts, and 142 responses were received. Although the response rate was lower than anticipated, the diverse sample ensured unbiased and reliable results.

The research aimed to identify and evaluate complexity factors through a three-step process: distribution of questionnaires, weighting factors via pairwise comparison, and assessing the proposed model. The complexity factors were categorised into six groups based on literature and expert input:

Scope of Project Planning: Factors arising from initial design changes.

Governance and Regulatory Requirements: Compliance-related complexities.

Resources: Issues regarding resource allocation and availability.

Contractor and Supply Chain Issues: Challenges in coordination and logistics.

Externalities: Uncontrollable factors such as climate change.

Expectations for Total Project Duration: Variances between planned and actual timelines.

The Analytical Hierarchy Process (AHP) method was used to weigh and rank these factors through pairwise comparisons. Externalities emerged as the most significant factor, attributed to insufficient data, lack of task-specific expertise, and unpredictable events impacting project outcomes.

Data was analysed using the Statistical Package for Social Sciences (SPSS). Two scales, nominal and ordinal, were employed for categorising variables. Nominal scales labelled variables without quantitative value, while ordinal scales ranked qualitative items (e.g., high, medium, low). Normality and scale reliability tests, including the Cronbach alpha test, were applied to validate the data.

Experts from academia and industry discussed and assigned sub-factors to each cluster factor. These discussions helped refine the factors and ensured their relevance. The research highlights that complexity factors often create discrepancies between planned and actual project implementation, underscoring the importance of addressing externalities and improving project planning methodologies.

3.1. The Use of AHP

Five factors were presented in the hierarchy model of complexity for project planning as the core variables. Therefore, a matrix of five columns and five rows is required for the analysis combined with the Analytic Hierarchy Process (AHP) decision-making method. The comparison matrix for core complexity factors identified for construction project planning is shown in the following Table 1.

Table 1. Comparison matrix of core complexity factors.

	Externalities	Governance and regulations	Resources	Contractor and supply chain	Scope	Eigenvector
Externalities	1	5	5	3	5	0.49
Governance and regulations	0.2	1	0.5	2	0.2	0.07
Resources	0.2	3	1	3	0.25	0.12
Contractor and supply chain	0.14	0.5	0.33	1	0.2	0.05
Scope	0.33	5	4	5	1	0.26

The eigenvector and eigenvalue are calculated based on the pairwise comparison scores responded by the participants. Therefore, matrix Si for the measurement of project planning (PP) complexity is:

$$S_i = \begin{bmatrix} 1 & 5 & 5 & 3 & 5 \\ 1/5 & 1 & 1/2 & 2 & 1/5 \\ 1/5 & 3 & 1 & 3 & 1/4 \\ 1/7 & 1/2 & 1/3 & 1 & 1/5 \\ 1/5 & 5 & 4 & 5 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 5 & 5 & 3 & 5 \\ 0.2 & 1 & 0.5 & 2 & 0.2 \\ 0.2 & 3 & 1 & 3 & 0.25 \\ 0.14 & 0.5 & 0.33 & 1 & 0.2 \\ 0.33 & 5 & 4 & 5 & 1 \end{bmatrix}$$

Then, the sum of each column is calculated as:

$$\begin{bmatrix} S_1 & S_2 & S_3 & S_4 & S_5 \\ 1.87 & 14.5 & 10.8 & 18 & 6.65 \end{bmatrix}$$

The next step is to normalize the matrix of S_i which is calculated by the deviance of each entry over the sum of the column as follows:

$$\text{Normalized Pairwise Matrix } |S_i| = \begin{bmatrix} 1/1.87 & 5/14.5 & 5/10.8 & 7/18 & 5/6.65 \\ 0.2/1.87 & 1/14.5 & 0.5/10.8 & 2/18 & 0.2/6.65 \\ 0.2/1.87 & 3/14.5 & 1/10.8 & 3/18 & 0.25/6.65 \\ 0.14/1.87 & 0.5/14.5 & 0.33/10.8 & 1/18 & 0.2/6.65 \\ 0.33/1.87 & 5/14.5 & 4/10.8 & 5/18 & 1/6.65 \end{bmatrix}$$

$$\text{Normalized Pairwise Matrix } |S_i| = \begin{bmatrix} 0.53 & 0.34 & 0.46 & 0.39 & 0.75 \\ 0.11 & 0.07 & 0.05 & 0.11 & 0.03 \\ 0.11 & 0.21 & 0.09 & 0.17 & 0.04 \\ 0.07 & 0.03 & 0.03 & 0.06 & 0.03 \\ 0.18 & 0.34 & 0.37 & 0.28 & 0.15 \end{bmatrix}$$

Then, the criteria weights (eigenvectors) are calculated by the sum of all entries divided by the number of criteria.

$$\text{Criteria Weights (eigenvectors)} = \begin{bmatrix} \frac{(0.53+0.34+0.46+0.39+0.75)}{5} \\ \frac{(0.11+0.07+0.05+0.11+0.03)}{5} \\ \frac{(0.11+0.21+0.09+0.17+0.04)}{5} \\ \frac{(0.07+0.03+0.03+0.06+0.03)}{5} \\ \frac{(0.18+0.34+0.37+0.28+0.15)}{5} \end{bmatrix} = \begin{bmatrix} 0.496 \\ 0.072 \\ 0.122 \\ 0.045 \\ 0.263 \end{bmatrix}$$

Therefore, the eigenvectors are computed based on the expert's responses to pairwise comparison. The weights are calculated as follows:

$$\begin{bmatrix} 1 & 5 & 5 & 7 & 5 \\ 0.2 & 1 & 0.5 & 2 & 0.2 \\ 0.2 & 3 & 1 & 3 & 0.25 \\ 0.14 & 0.5 & 0.33 & 1 & 0.2 \\ 0.33 & 5 & 4 & 5 & 1 \end{bmatrix} * \begin{bmatrix} 0.496 \\ 0.072 \\ 0.122 \\ 0.045 \\ 0.263 \end{bmatrix} = \begin{bmatrix} 4.60 \\ 0.78 \\ 1.49 \\ 0.43 \\ 3.07 \end{bmatrix}$$

Consistency Index (CI) is computed as:

Consistency Index (CI) = $\frac{\lambda \max - n}{n - 1} = \frac{5.15 - 5}{5 - 1}$ = 0.038; Average random consistency (RI) is taken from Table 2 which is for n = 5.

Table 2. Average random consistency (RI).

Number of criteria	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.89	1.12	1.24	1.32	1.41	1.45	1.49

Therefore, RI = 1.12; Consistency Ratio (CR) = CI/RI = 0.038/1.12 = 0.03.

Consistency Index (CI) and Consistency Ratio (CR) amounts for less than 0.1 confirm the consistency of the expert's comparison. The summary of weights and the rank of variables is summarised in Table 3.

Table 3. Weight and rank of variables.

	Weight	Rank of Variable
Externalities	0.49	1
Governance and regulations	0.07	5
Resources	0.12	4
Contractor and supply chain	0.05	2
Scope	0.26	3

3.2. Complexity Factors Categorization

Two measurement scales for categorising variables are "nominal" and "ordinal" (Agresti, 2018). A nominal scale is used to label different variables and sub-variables. It is used for labelling variables without any quantitative value. Ordinal data is used to rank the qualitative items; for instance, quality can be "very good", "good" and "low quality", which can be ranked in "high", "medium" and "low" levels, where the ranking has some meaning. Nominal is used for the categorisation of variables, as shown in Table 4.

