Integrated FAHP-FDEMATEL for Determining Causal Relationships in Construction Crew Productivity Modelling

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ABSTRACT

Construction crew productivity is affected by the motivation of the crew performing given activities and by situational/contextual factors forming the dynamic construction environment. The literature lacks a comprehensive analysis of causal relationships between crew motivation and situational/contextual factors for dynamic modelling of crew productivity. The contributions of this paper are 1) identifying a set of criteria for performing expert weight assignment for heterogenous group experts in productivity research, 2) proposing an integrated fuzzy analytic hierarchy process–fuzzy decision-making trial and evaluation laboratory (FAHP-FDEMATEL) approach that provides a systematic, structured method for determining causal relationship mapping between factors affecting crew productivity, and 3) proposing an approach for identifying

cause-and-effect groups amongst the situational/contextual factors and crew motivation, which can further be used to formulate strategic productivity improvement solutions. The proposed methodology is demonstrated using a case study on an actual industrial construction project in Alberta, Canada.

Keywords: construction crew productivity, construction crew motivation, fuzzy AHP, fuzzy DEMATEL, dynamic modeling

1. INTRODUCTION

Construction productivity plays a significant role in determining a construction project's success, therefore it is a major research area. Construction productivity problems include assessing factors that affect productivity and identifying improvement strategies for crew productivity. Previous studies attempted to identify factors that affect crew productivity and develop modelling approaches for monitoring and establishing improvement strategies to address productivity problems. Construction projects are performed in a dynamic environment with numerous interactions between work-setting conditions and situational/contextual factors related to tasks and resources, such as labour and materials, management, and project characteristics (Raoufi and Fayek 2018). Situational or external factors such as economic, social, and technological issues impact crew productivity and performance. These as well as contextual factors such as age, gender, culture, and personal interests are studied in crew productivity research (Raoufi and Fayek 2018). Crew productivity is a primary project performance indicator and can be described as a function of the efficiency of resource utilization (i.e., labour), which is affected by crew motivation. Thus, it is imperative to properly assess crew productivity by 1) identifying relevant factors (e.g., crew motivation, situational/contextual factors) that affect productivity of different crews in construction projects and 2) capturing existing complex causal relationships between these factors.

In the current construction literature for capturing the complex causal relationships for dynamic modelling of productivity, commonly used methods include literature reviews, modellers' assumptions, and verifying model assumptions using focus groups, questionnaire surveys, and/or semi-structured interviews (Nasirzadeh and Nojedehi 2013; Khanzadi et al. 2017; Gerami Seresht and Fayek 2018). Literature review methods are limited, because relationships between model variables can only be obtained through the literature if knowledge about those relationships exists. Moreover, methods such as focus groups, survey questionnaires, and interviews entail aggregating inputs collected during assessment involving multiple experts (Cyr 2016; Paradis et al. 2016). These experts usually have varying expertise levels, which contributes to the complexity of modelling crew productivity. Although the literature yields several productivity-related studies, a need exists to first, provide a systematic and structured methodology for establishing causal relationships in dynamic productivity modelling. This involves assessing the importance of and causalities between the situational/contextual factors and constructing causal loop diagrams (CLDs), which are functions of the dynamic relationships between system variables. Second, there is a need to consider importance weights in aggregating the opinions of heterogenous experts who participate in productivity-related decision making.

The decision-making trial and evaluation laboratory (DEMATEL) method uses graph and matrix theory to systematically structure cause-and-effect relationships between system elements (Nazeri and Naderikia 2017). However, application of DEMATEL for productivity is limited in some aspects of modelling in previous studies. There are limitations to the number of criteria considered to weigh expert input, the level of detail (i.e., sub-criteria) being considered for each criterion, and the ability to consider subjective uncertainties arising from the linguistic nature of expert inputs (e.g., "low" influence, "high" impact). Further, the literature lacks a framework for weighing the relative importance between productivity factors, which can enable modelers identify causal relationships, and mapping influences between system elements to complement dynamic modelling of crew productivity. The fuzzy DEMATEL method applies fuzzy set theory to capture subjective uncertainties in DEMATEL. Decision-making problems involve imprecision, because goals, constraints, and the set of possible actions can not be precisely known (Zadeh 1965). Hence, converting linguistic inputs into fuzzy numbers is a better approach for processing various experiences, opinions, ideas, and motivations of an individual or group decision maker (Aykuz and Celik 2015). This enables the capture of complex causal relationships that affect the overall productivity of a system, while also enabling modellers to assess each variable's influence using influence relation mapping (IRM) and other metrics (Bashardoost et al. 2018; Han and Wang 2018). Furthermore, a weighted approach to FDEMATEL involves integrating it with techniques such as fuzzy analytic hierarchy process (FAHP), which enables FDEMATEL to process inputs from heterogeneous experts whose inputs vary owing to their expertise level, educational background, or experience in related fields.

The research question addressed in this paper is: "How can the complex and dynamic interrelationship between crew motivation, and situational/contextual factors that affect crew productivity be captured while taking into account the construction environment?" In this regard, this paper has three objectives: 1) identify criteria to perform expert assessment for assigning importance weights of heterogenous experts in productivity research, 2) propose a systematic, structured methodology to define causal relationships between the most significant factors affecting crew productivity and analyse their interrelated impacts using IRM with FAHP–FDEMATEL, and 3) map causal relationships between crew motivation, situational/contextual factors, and crew productivity from FDEMATEL outputs, which can be used to perform qualitative SD modelling of crew productivity.

2. LITERATURE REVIEW

2.1 Construction crew productivity modelling

Productivity is a crucial metric for assessing overall crew performance in construction and usually involves several interrelated variables (Nasirzadeh and Nojedehi 2013). Construction crew productivity has been effectively defined as the ratio of measured output (completed work) to measured input (work effort) (CII 2006; Kedir et al. 2022).

Models that have implemented in studies on crew productivity modelling include statistical methods (Hiyassat et al. 2016; Ghodrati et al. 2018), artificial neural network (ANN) (Ma et al. 2016; Golnaraghi et al. 2019; Gutiérrez-Ruiz et al. 2020), discrete event simulation (DES) (Afifi et al. 2016; Larsson et al. 2016; Abbasi et al. 2020; Plamenco et al. 2021), agent-based modelling (ABM) (Shehwaro et al. 2016; Jabri and Zayed 2017; Dabirian et al. 2021; Wu et al. 2022), and system dynamics (SD) (Khanzadi et al. 2017; Gerami Seresht and Fayek 2018; Javed and Pan 2018; Al-Kofahi et al. 2020). These approaches have been used individually or in hybrid models, such as those incorporating fuzzy logic concepts (Mirahadi and Zayed 2016; Nojedehi and Nasirzadeh 2017; Gerami Seresht and Fayek 2018). Accordingly, productivity research modelling has mostly emphasized crew productivity as a dynamic problem due to the dynamic nature of construction projects. Moreover, dynamic modelling approaches are preferred because they allow modellers to track project changes that happen over time (Gerami Seresht and Fayek 2018) and capture causal relationships (Kim et al. 2020).

Several different dynamic approaches can be used to analyse causal relationships. Interpretive structural method (ISM) has an elaborate visual representation and enables grouping of factors into dependent, independent, autonomous, and linkage clusters, but it is unable to consider interactions between factors that belong to different categories (Tavakolan and Etemadinia 2017), such as crew-level versus project-level factors. Moreover, ISM cannot effectively capture subjective uncertainties and is unable to deal with the dynamic nature of variables that affect productivity (Siraj and Fayek 2021). Analytic network process is relatively simpler to understand and can establish relationships between different categories, but it results in high computational complexity (Valipour 2015; Li et al. 2019). Fuzzy cognitive mapping (FCM) can model complex relationships that involve causalities and feedbacks (Case and Stylios 2016). However, FCM is unable to capture time-concept (dynamism), its assumes linear causalities between variables, and it lacks the capability to capture uncertainty and represent conditional relationships or rule-based knowledge (Lazzerini and Mkrtchyan 2011; Mpelogianni and Groumpos 2018).SD is a modelling approach capable of capturing dynamic system behaviour, where changes in the system correspond to variables that make up the system (Shokouh-Abdi et al. 2011). SD captures the dynamic nature of systems that exhibit varying properties, using multiple feedback processes, interactions, and dependencies (Nasirzadeh et al. 2020). Thus, qualitative modelling of productivity in SD is the most important step in dynamic modelling, which entails the critical step of establishing CLDs and feedback relationships (Siraj and Fayek 2021).

