Predicting Communication Quality in Construction Projects: A Fully-connected Deep Neural Network Approach

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Abstract: Establishing high-quality communication in construction projects is essential to securing successful collaboration and maintaining understanding among project stakeholders. Indeed, poor communication results in low productivity, poor efficiency, and substandard deliverables. While high-quality communication is recognized as contingent on the interpersonal skills of workers, the impacts of communication quality on job performance remain unknown. This study addresses this deficiency by developing a method to evaluate construction workers' communication quality. A literature review is undertaken to capture salient interpersonal skills. Leadership style, listening, team building, and clarifying expectations are identified. A questionnaire survey is drafted to capture construction practitioners' perception of these skills' effects on communication quality, returning 180 responses. Next, an artificial neural network model, or Communication Quality Predictor (CQP), is developed, able to predict the quality of workers' interpersonal communication. The model accuracy on training is 87%; for testing, 79%. Finally, CQP is deployed in a real-time context in order to validate the reliability, returning an 80% prediction accuracy. This study is the first of its kind in offering a quantified, predictive model associating interpersonal skills with quality of communications in the context of the construction sector. In practical terms, the CQP can flag interpersonal conflicts before they escalate, while also guiding construction managers in the design of interpersonal skills training.

Keywords: Construction; Communication quality; Interpersonal skills; Predictive modeling; Artificial Neural Networks.

1. INTRODUCTION

Efficient communication is central to construction project performance [1,2]. Evidence of the link between communication and performance is well documented. As diverse places as Norway, Indonesia, and Australia reveal that the overall arrangement of a project team, working norms, and procedures have had to be adjusted several times in order to achieve the level of communication compatible with productivity [3,4] Similarly, Yolanda, et al. [5] found that communication barriers hinder the quality of employee performance, while a reduction in the number of barriers boosts quality.

There has been research interest in measuring the quality of communication in the construction industry [6-10], yet, no method has so far been proposed to evaluate the quality of communication as determined by individuals' interpersonal skills [11,12]. Strong interpersonal skills are an important asset in facilitating interpersonal communication with all stakeholders [13,14], building and maintaining relationships, and promoting employee attachment to an organization [11]. This dimension has been hitherto missed as previous studies have focused only on indicators affecting project communication. Skills, however, are integral to managing interpersonal communication [15]. Moreover, previous research was limited to methods using structural equation modeling [7], factor analysis [10], and chi-square test [6]. These methods are limited in having no predictive capacity. Moreover, extant studies on communication networks have not considered factor impacts, instead solely describing network relationships [16,17].

In addressing this deficiency, this study develops a predictive model – or Communication Quality Predictor (CQP) – to evaluate communication quality based on individuals' interpersonal skill set. These skills have been defined as the ability to engage with people and accept them non-prejudicially. It does not imply workers are necessarily deferential to coworkers, but rather that they can manage differences in order to effectively realize tasks [12]. That is, these skills are defined as the ability to appropriately respond to staff requirements, develop a conducive work environment, and delegate work packets [18]. In summary, the objectives of this study are:

- Identification of critical interpersonal skills; and
- Prediction of workers' interpersonal skills' effects on their quality of communication, as demonstrated across three cases studies.

The remainder of the paper is structured as follows. First, a comprehensive review of the related literature on the topic is presented. The research method section describes data collection protocols and the techniques used in analyzing the data. This step is followed by a description of the findings and discussion. The paper concludes by highlighting the novelty of findings, acknowledging limitations, and suggesting future areas for research.

2. CONTEXTUAL BACKGROUND

2.1. Quality of communication

High-quality communication is vital to the success of construction organizations [19], primarily by virtue of the role it plays in facilitating the effectiveness of construction teams [20,21]. According to Mohr and Sohi [9], researchers apply two indicators when evaluating the quality of communication. The first is to consider communication flows (e.g., the nature and frequency of communications). The second focuses on communication quality. Aubert, et al. [22] classify the main attributes of communications into form (e.g., timeliness) and content (e.g., accuracy), both being equally important.

Communication quality indicators that impact construction project management have been identified [23,6,8,24,10,25]. Armstrong and Taylor [26] argue that there is a negative correlation between the number of distinct geographic regions and communication quality, while a larger variety of cultural and ethnic groups is associated with diminishing communication effectiveness [27]. Tone, et al. [28] states that quality of communication hinges on the level of bureaucracy within an organization. Senescu, et al. [25] find that communication complexity profoundly impacts an organization's communication quality. Westin and Sein [29] consider accessibility an essential element of communications given the complicated nature of the tasks assigned to construction team members. Hosseini, et al. [7] introduced five more indicators (i.e., sense of presence, documentability, persuasiveness, accessibility, and relevancy). They ascertained that team members should have a holistic awareness of the project and its participants' roles in order to maintain high-quality communication. Similarly, in order to communicate well, Wang, et al. [30] finds that construction teams must first enjoy strong interrelationships. Documentation of exchanged information along with persuasiveness also augmented communicative quality [31]. A summary of communication quality indicators is provided in Table 1.

Table 1. Compilation of communication quality indicators (1995-2021)

No	Indicator	Definition or relevance	Frequency	Reference(s)
1	Accuracy	The data are correctly transferred without bias, distortion, or withholding of information.	8	[22,6,32-36,7]
2	Accessibility	Accessibility, as an element of communications, represents the speed with which communications and the exchange of information occur and whether they are easily possible.	2	[7,29]
3	Bidirectionality	Feedback, clarifications, and verifications are readily obtainable from the involved parties.	3	[22,9,7]
4	Clarity of scope and objectives	There is a positive correlation between clarity of scope and objectives and quality of communication.	2	[10,35]

5	Completeness	All the essential data are available, and no required information is missing.	6	[22,32,34,37,36, 7]
6	Complexity level of communication	Communications become distorted with increased complexity.	1	[25]
7	Documentability	Documentability of the information exchanged is an aspect of high-quality communications for these teams.	1	[7]
8	Frequency	It notes how often involved parties communicate with each other.	3	[38,9,7]
9	Formality	The extent to which communication flows are structured, planned, and routinized.	1	[9]
10	Inexperience of project managers	Inability to apply effective techniques, tools, knowledge, and skill to meet the project's requirements.	1	[39]
11	Persuasiveness	People communicate with other people to convince them that an idea or action has value, which involves persuasiveness.	2	[40,7]
12	Reliability	The receiver regards information as reliable.	4	[22,32,33,7]
13	Relevancy	Relevancy of communications is a measure that represents the extent to which the exchanged information is helpful for the receiver and applicable for the required task.	1	[7]
14	Sense of presence	Irrespective of the working arrangement, team members should have a sense of presence to maintain high-quality communications when interacting with each other.	2	[7,30]
15	Timeliness	Information is provided on time (not earlier and with no delay).	8	[22,6,32-36,7]
16	Top-down bureaucracy	It negatively affects the quality of communication.	2	[10,28]
17	Understandability	The audience easily comprehends the provided data and information.	6	[22,32-35,7]
18	Variety of geographic regions	A much smaller variety of cultural and ethnic groups can indeed establish effective communications.	2	[26,27]

2.2. Interpersonal skills

Robbins and Hunsaker [41] conducted an extensive review of the most common skills. Interpersonal skills divide into subcategories of motivation, leadership, and communication process. Negotiating is a yet another related skill. The skills categories and subcategories are depicted in Figure 1.

