Journal of Engineering Science and Technology
Vol. 19, No. 1 (2024) 35 - 54

A CRITICAL ANALYSIS OF TRADITIONAL AND AI-BASED RISK ASSESSMENT FRAMEWORKS FOR SUSTAINABLE CONSTRUCTION PROJECTS

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Abstract

Risk Assessments in construction projects help in cost savings, energy efficiency, as well as on time completion within the allocated budget. To meet these requirements, companies need to use analytical models that save time, deal with large amounts of data, and allow them to make better decisions more quickly. In addition, it will facilitate a fast, accurate, and automated process. This paper aims to provide a comprehensive critical analysis of traditional and AI-based risk assessment frameworks for sustainable construction projects (SCP) and the most practical framework. In this respect, the paper reviewed the literature and conducted semi-structured interviews on risk assessment and its application in construction projects. It also explored the advantages and disadvantages of traditional and AI-based risk assessments. A case study of modern sustainable construction projects in a selected country (Iraq) was undertaken to assess risk factors associated with these projects. An Analytical Hierarchy Process (AHP) and Artificial Neural Network (ANNs) approaches were used to reveal the variation of results between traditional and AI-based risk assessment regarding accuracy, reliability, and cost-effectiveness. An independent sample t-test was calculated to verify the differences in the results obtained by the AHP and the ANN methods. The findings show the advantages and disadvantages of traditional and advanced risk assessment in sustainable construction projects and establish recommendations for optimum practice in risk assessment methodologies. Also, the findings indicate that the value of the t-test was 0.7415, which is greater than 0.05; this means there is no substantial difference in the results of assessing the risk factors that impact sustainable construction projects if AHP or ANNs methods are used. The paper concludes that while traditional frameworks are still prevalent in the construction industry, advanced techniques can improve accuracy, reliability, and cost-effectiveness. The implications for sustainable construction practice and policy and identifies future research directions.

Keywords: Risk assessment, Sustainable construction, Traditional and advanced risk assessment.

1. Introduction

The construction industry has a notable impact on enhancing the performance and social welfare of the national economy. Indeed, it generates employment opportunities and income and creates considerable investment opportunities across diverse sectors. However, sustainable construction projects require risk assessments since they identify and mitigate potential hazards and uncertainties. Also, the construction sector contribution rose to 10% of the global gross domestic product (GDP) and 6-9% in developed countries [1]Click or tap here to enter text.. The study stressed the importance of the construction sector, where the employment rate reached 7% (approximately 273m+ people) of the worldwide workforce, and the total value of global output climbed to $10.8 trillion in 2017. Furthermore, the construction industry in the UK constitutes 8% of the GDP and employs 10% of the workforce [2]Click or tap here to enter text.. A report by ILFS indicated that Iraq's construction industry contributes 7.4% of the GDP, and 16.3 % of Iraqi workers are employed in the construction industry [3]. Moreover, the annual growth rate of Iraq's construction industry output will reach approximately 15.75% in 2023 [4].

However, the construction industry is perceived to be more vulnerable to challenges and risks. Nguyen and Macchion [5] listed the top risk factors that significantly impact the implementation of SC projects in Nigeria. They found the highest risks: the need for knowledge and awareness of this technology, cost, the availability of materials, and socioeconomic issues. Therefore, evaluating risks associated with SC projects to identify potential hazards and uncertainties, assign responsibilities, and determine proper procedures to mitigate these risks is crucial. According to Dai et al. [6], a risk assessment aims to assist organizations in understanding their risks. It can be defined as a systematic approach to determine the potential hazards that might affect the ability of organizations to carry out their operations. Also, it analyses risks, causes, and effects and sets control measures to reduce or remove them. Paltrinieri et al. [7] illustrated that risk assessment is pivotal in protecting critical industries like construction. However, SC projects face several challenges due to technological development and increased demand. Therefore, improved, and continuous risk assessments, learning from past lessons, and applying techniques to process relevant data are needed to help organizations deal with hazards and follow proper procedures to reduce and mitigate risks. In addition, different methods are used to assess and mitigate risk, including traditional and AI-based risk assessments.