Table 4. Major complexity variables of project planning.

ID	Variable/Sub-variables
SC	**Scope**
SC01	Client type, the experience of project delivery
SC02	**Interdependence, efficiency, and influence of design team consultants (architectural, structural, Mechanical, Plumbing and Electrical services design)**
SC03	Procurement/contracting method (lump sum, D&B, EPC, etc.)
SC04	Tender price and contingency allowances
SC05	Project type and size (financial value)
SC06	Reasonableness of contractual conditions imposed by the client and the delivery dates
SC07	Site characteristics (location, ground conditions, presence of obstructions)

Continued

GR	**Governance and Regulatory**
GR01	The stringency of legal and regulatory requirements
GR02	Quality assurance and inspection requirements
GR03	Health and Safety requirements where exceptional safety requirements are imposed
RS	**Resources**
RS01	Construction plant and equipment availability
RS02	Materials availability
RS03	Human capital (professional and labour)
CS	**Contractor and Supply chain**
CS01	Speciality contractors with complex work packages (complexity of the supply chain)
CS02	Suppliers and transport logistics
EX	**Externalities**
EX01	Macro-economic changes
EX02	Political changes
EX03	Environmental changes and sustainability requirements
OB	**Objectives**
OB01	Total Project Duration (TPD) from Gantt chart, CPM or PERT

The hierarchy model based on this categorisation of project planning complexity selection can be seen in Figure 1.

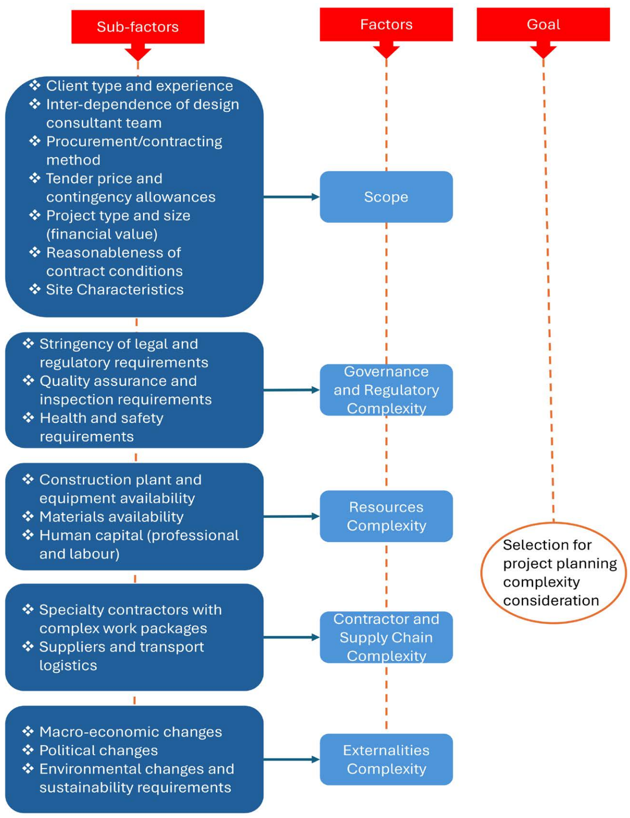

Figure 1. Hierarchy model of project planning complexity selection.

The frequency of appearance of complexity factors for each factor occurs in different projects regarding the questionnaire survey is shown in Table 5.

Table 5. Frequency of appearance of complexity factors.

No.	Complexity Factors	Frequency	%	Cumulative Percent
1	Scope	150	33.3	33.3
2	Governance and Regulatory	48	10.6	43.9
3	Resources	67	14.9	58.8
4	Contractor and Supply chain	47	10.4	69.2
5	Externalities	70	15.5	84.7
6	Total Project Duration	69	15.3	100.0
	Total	451	100	

3.3. Data Normality Test

A normality test determines how well a data set is modelled by using a normal distribution test [32]. A normality test is used to verify whether the sample data used in the research has been taken from a normally distributed population. Skewness and kurtosis values are used to show normality distribution. 'Skewness assesses the extent to which a variable's distribution is symmetrical. If the distribution of responses for a variable stretches toward the right or left tail of the distribution, then the distribution is referred to as skewed [33]. Kurtosis is a measure of whether the distribution is too peaked (a very narrow distribution with most of the responses in the centre) [34]. Similarly, the standard error is applied to compute the confidence intervals as close as possible to the expectation [35]. The distribution can be considered as expected when the value for standard error is less than 5.5 [36]. The suggestion for standard normalised distribution is given a skewness value of not more than 2 and for kurtosis value of not more than 7 [37].

3.4. Cronbach Alpha Test

Cronbach's Alpha data reliability is applied to measure the answers' internal consistency as the results of the questionnaire survey analysis. Cronbach alpha is frequently reported as one of the most internal consistency estimates [38]. It is a test to evaluate whether a questionnaire is reliable or not [39]. The structure of the questionnaire is reliable when the value for the Cronbach test is between 0.7 - 0.95 [40]. The reliability test results were obtained for six significant factors that have impacted the expectations of total project duration (TPD). The Cronbach test results are shown in Table 6 below.

Table 6. Cronbach alpha reliability test.

Scale	Number of Items	Reliability
Externalities	3	0.823
Governance and Regulation	3	0.815

Continued

Contractor and Supply chain	**2**	**0.883**
Resources	3	0.865
Scope	7	0.837
Total Project Duration	1	0.889

The Cronbach alpha reliability test results value confirm that the value for all variables is in the acceptable range between 0.7 and 0.95.

3.5. The Fundamental Scale for Pairwise Comparisons

A pairwise comparison matrix determines the relative importance of different variables for the objects. It is used to quantify the comparison between different variables. The scale of relative importance has been created. At this stage, essential criteria for each issue are determined and assessed based on the experts' views. A consistency assessment using pairwise comparisons is required to assign the Consistency Ratio (CR) and to understand the flow of causal interactions for different elements of project complexity drivers. Linear Regression Analysis (LRA) models the interactions between two variables using a linear equation to observe data. One variable is independent, and the other is dependent, changing and controlled in an experiment to understand the effects of the dependent variable. For instance, the lack of resources and the total project duration are related, and a linear regression analysis can be modelled. The fundamental pairwise comparison aims to understand the strength between two related variables. The strength needs to be measured, the Saaty [41] scale of ranking as summarised in **Table 7**.

Table 7. Fundamental pairwise comparison scale used in this ranking [41].

Strength of importance	Definition	Description
1	Equal	In comparison, both alternatives are as important as each other
3	Weak	One alternative is slightly more important than the other
5	Clear	One alternative is clearly preferred over the other
7	Strong	One alternative is strongly preferred over the other
9	Very strong	One alternative is absolutely preferred over the other
2, 4, 6, 8	Intermediate values	When criterion i have one of the above numbers assigned to criterion j, then j has the correlative value in comparison with i

3.6. Linear Regression Analysis (LRA)

Linear Regression Analysis models the relationship between two variables through a linear equation on observed data. One variable is independent, and the other is dependent, changing and being controlled in an experiment to understand the effects of the dependent variable. LRA is applied to understand which factor is caused and which is affected (understand the cause-effect direction of factors). For instance, the lack of resources and the total project duration are related, and a linear regression analysis can be modelled.