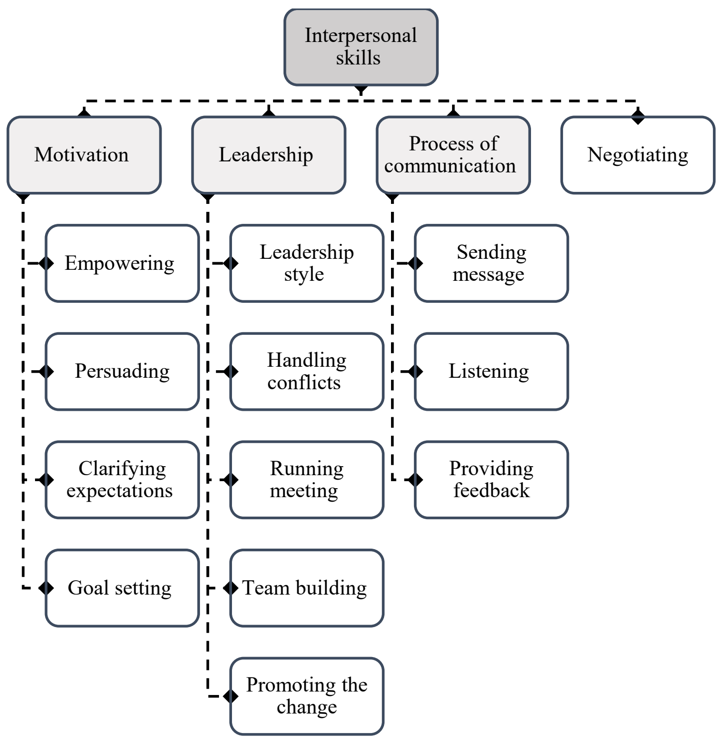
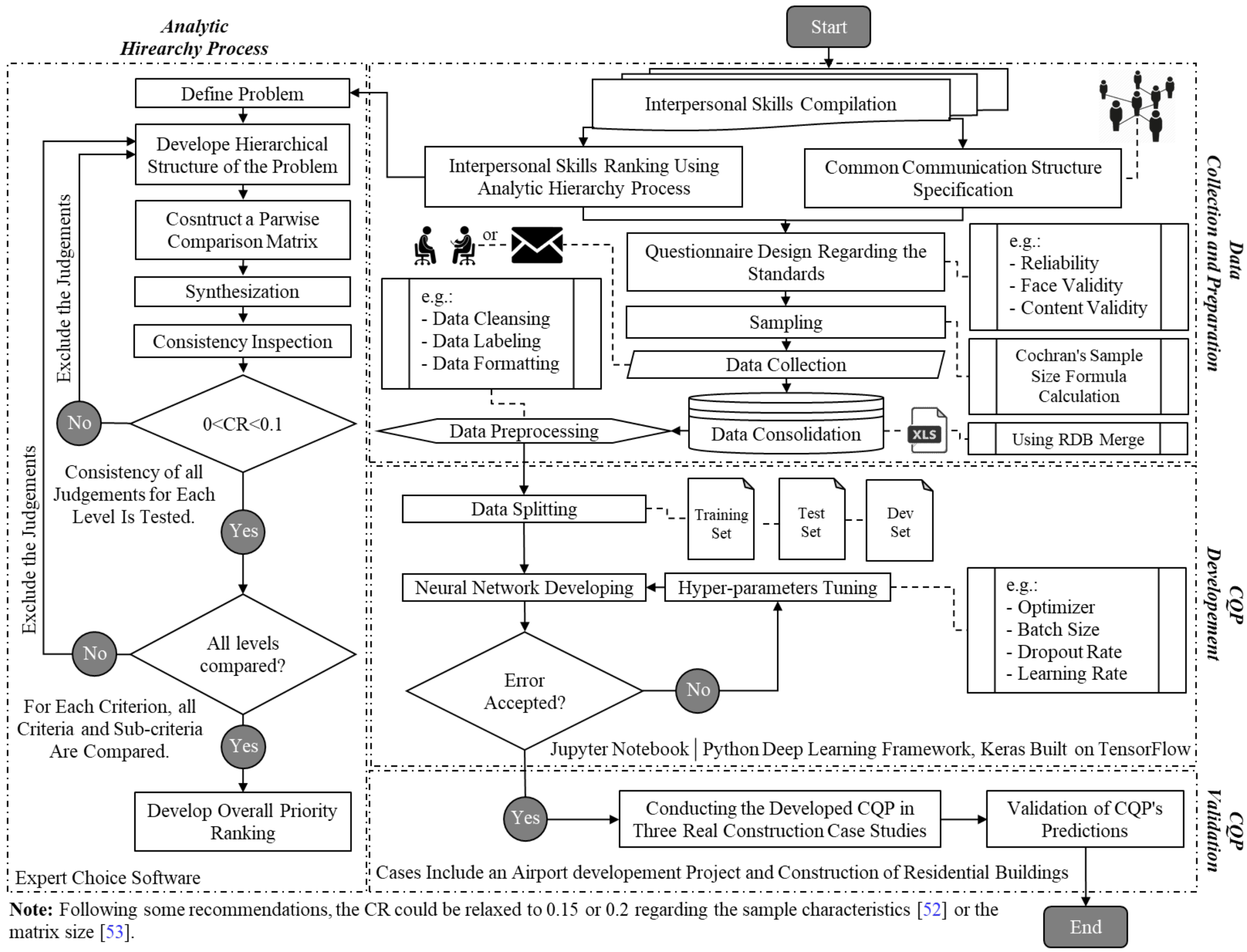


Figure 1. Conceptualization of interpersonal skills (adapted from *Robbins and Hunsaker [41]*)

As identified by Robbins and Hunsaker [41], the four skills sets combine to deliver effective interpersonal skills. Firstly, there is leadership. A leader should know how to rally a team to accomplish a common task and support the integration of group members in achieving that task [11]. To that end, leadership style, the ability to handle conflicts, approaches to running meetings, team-building skills, and the ability to promote and foster change all contribute to the success or otherwise of the leader. Secondly, another important role of the manager is to provide conditions by which people feel motivated to achieve the group's mission [11]. This involves the leader's ability to set goals, clarify expectations, persuade others to get on board and empower them to realize their contributory abilities. Thirdly, the foregoing depends on the leaders' ability and process used in communicating to others. Not is the ability at 'sending the message' important, but the leader also needs to be receptive to feedback and resistance, and to that end, he must be able to listen openly and provide relevant feedback. Finally, while the mission set by the leader may appear fixed, the means by which it is realized will involve many parties, all of whom will have views on the validity of the mission and how it is to be realized. In bringing people to a common purpose, the leader must negotiate and find a mutually acceptable compromise.

3. RESEARCH METHOD

This section describes data collection protocols, the techniques used to analyze the data, and CQP in detail. Overall, the method comprises six steps, commencing upon interpersonal skills prioritization and culminating in validating the developed neural network. See Figure 2. The interpersonal skills were initially compiled from the literature and then prioritized to more important ones be selected according to their impact on the quality of communication. AHP, made available in Expert Choice software, carried out this prioritization. Its capabilities, thoroughly discussed in the 3.3 sub-section, induced the research team to use it. Meanwhile, the relationships between practitioners, typical of the construction industry, were specified. This specification provided the respondents with further insight into the prevailing relationships in projects and led the questionnaire to be completed more accurately and optimally. Having completed these two steps, together with the aid of experts, the research group designed and then operationalized a questionnaire. The data collection was carried out by this toolkit, and it generally ran over five months in a row. The collected data were then cleansed, encoded, and formatted so appropriately that they were fed into a neural network to train and tailor CQP. Finally, CQP was validated in real construction case studies based in Tehran to test its predictions on what had happened to the quality of interpersonal communications between workers over time.



Note: Following some recommendations, the CR could be relaxed to 0.15 or 0.2 regarding the sample characteristics [52] or the matrix size [53].

Figure 2. Flowchart of the proposed method

3.1. Predictive modeling

Predictive models allow decision-makers to see the path forward regarding the available information [42] and primarily focus on demonstrating the chance that something will (or will not) take place. Generally, they come under two major types: 1) supervised learning and 2) unsupervised learning [42]. If the outputs are discrete, the problem is classification, while if the outputs are continuous, the problem is regression—The model defined in this paper counts as the former. This type indicates predictive models design with data that contain the results one is seeking to predict. The need for such data prompted the research team to gather the intended primary, cross-sectional dataset using the designed questionnaire.

3.2. Designing the questionnaire: the preliminary step

When it comes to eliciting knowledge from practitioners, quantitative data collection seems a suitable approach as it allows for a generalization of findings [43]. Hence, the questionnaire survey was chosen as the research instrument to collect data relating to individuals' interpersonal skills and their effects on communication quality.

3.3. AHP use in the study

As mentioned (sub-section 2.3), the research group exclusively adapted the model provided by Robbins and Hunsaker [41], where they synthesized 13 skills in total. Assessing all these skills is beyond doubt the best possible scenario. Nevertheless, there is a time-related restriction. The more skills to be put in the questionnaire, the more time is needed to address them all, with the panelists being usually short of time having their duty roster adding to this problem. It was therefore needed to prioritize them. In so doing, AHP, developed by Saaty [44], was applied for two primary reasons. First, it prioritizes a decision maker's judgment, emphasizing the significance of a decision maker's intuitive decisions and the consistency of the comparison alternatives in the decision-making process. Second, AHP consists with the behavior of decision-makers. This congruence is crucial as decision-makers usually make judgments based on their knowledge and experience.

What is more, AHP has gained a strong foothold in many areas for solving perplexing decision-making problems. Some examples of this include, but are not limited to, production factories, managerial policies, and others; e.g., intelligent building systems selection [45], project selection [46], selection of agile software development factors [47], and risk analysis and project management [48]. Such practicality of the AHP approach made it appropriate for the present paper.

3.3.1. AHP model description

A questionnaire was first developed to gather the required data from the experts, using a nine-point scale as recommended by Saaty [49,50] (Table 2).