Traditional risk assessment (TRA) is a systematic method to identify risks, analyse their causes and effects, and quantify risk levels [6]. The TRAs are carried out manually based on the experience of experts and professionals and mathematical analysis, while decision-making depends on knowledge and experience-based intuition [8]. Over recent years, considerable attention has been paid to adopting digitisation and the rapid development of advanced technology, such as artificial intelligence (AI), to overcome challenges. This is mindful of

current labour shortages, the effect of the COVID-19 pandemic on daily life, and the quick market response to provide SC [9].

Artificial intelligence (AI) is increasingly seen as the future of business technology and a valuable tool in risk assessment and strategic management. AI is an algorithm that can help to identify potential risks, analyse large amounts of data, and allow businesses to make more informed decisions [10]. Additionally, AI can assist with monitoring ongoing risks and implementing strategies to mitigate them.

A comprehensive literature review has been performed to understand the current status of traditional and AI-based risk assessment approaches in SC and determine both types of advantages and disadvantages. As such, the reviewing process followed the systematic literature review criteria as outlined by Emam et al. [11].

Different approaches used in risk assessment involve traditional and AI-based risk assessment. For instance, Habib et al. [12] used a traditional approach in their study, which was based on the Monte Carlo simulation (MCS) that presented a new process and prioritised project risks which impacted SC project time and cost in Egypt. Although this approach is relatively easy to understand and strong in assessing the risk factors of SC, the fundamental limitation of this approach is its difficulty in dealing with large amounts of data; it could, therefore, become computationally inefficient. Also, the MCS method still has trouble recognising probabilities since risk cannot be described as probabilistic.

Nguyen and Macchion [5] and Andal and Juanzon [13] identified and analysed risks associated with SC projects using an analytic hierarchy process (AHP) method. However, one significant drawback of this traditional method is its complexity, which makes it challenging to implement. Also, the input data needed for the AHP method is based on experience, knowledge, and judgment, which are subjective for each decision-maker. Furthermore, the AHP method becomes more complicated if more than one person is working on this method in the same project, as differing views about the weight of each risk can emerge among individuals, leading to inaccurate results.

A study by Tam [14] demonstrated the degree of impact of risks on the three main dimensions of economic, environmental, and social sustainability and how they influenced SC projects in Hong Kong using the Delphi method. The approach used in this study is characterised by its flexibility in geographical location, time, and cost-effectiveness when obtaining feedback from the expert group, and it has a structured communication system that enables the group to reach a consensus about the precise results that fit the research questions. However, the results mainly depended on the expert respondents.

Over the last two decades, there has been significant interest in using artificial intelligence applications as risk assessment tools in SC. A study by Alsheikh-Salem [15] evaluated and analysed the risk factors that substantially impact Jordanian SC projects. The study developed a risk assessment model using the Bayesian Belief Network (BBN), an artificial intelligence application. Although the BBN method is inconvenient for small probabilities, the study requires more data to obtain the best results.

Olanerwaju [16] developed an artificial neural networks (ANN) model to assess the impact of risk factors on sustainable building. However, the ANN model created is only suited for problems requiring classifications or patterns and does not apply to problems involving reasoning or decision-making. On the other hand, Lapidus et al. [17] assessed the risk factors affecting SC projects using a fuzzy inference system (FIS) method. However, the fuzzy inference system entirely depended on human knowledge and experience. Due to these limitations, many researchers have started to use a combination of two methods or hybrid approaches, such as ANN and AHP, to obtain a high degree of accuracy [18].

The problem tackled in this research is the risk assessment process in construction projects. To be more specific, there is a huge amount of data that could be useful for analysis. However, this huge amount of data cannot be tackled by humans; therefore, it should be done with an analytical model that makes quick predictions, saves time, deals with large amounts of data, and allows managers to make better decisions more quickly. Also, the research hypothesis is to identify critical risk factors that impact sustainable construction projects (SCP) and select a suitable analytical model with the expectation of high accuracy, quick predictions, and saving time.

Therefore, the objective of the current work is to critically analyse the advantages and disadvantages of traditional and AI-based risk assessment techniques in construction projects. It is also aimed to explore the potential benefits and drawbacks of AI-based risk assessment techniques through a case study for a modern SC project. Based on the findings of the comparison and analysis, the work recommends the best practices in the risk assessment of sustainable construction projects and future research.

