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Quantification of infrastructure downtime in earthquake reconstruction: A New Zealand study

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ABSTRACT

Knowing how to rapidly rebuild disaster-damaged infrastructure, while deciding appropriate recovery strategies and catering for future investment is a matter of core interest to government decision makers, utility providers, and business sectors. The purpose of this research is to explore the effects of decisions and outcomes for physical reconstruction on the overall recovery process of horizontal infrastructure in New Zealand using the Canterbury and Kaikōura earthquakes as cases. A mixed approach including a questionnaire survey and semi-structured interviews is used to capture perspectives of those involved in the reconstruction process and gain insights into the effect of critical elements on infrastructure downtime. Findings from this research show that technical capability of engineering professionals, availability of construction workers, uncertainty and variations to the scope of work, limited access to sites due to aftershocks and secondary hazards were the top five most significant factors affecting the pace of infrastructure recovery. The project improves our understanding of the process of earthquake reconstruction in the infrastructure sector and how New Zealand can better plan for a speedy recovery.

Keywords: Infrastructure, impeding factor, downtime, earthquakes, reconstruction, Canterbury earthquake sequence and Kaikōura earthquake, New Zealand

INTRODUCTION

Infrastructure damage following an earthquake can be extensive, due to periodic ground motions during the event as well as lasting uplift or subsidence of the founding soil on which the infrastructure is positioned [1]. While infrastructure is regularly constructed with rigidity to withstand design-level seismic events, there is regularly a degree of damage that takes place, requiring remediation and repairs [2]. Depending upon a number of factors, the extent of repair can range from minor cosmetic damage to destruction leading to the demolition and the reinstatement of new infrastructure.

The period of recovery following a significant earthquake can be in the order of months to years depending on the nature of the event [3,4]. The time for restoring the damaged built environment after a major earthquake is a critical issue in the study of urban reconstruction following the impact of natural events. Previous events highlighted that the route to recovery of infrastructure is very broad, dictated by the measures put in place by the acting governments and municipalities. There are implications associated with infrastructure downtime, which is the focus of many studies. Downtime is a measure for the amount of time for reestablishment of service of the system which includes the time necessary to plan, finance and complete repairs [5].

An earlier study investigated the critical elements (i.e. decisions, mechanisms, processes and factors) that had affected the reconstruction time in Christchurch following the 2010/11 Canterbury earthquakes, developing a system dynamics model representing the reconstruction process [6]. However, to improve the functionality of the model to exhibit how the decision variables can affect the rebuild progress, a greater understanding of the effect these different critical variables have against time is essential. The research reported in this paper aims to bridge this gap by surveying those who were involved in post-earthquake infrastructure reconstruction in Christchurch, New Zealand to understand and quantify to what extent critical variables influence its pathway to recovery. This research is aimed to provide reconstruction practitioners with greater foresight to assist in planning and decision making in disaster recovery.

EVALUATING INFRASTUCTURE RECOVERY DOWNTIME

With consideration to the infrastructure reconstruction, the recovery process has been divided into five discrete phases, as undertaken by [6]. These phases are roughly time progressional linear although there are factors within each phase that falls out of a typical construction sequence.

- *Inspection and Assessment: Time is taken to engage and mobilise engineering personnel, undertake inspections of affected infrastructure and make assessments of the extent of the damage.*
- *Decision Making: Time taken to progress through relevant regulatory processes, collaborate on the direction of the recovery pathway with adequate stakeholder input and ensure adequate resilience is incorporated into the guidelines and processes to reduce the likelihood of future harm.*
- *Financing: Time is taken to appropriate funding for reconstruction.*
- *Reconstruction capacity and capability: Time needed to engage and reach a contractual agreement with contractors, giving sufficient time to allow for the programming of the works and labour mobilisation and resourcing of equipment and materials.*
- *Completion: This is the time dedicated to the construction of the works and related aspects including rework time.*

Within each phase are a number of variables that have an impact upon the progression through the phase of recovery. These critical factors were drawn from literature observations and findings, which reflects the varying infrastructure recovery encounters. An initial list of critical factors was utilised from the research undertaken of [6], and advanced through this study. The list is considered to be a comprehensive representation of critical factors that contribute towards delay in the infrastructure reconstruction process and is presented in Table 1.

Many critical factors affect the pace of progression through each relevant phase. There is a limited amount of research that makes a direct comparison in the downtime between the different time categories. For example, literature does not asses the time involved in decision-making time in comparison to the adjustment time, whether one recovery phase creates larger delays than another. The report therefore, aims to evaluate the influence of these critical factors to affect the pace of recovery and the relationships between phases, to observe the resulting implications.