The level of importance is demonstrated on a scale of 1 to 9. While a value of 1 shows equal significance for two factors, a larger value shows a greater preference for one alternative. For instance, if an attribute is strongly favored over another, a value of 5 is assigned to it. If, conversely, the strong preference is for the other one, the reciprocal of that number, i.e., 1/5 or 0.2, is assigned. This scale should be consistently utilized in the pairwise comparison process to maintain the consistency of comparison.

Table 2. The fundamental scale for AHP preferences (adapted from Saaty [58])

Intensity of importance on an absolute scale	Definition	Explanation
1	*Equal importance*	*Two criteria contribute equally to the objective*
3	*Moderate importance*	*One criterion is slightly favored over another*
5	*Strong importance*	*One criterion is strongly favored over another*
7	*Very strong importance*	*A criterion is strongly favored and its dominance is demonstrated in practice*
9	*Absolute importance*	*The importance of one criterion over another is confirmed very strongly*
2, 4, 6, 8	*Intermediate values*	*Used to represent compromises between the levels listed above*
Reciprocals of previous values	*If factor "i" has one of the previously mentioned numbers assigned to it when compared to factor "j", then j has the reciprocal value when compared to i.*	A reasonable assumption
Rationales	*Ratios arising from the scale*	*If consistency were to be forced by obtaining n numerical values to span the matrix*

The AHP methodology proceeded in several steps. 1) The research problem is defined. 2) Hierarchy is structured. 3) Pairwise comparisons of elements are made, identifying relative contributions. 4) Judgments are made. 5) Priorities and testing consistencies are obtained. 6) Previous three steps are repeated for all levels. 7) Hierarchical composition weighs priorities and vectors, resulting in an overall hierarchy from lowest to highest. 8) Consistency of the hierarchy is validated.

3.3.1.1. Pairwise comparison

The comparisons are drawn pairwise. To compare the elements in a group on one level of the hierarchy regarding an element at the next higher level, an $n \times n$ matrix is constructed, wherein n indicates the number of elements in the group. The group's elements are put in the heading row and the heading column of the matrix. Using the predetermined scale shown in Table 2, these same-group elements are compared against each other in their intensity or strength of importance, preference, or influence on the element at the next higher level. The comparisons can therefore be represented by square matrices, such as matrix D in which every element a_{ij} $(i, j = 1, 2, \dots, n)$ is the quotient of weights of the criteria, as shown below:

$$D = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}, a_{ii} = 1, a_{ji} = \frac{1}{a_{ij}}, a_{ij} \neq 0. \tag{1}$$

Once all the pairwise comparisons matrices are developed, a vector of the weights W = [W_1, W_2, …, W_n] is populated following Saaty's eigenvector procedure. The largest eigenvalue is then calculated as a measure of the pairwise comparison consistency in the matrix, and the eigenvector relating to the largest eigenvalue (called the principal eigenvector) is estimated to give priority ordering for the assessed attributes. In making the individual pairwise comparisons, the geometric mean (Eq. 2), rather than the arithmetic mean, is utilized [51]. Therefore, the Excel GEOMEAN function was used.

$$\left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}} = \sqrt[n]{X_1 X_2 \dots X_n} \tag{2}$$

Where $\prod$ is the geometric mean, n is the number of values, and x_i indicates the values to average.

The Consistency Index (CI) was then applied. Saaty [49] defined it as Eq. (3):

$$\mathrm{CI} = \frac{(\lambda_{\max} - \mathrm{n})}{\mathrm{n} - 1} \tag{3}$$

Where λ_{max} is an approximation of the largest eigenvalue of the matrix, and n is the size of the comparison matrix.

The Consistency Ratio (CR) is also used to determine whether a matrix is sufficiently consistent. It is measured as the ratio of CI over the Random Index (RI), as shown in Eq. (4):

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{4}$$

According to Saaty [49], if n = 13, then RI = 1.56, which is obtained using a randomly generated pairwise comparison matrix. Also, if CR is less than 10% (0.1), the matrix can be determined as having adequate consistency, although this cut-off point can be relaxed to 0.15 or even 0.2 regarding sample characteristics [52] or matrix size [53].

Specifically, 15 experts who had an encyclopedic knowledge of the project management field and academics with pertinent subject expertise were tasked with prioritizing these initial 13 skills. At that point, AHP, as made available in Expert Choice software, was applied to combine and then prioritize the interpersonal skills. It is also worth noting that the term "Expert" was adapted from the definition of Hoffman [54] (expounded in Table 3) in this paper.

3.4. Designing the questionnaire: the final step

Next, a close-ended survey questionnaire containing Likert-scale ranging from 1 (Novice) to 5 (Expert) for the first two sections, and from 0 (Very Low) to 4 (Very High) for the third section was designed and developed through interviews and literature review (see Appendix I).

The reliability or internal consistency of the questionnaire was verified by Cronbach's alpha (α), [55], calculated by Eq. (5).

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_i^2}{\sigma_X^2}\right) \tag{5}$$

Where k is the number of items, σ_i^2 is the variance of the i_{th} item, and σ_X^2 is the variance of the total score formed by summing all the items.

α ranges from 0 (unreliable) to 1 (reliable). In case the items making up the score have so perfect correlation, then α = 1. However, the reverse is true when they are independent, in which α = 0. It is therefore clear that the reliability of the generated scale is positively correlated with the very score. In the present study, α was 83%, which was much higher than the threshold value of 70%. Additionally, the questionnaire's face validity and content validity were confirmed qualitatively and quantitatively by 20 experts familiar with the measured construct, following the approach suggested by Hosseini, et al. [56]. The quantitative value of face validity indicated that all the items in the questionnaire had an impact score of more than 1.5. Content validity of the items (selected interpersonal skills for use in the questionnaire) in the quantitative analysis was also measured and validated following the Content Validity Ratio (CVR), devised by Lawshe [57]. CVR is a linear transformation of a proportional level of agreement on how many panelists rate an item as "essential" calculated by Eq. (6):

$$CVR = \frac{n_e - \left(\frac{N}{2}\right)}{\frac{N}{2}} \tag{6}$$

Where n_e is the number of panel members indicating "essential," and N is the total number of panel members. The final evaluation to retain the items based on CVR comes down to the number of panelists. Since the number of panelists was 20, the minimum CVR must not be less than 0.42—all the items met this condition, and the CVR value for no item was less than 0.53.

The questionnaire was then operationalized as it is discussed next. In the first section, respondents were requested to do a self-assessment and rate their interpersonal skills level—the exact meaning of each level is well described in Table 3. The second section asked them to assess another employee with whom they communicate interpersonally, given the predetermined connections (see sub-sections 3.6 and 4.2). Finally, in the third section, they were asked to rate their quality of communication with that employee whom they had thought. This is the way by means of which the data necessary for developing the neural network model were gathered.

Table 3. The proficiency scale used in the survey (adapted from *Hoffman [54]*)

Proficiency level	Definition
Expert	*The distinguished or brilliant journeyman, highly regarded by peers, whose judgments are uncommonly accurate and reliable, whose performance shows consummate skill and*

	economy of effort, and who can deal effectively with certain types of rare or "tough" cases. Also, an expert is one who has special skills or knowledge derived from extensive experience with subdomains.
Journeyman	*Literally, a person who can perform a day's labor unsupervised, although working under orders. An experienced and reliable worker, or one who has achieved a level of competence. Despite high levels of motivation, it is possible to remain at this proficiency level for life.*
Apprentice	*Literally, one who is learning – a student undergoing a program of instruction beyond the introductory level. Traditionally, the apprentice is immersed in the domain by living with and assisting someone at a higher level. The length of an apprenticeship depends on the domain, ranging from about one to 12 years in the Craft Guilds.*
Initiate	*Literally, a novice who has been through an initiation ceremony and has begun introductory instruction.*
Novice	*Literally, someone who is new – a probationary member. There has been some minimal exposure to the domain.*