2. Research Methodology

The authors adopted two steps to achieve the research objectives, as outlined in Fig. 1.

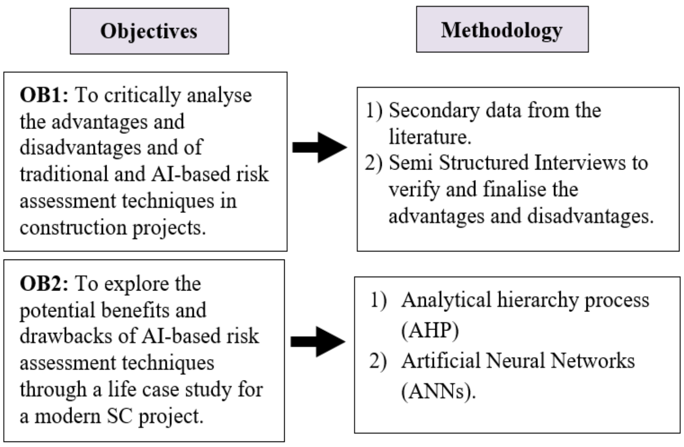

Fig. 1. Research methodology.

In the first step, a literature review and semi-structured interview were carried out to determine the advantages and disadvantages of traditional risk assessment (TRA) and AI-based risk assessment. The second step involved a life case study which used two different approaches, the Analytical Hierarchy Process (AHP) and Artificial Neural Networks (ANNs), to determine the potential benefits and drawbacks of AI-based risk assessment in sustainable construction (SC).

2.1. Literature review collection and comparative analysis

A comprehensive literature review has been performed to understand the status of traditional and AI-based risk assessment approaches in sustainable construction and determine both types of advantages and disadvantages, following the criteria recommended by Emam [11]. Click or tap here to enter text.

Keywords were used in the search engine: Google Scholar and ScienceDirect search engines to find relevant articles. Also, the authors used a variety of keywords including “sustainable construction", "risk assessment", "risk assessment in sustainable construction projects", "traditional risk assessment", and "AI-based risk assessment". In this respect, the search conducted led to 30 relevant articles and reports were gathered. However, only 21 articles and reports were focused on after the selecting and filtration step due to their content relevancy.

2.2. Semi-structured interview

Face-to-face and online interviews were held to fulfil the objectives. This method was adopted due to its effectiveness in explaining or exploring complicated phenomena or situations, which has been widely used in several studies [19]. Moreover, the primary purpose of an interview is to gain an in-depth understanding of the phenomenon and to gather more detail about the advantages and disadvantages [20]. Interviews were conducted with 15 professionals, experts, and academics to identify the advantages and disadvantages of traditional and AI-based risk assessments in SC. The authors followed all appropriate ethical protocols, including providing with an ethical sheet. As such, the distribution of the participants was 40% professionals, 33% experts and 27% academics. NVivo software was used to analyse the semi-structured interview data. NVivo is characterised by its ability to manage the interview transcription and support the execution of content analysis [21]. The semi-structured interview questions are presented in Table 1.

Table 1. Semi-structured interview questions.

Subject	Interview Questions
General	• What are the common risk assessment methods that are used in sustainable construction projects? Why?
Traditional Risk assessment	• What are the advantages of the traditional risk assessment? • What are the disadvantages of the traditional risk assessment?
AI-based risk assessment	• What are the advantages of AI-based risk assessment? • What are the disadvantages of AI-based risk assessment? • How do you see adopting artificial intelligence applications in risk assessment for sustainable construction? • Do you think using artificial intelligence applications is more expensive than traditional risk assessment methods? • Do the results obtain from AI applications accurately and reliably?

2.3. Extraction from the literature on the RA approaches

The authors identified the advantages and disadvantages of traditional and AI-based risk assessments from the literature review and semi-structured interviews. Tables 2 and 3 show the advantages and disadvantages of traditional risk assessment (TRA) and AI-based risk assessment.

Table 2. Advantages and disadvantages of traditional risk assessment (TRA) in construction.