To perform the qualitative aspect of SD modelling, productivity-related studies in the literature have utilized one or more approaches, such as literature reviews, modellers' assumptions, and experts' verification through focus groups, questionnaire surveys, or semi-structured interviews (Khanzadi et al. 2017; Gerami Seresht and Fayek 2018; Leon et al. 2018; Al-Kofahi et al. 2020).

In this regard, productivity research lacks a systematic method for gathering group knowledge from individuals with different expertise levels using techniques such as FAHP, capturing causal relationships between factors, and visualizing these complex cause-and-effect interrelationships using techniques such as FDEMATEL.

2.2 Fuzzy AHP

AHP is an extensively applied multi-criteria decision making (MCDM) method used to establish the weights of criteria and alternative priorities via pairwise comparisons (Liu et al. 2020). Integrating fuzzy logic with AHP enables the latter to process subjective uncertainties arising from the use of linguistic terms. To process the linguistic expressions used in experts' inputs, crisp numbers used in the AHP pairwise comparison matrix are replaced with fuzzy numbers. Fuzzy logic enables processing of imprecise data and ambiguous human judgement (Shokouh-Abdi et al. 2011; Seker and Zavadskas 2017).

In the area of construction management, FAHP is extensively applied, namely in problems related to project site selection, contractor selection and biding evaluation, selection of construction means and methods (Nguyen and Tran 2017; Prascevic and Prascevic 2017), and in construction risk analysis and risk assessment problems (Beltrão and Carvalho 2019; Lyu et al. 2021). FAHP is also prominently applied in emerging methods such as building information modelling (BIM) (Khanzadi et al. 2020; Figueiredo et al. 2021). In this regard, FAHP is one of the most useful approaches to decision making problems consisting of multiple criteria with uncertain, subjective, and linguistic data and involving a group of decision makers. FAHP can be improved through integration with other methods to improve overall decision making. For example, data collected from experts can be structured using Delphi method, spatial data can be processed using GIS, multivariate analysis can be used to structure different criteria. The alternatives of technique for order of preference by similarity to ideal solution (TOPSIS) and elimination et choix traduisant la realité (ELECTRE) can be used to rank alternatives, Monte Carlo simulation can be used to process uncertainties in the output, and mathematical programming can be used for optimization (Nguyen and Tran 2017).

2.3 Fuzzy DEMATEL

FDEMATEL applies fuzzy set theory to capture subjective uncertainties in DEMATEL, which extends the scope of the DEMATEL method and enables modellers to capture complex causal relationships affecting overall productivity while also enabling them to assess each variable's influence using IRM (Chien et al. 2014; Bashardoost et al. 2018). In construction research, FDEMATEL has mostly been applied to find interrelationships between system elements and identify causal mappings in the research areas of risk identification and assessment (Seker and Zavadskas 2017; Hatefi and Tamošaitienė 2019; Li and Xu 2021), sustainability (Jeong and Ramírez-Gomez 2018; Mavi and Standing 2018; Rostamnezhad et al. 2020; Li et al. 2022), safety (Shakerian et al. 2020; Chai et al. 2022), and planning (Jeong et al. 2016; Jeong and Ramírez-Gomez 2018). Although the literature is comprehensive regarding FDEMATEL application in other construction areas, it lacks studies on using FDEMATEL to identify causal relationships and map influence between system elements to complement dynamic modelling of crew productivity. Moreover, in previous studies the application of DEMATEL-based approach to productivity is limited in some aspects of modelling. In Jalal and Shoar's (2019) DEMATEL model, the criteria considered for performing expert weight assessment is limited and is utilized only at a higher level. For example, the criterion *experience* could be considered to capture an expert's general or specific experience. Thus, an expert could work for 20 years in construction (e.g., on highways) but still have limited experience in a different construction field (e.g., buildings). Assessment of experts' responses should consider multiple qualifying attributes such as education, and the quality of experts' responses should be assessed in terms of a more detailed set of criteria that is capable of giving consideration to other qualifying attributes such as education, knowledge, and professional performance.

3.0 METHODOLOGY

3.1 Stage 1: FAHP

3.1.1 Developing criteria lists and constructing the problem hierarchy

First, criteria for assessing expertise levels, and their corresponding qualification attributes used as subcriteria in this paper, were identified along with their measurement scales. A list of 7 criteria and 24 subcriteria was developed from construction management studies in the literature (Farrington-Darby and Wilson 2006; Monzer et al. 2019; Siraj and Fayek 2021) and modified to enable expert assessment in the productivity domain. (See the Results and Discussion section for a list of identified qualification attributes and related data.)

3.1.2 Obtain relative importance weights

To establish expert weight assessment for the FAHP process and conduct pairwise comparisons, the relative importance weights of the listed criteria were obtained. Expert ranking was performed based on the hierarchy shown in Figure 1, in which level-2 subcriteria n, p, and r are the number of subcriteria for criterions 1, 2 and n, respectively. The qualification attributes were measured using qualitative or quantitative scales (see table in Results and Discussion). The list of criteria was then evaluated via a survey completed by experts with extensive knowledge of the construction industry and productivity research. Likert scales are one of the most fundamental and frequently applied tools in research (Joshi et al. 2015). For qualification attributes that cannot be measured quantitatively, a predetermined Likert scale of 1–5 was adopted from Monzer et al. (2019) that enables objective quantification of the qualitative subcriteria for more accurate decision making. For example, participants used this Likert scale to rate the criterion *Personal attributes and skills* and its 5 subcriteria: *Level of communication skills*, *Level of teamwork skills*, *Level of leadership skills*, *Level of analytical skills*, and *Level of ethics.* The experts were also prompted to suggest additional criteria that were not yet listed.

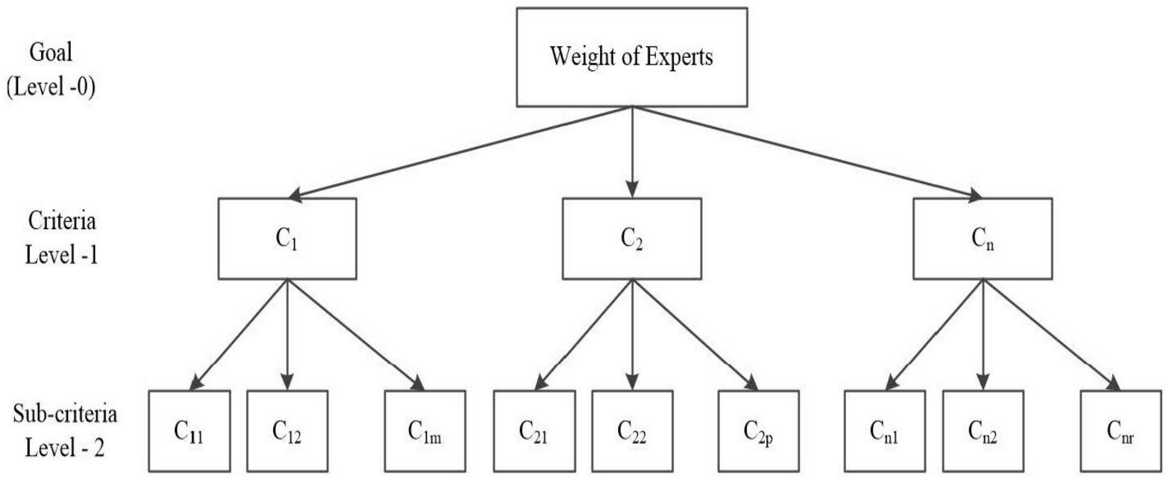

Fig. 1. Hierarchical structure for expert importance weight assignment.