3.5. Common communication structure specification

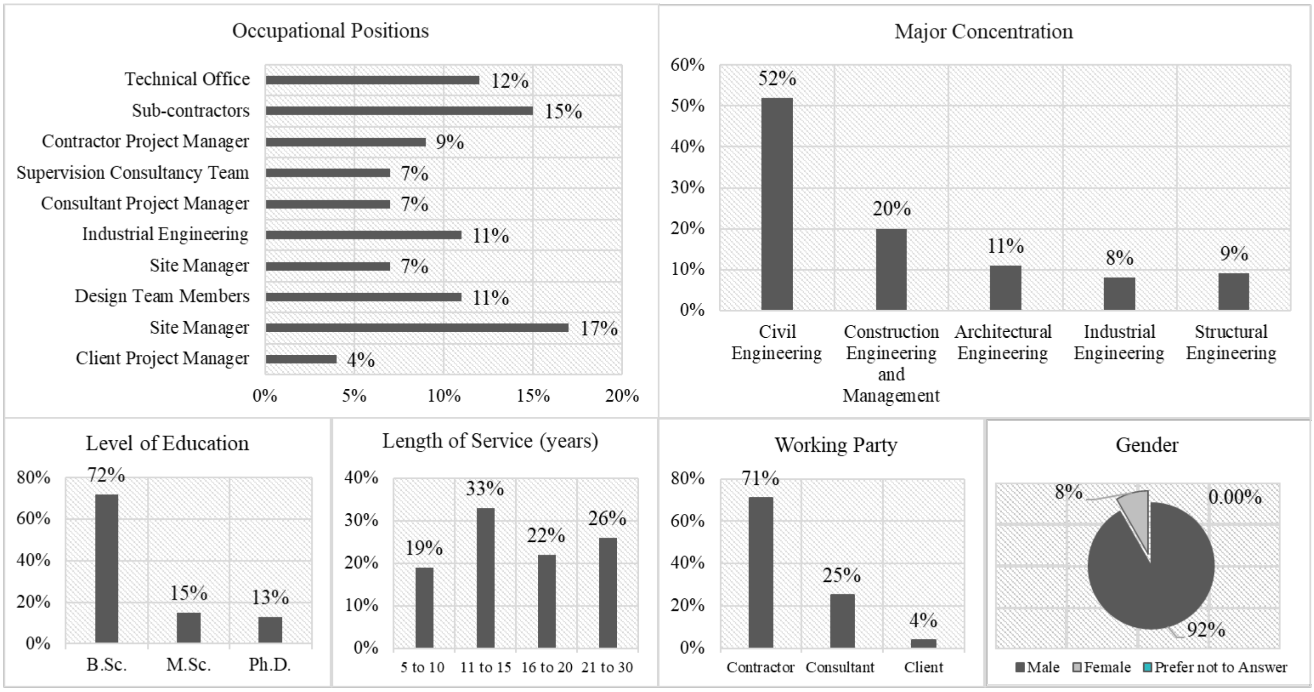
The typical communication network in construction projects was modeled based on the experience and opinions of experts who had rich knowledge about various types of construction projects. These relationships clarified the connections between one construction project worker, such as sub-contractor, and other workers in a project and were seen as the cornerstone of designing the questionnaire. In practice, the said relationships demonstrated who is connected with whom, which showed panelists whose interpersonal skills they should assess.

3.6. Sampling

Upon designing the questionnaire, the research group determined the statistical population of respondents. A list of certified construction companies was, in 2019, downloaded from the licensed contractors' data bank. By and large, sample sizes are large, and that difficulty is inherent in gathering a host of samples. Cochran's sample size formula (Eq. 7) reduces samples and logically determines the representative statistical population. With a precision of $\pm$5%, a confidence level of 95%, q = 0.5, and Z = 1.96 (Z^2 = 3.8461), the first recommended sample was 240 construction firms in Tehran (capital of Iran). Seventy-five companies finally helped to conduct the survey. Blank survey questionnaires were then distributed by mail or in-person to 230 senior employees claiming to have academics with pertinent subject expertise. Most of them held B.Sc. (72%), 15% M.Sc., and 13% Ph.D. in the construction relevant branches of science. Their length of experience was between 5 up to 30 years, with the majority of 11 to 15. The details, including the respondents' occupational position, major concentration, educational qualification, working party, work experience, and gender, are depicted in Figure 3. Nearly 90% of the respondents were from local governments, with key senior government positions, such as the vice mayor of Tehran's fifth division local government. The data collection ran over five months, and, in total, 185 correctly completed questionnaires (166 by men and 19 by women) were retrieved, with an 80% response rate.

$$n = \frac{\frac{Z^2pq}{e^2}}{1 + \frac{1}{N}\left(\frac{Z^2pq}{e^2} - 1\right)} \tag{7}$$

Where N is the population size, e is the desired level of precision, z is the selected critical value of desired confidence level, p is the estimated proportion of an attribute present in the population, and q = 1 – p. As the value of p is unknown, the value of 0.5 usually is used.



Note: The respondents were all Iranian and their ethnicities varied from Persians to Turkmens. Furthermore, the language they speak is Farsi.

Figure 3. Demographic profile of questionnaire respondents

3.7. Data cleansing, encoding, and formatting

Generally, data fall into three categories: structured, semi-structured, and unstructured. Structured data, contrary to the other two, are represented in matrix form with rows and columns. The collected data of this study are structured and contain ordinal variables with a finite number of classes or categories. Nonetheless, it is not what deep learning techniques, Artificial Neural Networks (ANNs) included, require. Instead, they need data in numerical form. To this end, each category was assigned an integer value between 1 to 5. That is to say, "Expert" was encoded with 5, "Journeyman" with 4, and the like. In the meantime, ordinal encoding was used to encode target values (last column), which indicates the quality of communication. Ordinal encoding assigns a sequence of numerical values between 0 and the number of classes minus one as per the order of data. In other words, "Very High" was encoded with 4, "High" with 3, and so forth (see Table 4). Ordinal encoding was performed with the use of the Scikit-learn library in PYTHON.

It is noteworthy that the dataset contains 5616 numerical values or, more precisely, 624 rows and nine columns. Appendix II provides a table that contains some of the actual data used in this paper.

Table 4. The select approach to numerical values encoding in this study

Proficiency level	Equivalent value	Communication quality	Ordinal encoded value
Expert	5	Very high	4
Journeyman	4	High	3
Apprentice	3	Medium	2
Initiate	2	Low	1
Novice	1	Very low	0

The survey data were then cleaned. This task was to deal with missing values (NaN entries) [58]. PYTHON data manipulation library was used for this purpose [59]. Furthermore, classes of communication quality were formatted using one-hot encoding to develop the intended model that predicts the probability of an instance belonging to each of five classes. Generally, in a multi-class classification problem, the target is a one-hot vector, which shows the probabilities of all classes. The vector entails one on a single position and zero for the rest. Once the cleansed, encoded, and formatted data were at hand, the neural network model was gradually developed.

3.8. Communication quality predictor design

The data were ultimately fed into several prediction models ranging from Logistic Regression and Decision Tree classifier to ANNs, to specify the best model with the highest performance; however, the results of the drawn comparison is the subject of another paper, as the primary goal of the present paper is only projecting the practicality of a predictive model in real contexts. Thus, the developed Neural Network, CQP, was brought here.

ANNs form a critical part of artificial intelligence. Their architecture bears a resemblance to human brain cells and nervous systems, managing to learn from their own experience [60]. Although no experts or programing are needed in the building process of a neural network model, the respective mathematics and statistical methods need knowledge concerning the interdependence nature of both input and output data.

The neural network lends itself to this study for one primary reason. The used dataset is tabular data (also known as structured data in the literature), a subcategory of heterogeneous data format usually presented in a table. Such a form of data, by all accounts, makes an artificial neural network outperforms [61]. In contrast, other models, such as Convolutional Neural Networks (CNN or ConvNet) or Recurrent Neural Networks, almost always best work for classifications tasks on homogenous data (e.g., image and text data) [62,63].

Also, ANNs have been the center of attention among researchers, regularly serving Architecture, Engineering, and Construction community as an artificial intelligence technique [64]. It boasts many applications in the industry ranging from cost prediction [65,66] to the classification of waste material [67]. For example, in a similar research study, a neural network was developed to predict the impact of 12 communication factors on the rework cost in the construction industry [36]. The proposed method reportedly helps managers reduce the number of reworks and both energy and resource consumption in construction projects.

3.8.1. The anatomy of CQP

Capturing the merits provided by predictive models, including ANNs, CQP used the current information deriving from construction practitioners' experience (as the input of CQP) to produce the knowledge (quality of communication, which is the output of CQP) that is not limited to the feedback provided.

The anatomy of CQP is drawn in Figure 4. The first step towards developing the model was data splitting. Data was at the outset segregated into three subsets, including training, testing, and validation. 75% of the data was randomly dedicated to the training dataset, 15% to testing, and 15% to the validation dataset. All the said parts were done with KERAS.

As mentioned in sub-section 3.8, data are labeled, with the predictive model aiming at learning the relationships between training inputs and training targets; hence the task at hand is supervised learning. The problem is also multi-class classification since the interpersonal skills were rated on a five-point scale and is single-label since each data point should be classified into one category, meaning that respondents were only allowed to opt for the extent of interpersonal skills to which they thought they are proficient (see proficiency scale in Table 3). Therefore, the problem is a single-label, multi-class classification with eight neurons (features) in the visible layer, 10, 12, 100, 50 neurons, respectively, in the hidden layers, and five neurons (labels/classes) in the output layer. The output of a fully-connected layer is the input of the subsequent layer and is calculated by Eq. (8), where $h^0 = x$ is the input of the network [68].

$$h^k = \sigma^k\left(b^k + W^k h^{k-1}\right) \tag{8}$$

Where k indicates the layer number, σ^k indicates the activation function of the layer k, h^k is the output array of the layer k, b^k is the array of bias values in the layer k, W^k is the matrix of the weights of the layer k.