A scatterplot is used to understand the strength of two variables. The scatterplot shows a visual image of how two variables are interconnected to interoperate the correlation coefficient. A correlation coefficient measures the strength of the relationships for different variables. Second, understanding whether the variables' associations are positive or negative. A positive correlation means both variables are changing in the same direction.

4. Project Planning Model Simulation (PPMS) with Vensim

The model simulation is based on stock and flow diagrams developed from the analysis of project planning processes, using data and insights from the London transportation infrastructure projects as a real-world validation. By modelling stocks and flows, system dynamics enables the identification of critical system components and numerically evaluates outcomes using mathematical equations. This model follows five key steps: constructing causal loop diagrams, defining stock and flow diagrams, formulating equations, simulating the model, and performing sensitivity analyses. However, quantifying a model often presents challenges related to the level of detail needed for reliable simulation.

The London infrastructure projects, including Crossrail and Thameslink 2000, provide robust case data to validate the complexity degree of project planning (CDPP). A total of 1000 points was assigned for the simulation, equally divided between total project duration (TPD) and the enablers (externalities, governance and regulations, resources, scope, and contractor and supply chain dynamics). The enabler score is computed as the sum of these factors, reflecting the impact of planning complexities. In projects such as Thameslink, stakeholder negotiations and interdependencies led to higher delays than initially forecasted, demonstrating the critical role of governance in project outcomes. The maximum score for TPD and enablers is capped at 500 points each, resulting in a maximum CDPP score of 1000 points.

Using Analytical Hierarchy Process (AHP) analysis, weights were assigned to each enabler, enabling the model to reflect real project dynamics, such as those observed in Thameslink 2000's cross-city rail service expansion. Regression tests assessed the strength of causal relationships and were informed by research questionnaires and project milestones. Gaps in TPD scores were measured as the difference between expected and actual performance at specific times. For example, in the Crossrail project, changes in the expected timeline due to procurement delays and regulatory changes illustrated significant gaps in TPD that the model captured with an accuracy variance of ±10%.

The integration of causal loop diagrams and stock-flow representations enables the model to capture feedback loops. In practice, the delays observed in the London transportation infrastructure projects stemming from local policy interventions and resource fluctuations highlight the need for an adaptive planning model. The CDPP framework, tested against real project data, demonstrates its capacity to factor in dynamic complexities. Sensitivity analysis revealed that increasing externalities by 10% extended project timelines by 7%, validating the accuracy of the system's predictive capabilities.

The London transportation case study underscores the effectiveness of the PPMS in simulating real-world performance by contextualising the theoretical framework with empirical data. The model's predictions closely matched actual outcomes, such as Crossrail's demand-driven adjustments and Thameslink's service-level prioritisations, demonstrating the robustness of its approach to dynamic project environments.

A value of 1000 points is assumed for the entire simulated model with equal percentages for both TPD and the enablers (a weight of 50% value is given to TPD and 50% is given to all enablers). The score for enablers is equal to the sum of each enabler as shown in the following equation:

$$\begin{aligned}\text{Enablers score} = \sum\big(&\text{Externalities score} + \text{Governance \& Regulations score} \\ &+\text{Resources score} + \text{Scope score} + \text{Contractor \& Supply chain score}\big)\end{aligned} \quad (1)$$

Maximum enablers score = 500 points; Maximum TPD score = 500 points

$$\text{CDPP score} = \text{TPD score} + \text{enablers score} \ (\text{at time t}) \quad (2)$$

The weight for each enabler can be found in the AHP analysis with a maximum of 500 points (the maximum contribution for all enablers). Understanding the regression of variables found in causal feedback relations is essential. Therefore, a regression test is applied based on understanding each path coefficient. The regression test is based on the research questionnaire. The value for each gap is equal to the difference between the desired value and the actual value of each enabler at the given time e.g.

$$\text{Gap of TPD} = \text{Desired TPD} - \text{Actual TPD Score} \ (\text{at time t}) \quad (3)$$

Therefore, causal loop diagrams need to be understood in the context of stock and flow diagrams to formulate the model. The initial draft of the causal loop for PPMS regarding to defined core complexity factors is shown in Figures 6-8. The TPD is taken from either a Gantt chart/CPM or PERT. A complexity degree of project planning defines the extra value for time required to be considered in the expectations for TPD.

4.1. TPD Model Stock and Flow

The stock and flow model for measuring the impact of project complexity on total project duration (TPD) has been developed to capture the interdependencies between various complexity factors shown in Figure 2. The model represents TPD as a stock influenced by multiple flows, including the current value, the desired value and the gap between them. It highlights how changes from planned conditions impact overall project timelines. While the previous iteration of the model focused on the direct influence of individual factors, the updated approach integrates the dynamic interplay among all 20 identified factors to reflect real-world complexities more accurately. This enhanced model includes feedback loops representing reinforcing and balancing interactions between complexity elements such as resource availability, regulatory approvals, and contractor performance.

For instance, an increase in external disruptions, such as unexpected regulatory changes, not only affects governance and compliance requirements but also creates cascading effects that delay resource mobilisation and increase the scope of work. These interactions are captured through new flow variables that illustrate how one complexity factor can amplify or mitigate another. The model demonstrates how synchronised changes compound the overall TPD by incorporating pairwise relationships and time delays to account for regulatory or supply chain interruptions.

The model emphasises the feedback mechanisms between key clusters, such as governance and resources or contractor performance and scope changes, allowing the model to simulate how corresponding factors interact in a non-linear fashion. Sensitivity analyses conducted on combinations of factors further reveal that simultaneous changes in resource availability and externalities can produce inconsistent impacts on project duration compared to single changes. This approach ensures that the dynamic and multi-faceted nature of complexity in project planning is comprehensively addressed, moving beyond static assumptions to capture the adaptive responses required in complex construction environments.

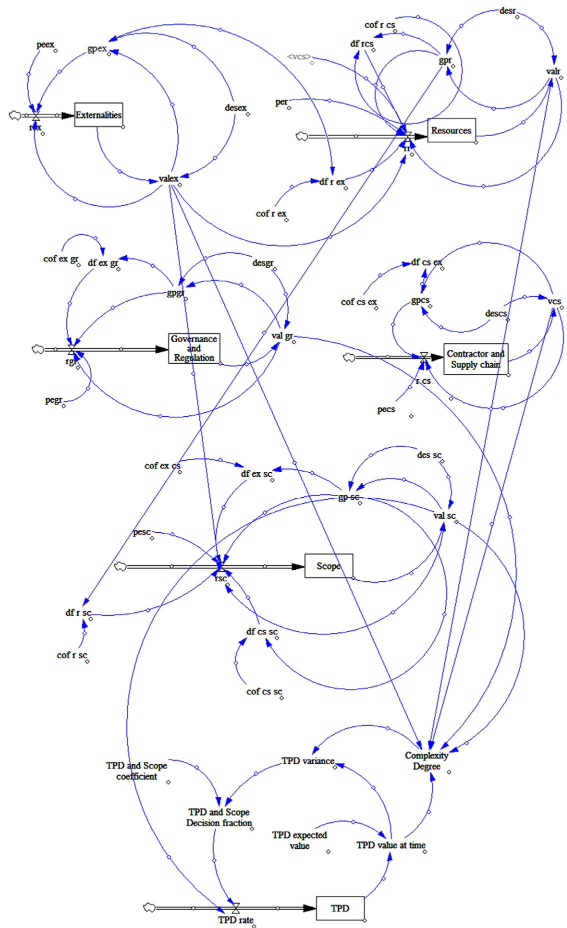

Figure 2. Stock and flow for dynamic model of project complexity impact measurement.