Next, the fuzzy pairwise comparison matrix for performing expert weight assessments was established, in which each criterion's relative importance for performing expert weight assessment is obtained using a predetermined scale. FAHP uses crisp inputs while assessing the relative importance of criteria, and an FAHP pairwise comparison matrix uses fuzzy numbers instead of crisp inputs to represent the linguistic terms used during information synthesis. Each linguistic term is associated with its own fuzzy set. A series of such fuzzy sets combine to form a fuzzy scale for describing the levels of the linguistic terms, thus linking the verbal and numerical expressions.

The most common fuzzy scales in the literature are nine-level and five-level fuzzy scales (Liu et al. 2020). For this paper, Zimmer et al.'s (2017) five-level fuzzy scale was used, where 1 = *Equally important*, 2 = *Weakly important*, 3 = *Fairly strongly important*, 4 = *Very strongly important*, and 5 = *Absolutely important*. The type of fuzzy set used to represent the fuzzy scale also depends on several factors. In this study, the tree-diagram approach for selecting fuzzy sets was used to select triangular fuzzy numbers.

In the fuzzy pairwise comparison matrix F_m is shown in eq. 1, F represents the pairwise matrix of an expert m and comprises triangular fuzzy numbers that assess the relative importance of criterion i (c_i) over criterion j (c_j):

$$F_m = \begin{bmatrix} (1,1,1) & \tilde{c}_{12}^{(m)} & \cdots & \tilde{c}_{1n}^{(m)} \\ \tilde{c}_{21}^{(m)} & (1,1,1) & \cdots & \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{c}_{n1}^{(m)} & \tilde{c}_{n2}^{(m)} & \cdots & (1,1,1) \end{bmatrix} \qquad (1)$$

where $\tilde{c}_{ij}^{(m)} = 1/\tilde{c}_{ji}^{(m)}$.

Each expert's judgements (F_m) were checked for consistency using Saaty's consistency ratio (Saaty 2008; Liu et al. 2020), shown in eqs. 2 and 3. This is performed using the principle of crisp consistency, whereby the fuzzy numbers in the TRM are defuzzified before the consistency ratio is computed:

$$CI \rightleftarrows = \frac{\lambda_{max}}{n-1} \qquad (2)$$

where CI = consistency index, $\lambda_{\max}$ = the largest eigenvalue of the comparison matrix, and n = dimension of the square matrix; and

$$CR = \frac{CI}{RI(n)} \qquad (3)$$

where n = dimension of the square matrix, CR = consistency ratio, and RI = random index, obtained from the random index table of different matrix sizes (Zadeh 1965).

A CR value of ≤0.1 is acceptable for a consistent matrix (Saaty 2008). If the matrix does not comply with this requirement, the expert is prompted to repeat the pairwise comparisons until such criteria are met. Expert inputs are then aggregated to construct the representative matrix that combines the inputs of all involved experts. The subsequent steps (i.e., aggregation of expert inputs; obtaining fuzzy weights; defuzzification) to obtain the ranking of expert assessments were adopted from Monzer et al. (2019).

3.1.3 Assign experts' weighted importance

The final step in FAHP is using the matrix outputs (i.e., relative importance weights between criteria) and assigning relative importance weights to experts. To achieve this, results of the subcriteria assessment are normalized in the range of [0–1] and used to evaluate each expert involved in the decision-making process of assessing the causal relationships between factors. Thus, weights obtained for criteria and subcriteria levels are applied to score each expert's expertise level, using eq. 4:

$$S_i = \sum_{j=1}^{n} \sum_{k=1}^{nC_j} w_{C_j}\, w_{S_{jk}}\, I_{S_{jk}}(i), \qquad i = 1 \ldots, E \qquad (4)$$

where $I_{S_{jk}}(i)$ is the normalized evaluation of expert j in a total of E experts, based on subcriterion k and criterion C_j; w_{C_j} is the weight of criterion C_j; $w_{S_{jk}}$ is the weight of subcriterion S_{jk}; n is the total number of criteria C_j; and nC_j is the total number of subcriteria k.

The eq. 4 scores are then normalized using eq. 5 and used as weights by multiplying each expert's assessment with the importance weight (*IW*) of each expert:

$$IW_i = \frac{s_i}{\sum_{m=1}^{E} s_m}, \quad i = 1\ldots, E \qquad (5)$$

A survey was prepared to formulate the application of FAHP discussed above and provide inputs for FDEMATEL. In this survey, the criteria and subcriteria identified through FAHP were presented in a question format to profile the participating experts. The resulting outputs were used to determine the experts' importance weights.

3.2 Stage 2: FDEMATEL process

3.2.1 Factor identification

Factors that affect crew motivation and productivity were identified and collected from the literature (Nasirzadeh and Nojedehi 2013; Tsehayae and Fayek 2016; Khanzadi et al. 2017; Gerami Seresht and Fayek 2018; Raoufi and Fayek 2018). The identified factors were grouped into situational/contextual factors at the crew and project levels. Crew-level factors were subcategorized into task-, labour-, and foreman-related factors, and project-level factors were subcategorized as task-related, management-related, work-setting conditions, resources, and safety (Raoufi and Fayek 2018).

The most critical factors affecting crew productivity were then identified using expert inputs. Interview surveys were designed to elicit knowledge from experts (i.e., project management, tradespeople staff). Based on their individual knowledge, experts ranked the influence of factors on crew productivity, which was reflected in two scores: 1) the agreement score, showing the extent to which the expert agrees the factor is present in their project, and 2) the impact score, showing the extent to which the factor impacts productivity. In this study, as recommended in CII (2006) and Taherdoost (2019), a seven-point Likert scale consisting of *Strongly Disagree*, *Disagree*, *Slightly Disagree*, *Neither Agree nor Disagree*, *Slightly Agree*, *Agree*, and *Strongly Agree* was used to measure the agreement score, and the impact score was measured using the seven-point Likert scale of *Strongly Negative*, *Negative*, *Slightly Negative*, *No Impact*, *Slightly Positive*, *Positive*, *Strongly Positive*. After expert inputs on these factors were collected, statistical analysis was performed to select factors with the maximum positive or negative impact on crew productivity (Gerami Seresht and Fayek 2020). Pearson correlation analysis is the most commonly preferred technique for correlation analysis (Bobko 2001; Pandey 2020). Pearson's coefficient indicates relationship, such as between independent variables (e.g., motivational and situational/contextual factors) and dependent variables (e.g., crew productivity). (Note that Pearson correlation analysis does not establish causation between factors, per Gogtay and Thatte 2017). Once a strong relationship between factors is established, these factors are used to define system elements in subsequent steps of the FDEMATEL process.

3.2.2 Define system elements and generate expert assessments

The next FDEMATEL step is defining system elements that influence the system's behaviour (Rostamnezhad et al. 2020). In this study, system elements are the identified list of top factors affecting crew productivity. A survey was first prepared to provide inputs for FDEMATEL, using fuzzy linguistic scales (Seker and Zavadskas 2017; Mavi and Standing 2018) to generate expert assessments on causal relationships between the factors using expert inputs. The linguistic terms *No influence* (NI), *Very low influence* (VL), *Low influence* (L), *Medium influence* (M), *High influence* (H), and *Very high influence* (VH) were represented by the fuzzy numbers (0.00 0.00 0.00), (0.00 0.00 0.25), (0.00 0.25 0.50), (0.25 0.50 0.75), (0.50 0.75 1.00), and (0.75 1.00 1.00), respectively. This survey was also used to determine whether the polarity of causal relationships between variables was positive or negative. Polarity between two elements is positive if an increase/decrease in system element *i* causes an increase/decrease in element *j*. A positive link implies a similar change of direction between the factors; for example, increase/decrease in crew size can lead to increase/decrease in congestion. Negative polarity of a causal relationship/link implies an opposite change of direction between the factors such as when greater rework volume causes reduced project progress.