Hidden layers encompass an activation function. It is practical to use different activation functions per node in a hidden layer, as it is to use one activation function. Activation functions add non-linearity to the relations between the input and output variables. Without an activation function, a dense layer would consist of two linear operations, so the layer only learns linear transformations of the input data. Therefore, a non-linearity function is needed to access a richer hypothesis [69]. Among all functions available, Rectified Linear Unit (ReLU) is quite popular [70] due to its simple implementation and outstanding performance on a range of predictive models. What It provides is a straightforward nonlinear transformation. In this regard, if x is the input to a neuron, the said function is defined as the maximum of x and 0, as shown by Eq. (9):

$$ReLU\ (x) = \max(x, 0) \tag{9}$$

In other words, ReLU only retains positive values and snaps the zero and negative elements to 0. In this study, ReLU was ascertained as the best activation function, compared to other options, say, Hyperbolic Tangent (Tanh) or Logistic (Sigmoid), for all four hidden layers.

During training, the performance of a model has to be monitored. Here, a measure taking this responsibility is needed. The loss function is precisely what a model requires and needs to be minimized in the meantime [69]. Given the nature of the problem at hand that is single-labeled, multi-class classification, the standard Categorical Cross-entropy, given by Eq. (10), was used.

$$J_{cce} = -\frac{1}{M}\sum_{k=1}^{K}\sum_{m=1}^{M} y_m^k \times \log\left(h_\theta(x_m, k)\right) \tag{10}$$

where M is the number of training examples, K indicates the number of classes, y_m^k indicates target label for training example m for class k, x is the input for training example m, and h_θ is the model with neural network weights θ.

The next step was optimizer selection. In addition to most of the model's hyper-parameters, this optimization algorithm was tuned using Grid Search. An optimizer specifies how the network will be updated concerning the loss function that is to be minimized [69]. In this network, the Adaptive Moment Estimation (Adam) optimizer [71] was applied as the dominant optimizer compared to its tested counterparts, including Root Mean Square Propagation (RMSprop) and Adaptive Gradient Algorithm (AdaGrad). RMSprop and Adam and conceptually alike. For example, they update the initial learning rate for different weights during optimization, but Kingma and Ba [71] showed that Adam predominantly outperforms. The Adam algorithm alters the learning rate of step t by the first moment m_t, and the second moment, v_t, of past gradients, as shown in Eq. (11) and Eq. (12):

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla_\theta J(\theta) \tag{11}$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)\left(\nabla_\theta J(\theta)\right)^2 \tag{12}$$

where β_1 and β_2 are user-defined constants. Since m_0 and v_0 are typically initialized as zero vectors, the values of m_t and v_t tend to remain close to zero in the subsequent iterations. To address this issue, Kingma and Ba [71] proposed using the following bias-corrected formulas:

$$\widehat{m_t} = \frac{m_t}{1 - \beta_1^t} \tag{13}$$

$$\widehat{v_t} = \frac{v_t}{1 - \beta_2^t} \tag{14}$$

Finally, based on the Adam algorithm, the parameters are updated by Eq. (15):

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\widehat{v_t}} + \epsilon} \widehat{m_t} \tag{15}$$

They suggested $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 10^{-8}$. These are the algorithm's inherent features and normally are not altered by data analysts.

Learning rate was another tuning parameter to adjust. It is the most significant hyper-parameter to setting deep neural networks [72]. A low learning rate will result in an algorithm converging slowly, while a large rate will make the model converge too quickly to a suboptimal solution [73]. Consequently, adjustments must be made to establish the proper learning rate and schedules [72]. The grid search parameters concerning learning rate included 0.001, 0.01, 0.1, 0.2, and 0.3. The best results were achieved when using a learning rate of 0.01. Moreover, batch size was tuned, too. The grid search parameters included 5, 10, 20, and 30. The batch size of 30 achieved the best results.

To combat overfitting, additionally, Dropout [74] was considered necessary. Dropout is implemented per layer in a neural network. It is applied with most types of layers, including dense fully-connected, recurrent layers and convolutional ones [67]. When using it, some nodes and links are, in accordance with a predetermined rate of p, dropped out in each training epoch. Mathematically, dropout is defined as follows. Take a neural network with L hidden layers, each indexed with $l \in \{1, \ldots, L\}$. Let $z^{(l)}$ and $z^{(l+1)}$ indicate the vector of inputs and outputs to layer l. $W^{(l)}$ and $b^{(l)}$ are the weights and biases at the very layer. So, the feed-forward operation for any hidden unit i can be shown as Eq. (16):

$$z_i^{(l+1)} = a\left(w_i^{(l+1)} z^{(l)} + b_i^{(l+1)}\right) \tag{16}$$

Where a(.) denotes any activation function, dropout turns this operation into:

$$r_i^{(l)} \sim Bernoulli(p) \tag{17}$$

$$\tilde{z}^{(l)} = r^{(l)} * z^{(l)} \tag{18}$$

$$z_i^{(l+1)} = a\left(w_i^{(l+1)}\tilde{z}^{(l)} + b_i^{(l+1)}\right) \tag{19}$$

$r^{(l)}$ is a vector of independent Bernoulli random variables with a specific probability p of being 1. The said vector is sampled and multiplied element-wise ($*$) with the outputs of that layer to develop the thinned outputs $\tilde{z}^{(l)}$. The thinned outputs are subsequently used as the inputs to the subsequent layer. The grid search parameters respecting this included 0.0, 0.1, 0.2, 0.3, 0.4, and 0.5. The value of 0.5 ended up resulting in the best results.

Next, in the output layer (final layer) of the network, the SoftMax activation function, shown by Eq. (20), was used.

$$Softmax\left(\vec{Z}\right)_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \tag{20}$$

Where $(\vec{Z})_i$ = input vector, e^{z_i} = standard exponential function for input vector, K = number of classes in the multi-class classifier, e^{z_j} = standard exponential function for output vector, i = 1, …., k, z = (z_1, …, z_k) ∈ R^k, and $R^k \to [0,1]^k$. The equation above ensures several things happen. Due to the exponential function, the negative inputs will be converted to non-negative ones. Each input will be in the interval (0, 1). And, since SoftMax uses the same dominator in each computation, the values become proportional to one another, which ensures that they together sum to 1.

All the said hyper-parameters, such as optimization algorithm, learning rate, activation function, dropout regularization, and the number of layers, were all tuned using Grid Search, provided in the GridSearchCV class in Scikit-learn, or through extensive trial and error. Grid Search was used because of being renowned for the simplicity of implementation and reliability in low-dimensional spaces [75]. Table 5 summarizes the typical hyper-parameters and the adopted values in this paper.

It is also noteworthy that the experiment has been performed on a personal laptop with Intel® Core TM i7 and 4 GB RAM under Windows 10 Ultimate 64-bit operating system.

Table 5. Hyper-parameters of the developed neural network

Hyper-parameters	Status
Type of layers	Fully-connected layers
Hidden layers activation function	ReLU
Output layer activation function	SoftMax
Optimizer	Adam
Loss function	Categorical Cross-entropy
Number of epochs	200
Batch size	30
Number of hidden layers and their nodes	1_{st} (10), 2_{st} (12), 3_{st} (100), 4_{st} (50)
Dropout rate	0.5
Learning rate	10^{-2}