Downtime was assumed to be linear which allows phase delays to be treated as linear operators. The reconstruction time for infrastructure in type i and located in area j can be described as:

$$T_{downtime} = TA_{i,j} + TD_{i,j} + TF_{i,j} + TM_{i,j} + TC_{i,j}$$

Equation 1 - Representation of infrastructure downtime.

$TA_{i,j}$ is the time needed for inspections and damage assessment, $TD_{i,j}$ is the time needed for decision making of recovery strategies, $TF_{i,j}$ is the time needed for establishing the financing mechanisms of recovery, $TM_{i,j}$ is the time needed for mobilisation of construction resources, $TC_{i,j}$ is the time needed for undertaking construction work.

For each of recovery phase, an empirical equation can be produced to describe the relationship, with an infrastructure dependent variance to allow the coefficients and the error term to be different among the different types of infrastructure. The equation below describes the mathematical relationship between the time delay of the phase as a latent dependent variable and its critical contributing factors/indictors which are the independent variables.

$$\mathrm{TD(i,j)} = \alpha_{0,j} + \sum_{m=1}^{p} \alpha_{m,j} \times k_{m,j} + \sum_{n=1}^{q} \beta_{n,j} \times IT_{n,j} + \varepsilon_{i,j}$$

Equation 2 - Representation of discrete recovery phase.

Where $\alpha_{0,j}$, $\alpha_{m,j}$ and $\beta_{n,j}$ are the model parameters and are independently distributed in category i; $k_{m,j}$ is the critical contributing factor; p is the number of critical contributing factors associated with the delay estimated; $IT_{n,j}$ represents the interaction terms; q is the number of all possible interaction terms between individual critical contributing factors; and $\varepsilon_{i,j}$ is the error term. An equation for delay time within each phase can be produced from the relevant delay factors, quantifying the parameters of this equation. The equations act as components, to be compiled to address the overarching equation of delay time in infrastructure reconstruction. The equations can be studied by utilising the recovery experiences of those involved in infrastructure reconstruction in Christchurch, through the SCIRT recovery alliance.

Table 1. Critical factors influencing infrastructure recovery.

Focus phase	Critical contributing factor	
Inspection and assessment time	I-1	Technical capability of engineering professionals
	I-2	Access to site due to safety concerns
	I-3	Speed of engineer mobilisation and assessment
	I-4	Availability of engineers
	I-5	Fatigue of engineering assessors
	I-6	Frequency of ongoing after shocks
	I-7	Existence of a robust building inspection methodology
Decision making time	II-1	Changes to building standards and practices
	II-2	Land zoning decisions
	II-3	Consenting and permitting process
	II-4	Incorporation of resilience and performance-based systems
	II-5	Information management - database information
	II-6	Process of securing finance
	II-7	Setting up recovery governance
	II-8	Coordination with rebuild sectors
	II-9	Community engagement in decision making
Financing time	III-1	Availability of loss adjusters/quantity surveyors
	III-2	Productivity of quantity surveying
	III-3	Work hours of loss adjusters/quantity surveyors
	III-4	Pace of capital pooling
Reconstruction capacity and capability time	IV-1	System constraint of construction businesses to take on further work
	IV-2	Availability of construction manpower
	IV-3	Viability of economy in Christchurch to attract workers from elsewhere
	IV-4	Economic conditions elsewhere (Construction demands elsewhere in New Zealand or overseas)
	IV-5	Availability of accommodation
	IV-6	Availability of construction materials
	IV-7	Delay of construction planning landing for construction
Completion time	V-1	Speed of design process
	V-2	Procurement method
	V-3	Repair scope variations incurred through construction
	V-4	Uncertainty of the scope of works
	V-5	Labour wage inflation
	V-6	Competency and productivity of Contractors involved
	V-7	Long lead time components and supply chain issues
	V-8	Rework time such as repairing defects