Advantages	Disadvantages	Reference
Simple, flexible, and easy to understand.	Reporting is the fundamental limitation of TRA. The process of collecting related information from experts or the board takes a long time.	Click or tap here to enter text.[22] and interviews
TRA is an effective tool in risk prediction, assessment, and mitigation.	It can operate only with a small amount of data.	Interviews
Cost-effective, time efficient and cost saving	Some TRA approaches are unable to adapt to changing scenarios. Also, it is inefficient in coping with risks in modern complex technological systems.	[23] and interviews
Suitable for small projects in terms of risk mitigation and monitoring issues.	Some TRA methods are less accurate as they depend on human intuitions and personal judgment.	[24] and interviews
Use previous lessons to create awareness about possible risks in the future.	TRA approaches cannot be applied to complex systems that change their state over time.	[25] and interview

Table 3. Advantages and disadvantages of artificial intelligence (AI) in construction.

Advantages	Disadvantages	Reference
Faster, more consistent than humans. Prioritises risk on the job site, provides high accuracy and reliability, and improves monitoring issues.	Construction stakeholders may not adopt AI-based risk assessment in their projects due to the difficulty in understanding the analysis process of AI applications. There may be a lack of trust in the systems and worry about the loss of jobs or positions to machines.	[9, 26, 27] and interviews
Increases safety, improves risk assessment quality, and minimises human error. errors.	-Requires skilled professionals to use. -Needs advanced hardware and software.	[28, 29] and interviews
Operates with large amounts of data and can learn from previous lessons and historical records, time efficient, and increased productivity.	High cost of maintenance and repair	[26, 28]
Easy access to relevant information and the ability to identify new patterns which are undetectable by humans; keeps risk assessments up to date while information accumulates exponentially.	The results could be inaccurate if using a small amount of data in some AI-based risk assessment approaches.	[26, 28, 29]

3. Research Case Study

The authors have chosen five completed SC projects in Iraq (See Table 4) to evaluate the impact of the associated risk factors and compare the results in terms of accuracy. This has been undertaken using the following two different approaches:

- **Approach 1:** Analytical hierarchy process (AHP), which is a traditional risk assessment (TRA).
- **Approach 2:** Artificial neural networks (ANNs), which is a branch of AI.

Table 4. The five SC projects were selected in Iraq.

Project	Information	Sustainable Features	References
A	College of Medicine	• Energy & water efficiency. • Waste management.	Interviews
B **C** **D**	Residential units Schools Hospital	• Sustainable architectural design (passive cooling and heating technique). • Energy & water efficiencies. • Indoor air quality. • Sustainable materials. • Regulatory compliance & certification.	[30]
E	Sustainable building	• Sustainable design. • Energy & water efficiencies. • Indoor air quality. • Use of sustainable materials. • Re-use, recycling. • Adaption to a changing environment. • Renewable energy.	[31]

3.1. Approach 1: Analytical Hierarchy Process (AHP)

AHP is one of the traditional risk assessment approaches introduced and developed in 1980 by Saaty [32]. It can be applied to formulate appropriate decisions and analyse and solve complex problems. It is characterised by its ability to analyse individual objective and subjective factors using pairwise comparison matrices [33]. A study by Aminbakshs et al. [34] showed the importance of using AHP in risk assessments as it validates and minimises inconsistency in experts' decisions. Also, it describes and evaluates the interchange between relationships and highlights the increasing impact of risk factors, from the most to the least important. The prominent features of AHP in the construction engineering field, such as construction risk assessment, include the following:

- Flexibility, simplicity, and a high level of consistency.
- The ability to find a solution to settle conflicts in opinion and establish priorities.
- The ability to analyse complex scenarios and create an appropriate decision hierarchy.

Several phases must be followed to develop an AHP risk assessment for SC, as follows:

Phase 1: Identification of the main and sub-risk factors

In this phase, a focus group discussion was held with 10 managers, consultants, professionals, and contractors to elicit opinions and identify the risk factors affecting SC in Iraq. It is worth mentioning that all participants in the group discussion had at least 15 years of work experience in the field of SC. Moreover, this approach was used as there are few studies on risk associated with Iraq's SC. According to Al-Mhdawi et al. [35], group sessions are valuable for exploring and analysing complex phenomena. It has been widely used in previous studies to determine the risks associated with construction and engineering management [36]. Table 5 depicts the risk factors identified that significantly impact SC projects in Iraq.