3.2.3 Constructing IRM maps

The generated expert assessments were used to obtain an initial fuzzy matrix for each expert, in the form of fuzzy matrix $\tilde{X}^E$, shown in eq. 6:

$$\tilde{X}^E = \left[\tilde{x}_{ij}^{(e)}\right]_{nxn} = \begin{bmatrix} 0 & \tilde{x}_{12}^{(e)} & \cdots & x_{1n}^{(e)} \\ \tilde{x}_{21}^{(e)} & 0 & \cdots & \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{n1}^{(e)} & \tilde{x}_{n2}^{(e)} & \cdots & 0 \end{bmatrix} \qquad (6)$$

where *i,j = 1,2,...n*; *e =1,2,...E*; *n* = total number of elements in the system; and *E* = total number of experts assessing the causal relationships.

The set of initial fuzzy matrixes obtained from a set of experts *E* were aggregated to form the aggregated direct relation matrix $\widetilde{D}$. Each element in the aggregated matrix was obtained by multiplying the weights of the experts (*w*) obtained from the FAHP process with the elements in the direct matrices of respondents, as shown in eqs. 7 and 8 (Seker and Zavadskas 2017):

$$\widetilde{D} = \sum_{e=1}^{E} w_e \otimes \tilde{x}_{ij}\, , where\ \tilde{x}_{ij} = (x_{ij}^{l}, x_{ij}^{m}, x_{ij}^{u}), \text{ and } i,j = 1,2...n \qquad (7)$$

Hence,

$$\widetilde{D} = \left[\, \tilde{d}_{ij} \right]_{nxn}, where\ \tilde{d}_{ij} = (d_{ij}^{l}, d_{ij}^{m}, d_{ij}^{u}) \qquad (8)$$

This direct relation matrix $\widetilde{D}$ was used to obtain the normalized fuzzy aggregated direct relation matrix *N*, as shown in eqs. 9 and 10:

$$\widetilde{N} = \widetilde{D} * \lambda \qquad (9)$$

where:

$$\lambda = \frac{1}{max_{1 \le i \le n}\left(\sum_{j=1}^{n} d_{ij}\right)}, \quad i, j = 1,2, \ldots n \qquad (10)$$

The fuzzy total relation matrix *T* represents the total degree of causal influence of factor *i* on factor *j*, which was obtained using eqs. 11–13 (Rostamnezhad et al. 2018).

$$T = D(I - D)^{-1} \qquad (11)$$

where:

$$\tilde{T} = D + D^2 + D^3 + \cdots + = \sum_{i=1}^{\infty} D^i \qquad (12)$$

and *I* is represented by an $n \times n$ identity matrix. Hence:

$$\tilde{T} = \left[\, \tilde{t}_{ij} \right]_{nxn}, where\ \tilde{t}_{ij} = \left(t_{ij}^{l}, t_{ij}^{m}, t_{ij}^{u}\right), and\ i, j = 1,2, \ldots n \qquad (13)$$

Next, the sum of rows (r_i) and sum of columns (c_j) were computed as shown in eqs. 14 and 15, then ($R_i + C_j$) and ($R_i - C_j$) were calculated using eqs. 16 and 17. These calculations were used to construct IRM maps in which the defuzzified values of horizontal axis ($R_i + C_j$) are referred to as *prominence* (Zhou et al. 2014) and signify the degree of relationship of each factor with all other factors. Higher $R_i + C_j$ values indicate higher causal relations with other factors. Defuzzified values of the vertical axis ($R_i - C_j$) are referred to as *relation* (Zhou et al. 2014). Positive relation values indicate that factors are in the cause group. Negative relation values indicate that factors are in the effect group.

$$r_i = \sum_{1 \le j \le n}^{n} t_{ij} \quad \forall i \qquad (14)$$

$$c_j = \sum_{1 \le i \le n}^{n} t_{ij} \quad \forall j \qquad (15)$$

$$(R + C)_i = r_i + c_j \quad i, j = 1, \rightleftarrows 2, \ldots n \qquad (16)$$

$$(R - C)_i = r_i - c_j \quad i, j = 1, \rightleftarrows 2, \ldots n \qquad (17)$$

3.2.4 Establishing CLDs for SD

Finally, CLDs, which present the causal relationships between crew motivation and situational/contextual affecting crew productivity, are established for use in SD modelling of productivity. The total relation matrix T obtained in eq. 13 was defuzzified using the center-of-area method to achieve the T^{def} matrix, which represents the degree of causal influence between the factors affecting crew productivity. Thus, T_{ij} represents the degree of causal influence of factor i on factor j. The direction of arrows in the CLD indicate how factors in each row affect the factors of the matrix's columns. T_{ij} values that signify a stronger relationship between factors i and j are selected using a threshold value, which filters out negligible effects between factors that can otherwise make the resulting model too complex to comprehend (Si et al. 2018). The threshold value can be obtained using expert inputs (Li and Tzeng 2009) or brainstorming (Azadeh et al. 2015), or it can be based on a given percentile (Si et al. 2018), the average of the elements in the matrix (Sumrit and Anuntavoranich 2013), or other approaches. T_{ij} values meeting the threshold requirement are selected to plot the relationship maps that form the CLDs.

4.0 CASE STUDY

The proposed FAHP-DEMATEL method was demonstrated using data collected over a period of three months from a real-world industrial construction project in Alberta, Canada. These data comprised the findings on factors affecting crew motivation and performance (Raoufi and Fayek 2018) in this project's context. Determining the sample size (i.e., the number of respondents surveyed from the total population) is critical to ensure the reliability of results. The population for this survey was made up of various personnel who assess a construction project. Random sampling ensures that all members of a population (e.g., respondents) have an equal chance of being selected, to help prevent biased selection based on convenience (Robinson 2014; Fellows and Liu 2015). An adequate sample size was used to ensure proper representation of the population as a whole. To identify system variables (i.e., motivational and situational/contextual variables), a survey was distributed at a construction company with 25 supervisors and 54 craftspeople. A total of 23 supervisors and 15 craftspeople responded (Raoufi and Fayek 2018). For the craft and supervisor survey, 80% and 99% confidence intervals were achieved, respectively, with 10% margin of error. For the population of 79 people, 38 responded, which achieved a 90% confidence interval with 10% margin of error.

Surveys for the case study were conducted in two stages. In Stage 1, a survey was conducted with experts who have extensive knowledge in construction and related productivity research. Survey results were used to validate and weigh the criteria identified for expert ranking, as described in the Methodology section above. The experts' responses were obtained in the form of a pairwise comparison matrix as input for the FAHP process. Participating experts had an average of >15 years' experience in the construction industry and had previously participated in productivity research. Table 1 presents profiles for this group of experts.

Table 1. Profile of experts in the FDEMATEL process.

	Education (civil engineering)	Work experience - Industry	Current profession
Expert 1	MSc	<5 years	Researcher
Expert 2	PhD	>10 years	Project control
Expert 3	PhD	>10 years	Project manager
Expert 4	MSc	5 years	Researcher
Expert 5	PhD	>10 years	University professor
Expert 6	PhD	<5 years	Researcher

In Stage 2, factors affecting crew motivation and performance were prioritized using data collected for the actual construction project (Raoufi and Fayek 2018). For this case study, data on situational/contextual factors, crew motivation, and several crew performance measures were collected using interview surveys, project documents such as safety logs, and external databases such as weather data. The data from interview surveys with crew members, supervisors, and project managers were utilized to rank the factors impacting crew motivation and performance, where respondents were prompted to assess the extent to which a factor existed in the project and also evaluate its corresponding degree of importance. Data collected on situational, contextual, and crew motivational factors were analysed to identify the most important factors that affect crew productivity. A total of 129 situational/contextual factors that affect crew performance were identified at the crew level (Raoufi and Fayek 2018).