METHODOLOGY

Christchurch Earthquake Recovery

The impacts of the 2010-2011 Canterbury earthquakes has been a topic of many studies across urban, engineering and anthropogenic research fronts; including the field of disaster management. It is the first major earthquake to occur in New Zealand since the 1987 Edgecumbe Earthquake and more impacting than the 1931 Hawkes Bay Earthquake. Responding to the larger February earthquake in 2011, the Stronger Canterbury Infrastructure Rebuild Team (SCIRT) was formed to manage and deliver the reconstruction works. The organisation was formed as an alliance between four civil contractors, Christchurch City Council and the New Zealand Government. This is the first instance of disaster alliancing in New Zealand; the alliance developed incrementally and was adaptive to changes. Continuous growth was central to the organisation, which documented and freely published learnings from its active years [4,7]. This is supplemented by ongoing domestic and international academic research. Researchers have and remain to be active in conducting research on the organisation, given the size of accomplishment and unprecedented scale of project delivery. SCIRT proved to have been the only feasible answer to delivering the volume in the required timeframe [7,8]. The lifespan of the alliance lasted for 5 years to 2016 before demobilising. Along that time, the alliance repaired 533km of wastewater pipes, 56km of stormwater pipes and 91km of freshwater pipes along with many bridges, retaining walls, pump stations and hundreds of kilometres of roadway [9]. The response mechanism to infrastructure recovery in Christchurch was transferred to Kaikōura earthquake in 2016 when large-scale infrastructure network such as roads and railways suffered widespread damage.

Research methods

Data collection

The questionnaire was designed to evaluate the relative importance of the different factors in influencing infrastructure recovery time, to understand the effect on the recovery of infrastructure in Christchurch. The core section of the survey aimed to identify the relative importance of critical factors in the recovery process. It utilised a Likert scale response to gauge the relative influence of each factor. The Likert scale was adopted as the influence of these factors is best represented by a continuous data set [10]. A seven-point scale was selected, allowing for the option to collapse responses into condensed categories if required during analysis. The range of scale varies from 1 (least important) to 7 (most important).

The survey was delivered to respondents by email. Respondents were engaged through the following organisations; Engineering New Zealand – Canterbury Branch, Contractors Federation of New Zealand, Lifelines Group of New Zealand, Aurecon New Zealand and personal contacts. As others facilitated the distribution of the survey within these organisations, the number of people invited to complete the survey is not known, and the response rate cannot be calculated. The survey was anonymous, the origins of the respondent sample could not be investigated. An uneven distribution of results from stakeholder groups may be present. The expected time to complete the survey was set at 10 minutes. Any longer and it was considered that respondents would not be willing to complete the survey; providing a partial response or none at all. With a longer survey, more questions about the influence of delay factors could have been asked.

A total of 48 responses was attained from the representative population sample of 100 people, meeting the 33% data collection threshold people. From the population size, estimated at 5000, where considering a confidence level of 95%, the resulting margin of error is 16%. The margin of error exceeds the width of a Likert interval of 14%. The view of the overall population is +/- 16% of the survey results, or plus/minus one interval on the Likert scale of each question.

Data analysis

Data collected in Google Forms was exported as a .csv file and imported by IBM SPSS Statistics Version 25. Data were screened for missing responses and checked for outlying responses. Responses with missing values were populated with the mean value of the variable. Kurtosis and skewness were measured. The engagement was assessed by checking the responses for adequate variance with a standard deviation above 0.5 as a rule of thumb, which was delivered by all datasets in the sample [11]. SPSS software includes the VALIDATEDDATA procedure that helps to identify any invalid causes and data issues.

Descriptive statistical testing and T-test analysis were undertaken to draw a maximum inference from the data. An inspection of the surveyed data shows that 13 factors were rated above a five out of seven on the Likert scale, and only three factors were rated at less than a four. This highlights that respondents were in a general agreement that the factors presented a measurable level of influence and provides validation to their inclusion. The T-test results show that all factors are important to infrastructure reconstruction, having a p-value of less than 0.05.

Table 2. Statistical summary of quantitative variables in the database.

	I. Inspection and assessment	4.7	II. Decision Making	4.8	III. Financing	4.0	IV. Reconstruction capacity and capability	4.9	V. Construction	5.2
	Factor	Mean	Factor	Mean	Factor	Mean	Factor	Mean	Factor	Mean
1	Technical capability of engineering professionals	6.0	Information management - database information	5.8	Pace of capital pooling	4.1	Availability of construction manpower	5.8	Competency and productivity of Contractors involved	5.9
2	Availability of engineers	5.4	Setting up recovery governance	5.7	Productivity of quantity surveying	4.0	Delay of construction planning landing for construction	5.5	Uncertainty of the scope of works	5.4
3	Existence of a robust building inspection methodology	5.0	Coordination with other rebuild sectors	5.3	Availability of loss adjusters/quantity surveyors	3.9	System constraint of construction businesses to take on further work	5.1	Speed of design process	5.3
4	Frequency of ongoing after shocks	4.7	Land zoning decisions	4.8	Work hours of loss adjusters/quantity surveyors	3.8	Availability of accommodation	4.9	Repair scope variations incurred through construction	5.3