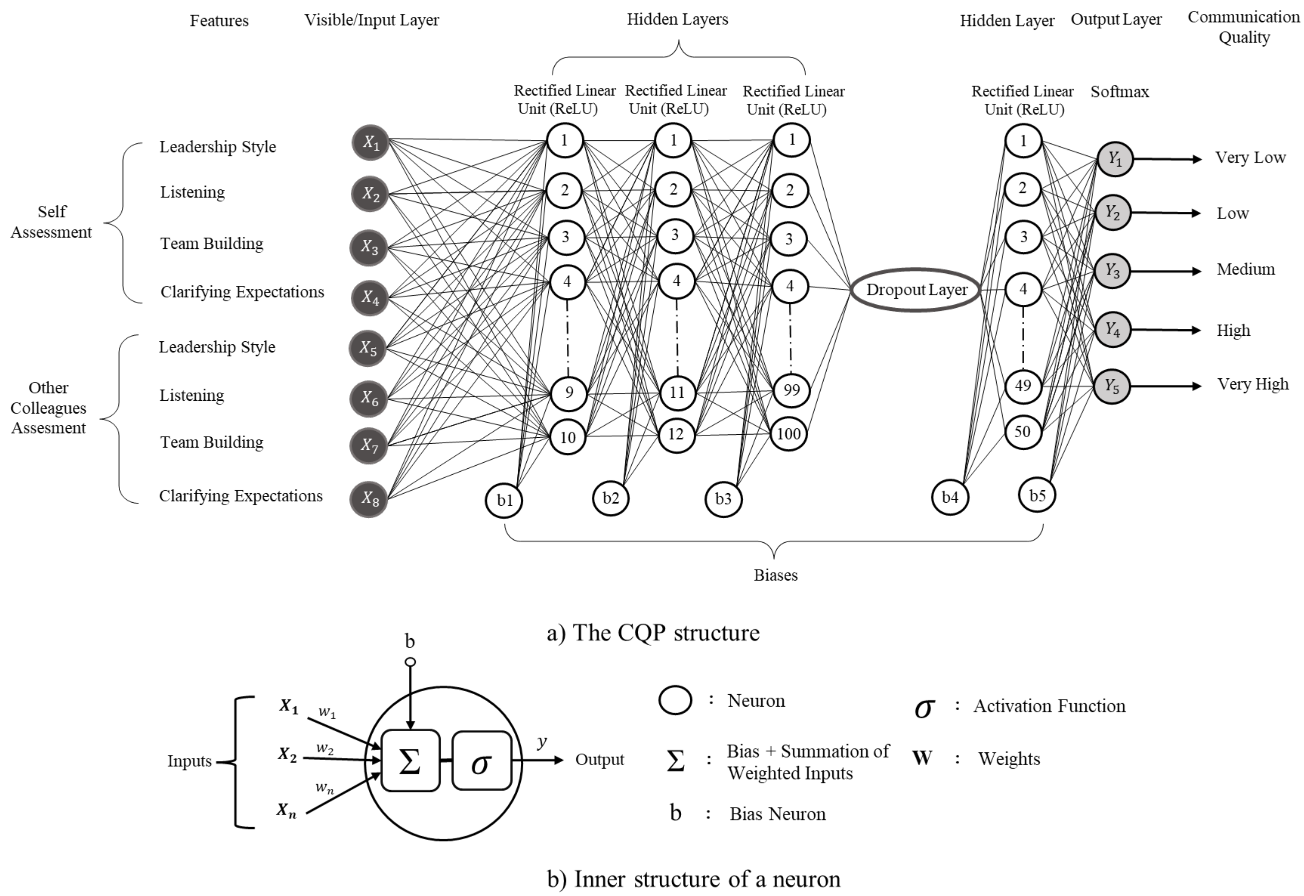


Figure 4. The anatomy of CQP showing a) the structure of the developed network and b) the inner structure of a neuron

3.9. Validation of CQP in real context

CQP was ultimately conducted in three real case studies to evaluate its predictions (Figure 2). The cases are similar in size, but not in the scale and the cities where they were being conducted. These similarities aside, availability was another contributing project selection criterion that the research team could not help but consider.

One case (case study I) was an airport development project, and the other two (case study I and II) were both construction of residential buildings. They were selected for two primary reasons. Firstly, their contractors and consultant had a good reputation and extended history in the field and recognized success in various construction projects. According to the Iran contractors' classification, their firms were also classified in the top-rank organizations. Secondly, because of their employees' interest in this research, their firm commitment, and the clients' cooperation in providing access to the research-related data. Table 6 shows the detailed introductory information of each one.

Ethical considerations were also addressed before taking any further steps. In this regard, all project participants were informed of the study objectives and individuals by whom the study findings will be used. On top of that, the protection of the participants' privacy, sufficient confidentiality of the study data and particulars, and anonymity of workers were all ensured at the outset.

There were no archival records or documents suitable for the research objectives for this collective case study. There were also no physical artifacts available, helping along with the process. Thus, direct observation seemed to be the best bet at the time. In each case, an expert with the most connections with projects personnel (see further information in sub-section 4.2) was tasked to validate the predictions CQP once had made on what truly happened between construction workers over time. In order to better capture the CQP's conduct, evaluated workers accounted for a selection of team members from various departments and levels. The experts needed to say whether a relationship has experienced interpersonal problems or mistreatment behaviors contrary to the spirit of the workplace. This step of the study was carried out in 2020 and ran over eight months from the prediction of 183 qualities to finalizing the experts' evaluation.

Table 6. The characteristics of the case studies

Projects	Number of project participants	Number of communication-quality predicted	Observation hours per day (hrs/day)	Size	Type of contract	Sector	Description
Case study I	32	53	Approximately 5-10 hrs/day	Large-sized licensed	Design-bid-build	Building	Airport development project
Case study II	41	66	Approximately 3-12 hrs/day	Large-sized licensed	Design-bid-build	Building	Construction of residential buildings

Case study III	23	64	Approximately 3-15 hrs/day	Large-sized licensed	Design-bid-build	Building	Construction of residential buildings

4. FROM DATA TO FINDINGS

In this section, we delve into the outputs of each section separately. The first two parts are seen as the minor findings paving the way for preparing and training the predictive model as the foremost objective in the present paper.

4.1. Interpersonal skills prioritization

All the interpersonal skills are significant in one way or another; however, considering them all in the questionnaire seemed unreasonable. This could have made responding much more time-consuming while also pushing the panelists to complete the questionnaire more distractedly, as they are generally short of time. Having identified the relative importance of each skill using AHP, the authors narrowed down the skills pool to four—based on the judgment and timeframe, the number of skills taking the shortest time from respondents to assess while keeping the accuracy of the responses as high as possible was considered to be 4; they are leadership style, listening, team building, and clarifying expectations (Figure 5). The selected ones were considered in the questionnaire, and respondents were tasked to separately determine to what extent they think they are strong in these skills. In the meantime, each skill's definition or explanation was doled out to the respondents to understand the assessed items better. It is noteworthy that the consistency ratio of the prioritization was less than 10%, indicating that the given matrix was sufficiently consistent.

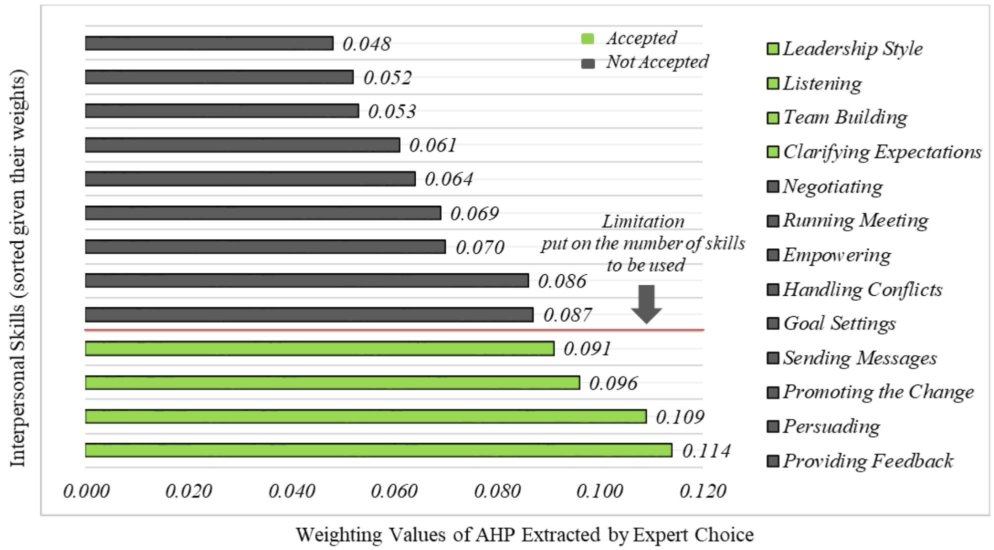


Figure 5. AHP output demonstrating the significance of the interpersonal skills based on experts' judgment

4.2. Communication structure typical of construction projects

Figure 6 shows the ubiquitous network of participants in construction projects, consisting of 10 major roles and 23 connections thereof. All the experts were unanimous on this formal communication network shown in Figure 6. As shown, the site manager and supervision consultancy team have the most links with other members. The connections shown in the figure play an essential role in the questionnaire. As mentioned (sub-section 3.5), in the first two sections of the questionnaire, respondents were requested to do a self-assessment regarding the given four interpersonal skills and assess other employees with whom they communicate regarding the predetermined connections shown in Figure 6. For example, Respondents in the position of sub-contractors were tasked to do a self-assessment and then assess their colleagues in the positions of the site manager, HSE, site engineers, and other sub-contractors based on the figure below. Other roles responded to the questionnaire in much the same way, and the data were gathered precisely in this way.