5.0 RESULTS: THEORETICAL AND PRACTICAL IMPLICATIONS

Per the methodology, experts identified and validated a list of criteria. Table 2 presents the results of relative importance weights for each criterion and subcriterion. The normalized expert weight assessment performed on the six experts (E_1, E_2, E_3, E_4, E_5, E_6) was computed as (0.13, 0.17, 0.21, 0.16, 0.19, 0.14). Of a total 129 situational/contextual crew-level factors, Pearson's correlation coefficient values of >0.5 were chosen based on Pearson correlation analysis that identified 38 factors as having a strong relationship with crew productivity.

Table 2. Calculated weights of criteria and weights, scales of measure, and range of data input for subcriteria.

No.	Criterion	Weight	Subcriterion	Weight	Scale of measure	Range of data input
1	Experience	0.16	1.1. Total years of experience	0.60	Integer	0–35
			1.2. Relevant experience	0.40	Integer	0–20
2	Knowledge	0.16	2.1. Academic knowledge	0.21	Integer	0–5
			2.2. Education level	0.30	1–5 rating	1–5
			2.3. On-the-job training	0.49	Integer	0–10
3	Professional performance	0.15	3.1. Current occupation in the company	0.40	1–5 rating	1–5
			3.2. Years in current occupation	0.60	Integer	0–35
4	Productivity-related project management practices	0.31	4.1. Average hours of work in productivity-related work per week	0.35	Integer	0–20
			4.2. Level of management training related to productivity	0.30	Integer	0–5
			4.3. Experience in conferences related to productivity management	0.15	Integer	0–5
			4.4. Functional skills related to productivity management	0.20	1–5 rating	1–5
5	Project specifics	0.06	5.1. Project size limit	0.26	Integer	1mil – 2 bil
			5.2. Commitment to time deadlines	0.23	Integer	0–100
			5.3. Commitment to cost budget	0.23	Integer	0–100
			5.4. Safety adherence	0.16	Integer	0–5
			5.5. Geographic diversity experience	0.12	Integer	0–20
6	Reputation	0.03	6.1. Social acclimation	0.34	1–5 rating	1–5
			6.2. Willingness to participate in survey	0.33	1–5 rating	1–5
			6.3. Professional reputation	0.33	1–5 rating	1–5
7	Personal attributes and skills	0.13	7.1. Level of communication skills	0.24	1–5 rating	1–5
			7.2. Level of teamwork skills	0.24	1–5 rating	1–5
			7.3. Level of leadership skills	0.27	1–5 rating	1–5
			7.4. Level of analytical skills	0.14	1–5 rating	1–5
			7.5. Level of ethics	0.11	1–5 rating	1–5

Per the FDEMATEL results, experts' survey responses were converted from a linguistic scale to triangular fuzzy numbers. Table S1 depicts a sample section of the fuzzy total relation matrix $\tilde{T}$. Table S2 depicts a sample section of the defuzzified total relation matrix T_{def}. [See end of this post-print document for Tables S1 and S2.] The matrices and diagrams represent contextual relationships between the factors in the system, whereby the numeric value measures the strength of influence (Bavafa et al. 2018). *Prominence* is a measure of each factor's role on the overall system in terms of its causality. Hence, greater prominence values indicate higher causal relations with other factors. *Relation* values in the vertical axis allow assessment of the factors by categorizing them into cause-and-effect groups. Hence, factors with positive relation values are categorized into the *cause* group, and those with negative values form the *effect* group. The top prominence and relation values are summarized in section 5.1.2, *Relative criteria importance*, below. The values of prominence ($R + C$) and relation ($R - C$) can be simultaneously analysed by mapping these values to formulate IRM, as shown in Figure 2.

Outputs of the FDEMATEL process, namely the defuzzified values of the T matrix, were used to map the causal influence relationships between factors. While constructing the CLD, it is imperative to consider the extent of causal relationships between variables (e.g., in a matrix of 38 variables, 1,444 potential relationships exist). Considering these relationships can become too complex and unfeasible to implement. Therefore, from causal relationships that exist between any two variables, a threshold value of 75th percentile of the defuzzified total-relation matrix T was set by selecting values ≥ 0.021. Hence, only the strong relationships are used to map causal relationships between variables. In comparison with previous studies, the number of 38 nodes used in this study is significantly higher. Researchers have utilized nodes in the range of five or lower (Yazdi et al. 2015) and fifteen or higher (Zhou et al. 2014; Akyuz and Celik 2015; Aliakbari Nouri

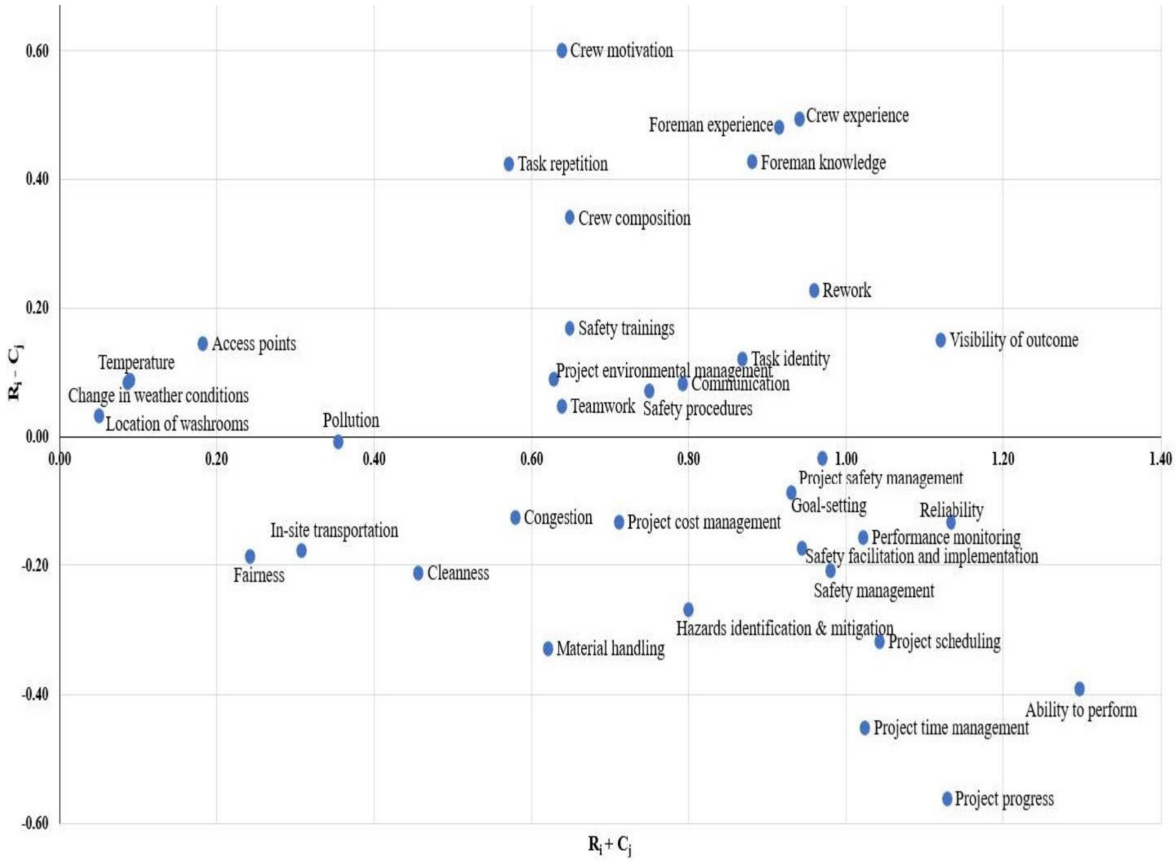

Fig. 2. Influence relation map (IRM).

and Shafiei Nikabadi 2017; Selvaraj et al. 2018). However, most researchers used nodes within the range of 5–15 (Seker and Zavadskas 2017; Bavafa et al 2018; Can and Toktas 2018).