The small sample size controls the extent of data analysis that is achievable through regressional modelling, by limiting the number of variables available for inclusion. As a general rule, where regression equations use six or more predictors, an absolute minimum of 10 participants per predictor variable is appropriate [12,13]. This therefore means that within each recovery stage, a maximum of four variables can be considered. The four most significant factors of each phase are presented in Table 2 below. Prior to undertaking regressional modelling, the top four most influential factors of each recovery phase were expected to represent each regression equation with the remaining variables neglected.

As the variables were measured by means of a Likert scale, a scaled regressional analysis proved to be the most suitable form for dealing with continuous data. This is unlike log-log (sometimes called doublelog), semilog, reciprocal, and polynomial forms [14]. While these approaches are reportedly more popular, they are better suited to variables that can take on a binary value of 1 or 0 which is not applicable for this data set. All the constructs were involved in the model. Sequential constructs were linked together along with every latent variable connected to the confirmatory construct, *Downtime*.

Linearity between independent and the dependent variables could not be assessed as downtime and the recovery phases are not directly measured variables, rather inferred constructs. Establishing a means for applying a regressional analysis to the data proved challenging with the constraints of data size, number of measured variables and the nature of the data itself.

PLS-SEM Models

Three techniques were considered for means of regressional analysis; Latent Variable Multiple Linear Regression (LV-MLR), Covariance based Structural Equation Modelling (CB-SEM) and Partial Least Squares Structural Equation Modelling (PLS-SEM). PLS-SEM was considered most applicable by means of elimination; the small sample size prevents a valid CB-SEM to be performed. As the observed variables(factors) and the latent variables are both continuous rather than discrete, LV-MLR presented a less-effective regressional tool [15].

PLS regression modelling is used as a statistical multivariate method to test and quantify the relationships between factors. PLS modelling is a well-established statistical methodology for the examination of measured indicators on inferred variables and the relationship between variables. PLS models test the projection of indicators (critical factors) into a set of latent variables (phases in infrastructure reconstruction) and corresponding scores, minimising the collinearity between predictors and maximising the covariance between variables [16]. Analysis of the survey information was undertaken using SmartPLS Version 3.2.7, for Microsoft Windows, produced by [17].

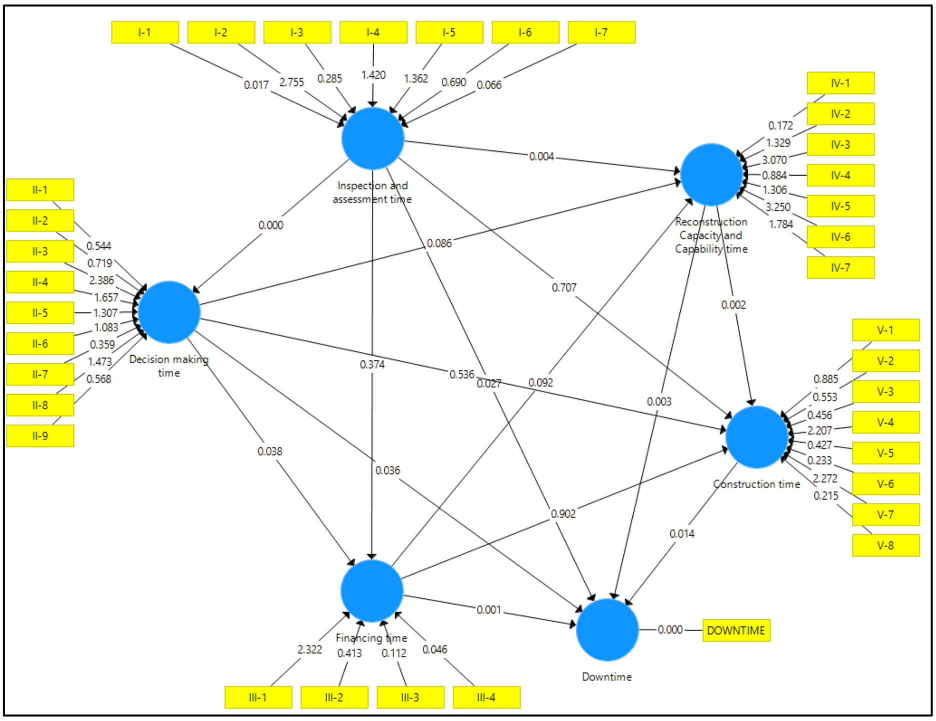

Figure 1. PLS-SEM model.