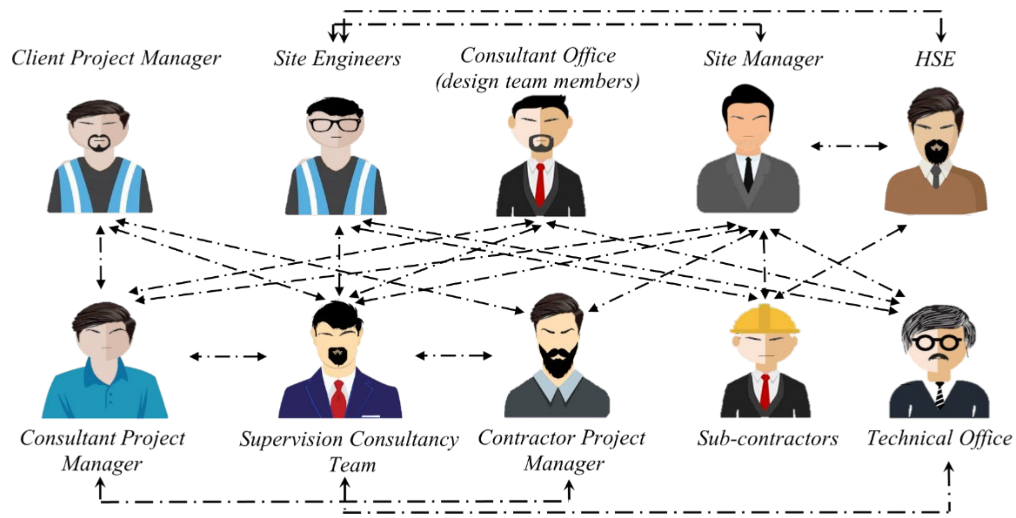


Figure 6. Highly-frequented connections among construction projects participants

4.3. Communication quality predictor performance during training

The preliminary steps were taken to develop the neural network except for one more thing, a metric to evaluate CQP during training and testing. Here, the focus is on accuracy. As Figure 7 shows, two quantities are displayed during training: the network's accuracy and loss over the training data. Following Figure 7 (the above plot), the training accuracy of the designed CQP (black) and test accuracy (grey) grow hand-in-hand from the early epochs until reaching an acceptable accuracy. The best training set accuracy showed a slight difference of 2% higher than the best test set accuracy, 81% and 79%, respectively. These confirm that the model generalizes well from the training dataset to the test dataset (the unseen data). Form the plot of loss (Figure 7, the below plot), additionally, the model shows a comparable performance on both datasets. These parallel plots start to depart after ten epochs; nevertheless, both of them decline consistently.

All in all, CQP was carefully crafted and shows a good convergence behavior yet somehow bumpy to predict the interpersonal communication quality between projects participants with acceptable accuracy.

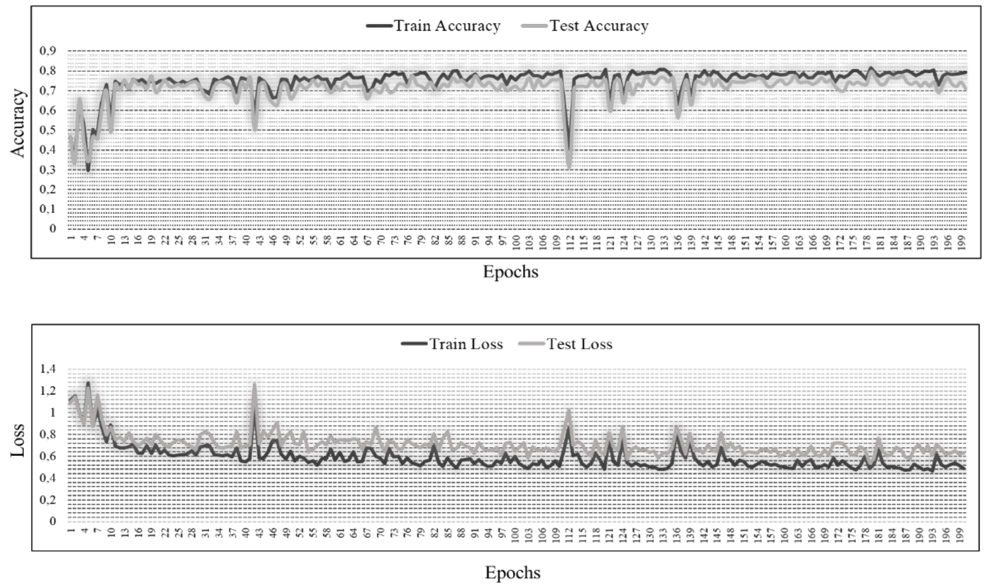


Figure 7. Model accuracy and loss on training and test datasets

4.4. CQP validation results

CQP was in the final step applied in real contexts to validate its predictive capabilities. In total, it predicted 183 interpersonal communication qualities. As Figure 6 demonstrates, the site manager and supervision consultancy team have the most connections with other project members; thus, one of them was tasked to evaluate whether the relationships had faced interpersonal problems or opposition of interests over time.

Among predictions, sixty were predicted as "Very High" or "High" quality. Among them, 51 had shown no signs of mistreatment or interpersonal problems, be it unwillingness to cooperate, tension, or interpersonal communications issues, and nine had experienced interpersonal conflicts or other types of interpersonal issues at some level. Meanwhile, eighty-four qualities were predicted as "Medium." In between, 67 relationships had not faced conflicts of any kind, but 17 ones had faced. Among the rest of 39 relationships predicted as "Low" or "Very Low," 11 had had simple or no conflicts, but 28 had struggled with interpersonal problems of relatively high intensity, such as rudeness or yelling. If those predicted as

"Medium" have not been expected to have interpersonal problems, CQP was correct in predicting 146 interpersonal communication qualities, meaning it was accurate in nearly 80% of the cases.

Furthermore, periodic eyewitness reports on the collective case study suggested that the most common interpersonal conflict between practitioners was pseudo-conflict, where there was a perceptual difference between partners, followed by value (attitude) conflict where workers were in disagreement about their moral beliefs. These two stood before the last highly-frequented yet fleeting conflict, fact (or belief) conflict, in which a dispute over the truth of several separate bits of information arose. The last conflict reported was ego conflict, which rarely took place.

5. DISCUSSION OF FINDINGS

5.1. Comparison against past research

The findings of the study offer a range of novel insights. Previous studies, including those in the construction context, have focused on providing deterministic recommendations with regard to the importance of quality of communication [76]. This study elevates the debate by providing a model that predicts the quality of communication in respect of an individual's interpersonal skills. Moreover, findings identify a linkage between the personal attributes of workers and the resultant quality of communication in construction projects. Findings add value to the theoretical foundations of quality of communication in the construction industry in several ways. First, the network of relationships (Figure 6) offered in this paper presents an account of the prevailing communication style used in construction projects [76]. It spotlights the differences between individualistic cultures (the Unites States and European countries) and collectivistic cultures (Asian countries), as well as between low-context (LC) and high-context (HC) communications. Therefore, the network aligns with Gudykunst and Ting-Toomey [77] in that LC and HC communications are ubiquitous in individualistic and collectivistic cultures, respectively. However, findings contradict the findings of Hosseini, et al. [56], who argued that national culture has no bearing on the effectiveness of construction project teams or the way in which team members collaborate.

Quality of communication indicators, as revealed in Table 1, dominate the literature. Noticeably absent are interpersonal skills, despite their recognized importance. This study augments this deficiency by proposing the CQP, which predicts and quantifies the relationship between interpersonal skills indicators and the quality of communication while also considering the effects of concurrent or co-existed indicators that may positively or negatively impact each other. Such considerations are achieved by using a developed neural network or, more precisely, a fully-connected deep neural network.

In this study, Social Network Analysis (SNA) has been linked to the quality of communication in a novel method. This development is significant as construction projects are now regarded as network-based organizations Zheng, et al. [78]. Upon predicting the quality of interpersonal communication using CQP, the connections or links between different workers will carry different values or weights. Each weight of a link distinguishes one link from the points of resistance, intensity, or capacity. The weight of links, not least in the communication network, can make a difference when using the weight of links dependent network metrics, such as the shortest path between workers. While other studies have also analyzed the network of communications, they have all used weights derived from other indicators, such as accuracy [16,17], or the total number of links sent by one participant and received by another [79], while none up until now have considered weights stemming from interpersonal skills. It is this insight that adds to the significance of this study.

5.2. Practical implications

5.2.1. Conflict resolution

In terms of practical implications, the case study by Mignone, et al. [3] revealed that leaders intervene immediately when disagreements and differences of opinions rise to the level of interpersonal conflict. Leaders, however, are expected to predict such issues and intervene beforehand to avoid the loss of productivity. CQP, with its predictive nature, provides a remedial solution. Firstly, it predicts the quality of communication, considering different levels for quality of communication, which is consistent with the work by Pryke, et al. [16]. Researchers of the very study considered the quality of communication with three levels (low, medium, and high). Secondly, it has been built upon interpersonal skills and makes predictions accordingly, which lays the foundation for leaders to intervene, hopefully, before interpersonal communication conflicts arise. This ability supports the claim of Brockman [80] that early identification of interpersonal conflicts is one of two keys to cultivating an efficient and amicable workplace. In fact, CQP is novel in terms of shifting the discourse around communication quality from the approach depending on conflict resolution to a predictive one that helps management expect conflicts in projects in advance, which is on par with the argument about predictive modeling made by Omar, et al. [81].