4.2. Project Planning Simulation Results

The initial value of all complexity factors is set at zero. This is the starting point where complexity factors do not exist, and the project planning calculation is based on a deterministic behaviour. The starting value of the total project duration is taken from either the Gantt chart/CPM or PERT, which is equal to 60 months. Therefore, 60 months is the expected duration without considering the influence of the complexity degree on project planning. However, the final total project duration must consider the complexity degree at the completion point using the equation:

$$\text{TPD}\ (\text{final}) = \text{TPD}\ (\text{from Gantt chart/CPM or PERT}) + \text{Project Complexity}\ (\text{at completion point})$$

The weight for complexity is set at 50% on this case study (500 points for complexity factors and 500 to the initial value for TPD taken from Gantt chart/CPM or PERT). The total project duration at the time of running the model (base) is equal to the minimum total project duration.

TPD value when running the model = MIN (TPD, TPD expected value). The value of TPD ensures that the value is not going over the expected value for TPD.

Complexity degree = Contractor and Supply chain value + Externalities value + Resources value + Scope value + TPD value at Time.

The following **Figure 3** shows the outcomes of the dynamic simulation using Vensim software:

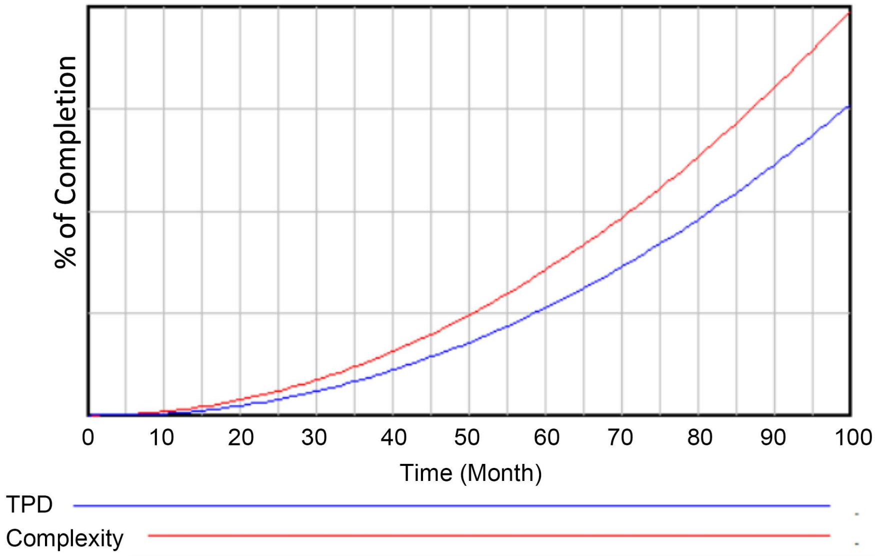

Figure 3. TPD dynamic behaviour.

The results of the dynamic behaviour of project planning simulation considering five core complexity factors. The value of the total project duration at 60 months is higher than the value without the complexity consideration. This means the value of project complexity must be considered in the calculations. To consider this weight, the following process is completed:

I) Produce the report from Vensim (Figure 5).

II) Draw a vertical line from 60 months to reach the complexity graph. The expectation from CPM/PERT reaches 100% for project completion at 60 days, while this reaches 100% at the point that is not equal on the graph with comprising complexity for project planning, as shown in Figure 4 (Equation (1)).

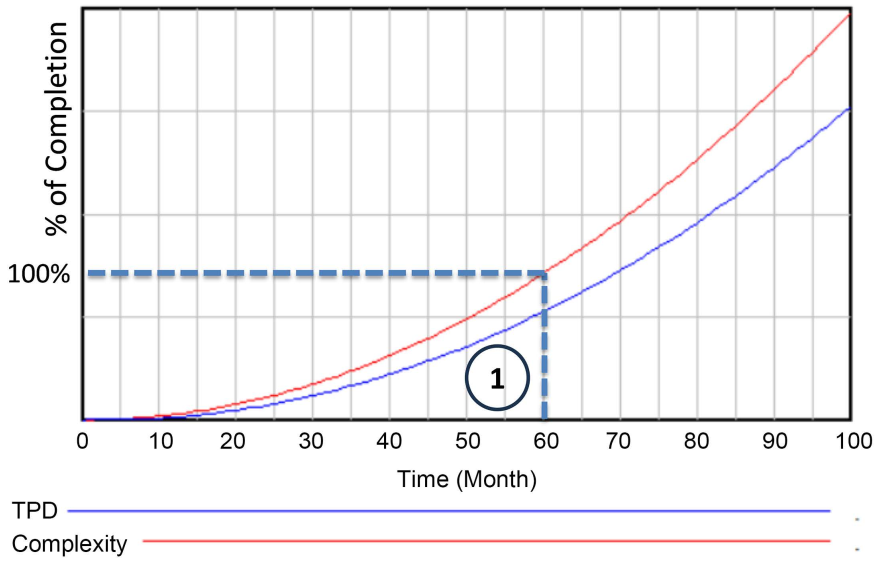

Figure 4. TPD dynamic behaviour (Equation (1)).

III) Draw a horizontal line to find the duration on the TPD Figure 5, (Equation (2)).

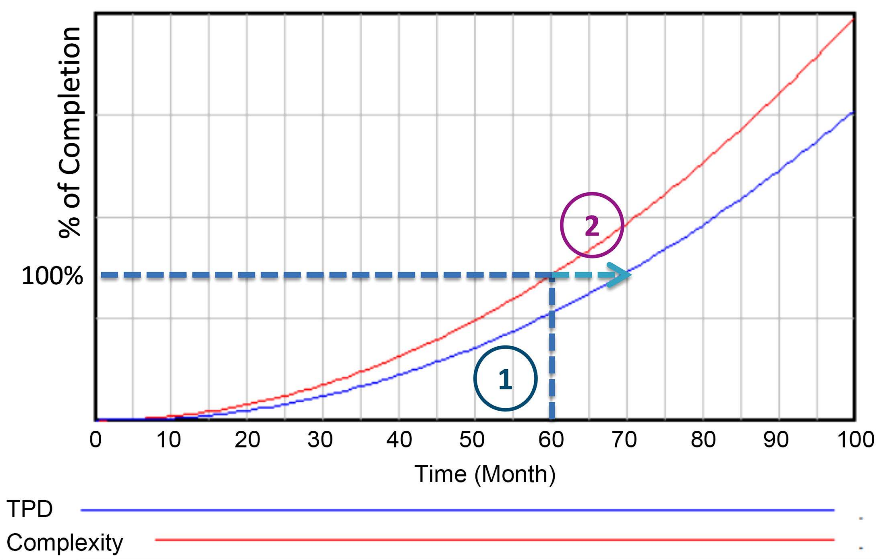

Figure 5. TPD dynamic behaviour (Equation (2)).