Table 5. Risk factors that significantly impact sustainable construction projects in Iraq.

Code	Main Risk	Code	Sub-Risk Factors
IQ-1	Management Deficiency	**RF1**	Slow adoption of modern technology
		RF2	Lack of database and information for SC
		RF3	Poor skills among SC managers and teams
		RF4	Lack of use of international risk management standards and codes
IQ-2	Financial	**RF5**	Instability of currency exchange rate
		RF6	Increased price of sustainable materials
		RF7	Market inflation
		RF8	Delays in approving the governmental general budget
IQ-3	Supply chain management	**RF9**	Low productivity of labour in the SC site
		RF10	Changes in sustainable materials type during construction
		RF11	Damages in SC materials during transportation
		RF12	Difficulties in customs clearance at border crossings
IQ-4	Contractual	**RF13**	Lack of contract arbitration
		RF14	Contract termination
		RF15	Legal disputes
		RF16	Changes to law

Consequently, the Risk Factors Value (RFV) can be calculated using Eq. (1)

$$\mathrm{RFV} = \mathrm{PO} \times \mathrm{RS} \times \mathrm{RD} \times \mathrm{EC} \tag{1}$$

where PO refers to the probability of occurrence of the risk, RS refers to the risk severity, RD refers to risk impact duration on the project, and EC refers to the estimation cost.

Phase 2: AHP model establishment

In this phase, the decision-making process begins by dividing the problems into seven main risk factors that impact SC. Each of the principal risk factors is divided into other sub-risk factors. These hierarchical structures make the problem more uncomplicated and more understandable [37]Click or tap here to enter text.. Figure 2 shows the AHP risk assessment model for SC.

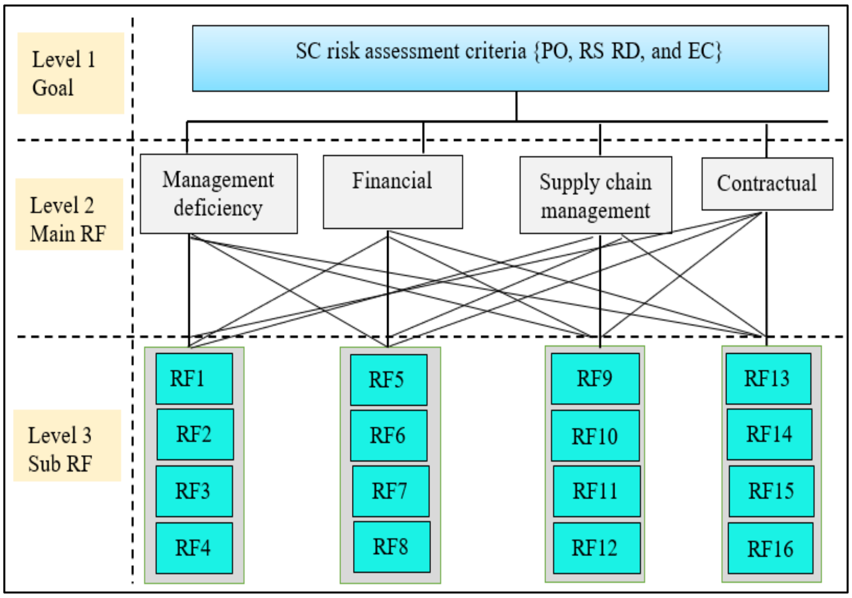

Fig. 2. The AHP risk assessment model.

Phase 3: Pairwise comparison development

Using the ranking scales developed by Saaty [38], a pairwise set of comparison matrices has been generated for the main RF layer and the Sub-RF layer to determine the significance of the comparisons, as shown in Table 6. The five linguistic terms used (equally important, moderately important, strongly important, very strongly important, and extremely important) are converted to numerical values equivalent to 1, 3, 5, 7 and 9.

Table 6. The scale of pairwise comparison for the main risk factors.