RESULTS AND DISCUSSION

A PLS-SEM model representing the infrastructure reconstruction process was developed, presenting the relationships between recovery phases and the reconstruction pathways. This is provided in Figure 1 below. The blue circles represent phases of infrastructure recovery, modelled as latent variables. Each yellow bock is a critical factor that contributes towards the relevant recovery phase, modelled as formative factors.. All considered links between latent variables have been modelled, with internal influence between recovery phases and all influencing *Downtime*. The factor tied to *Downtime* is a sum of the Likert values corresponding to the indicators. While not statistically significant, the model provides insight into the relative influence of each factor on the recovery phase which are presented as T-values. Many of the factors do not meet the threshold T-value measure to be considered statistically significance. The links between latent variables are evaluated by P-values, with many below 0.05 (achieving 95% significance).

A reduction in factors is required in order to achieve validity with respect to the sample size. There are a number of conditions that must be met in order to attain a valid model:

1. The model is restricted to a maximum of four factors for each latent variable, due to sample size limitations
2. All variables must be statistically significant – test of T-value, p-value and R^2
3. There must be a check for collinearity between indicators
4. Links between latent variables must be statistically significant
5. Moderation must be considered

The factors are formative, whereby changing one factor affects the outcome of the latent variable. As many measured indicators were not included in the model which affect the construct, the accuracy of the model is reduced to maintain validity and creates bias within the recovery phases. A factor analysis was initially undertaken to review the outer weights, construct reliability and validity of the indicators and latent variables. This was undertaken considering the full array of 35 indicators, to assess the most significant factors of each construct, to complement the SPSS assessment undertaken prior. With allowance of four variables per construct, a reduction of factors ensued. The process involved selecting the four highest weighted indicators to each latent variable. A bootstrapping assessment was also undertaken to check significance of the indicators by T-values, to be greater than 1.28 for two tail 80% significance (1.96 for 90% significance was considered too high for this early assessment).

Even at four indicators per phase, statistical significance was not achieved for all factors and further reductions took place. The *Decision making,* and *Reconstruction capacity and capability* have four factors, *Inspection and assessment* and *Construction* have three factors while *Financing* has just a single contributing factor, as shown in Figure 2. The final factors differ from the selection of factors by review of highest mean, as presented in Table 1, creating contradiction for the selection of factors as indicators. The adjusted SEM-PLS model presents the remaining indicators that provides the maximum amount of explained variance by the corresponding latent variables. The values of the latent variables are the R^2 Adjusted values; a measure of the proportion of the variation in the latent variables explained by your indicator variables, adjusted by the number of indicators in the model. While the adjusted R^2 values are generally low for the recovery phases, it is relatively high for *Downtime* at 95.6% or 78% of standard deviation explained. Variable inflation was assessed to check for collinearity between variables. All indicator factors measured were satisfactorily low, with values well below 3. Inner VIF values were also checked between inferred factors, with similarly low values. All included variables are statistically valid and suitable for inclusion in the PLS model.