As described in the methodology, the direction of the arrows for drawing the CLD is obtained from the *T* matrix, whereby factors in each row affect the factors of the matrix's columns. Thus, the CLD was progressively and hierarchically constructed by first considering contextual/situational factors at the crew level. The contextual/situational factors at the foreman and project levels were subsequently introduced into the crew-level variables (see Figures S1, S2, and S3 [end of this post-print document]). CLDs were constructed for the system in general and for the different hierarchies of the crew, foreman, and project levels. For example, the CLD in Figure 3 presents an interaction between situational/contextual factors in terms of reinforcing feedback loops R1, R2, and R3.

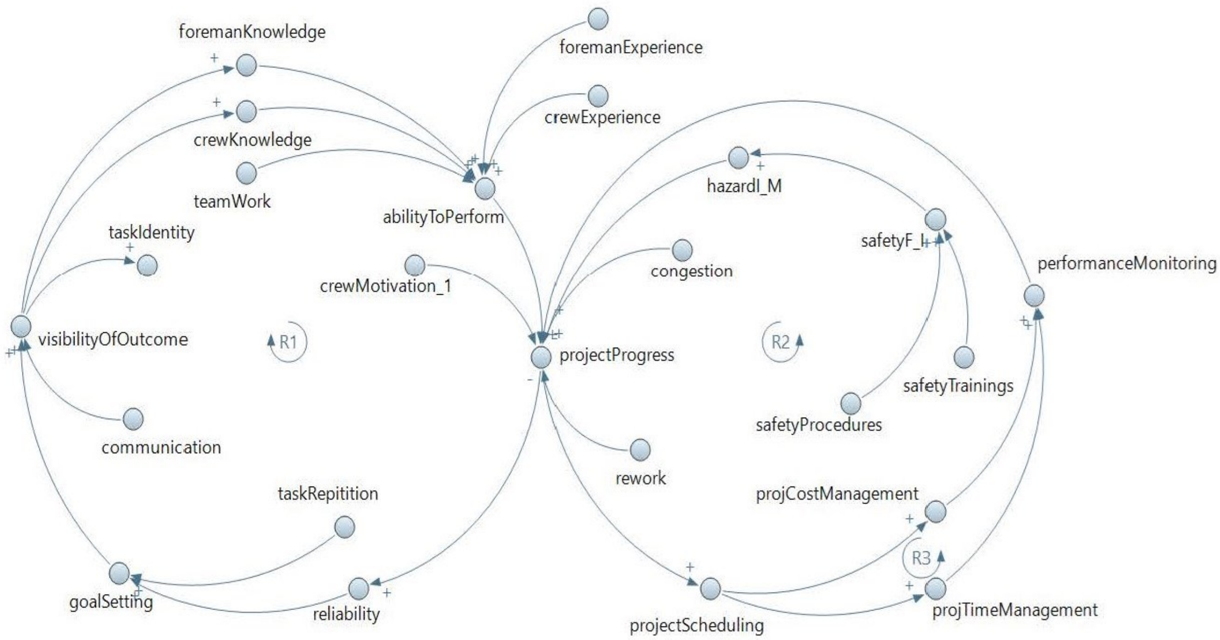

Fig. 3. Example of reinforcing loops in a causal loop diagram (CLD).

5.1 Expert weight assessment

Findings of the expert weight assigning model (Stage 1) identified *Productivity-related project and construction management practices* amongst the list of criteria unique to assessing decision makers' inputs in the area of productivity. The related subcriteria are: *Average hours of work in productivity-related work per week*; *Level of management training related to productivity*; *Experience in conferences related to productivity management*; and *Functional skills related to productivity management.* The criterion *Productivity related project management practices* had an overall weight of 0.31 and thus the highest relative importance in terms of the expert importance weights. This indicates the need to give relatively more consideration for experts' involvement in productivity-related activities during the decision-making process. The criteria *Experience* and

Knowledge were both ranked second, with an overall weight of 0.16, while *Reputation* was ranked as the criterion with the lowest importance for expert assessment.

5.2 Relative criteria importance

Using FDEMATEL to identify cause-and-effect groups within the factors affecting crew productivity and draw influence relation maps between the factors, the $\tilde{T}$ matrix values were used to obtain the prominence and relation values. Factors with higher prominence values indicate higher causal relations with the other factors presented. Factors with the five highest prominence values were *Ability to perform* ($R_i + C_j$ = 1.297), *Reliability* (1.133), *Project progress* (1.128), *Visibility of outcome* (1.120), and *Project scheduling* (1.042). Hence, these five factors have a greater strength of interrelationship with and strongly influence other factors. Conversely, *Location of washrooms*, *Change in weather conditions*, *Temperature*, *Access points*, and *Fairness* were found to be the factors with minimum prominence values, indicating their relatively low influence over other factors.

For relation values, the factors were categorized into cause-and-effect groups based on positive and negative relation values. *Crew motivation* ($R_i – C_j$ = 0.60), *Crew experience* (0.49), *Foreman experience* (0.48), *Foreman knowledge* (0.43), *Task repetition* (0.42), *Crew composition* (0.34), and *Rework* (0.23) were among the top cause factors. These factors are shown to impose more impact on the system (*R* values) than they receive (*C* values), meaning they have greater causal influence on other factors and the system's overall behaviour. Therefore, improving these factors can result in the best improvement of crew productivity measures. Conversely, *Project progress* ($R_i – C_j$ = –0.56), *Project time management* (–0.45), *Ability to perform* (–0.39), *Material handling* (–0.33), *Project scheduling* (–0.32), *Safety management* (–0.21), *Safety facilitation and* *implementation* (–0.17), *Performance monitoring* (–0.16), and *Reliability* (–0.13) were the top factors with a high degree of being strongly influenced by other factors.

The prominence and relation values were also used to plot IRM, which analyses cause-and-effect groups and their overall influence on system behaviour. *Crew experience, Foreman experience, Foreman knowledge, Crew motivation, Crew composition, Visibility of outcome,* and *Rework* were found to factors with higher combined prominence and relation values relative to the other factors affecting crew productivity. In terms of managerial decision-making to improve the system's overall behaviour and improve crew productivity, these results show it is imperative to focus on improving factors with a higher measure of both prominence and relation values. Factors that registered the highest prominence values and were categorized as ranking highest under the effect group, as noted above, are therefore affected most by the other factors and have more interaction with the other factors in terms of causal relationships. Improving these factors, which have most interactions and the highest causal impact on other situational/contextual factors, can significantly improve factors categorized as ranking highest under the effect group, thereby improving the system's overall behaviour and crew productivity.

5.3 CLDs

The FDEMATEL output was used to obtain the CLDs and feedback loops crucial in the qualitative modelling step of SD modelling. At the crew level, ability to perform is a factor of both the crews' and crew foremen's knowledge and experience. Hence, increasing crews' ability to perform tasks at the activity level can be facilitated through choosing the right combination of foreman and crew members with appropriate knowledge and experience, which can in turn bring about a positive project progress. In Figure 3, in reinforcing causal loop R1, positive *Project progress* leads to an increase in the *Reliability* of crews to perform tasks. The reliability of crews in performing their tasks is a crucial input towards goal-setting and task assignment while planning the set of activities crews will perform. Thus, clearly communicating outlined goals can lead to a better perception of outcome in crews' task performance (i.e., better visibility of outcome). This in turn can help crews and crew members better identify with their tasks, which adds to their knowledge about and ability to perform tasks. Conversely, reinforcing causal loops R2 and R3 in Figure 3 show the impact of better project progress resulting in better execution and monitoring of project schedule, which results in better project-level time management and cost management, and consequently better monitoring of project performance. Thus, improved performance measures reinforce project progress.