Importance scale	Description
1	Equal importance
3	Moderate importance of one over another
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6	Intermediate values between the two adjacent judgements.
1/3, 1/5, 1/9	Value of inverse comparison (If activity i has one of the above numbers assigned to It when compared with activity j, then j has the reciprocal value when compared with i

To effectively use Table 7, the participants (Experts and professionals) were asked four directed questions concerning the interconnected relationships of the sub-risk factors and their analysis parameters. The questions posed by the authors were as follows:

Q1: What is the probability of risk occurrence?
Q2: What is the level of risk severity?
Q3: What is the risk detection level of the team?
Q4: What is the estimated cost required to solve the impact of the risk?

Table 7. The scale of pairwise comparison for the sub-risk factors.

Importance scale	Description
1	Equal
3	Moderate
5	Strong
7	Very strong
9	Extreme
2,4,6	Intermediate
1/3, 1/5, 1/9	Value of inverse comparison

Furthermore, the authors developed a survey to compute the weight of each main risk factor and each sub-risk factor that substantially impacts SC projects in Iraq. The survey consisted of two sections:

Section 1: General information about respondents, which included three questions about respondents' educational degrees, years of experience, and job positions in their organisation.

Section 2: 16 risk factors identified from the focus group to quantify the weight of the main risk factors and sub-risk factors, as based on the work by Saaty [39].

The surveys were distributed to 100 SC construction managers, professionals, contractors, and architects from the five Iraqi SC projects selected, and 42 surveys were received and used in the analysis. The survey results showed that 48% of the respondents have a BSc degree, 33% have an MSc degree, and 19% have a PhD degree. Moreover, 17.75% have work experience of more than 25 years, 15.30% of the respondents have work experience from 16-25 years, 6.7% of respondents have work experience from 6-15 years, and 2.25% of the respondents have work experience from 1-5 years. Finally, among the respondents, 31% were professionals, 19% were managers, 24% were architects, and 26% were contractors.

Subsequently, the surveys were collected from experts, and the authors computed the geometrical mean using Eq. (2). Afterwards, Eq. (3). placed geographical means into pairwise comparison matrices.

$$aij = \sqrt[u]{aij1 \times aij2 \times \ldots . \times aiju} \tag{2}$$

where ai (i, j=1, 2,…u) indicates to the comparison ratio in the pairwise comparison matrix, u indicate to the number of elements

$$F = \begin{bmatrix} a11 & \cdots & a1u \\ \ldots & \ldots & \ldots \\ au1 & \cdots & ann \end{bmatrix} \tag{3}$$

where F is a pairwise comparison matrix with its properties listed below:

aij > 0; $aij = \frac{1}{aji}$ $\forall I$ *where j* =1, 2, …, *u.*

Phase 4: Normalise the pairwise comparison matrices.

The major objective of this phase was to normalise the pairwise values for the main risk factor and Sub-Risk factor by using Eq. (4), which calculates the total sum of the elements in each column (matrix cell's values). Moreover, each element in each column was divided by the sum of its column using Eq. (5).

$$S = \sum_{k=1}^{n} aky \quad (4)$$
$$N = akyl \sum_{k=1}^{n} aky \quad (5)$$

Phase 5: Calculation of consistency ratio

1) The authors calculated the local priorities (weights of the factors {W}), which were obtained by computing the average of the matrices rows values. We then calculated the maximum or principal eigenvalue (called λmax) of each matrix of pairwise comparisons to verify the consistency of the factors layer. This was calculated by using the following:

a. Eq. (6). To compute $\{Ws\}$ to obtain weight sums vector.

b. Eq. (7) To compute $\{Cv\}$ to get the consistency vector.

Eventually, we calculated the λmax value for each matrix by averaging.

$$\{Ws\}=[\mathrm{A}] \ \{W\} \quad (6)$$

$$\{\mathrm{Cv}\}=\{W\mathrm{s}\}*1/\{W\} \quad (7)$$

2) The authors computed the consistency ratio for all reception matrices using Eqs. (8) and (9) to check the consistency of the expert judgement.

$$\text{Consistency Index } (CI) = \frac{\lambda max - z}{z-1} \quad (8)$$

$$\text{Consistency Ratio } (CR) = \frac{CI}{RI} \quad (9)$$

where, λmax = maximum eigenvalue, Z =The number of criteria, and RI= consistency index of pairwise comparison matrix (see Table 8).