5.2.2. Human resources and recruitment procedures

CQP could also aid decision-makers and employers in the recruitment phase. This approach helps managers analyze the interpersonal communication proficiency of job applicants. This helpfulness is essential as, in some countries like Australia and New Zealand, an average of 61.68% of all advertisements look for good interpersonal skills from project managers [82]. Figure 8 demonstrates the application of CQP in this phase.

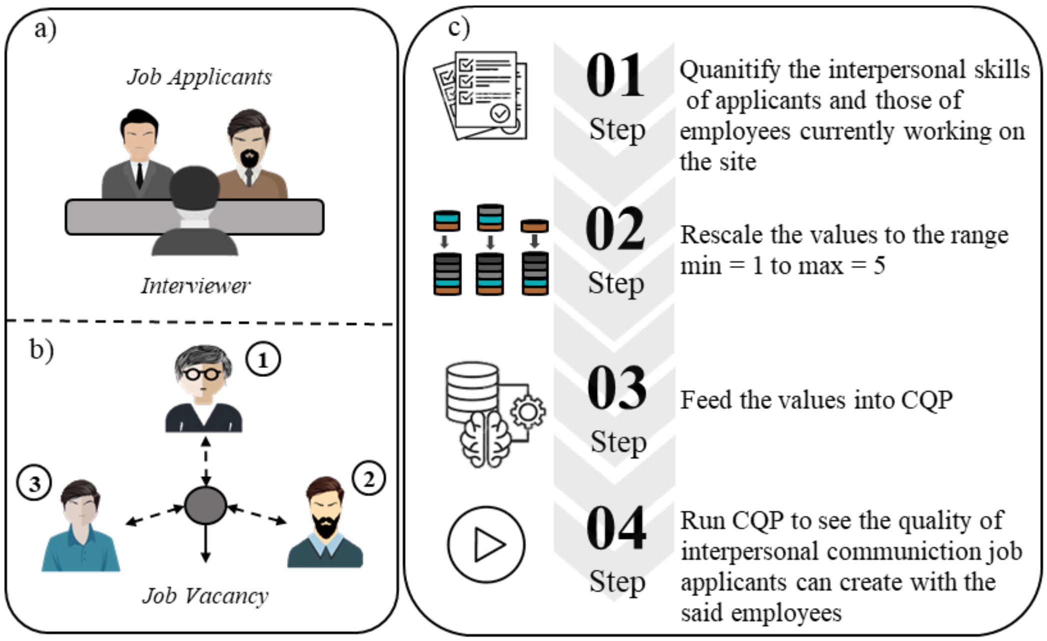


Figure 8. CQP in the hiring phase as an example of its implication

As the right part of the figure shows (figure 8c), first, interpersonal skills must be quantified for all the applicants and project participants connected with the job vacancy. For example, in figure 8a are applicants applying for a job vacancy shown in figure 8b. In the next stage, the values must be rescaled to the range minimum = 1 to maximum = 5 and then fed into CQP. Finally, CQP should be run per connection (the link between that job vacancy and the project participants number 1, 2, and 3). The outputs will show which applicant is better able to make communication of higher quality with other employees.

5.2.3. Team development

The proposed method could be used during a project with the same purposes and in the same way. From the lens of interpersonal communication, CQP can inform managers of the extent of their workers' abilities to make high-quality communication. Therefore, they can arrange and develop their team more optimally. Using CQP will help project management team to reduce problems and enhance cooperation through anticipating their workers' actions, acknowledging their concerns related to interpersonal skills, and following up on their issues. These all are consistent with the statements in the PMBOK guide [83].

5.2.4. Job-site productivity

Job-site productivity is affected by many factors, workers' interpersonal skills included [84]. CQP shows how workers can relate to their peers in an effective and productive manner. Understanding such abilities of workers is essential as lower-skilled workers will reduce efficiency and productivity as a result of an increase in the number of communication, training, and cooperation needed [83].

6. CONCLUSION

While the impact of interpersonal skills on the communication quality is generally appreciated, no research has attempted to develop a method to predict the quality of communication given such skills. Such a prediction advances workers' understanding of the quality of their communication and forewarns them about potential interpersonal conflicts before they escalate. This study bridges this gap in two ways. From a theoretical perspective, it identified the conceptual linkages between interpersonal skills and communication quality. From a practical perspective, it developed a method, here dubbed CQP, to predict workers' communication quality. CQP utilized the compiled interpersonal skills as ranked by AHP. The selected skills with the highest importance, together with their weights, are Leadership Style (0.114), Listening (0.109), Team Building (0.096), and Clarifying Expectations (0.091).

Project managers may utilize the proposed method to assess the quality of interpersonal communication between projects participants. This research contributes to the field by postulating an innovative way to draw more precisely from the predictive models. Practitioners may press this method into service in order to obtain further insight into the quality of interpersonal communication in their projects. The method may also warn managers of looming interpersonal conflicts. Furthermore, social network analysts in the project management domain can now model the interpersonal communication networks as a weighted graph and calculate those weights-of-links dependent metrics.

Despite the contributions, as discussed, any research study has its limitation. This study is no exception. This study's primary limitation to be acknowledged relates to the relatively small sample size of available participant experts. The other limitation relates to the nature of employment of respondents; mostly working for the local government. Though most of these represent project clients delivered across the country, future studies need to repeat the work with various types of roles and employee demographics. Nevertheless, the number of respondents is considered adequate as their data come from a remarkably large set of seventy-five companies. Finally, ten different working parties' views of communication quality were considered all the way through in this study, making it all the more representative of the construction sector.

CQP is novel, being in its infancy. The dataset, for example, is cross-sectional and was gathered through a survey questionnaire. In other words, CQP can be advanced by using an alternative online platform to review the quality of communication between projects participants with live data and the ability to update it momentarily. At the same time, other interpersonal skills remain undiminished and further studies should reembrace them. Moreover, CQP can bring researchers and practitioners one step closer to more accurately evaluating the effectiveness of communication training when covering the full set of interpersonal skills. Budhwar and Mellahi [85] argued that companies expect to see a return on their investment, but this is not easy to establish, especially in soft training, such as communication, leadership, and teamwork. Moreover, future work should investigate whether the importance of the links between different construction roles, shown in Figure 6, differ. For example, researchers should explore whether the link between a consultant project manager and a client project manager holds the same weight and importance as the link between a contractor project manager and a consultant project manager, and how the potential differences could affect the predictions.

Acknowledgments

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Appendix I

Self-assessment				*Other Colleagues Assessment*				*To What Extent Do You Feel that Your Communication with Each Other Is:*
Leadership Style	*Listening*	*Team Building*	*Clarifying Expectations*	*Leadership Style*	*Listening*	*Team Building*	*Clarifying Expectations*	
Expert	*Expert*	*Expert*	*Expert*	*Expert*	*Expert*	*Expert*	*Expert*	*Very High*
Journeyman	*Journeyman*	*Journeyman*	*Journeyman*	*Journeyman*	*Journeyman*	*Journeyman*	*Journeyman*	*High*
Apprentice	*Apprentice*	*Apprentice*	*Apprentice*	*Apprentice*	*Apprentice*	*Apprentice*	*Apprentice*	*Medium*
Initiate	*Initiate*	*Initiate*	*Initiate*	*Initiate*	*Initiate*	*Initiate*	*Initiate*	*Low*
Novice	*Novice*	*Novice*	*Novice*	*Novice*	*Novice*	*Novice*	*Novice*	*Very Low*

Appendix II

Self-assessment				Other Colleagues Assessment				Communication Quality
Leadership Style	Listening	Team Building	Clarifying Expectations	Leadership Style	Listening	Team Building	Clarifying Expectations	
4	3	4	3	3	4	4	4	3
5	5	5	5	4	4	5	4	3
3	4	4	4	4	3	2	2	1
3	5	4	3	2	3	2	3	1
4	5	5	5	3	4	4	4	3
4	5	4	5	3	3	3	3	3
4	4	5	5	5	3	3	4	4
3	4	3	4	3	4	3	3	3
3	2	3	2	3	2	2	2	1
4	4	3	3	2	2	2	3	1
4	4	5	5	3	4	3	3	3
4	4	3	3	4	3	3	4	3
4	3	4	4	3	3	3	3	2
4	5	5	4	4	4	4	4	4
4	5	3	3	3	4	3	3	4
3	4	3	4	4	4	3	3	2
4	5	4	4	4	2	4	3	3
4	3	4	4	4	3	3	4	3
4	4	4	5	3	2	2	1	0
4	5	5	4	2	2	2	3	2