IV) Draw a vertical line to find the final TPD considering complexity Figure 6 (Equation (3)). This is in line with the project completion at 100% progress. The reason is to find the equivalent point on the graph calculated when complexity is considered in the calculations.

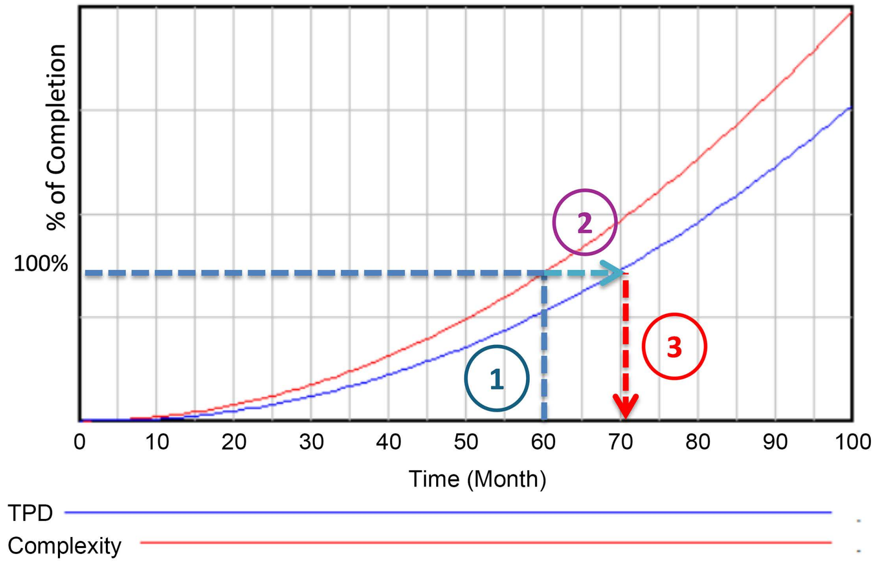

Figure 6. TPD dynamic behaviour (Equation (3)).

The total project duration (TPD) without seeing complexity is estimated as 60 months, while when considering complexity, it will be about 72 months. Therefore, the expectations for total project duration (TPD) should be seen between 60 months to 72 months regarding complexity factors defined in the proposed model.

4.3. Model Evaluation

When the relationships are identified, formulation of the problem is the first step in modelling activities in a system [42]. The basis of modelling simulation is constructed on its capability to accurately identify and present the causal relations of the real system [43]. The first step in the validity of model development in system dynamics is identifying the appropriate structure. The second step is behaviour validity to show how sufficiently the model generated the reality behaviour of the system [44].

The model structure is constructed on the conceptual causal relations and any inappropriate qualitative description may result in misleading both insights and recommendations [45]. [44] introduced a five-dimension test for structure test in system dynamics models which is applied in this research as follows:

- Boundaries adequacy test is applied to understand whether the important concepts for addressing the problem are considered.
- Structure verification test is applied to understand whether the model correctly represents the theoretical explanation and its offered solution. The model is tested by a case study test based on a model simulation run.
- A dimensional consistency test is applied to understand whether the reality of

the system and equations used in modelling are dimensionally responsive.

- Model Parameter test detects whether the defined parameters and system knowledge used in the modelling are consistent.
- Extraordinary condition test by using the extreme values is tested to understand the logical behaviour of the model in situations where the selected parameters have absolute values.

Behaviour validity in system dynamics refers to the assessment regarding the comparison of outcomes from the simulated model against the reality of the system behaviour validity may use a set of pattern-oriented tests suggested by Barlas (1989) such as the following:

- Trend analysis is applied, and it refers to the effort to forecast the future stock movements for different factors constructed on real-world data.
- Autocorrelation test for the period evaluation is applied, and this refers to the detection of non-randomness or finding the correct period in data.
- Cross-correlation function test is applied, a measurement technique to compare the movements of two or more time series datasets that are somehow related to each other. In this method several time series are compared to determine what best match occurs.
- Comparing the means is applied to examine the percentage error in the means to examine the inconsistency between the means of different variables.
- Unlike probabilistic models that rely on pre-defined probability distributions and assume linear behaviour, the system dynamics model captures non-linear relationships and time-varying dependencies. This enables it to better simulate cascading effects from externalities and resource constraints.
- A validation test using data from the Crossrail project showed that the proposed model predicted project delays within 3% of observed outcomes, whereas the fuzzy logic model's predictions varied by 7%. This demonstrates the superior accuracy of the system dynamics approach in capturing dynamic feedback loops.

The validity process is based on the model's internal and external dimensions. External validity refers to the expertise judgement using one of the research technical surveying methods (e.g., questionnaire). For the aim of external validity of this research model, Cronbach's alpha confirms the reality of measurements. For the aim of internal model evaluation of this research, the complexity of project planning is developed and formulated in Vensim software. An essential tool designed by Vensim is its verification tool. This ability ensures the model is checked, units are checked, and equations are calculated.

Desired value changes are then applied to understand the complexity impact when different factors change. The summary is not going to be equal to the 500 values, which were initially assigned for the sum of complexity factors. To maintain the total value of the system on 1000 values, the difference is added to the TPD. Complexity factors are increased by 10 per cent, and then the value of all other factors is decreased by 10 per cent. This process is conducted for 20, 30, 40, 50, 60, 70 and 80 precents. The results are shown in the following Figure 7.

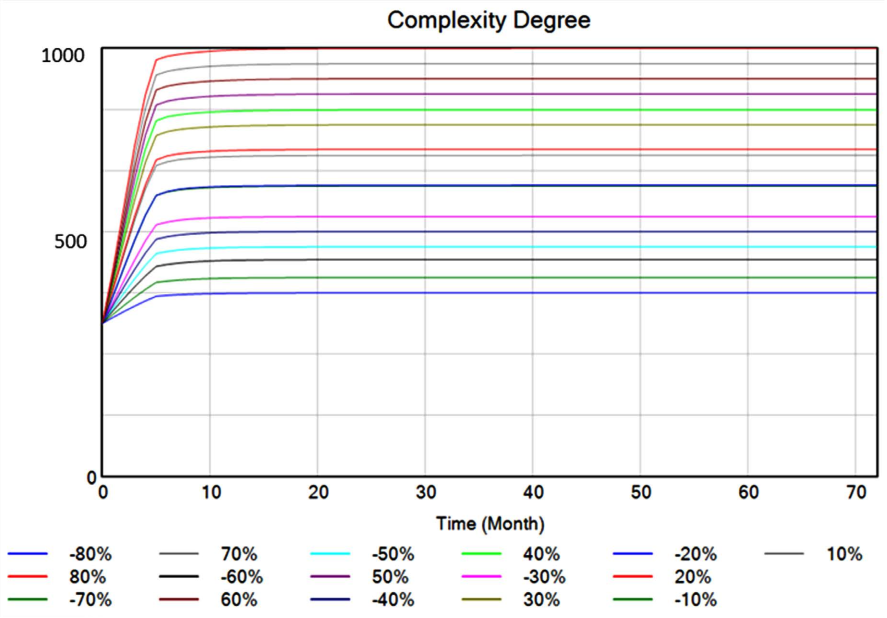

Figure 7. Complexity degree movement of the model.