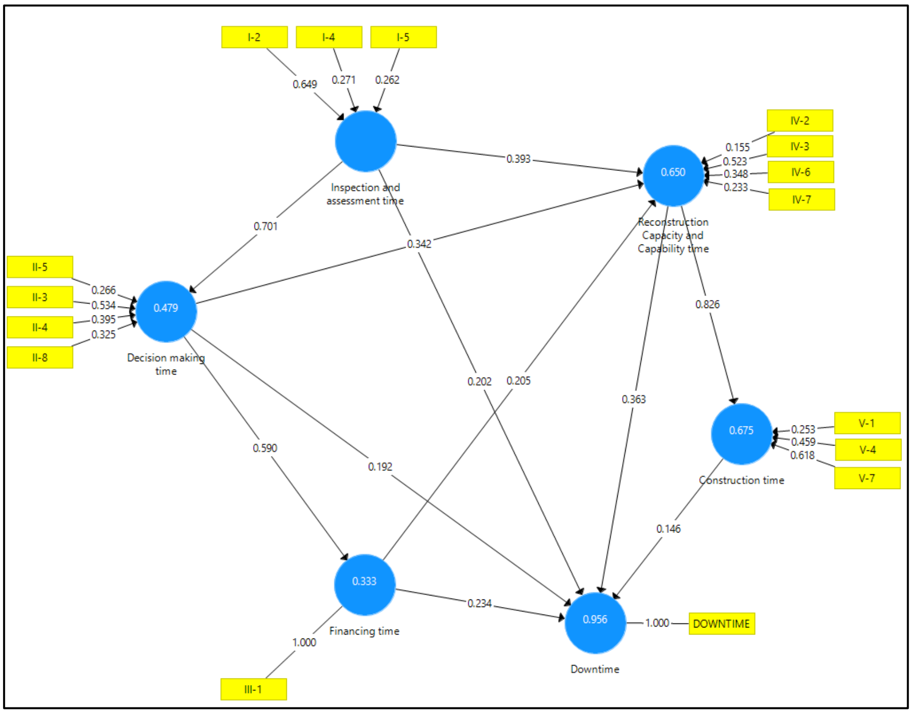

Figure 2. Modified PSL-SEM model.

Moderation was considered of the latent variables on the construct *Downtime.* Moderation was assessed between all factors. Ten different moderation combinations were tested, for example *Inspection and assessment* as a moderator variable to *Construction* as an independent variable. In each case, the t-statistic outcomes suggest that none of the moderators held significance. These moderating variables were then excluded from the model.

The selection of paths was undertaken by reviewing the p-values of the links. The amount of links were reduced until all were significant at the 95th percentile(<0.05). Links that did not meet this requirement were removed and the model subsequently re-run to assess the updated values. A second measure used the f-square statistic to test the links. All remaining relationships were in excess of 0.25, having a strong effect on the model. In Figure 2, the p-values of the remaining links are displayed, while Figure 3 below provides the path coefficients between variables highlighted by absolute values. The strongest advance of links appears to follow the time-linear progression of phases with financing and construction time appearing as outliers.

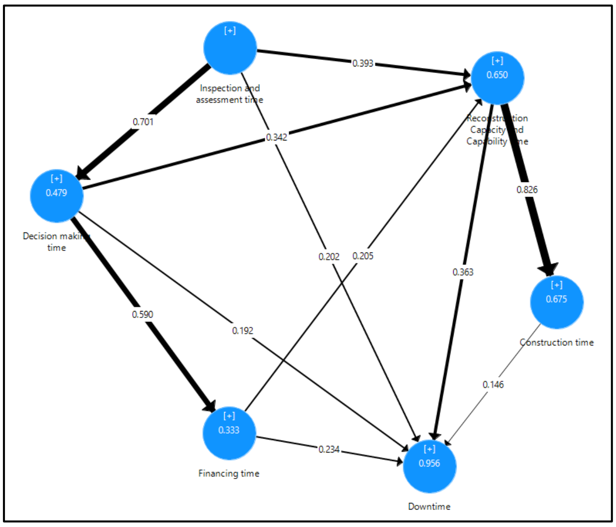

Figure 3. Path coefficients between recovery phases.

Table 2. Path Coefficients between recovery phases.

		Recipient Phase					
		TA	TD	TF	TM	TC	T_{Down}
Origin Phase	TA	-	0.70	-	0.39	-	0.20
	TD	-	-	0.59	0.34	-	0.19
	TF	-	-	-	0.20	-	0.23
	TM	-	-	-	-	0.83	0.36
	TC	-	-	-	-	-	0.15
	T_{Down}	-	-	-	-	-	-

Manipulation of the model and drawing relevant factors allows for overall inferences to be made for the quantification of infrastructure recovery time. Infrastructure downtime is represented by a culmination of recovery phases, as provided previously in equation 1, presented previously, and represented below in an adjusted form.

$$T_{d,i} = (TA_{i,j} + TD_{i,j} + TF_{i,j} + TM_{i,j} + TC_{i,j}) \pm \varepsilon_j$$

Equation 3- Modified representation of infrastructure downtime.

The model provides forms of feedback that are valuable in the production of the equations. These variables are listed below:

- Path weights between recovery phases – Presented in Table 2
- Indirect effects of the considered recovery scenario - Presented in Table 3
- weightings of critical factors within each recovery phase - Presented in Table 4

Alternate pathways to recovery were assessed, with relevant path coefficients utilised as a comparative measure to the conventional pathway of following phases 1 to 5 sequentially. There is still some rigidity to this order, following a downstream progression as a shift from higher to lower phases was not allowed for in the model. Estimates of recovery time can be made without requiring full knowledge of the impacts of all recovery phases. Some recovery phases can be omitted, yet recovery estimates are still achievable by considering indirect effects. For the most accurate measure, with least uncertainty, the predictive equation should include all recovery phases. Table 3 summarises the variables and weightings included.