6.0 CONCLUSIONS AND FUTURE WORK

Improving construction crew productivity is a complex process because of a combination of multiple challenges such as being able to identify factors that can be used as productivity predictors, identifying issues that can contribute to productivity improvement, and proposing mitigation measures for crew productivity improvement. These processes mostly involve input from heterogenous experts, meaning the experts have varying backgrounds, experience, and expertise areas. Furthermore, capturing the inherent causal interrelationships between factors that can contribute to productivity improvement. Capturing these relationships between factors used as predictors for crew productivity is also crucial to formulating a comprehensive solution for the productivity problem. Thus, the main goal of this study was to address productivity by proposing a systematic, structured methodology integrating fuzzy set theory, AHP, and DEMATEL approaches for use in dynamic modelling of crew productivity.

This paper identifies criteria for assigning expert weights in productivity studies. FAHP enables expert weight assessment to account for heterogenous experts involved in productivity studies.

FDEMATEL identifies cause-and-effect groups within the factors affecting crew productivity and thus captures the influencing relationships between factors, which can be used in strategic decision making on productivity improvement. Further, FDMATEL can be used to obtain CLDs and feedback loops. The outputs of FAHP-FDEMATEL form a crucial input for a more representative modelling of dynamic construction productivity compared with other techniques. Moreover, the identified cause-and-effect groups can serve as crucial inputs for strategic decision making in productivity improvement.

The contributions of this paper are 1) identifying a set of criteria to perform expert weight assignment for heterogenous group experts in productivity research, 2) proposing an integrated FAHP-FDEMATEL approach as a systematic, structured method for determining causal relationship mapping between crew motivation, situational/contextual factors, and crew productivity, and 3) proposing an approach for identifying cause-and-effect groups amongst situational/contextual factors and crew motivation, which can be used to formulate strategic productivity improvement solutions. Validity of the proposed method was demonstrated using a case study of a real-life construction project.

Future work will include developing the proposed FAHP to perform expertise-level assessment that considers dependency between the hierarchy elements. FAHP will also be improved to consider the dependence between multiple criteria and/or subcriteria using other approaches, such as fuzzy analytic network process. Sensitivity analysis will also be provided to study relationship strengths and how each relationship is sensitive to changes from input parameters. Furthermore, additional studies will be conducted to reduce the complexity resulting from using higher number of nodes and system variables. In effect, comparative analysis will be performed by comparing the current number of nodes in this study versus the number of nodes obtained using the results of sensitivity analysis to further reduce the system variables. Moreover, the effect of varying threshold selection approaches (i.e., higher percentile thresholds, average of the elements in the matrix, expert inputs) while developing CLDs from defuzzified TRM values can also be explored.

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Competing Interests Statement

The authors declare there are no competing interests.

Author Contributions

NK: Conceptualization, formal analysis, investigation, methodology, writing – original draft, writing – review & editing. **ARF**: Conceptualization, funding acquisition, project administration, supervision, writing – review & editing

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Data Availability

Data generated or analysed during this study are provided within the published article and its supplementary materials, or are available from the corresponding author on reasonable request, with the exception of any confidential data that are not publicly available.

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Supplmentary Materials

Table S1. Sample section of fuzzy total relation matrix.

T			**T1**			**T2**		**…**		**T37**			**T38**	
		T_l	T_m	T_u	T_l	T_m	T_u		T_l	T_m	T_u	T_l	T_m	T_u
	ID		**1.1**			**1.2**		**…**		**7.1**			**7.2**	
T1	**1.1**	0.0	0.00	0.00	0.01	0.02	0.03	. . .	0.01	0.02	0.03	0.00	0.00	0.00
T2	**1.2**	0.0	0.01	0.02	0.00	0.00	0.00	. . .	0.00	0.01	0.02	0.00	0.00	0.00
T3	**1.3**	0.0	0.00	0.01	0.02	0.03	0.04	. . .	0.00	0.00	0.01	0.00	0.00	0.00
.	**.**	.	.	.	.	.	.	. . .	.	.	.	.	.	.
.	**.**	.	.	.	.	.	.	. . .	.	.	.	.	.	.

.	**.**	.	.	.	.	.	.	. . .	.	.	.	.	.	.
T37	**7.1**	0.0	0.0	0.00	0.00	0.00	0.00	. . .	0.00	0.00	0.00	0.01	0.02	0.03
T38	**7.2**	0.0	0.0	0.00	0.00	0.00	0.00	. . .	0.03	0.04	0.04	0.00	0.00	0.00

Table S2. Sample section of defuzzified total relation matrix.

	ID	**T1**	**T2**	**T3**	**T4**	**T5**		**T34**	**T35**	**T36**	**T37**	**T38**
T1	**1.1**	0.0	0.021	0.031	0.010	0.0	. . .	0.0	0.0	0.0	0.0	0.021
T2	**1.2**	0.01	0.000	0.039	0.003	0.0	. . .	0.0	0.0	0.0	0.0	0.010
T3	**1.3**	0.003	0.031	0.000	0.010	0.0	. . .	0.0	0.0	0.0	0.0	0.003
T4	**1.4**	0.039	0.031	0.031	0.0	0.0	. . .	0.0	0.003	0.0	0.0	0.003
.	**.**	.	.	.	.	.	. . .	.	.	.	.	.
.	**.**	.	.	.	.	.	. . .	.	.	.	.	.
.	**.**	.	.	.	.	.	. . .	.	.	.	.	.
T34	**6.5**	0.0	0.0	0.0	0.0	0.0	. . .	0.0	0.0	0.0	0.0	0.0
T35	**6.6**	0.0	0.0	0.0	0.0	0.0	. . .	0.010	0.0	0.0	0.0	0.0
T36	**6.7**	0.0	0.0	0.0	0.0	0.0	. . .	0.010	0.0	0.0	0.0	0.0
T37	**7.1**	0.0	0.0	0.0	0.0	0.0	. . .	0.031	0.010	0.0	0.0	0.021
T38	**7.2**	0.0	0.0	0.0	0.0	0.0	. . .	0.031	0.003	0.0	0.039	0.000

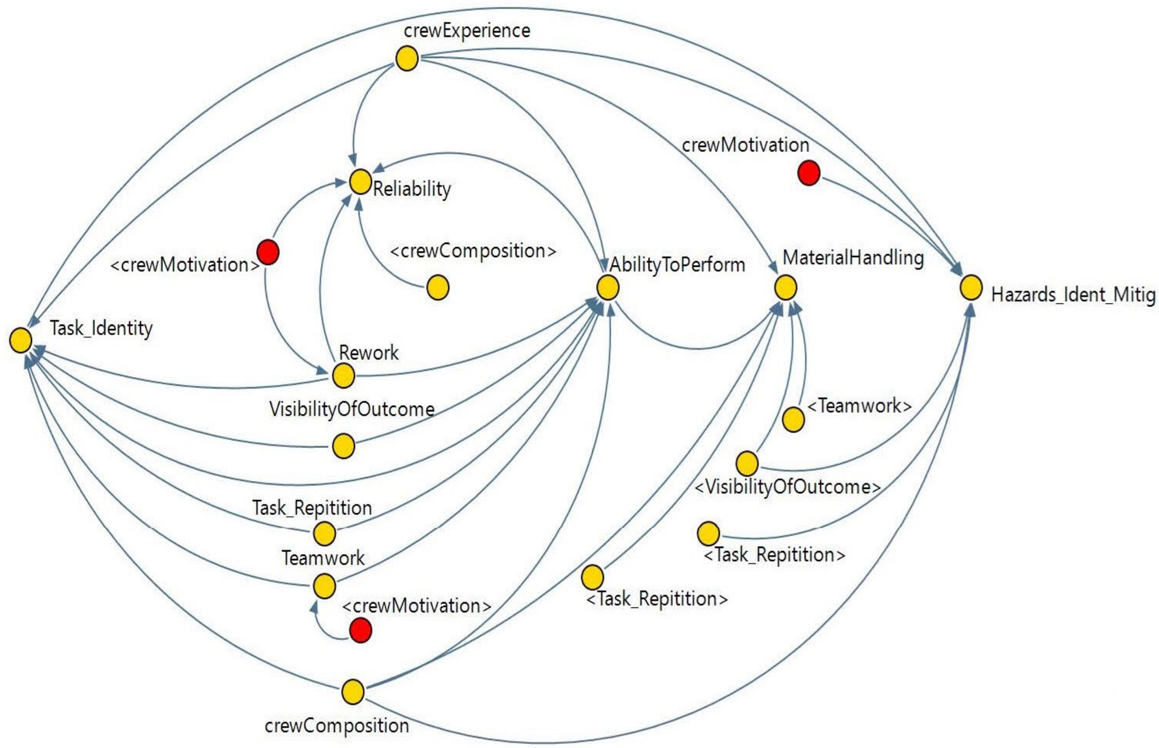

Fig. S1. CLD between factors affecting productivity at the crew level.