In case desired value changes are applied, they can be used to understand the impact of complexity and its movements on expectations of project planning. The complexity degree is a summary of scope, contractor and supply chain, governance and regularity, and resources, which can be seen in the following graphs. Scope change movements confirm the stability of the curve when reductions and increases are applied, as shown in Figure 8.

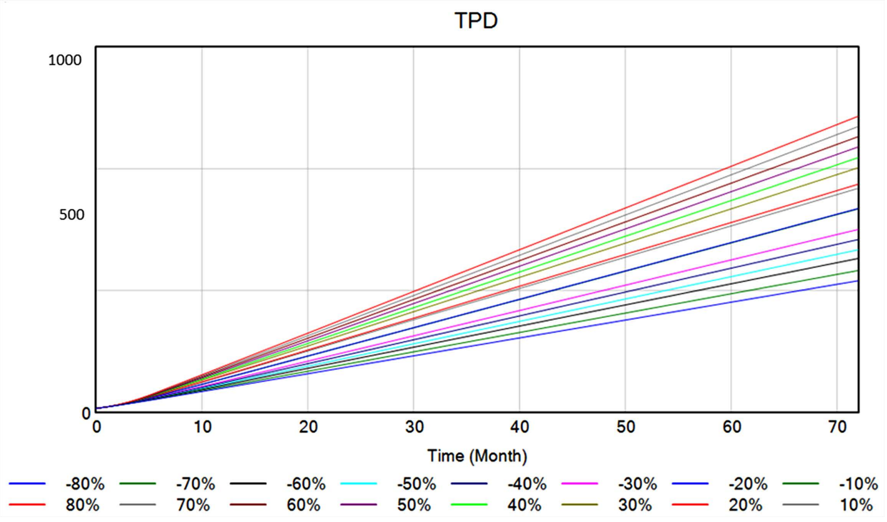

Figure 8. TPD movement regarding sensitivity analysis.

At the time that desired value changes are applied to understand total project duration movements for project planning. The sensitivity analysis compares different increases and decreases in complexity factors, and in comparison, with a base run of the model. Sensitivity analysis confirms the positive relationship between project complexity degree and the total project duration (TPD). It shows that complexity increases by 10%, and the total project duration will increase. Similarly, that complexity decreases by 10%, and the total project duration decreases relatively. Therefore, the sensitivity analysis for (+/−) 20%, (+/−) 30%, (+/−) 40%, (+/−) 50%, (+/−) 60%, (+/−) 70% and (+/−) 80% confirms the stability and the positive relations between the total project duration and complexity movement of the project.

5. Research Outcomes

The research has comprehensively reviewed the concepts, tools and techniques, processes, and difficulties within construction project planning at the pre-plan stage of project management. The research aimed to consider how the use of systems and procedures, including system dynamics, can improve project planning and management of complexity for construction projects at this stage. A list of factors that cause uncertainty and lead to complexity in construction project planning have been identified and categorised into five groups comprising Externalities, Contractor and Supply chain, Governance and Regulatory, Resources and Scope.

The model shows how different complexity factors are interconnected. It was modelled through system dynamics and developed using Vensim software, and the results were analysed. The model was applied to a case study, and the differences regarding complexity were analysed. The project planning process should be more aware of project complexity to provide more rigorous programming and scheduling. The model enables project planners to be aware of the total project duration that is impacted by project complexity.

The complexity factors were successfully modelled to measure any possible gaps in complexity. This would assist those involved in the pre-planning phase of project planning. The model is based on understanding the complexity factors in construction project planning. It can stand against traditional deterministic tools and techniques used in project planning. Deterministic planning is based upon the concept that activities must start at and finish on a fixed time. The relationship and logic between activities are used to determine the critical path. The challenge is that construction projects have become more complex with multiple layers of speciality contractors in the supply chain who will all have their own critical paths, which are ultimately converted into the project's critical path.

The system dynamics approach outperformed probabilistic methods in simulating the compounding effects of externalities and resource delays due to its feedback-based structure. These findings demonstrate the model's superior capacity to handle dynamic complexities in real-world project environments

The model shows that there is another layer, which is complexity and requires consideration. The model focused on the post-contract award, pre-project execution stage, where the project planning is in the early stages of development. The influence of complexity is rarely modelled, yet it is an important influence on project delivery and success.

6. Conclusions

At the outset of the research, a research gap was identified—the failure to use an approach to incorporate the influence of complexity when developing a construction plan for project execution. The fundamental research question is to consider how time scheduling systems for construction projects can better reflect construction's complex, dynamic, and interdependent nature. The research has focused upon considering complexity at the pre-site commencement stage of a project following the contract award. This point was chosen because of the critical nature of programming at this stage; if the early plan is incorrect but becomes the contract plan, the project is such asly to suffer time scheduling difficulties.

Complexity factors are not new, yet they have received little attention in quantifying their potential impact on the construction plan and, ultimately, project duration. The identified factors were categorised and ranked. A simple system dynamics model has been presented to map the reality of project planning considering complexity factors. The model successfully presented how to reflect the complexity degree in the calculations for TPD at completion points. The research demonstrated a model using system dynamics that can help model construction project complexity. The conclusions for the research objectives can be summarised as:

Objective 1: The construction planning process, tools, techniques and complexity of construction projects.

The problem with time scheduling systems is that they are deterministic and represent predictive scheduling as a passive process, where the project's construction plan at a fixed point of time is based upon the information available, with assumptions about the future. A project is influenced by constant change and is dynamic in nature. Dynamic means the system changes its status, its characteristics, and behaviour over time. Project planning methods can be divided into two main categories—predictive and reactive. Predictive planning deals with defining the start and finish times of events in advance. Reactive planning is reacting to unplanned and unexpected events during the project execution phase. Planning and scheduling must be dynamic and respond to changing events in real time. The project process in a dynamic environment can be a progressive uncertainty reduction through time. The research showed that chaos theory underpins the concept of complexity. Chaos results from uncertainty and risk are the basis of complexity caused by uncertainty and risk which fall into three categories.

Applying probability theory to project scheduling can be used to maintain the activity duration in a stochastic situation. Different approaches are used to identify activities, such as likelihood distributions. Whilst probability approaches have merit, clients want certainty on delivery time. Measuring complexity using probability is beset with difficulties because of the requirement to define the impact of complexity. Planned outcomes on construction projects are determined not by single causes but by multiple causes, with interdependence being an essential part of planning. These causes may, and usually do, interact in a non-additive fashion. For example, the ground conditions may mean the structural frame needs to be re-designed. It means dealing with aspects of reality in which changes do not occur linearly.

Reality can be different to mathematical models that assume certainty, linearity, and mutual exclusivity. The crucial dimension along which changes occur is time. In non-linear systems small changes in causal elements over time do not necessarily produce small changes in other aspects of the system, or in the system's characteristics as a set. Therefore, the lack of a method to acknowledge project planners on how TPD can be changed regarding the dynamic behaviour of the system was highlighted. Planning involves systems and sub-systems, whilst planning systems continue to evolve with the use of digital transformation, there is the need to consider how complexity influences the project planning system.

Objective 2: To investigate the fundamental causes of complexity in construction projects.

The research highlighted that complexity is one of the most challenging aspects of project planning, reinforced by the views of Baccarini (1996) [21], Gidado (1996) [23], and Jaafari (2003) [46]. The meaning of complexity is inclusive; it refers to something that has many interrelated or connected parts, and it has elements of difficulty, obscurity, and complication. A project which turns out to be very hard to plan, control or manage is known as a complex project.