Table 3. Pathways to estimating downtime.

No.	Recovery Phases					Indirect Effect, $\varepsilon_{i,j}$
	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	
1	TA	TD	TF	TM	TC	0.01
2	TA	TD	-	TM	TC	0.028
3	TA	TD	TF	TM	-	0.03
4	TA	TD	-	TM	-	0.085
5	TA	TD	TF	-	-	0.098
6	TA	TD	-	-	-	0.137
7	TA	-	-	TM		0.147
8	TA	-	-	TM	TC	0.335
9	TA	TD	TF	-	TC	NA
10	TA	-	TF	TM	TC	NA
11	TA	TD	-	-	TC	NA
12	TA	-	-	-	TC	NA
13	TA	-	TF	-	-	NA

Table 4. Indicator Weightings.

Phase	**Critical Factor (Indicator),** $\alpha_{m,j}$														
	I-2	I-4	I-5	II-3	II-4	II-5	II-8	III-1	IV-2	IV-3	IV-6	IV-7	V-1	V-4	V-7
TA	0.65	0.27	0.26	-	-	-	-	-	--	-	-	-	-	-	-
TD	-	-	-	0.53	0.40	0.27	0.33	-	-	-	-	-	-	-	-
TF	-	-	-	-	-	-	-	1.00	-	-	-	-	-	-	-
TM	-	-	-	-	-	-	-	-	0.16	0.52	0.35	0.23	-	-	-
TC	-	-	-	-	-	-	-	-	-	-	-	-	0.25	0.46	0.62
Likert Value	4.4	5.4	4.2	4.0	4.8	5.8	5.3	3.9	5.8	4.6	4.6	5.5	5.0	3.4	5.3

Lines with red text are not applicable due to absent path coefficients. Indirect effects are high between individual phases, suggesting that there is significant uncertainty when considering few variables. Further investigations uncovered much lower indirect effects where all factors are considered, as is the intended method where making inferences from using this model.

The indicator weightings in table 4 have not been adjusted from the output of the model. A normalisation of factor values was considered and attempted to instead produce relative loadings for more clarity in the application of the factors, whereby the combined weightings of any phase would sum to 1.0. However, it was elected to instead include a modification factor within the phase calculation equation, so not all factors require inclusion for the equation to be functional.

Drawing maximum inference from the model, a modified representation of the phase development equation is presented below.

$$\mathrm{T(i,j)} = \sum_{m=1}^{p} \alpha_{m,j} \times k_{m,j} + \sum_{n=1}^{q} \beta_{n,j} \times IT_{n,j}$$

Equation 4 – Phase recovery equation.

Where $\alpha_{m,j}$ is the loading of the critical contributing factor, as presented in table 4. $k_{m,j}$ is the time delay of the contributing factor and p is the number of critical contributing factors associated with the relevant recovery phase. Should time-measurements be available from statistical records of an events or from estimation, $k_{m,j}$ may be populated. However, the model is equally suitable for speculative comparisons if this variable is omitted. $\beta_{n,j}$ are the path loadings of the latent variable, considering the relationship with the preceding recovery phase. $IT_{n,j}$ is the interaction term and can be represented as a time-variable; the time for progressing between phases. q is the number of all possible interaction terms between individual critical contributing factors. An equation for each time delay phase are produced from the relevant delay factors, quantifying the parameters of this equation. The equations act as components to be compiled to address the overarching equation of delay time in infrastructure reconstruction, from equation 3.

The data available for this research has allowed for some aspects of the predictive equation to be computed. Data collection did not request information on the progression time of recovery phases of any specific scenario. For the purposes of this study, the mean values from the measured data can be utilised to provide an indicative rating of the downtime experienced between each phase. The Likert scale data is utilised as a basis for estimating the downtime of each phase. Applying the values obtained from the model, the following equations can be produced. These series of equations draw upon all included factors from the model. The worked example relates to Recovery pathway No.1 where all 5 recovery phases are included. Downtime is provided in reference to the other phases.