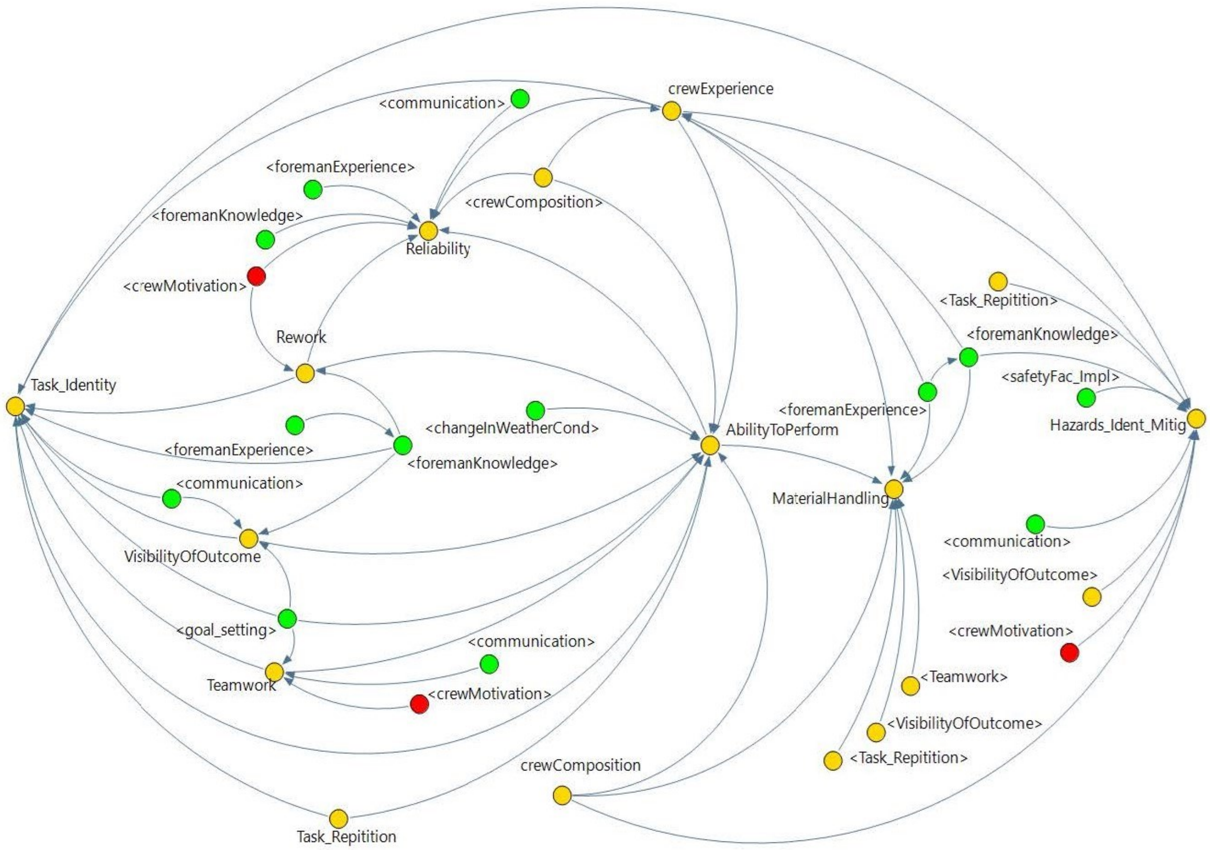

Fig. S2. CLD between factors affecting productivity at the crew level, including foreman-related factors.

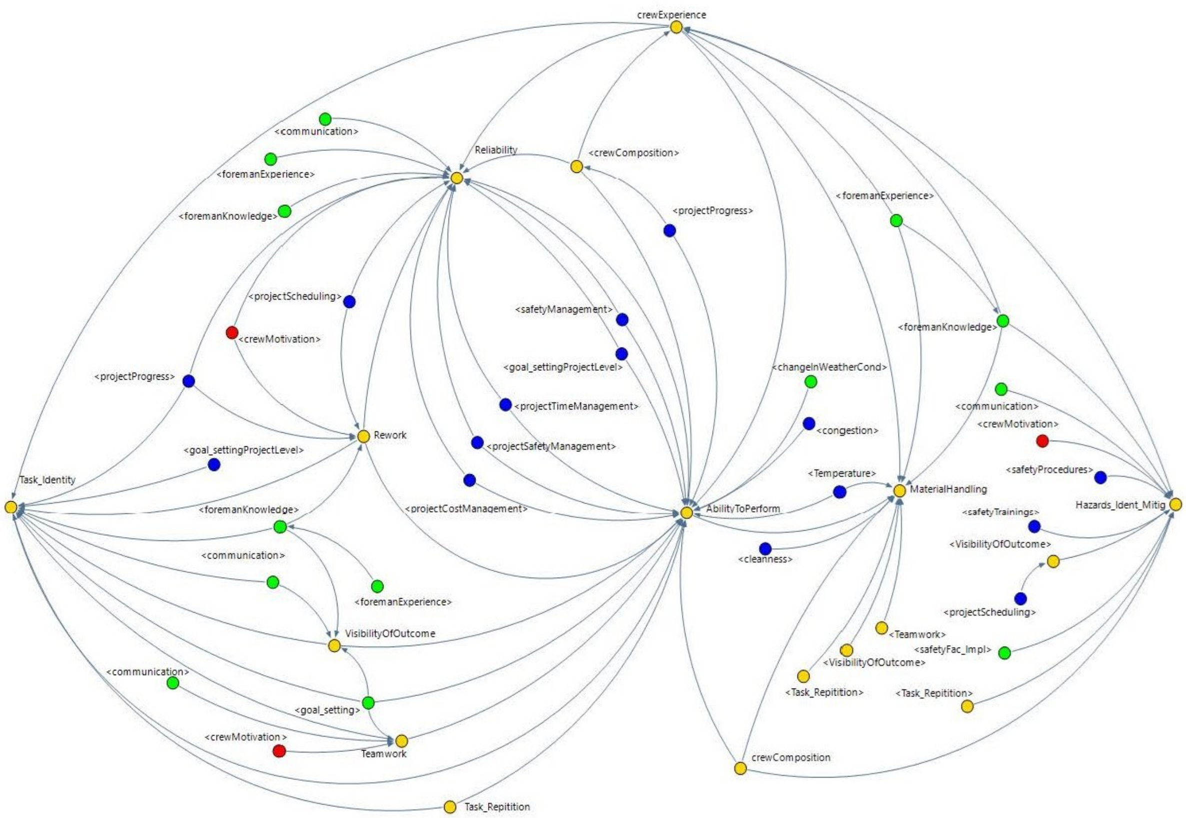

Fig. S3. CLD between factors affecting productivity at the crew level, including foreman-related and project-level factors.