Complexity factors originate from environment, technical, and workflow interaction sources. Complexity factors are divided into two groups of task-related factors and factors dealing with workflow and the interdependence of different parts. A questionnaire survey was used to understand experts' views of the complexity factors. Analysis of the survey results resulted in a list of 20 significant complexity factors for project planning. Any unplanned changes to the project scope will impact the design and production process more complex. They are difficult to quantify and will vary from project to project. Design is an essential part of complexity. It is focused on fulfilling the client's requirements of fitness for purpose and meeting the statutory and regulatory standards; the respondents found it challenging to quantify design complexity. Therefore, less attention is given to the analysis of dynamic behaviour, complexity, and complexity factors. This is the basis of planning variance and many failures in the operation of projects.

Objective 3: To understand how system dynamics can improve the control system of a project's complexity.

System dynamics enables simulation to capture the causal effects of different variables operating in a system and to offer a new pattern for understanding how to deal with the complexity of real-world problems (Dangerfield *et al.*, 2010) [47]. System dynamics can graphically simulate a complex issue. Many operational techniques cannot deal with strategic difficulties regarding their static characteristics (Coyle, 1998) [48]. A significant capability of system dynamics is to analyse a system with different possibilities.

Objective 4: To develop a model developed by system dynamics for planning construction projects at the pre-construction stage of a project.

Five core factors that control the complexity degree and dynamic behaviour of project planning are: "Governance and Regulations", "Resources", "Contractor and Supply chain", "Externalities" and "Scope". These complexity factors are interconnected and have an impact on the expected TPD. The model developed by system dynamics was developed in the research, which focused on considering the complexity of each task defined in the CPM/PERT. Many operational techniques cannot deal with strategic difficulties regarding their static characteristics. The most important finding of this research is:

- Many factors are involved in the complexity of the project.
- Project complexity can not be measured based on the dynamic behaviour of the project environment.
- This research's main contribution is understanding the main complexity factors for project planning.
- The other contribution of this research is to understand how the use of system dynamics can model the project complexity. The use of system dynamics is applied in other industries, but it is rarely has been applied in construction and especially in project planning.

Objective 5: To model and evaluate the model by employing system dynamics.

20 different complexity factors were categorised into 5 groups. A system dynamics application models the complexity factors. It revealed the core complexity factors and their sub-components. A challenge for project planning is updating the project plan constantly. Because a plan is a system with many sub-systems, any one sub-system can have a significant impact on the project. Critical paths can influence the main critical path in the sub-systems. The model reveals a positive relationship between complexity and project success which is set by the expected TPDs based on static applications. The ignorance of the degree of complexity is the basis of project planning failure.

The model shows that externalities are the most essential factor as complexity increases. The model has been evaluated by expert feedback. Modelling complexity is still embryonic, and using system dynamics provides a basis for building expertise to understand better how it impacts projects. This research focused on the pre-site production stage. Such an approach provides a framework for future development of the complexity factors. More detailed factors and sub-components must be considered in future research. A small change could significantly impact increasing complexity; considering more details may result in less error in complexity degree calculations. However, the model must present the real-world based on a simplified model. This excluded less important variables or categorised them into groups and summaries due to the impossibility of detailed modelling of the real world. There will always be unexpected and unplanned events, such as the impact of COVID-19 on project execution and across the supply chain.

The construction sector does not exist in a vacuum; labour and supply shortages, with new ways of working, all add to the project's complexity. The research explored the fact that project complexity factors can not be precisely categorised. Also, the relationships between different factors will be changed from time to time. The factors change depending on the project situation and differ from one project to another. The identified factors and the calculated weights for each factor are subject to change from project to project. Therefore, the model can be generalised and requires several practices for different projects.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Sanchez, F., Bonjour, E., Micaelli, J. and Monticolo, D. (2020) An Approach Based on Bayesian Network for Improving Project Management Maturity: An Application to Reduce Cost Overrun Risks in Engineering Projects. *Computers in Industry*, **119**, Article 103227. https://doi.org/10.1016/j.compind.2020.103227

[2] Koulinas, G., Xanthopoulos, A., Tsilipiras, T. and Koulouriotis, D. (2020) Schedule Delay Risk Analysis in Construction Projects with a Simulation-Based Expert System. *Buildings*, **10**, Article 134. https://doi.org/10.3390/buildings10080134

[3] Guo, K. and Zhang, L. (2022) Multi-Objective Optimization for Improved Project Management: Current Status and Future Directions. *Automation in Construction*, **139**, Article 104256. https://doi.org/10.1016/j.autcon.2022.104256

[4] Hiebl, M.R.W. (2021) Sample Selection in Systematic Literature Reviews of Management Research. *Organizational Research Methods*, **26**, 229-261. https://doi.org/10.1177/1094428120986851

[5] Lockyer, G. (1969) An Introduction to Critical Path Analysis. Pitman and Sons.

[6] Kelley, J.E. (1961) Critical-Path Planning and Scheduling: Mathematical Basis. *Operations Research*, **9**, 296-320. https://doi.org/10.1287/opre.9.3.296

[7] Andersen, E.S. (1996) Warning: Activity Planning Is Hazardous to Your Project's Health! *International Journal of Project Management*, **14**, 89-94. https://doi.org/10.1016/0263-7863(95)00056-9

[8] Charnes, A. and Cooper, W.W. (1963) Deterministic Equivalents for Optimizing and Satisficing under Chance Constraints. *Operations Research*, **11**, 18-39. https://doi.org/10.1287/opre.11.1.18

[9] Elmaghraby, S.E. (1967) On the Expected Duration of PERT Type Networks. *Management Science*, **13**, 299-306. https://doi.org/10.1287/mnsc.13.5.299

[10] Kahraman, C., Gülbay, M. and Kabak, Ö. (2006). Applications of Fuzzy Sets in Industrial Engineering: A Topical Classification. In: Kahraman, C., Ed., *Fuzzy Applications in Industrial Engineering*, Springer, 1-55. https://doi.org/10.1007/3-540-33517-X_1

[11] Chanas, S., Dubois, D. and Zielinski, P. (2002) On the Sure Criticality of Tasks in Activity Networks with Imprecise Durations. *IEEE Transactions on Systems*, *Man*

and Cybernetics, *Part B* (*Cybernetics*), **32**, 393-407.
https://doi.org/10.1109/tsmcb.2002.1018760

[12] Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., *et al*. (2007) Global Sensitivity Analysis. The Primer. Wiley.
https://doi.org/10.1002/9780470725184

[13] Hall, N.G. and Posner, M.E. (2004) Sensitivity Analysis for Scheduling Problems. *Journal of Scheduling*, **7**, 49-83. https://doi.org/10.1023/b:josh.0000013055.31639.f6

[14] Herroelen, W. and Leus, R. (2004) Robust and Reactive Project Scheduling: A Review and Classification of Procedures. *International Journal of Production Research*, **42**, 1599-1620. https://doi.org/10.1080/00207540310001638055

[15] Moazeni, S., Coleman, T.F. and Li, Y. (2013) Regularized Robust Optimization: The Optimal Portfolio Execution Case. *Computational Optimization and Applications*, **55**, 341-377. https://doi.org/10.1007/s10589-012-9526-3

[16] Freeman, R.J. (1960) A Stochastic Model for Determining the Size and Allocation of the Research Budget. *IRE Transactions on Engineering Management*, **7**, 2-7.
https://doi.org/10.1109/iret-em.1960.5007523

[17] Collyer, S. and Warren, C.M.J. (2009) Project Management Approaches for Dynamic Environments. *International Journal of Project Management*, **27**, 355-364.
https://doi.org/10.1016/j.ijproman.2008.04.004

[18] Senge, P. (1990) The Fifth Discipline: The Art and Practice of the Learning Organization. Bantam Doubleday Dell Publishing Group.