Event => <u>(1) Inspection and assessment phase</u>

$$TA_1 = (0.65(\text{I-2}) + 0.27(\text{I-4}) + 0.26(\text{I-5})) \times 1.0$$

$$TA = 5.4 \text{ units}$$

(1) Inspection and assessment phase => <u>(The 2009 Victorian Bushfires Royal Commission) Decision making phase</u>

$$TD_1 = (0.53(\text{II-3}) + 0.40(\text{II-4}) + 0.27(\text{II-5}) + 0.33(\text{II-8})) \times 0.7$$

$$TD_1 = 5.15 \text{ units}$$

(2) Decision making phase => <u>(3) Financing phase</u>

$$TF_1 = (1.0(\text{III-1})) \times 0.59$$
$$TF_1 = 2.3 \text{ units}$$

(3) Financing phase => <u>(4) Mobilisation phase</u>

$$TM_1 = (0.16(\text{IV-2}) + 0.52(\text{IV-3}) + 0.26(\text{IV-6}) + 0.23(\text{IV-7})) \times 0.20$$

$$TM_1 = 1.23 \text{ units}$$

(4) Mobilisation phase => <u>(5) Construction phase</u>

$$TC_1 = (0.25(\text{V-1}) + 0.46(\text{V-4}) + 0.62(\text{V-7})) \times 0.83$$

$$TC_1 = 5.06 \text{ units}$$

(5) Construction phase => <u>Completion</u>

$$T_{d,i} = (TA + TD + TF + TM + 0.15 \times TC) \pm \varepsilon_{i,j}$$

where $\varepsilon_{i,j} = 0.01 \times (TA + TD + TF + TM + 0.15 \times TC)$

$$T_{d,1} = 14.90 \pm 0.15 \text{ units}$$

Using a similar approach, the other recovery pathways can be assessed to estimate the extent of downtime incurred. This is presented in table 5. Some of the intermediate phases were neglected, as if to consider them as a non-occurrence within the recovery pathway. While not realistic, this allows for comparison between recovery paths by focusing on the influence of the overall downtime. As is expected, pathway 1, which is most comprehensive incurs the greatest downtime of 14.90 units, and the least error of 1%. The pathway that incurs the least downtime takes place where the decision making and financing phases are omitted. The inspection and assessment phase is included in all instances.

Table 5. Summary of Downtime incurred between recovery pathways.

No.	Recovery Phases					$T_{d,1}$	$\pm\varepsilon_{i,j}$
	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5		
1	5.4	5.2	2.3	1.23	5.06	**14.90**	0.15
2	5.4	5.2	-	2.09	5.06	**13.45**	0.38
3	5.4	5.2	2.3	1.23	-	**13.34**	0.40
5	5.4	5.2	2.3	-	-	**11.13**	1.09
4	5.4	5.2	-	2.09	-	**7.49**	0.64
8	5.4	-	-	2.40	5.06	**5.40**	1.81
6	5.4	5.2	-	-	-	**6.39**	0.88
7	5.4	-	-	2.40	-	**6.26**	0.92

The equations would suggest that the greatest sources of downtime take place at the early phases of (1) Inspection and assessment at 5.4 units, Decision making phase at 5.2 units and the final phase (5) Construction at 5.06. There may instances where the recovery pathways have been represented, with limited clarity and applicability in the outcome. There is a very strong likelihood that only recovery phase 1, where all phases are considered, would be suitable for future regressional exercises.

It is necessary to also reflect on the amount of data that has been drawn upon to produce these relationships; with just a few indicators to represent the recovery phases, the assessment would always be prone to destabilising influences, significant uncertainty and caveats of the level of accuracy. However, the process of drawing information and undertaking a quantification study has been solidified through the trials of this research, which offers a foothold for future studies to consider where implementing more comprehensive assessments.

CONCLUSIONS

Deciding appropriate recovery strategies and catering for all stakeholders is of core interest many stakeholders. Providing outlets to better understand the underlying relationships within infrastructure recovery aids in the decision making and subsequently the outcomes on the overall recovery process of horizontal infrastructure. This research was an early design concept of a tool to help in the forward-planning for addressing infrastructure recovery across the full recovery continuum. The model developed provides direction for the process of undertaking a quantification study and formative SEM regressional modelling to assist others in future modelling efforts. The impeding factors that have played a major role in infrastructure recovery from Christchurch and Kaikōura earthquakes can assist reconstruction practitioners in planning and decision making in disaster recovery to address future events.

The findings indicated that the pathways to recovery as well as downtime between reconstruction phases are variable. This study was limited in two ways; firstly, there was insufficient data from the distributed research questionnaires to allow for adequate modelling to occur. Secondly, a lack of validation using time-data and not relative weightings also affects the strength of the findings. Addressing these two limitations in future research efforts is an area of interest for the researchers involved as well as delivering a useful series of reconstruction predictions to industry representatives.

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