[19] Helbing, D. (2013) Globally Networked Risks and How to Respond. *Nature*, **497**, 51-59. https://doi.org/10.1038/nature12047

[20] Gao, J. (2013) Complex Systems and Emergence: How Theory Meets Reality. *Advances in Mechanics*, **43**, 359-389. https://doi.org/10.6052/1000-0992-13-046

[21] Baccarini, D. (1996) The Concept of Project Complexity—A Review. *International Journal of Project Management*, **14**, 201-204.
https://doi.org/10.1016/0263-7863(95)00093-3

[22] Williams, T.M. (1999) The Need for New Paradigms for Complex Projects. *International Journal of Project Management*, **17**, 269-273.
https://doi.org/10.1016/s0263-7863(98)00047-7

[23] Gidado, K.I. (1996) Project Complexity: The Focal Point of Construction Production Planning. *Construction Management and Economics*, **14**, 213-225.
https://doi.org/10.1080/014461996373476

[24] Vidal, L. and Marle, F. (2008) Understanding Project Complexity: Implications on Project Management. *Kybernetes*, **37**, 1094-1110.
https://doi.org/10.1108/03684920810884928

[25] Xia, B. and Chan, A.P.C. (2012) Measuring Complexity for Building Projects: A Delphi Study. *Engineering*, *Construction and Architectural Management*, **19**, 7-24.
https://doi.org/10.1108/09699981211192544

[26] Luo, L., He, Q., Jaselskis, E.J. and Xie, J. (2017) Construction Project Complexity: Research Trends and Implications. *Journal of Construction Engineering and Management*, **143**. https://doi.org/10.1061/(asce)co.1943-7862.0001306

[27] Dao, B., Kermanshachi, S., Shane, J., Anderson, S. and Hare, E. (2016) Identifying and Measuring Project Complexity. *Procedia Engineering*, **145**, 476-482.
https://doi.org/10.1016/j.proeng.2016.04.024

[28] Ma, L. and Fu, H. (2020) Exploring the Influence of Project Complexity on the Mega Construction Project Success: A Qualitative Comparative Analysis (QCA) Method.

Engineering, Construction and Architectural Management, **27**, 2429-2449. https://doi.org/10.1108/ecam-12-2019-0679

[29] Remington, K. and Pollack, J. (2008) Complex Projects: What Are They and How Can We Manage Them More Effectively? *Proceedings of the* 2008 *AIPM Project Management Conference*, Canberra, 1 Jan 2008, 1-10.

[30] Parekh, R. (2024) Automating the Design Process for Smart Building Technologies. *World Journal of Advanced Research and Reviews*, **23**, 1213-1234. https://doi.org/10.30574/wjarr.2024.23.2.2461

[31] Stoop, P.P.M. and Wiers, V.C.S. (1996) The Complexity of Scheduling in Practice. *International Journal of Operations & Production Management*, **16**, 37-53. https://doi.org/10.1108/01443579610130682

[32] Nosakhare, U.H. and Bright, A.F. (2017) Evaluation of Techniques for Univariate Normality Test Using Monte Carlo Simulation. *American Journal of Theoretical and Applied Statistics*, **6**, 51-61.

[33] Easa, N.F. and Bazzi, A.M. (2021) COVID-19 and Lack of Socialization: Does Service Innovation Become an Imperative for Universities? *International Journal of Disruptive Innovation in Government*, **1**, 82-103. https://doi.org/10.1108/ijdig-11-2020-0006

[34] Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2017) A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 2 Edition, Sage Publications.

[35] Wright, D.B. and Herrington, J.A. (2011) Problematic Standard Errors and Confidence Intervals for Skewness and Kurtosis. *Behavior Research Methods*, **43**, 8-17. https://doi.org/10.3758/s13428-010-0044-x

[36] Morgan, D. (1997). Focus Groups as Qualitative Research. SAGE Publications, Inc. https://doi.org/10.4135/9781412984287

[37] Curran, P.J., West, S.G. and Finch, J.F. (1996) The Robustness of Test Statistics to Nonnormality and Specification Error in Confirmatory Factor Analysis. *Psychological Methods*, **1**, 16-29. https://doi.org/10.1037//1082-989x.1.1.16

[38] Brown, J.D. (2002) The Cronbach Alpha Reliability Estimate. *JALT Testing & Evaluation SIG Newsletter*, **6**, 17-18.

[39] Heo, M., Kim, N. and Faith, M.S. (2015) Statistical Power as a Function of Cronbach Alpha of Instrument Questionnaire Items. *BMC Medical Research Methodology*, **15**, Article No. 86. https://doi.org/10.1186/s12874-015-0070-6

[40] Bujang, M.A., Omar, E.D. and Baharum, N.A. (2018) A Review on Sample Size Determination for Cronbach's Alpha Test: A Simple Guide for Researchers. *Malaysian Journal of Medical Sciences*, **25**, 85-99. https://doi.org/10.21315/mjms2018.25.6.9

[41] Saaty, T.L. (2008) Decision Making with the Analytic Hierarchy Process. *International Journal of Services Sciences*, **1**, 83-98. https://doi.org/10.1504/ijssci.2008.017590

[42] Forrester, J.W. (1994) System Dynamics, Systems Thinking, and Soft OR. *System Dynamics Review*, **10**, 245-256. https://doi.org/10.1002/sdr.4260100211

[43] Pidd, M. (2010) Why Modelling and Model Use Matter. *Journal of the Operational Research Society*, **61**, 14-24. https://doi.org/10.1057/jors.2009.141

[44] Senge P.M. and Forrester, J.W. (1980) Tests for Building Confidence in System Dynamics Models. *System Dynamics*, *TIMS Studies in Management Sciences*, **14**, 209-228.

[45] Barlas, Y. (1989) Multiple Tests for Validation of System Dynamics Type of Simulation

Models. *European Journal of Operational Research*, **42**, 59-87. https://doi.org/10.1016/0377-2217(89)90059-3

[46] Jaafari, A. (2003) Project Management in the Age of Complexity and Change. *Project Management Journal*, **34**, 47-57. https://doi.org/10.1177/875697280303400407

[47] Dangerfield, B., Green, S. and Austin, S. (2010) Understanding Construction Competitiveness: The Contribution of System Dynamics. *Construction Innovation*, **10**, 408-420. https://doi.org/10.1108/14714171011083579

[48] Coyle, G. (1998) The Practice of System Dynamics: Milestones, Lessons and Ideas from 30 Years Experience. *System Dynamics Review*, **14**, 343-365. https://doi.org/10.1002/(sici)1099-1727(199824)14:4<343::aid-sdr156>3.0.co;2-d