Table 8. Consistency index Saaty [39].

n*	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Phase 6: Validation of Consistency Ratio

Depending on the CR values, the pairwise comparison matrices were evaluated by following consistency assessment approach by Ojiako [40]. If the CR value is 10% or more, the matrix consistency is poor and unsuitable for analysis. On the other hand, if the CR value is less than 10%, the matrix is acceptable and usable for further analysis. As such, the authors conducted an AHP analysis after collecting the distributed surveys. The risk factor values (RFV), and the consistency ratio (CR) were determined to verify the consistency of the expert judgment across all matrices was computed, as presented in Table 9. Additionally, the ranking of the sub-risk factors was calculated, as shown in Fig. 3.

From Table 9, it can be noticed that the CR for IQ-1(management deficiency) is 0.0818, while the CR of IQ-2 (financial) risk factor is 0.63. The CR for IQ-3 (supply chain management) risk factor is 0.7712, and the CR for IQ-4 (contractual) risk factor is 0.0531< 0. Therefore, the CR values of the four main risk factors are less than 0.1, which is an acceptable ratio.

Table 9. Analysis of the AHP approach.

MRF	CR	Code	PO	RS	RD	EC	RFV	Rank
IQ-1	0.0818	RF1	4.982	3.924	4.391	1.991	170.909	7
		RF2	3.442	1.321	4.335	5.82	114.716	11
		RF3	4.342	2.753	5.88	4.75	333.861	3
		RF4	4.235	6.998	4.302	3.331	424.69	1
IQ-2	0.631	RF5	2.859	2.889	3.695	4.623	141.091	8
		RF6	2.982	2.785	5.889	4.755	232.554	5
		RF7	3.751	4.544	3.87	2.954	194.852	6
		RF8	3.985	3.212	6.325	3.551	287.484	4
IQ-3	0.7712	RF9	3.594	1.30	2.891	8.545	115.420	10
		RF10	2.354	2.452	5.013	1.772	51.272	16
		RF11	2.674	5.674	53.954	1.40	83.987	14
		RF12	3.529	1.253	2.944	7.993	104.051	12
IQ-4	0.0531	RF13	5.114	4.943	3.998	3.521	424.69	2
		RF14	1.765	2.956	5.110	2.339	62.359	15
		RF15	4.453	3.630	1.25	6.451	130.345	9
		RF16	4.662	4.334	2.852	1.511	87.071	13

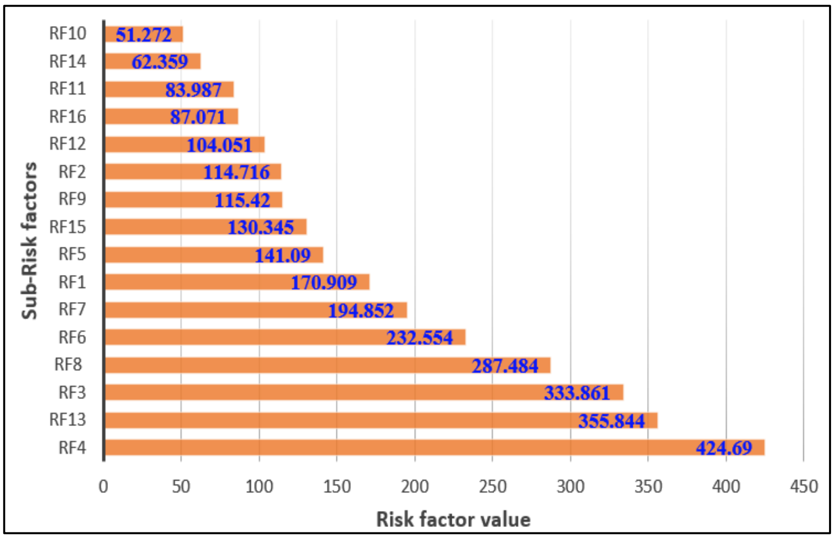

Fig. 3. Ranking of the sub-risk factor using AHP.

3.2. Approach 2: Artificial neural networks (ANNs)

Artificial neural networks (ANNs) are a subset of artificial intelligence (AI) that processes data to simulate the human brain. It is a suitable tool for analysing and conducting pattern recognition to make decisions, define classifications and describe complex relationships between inputs and outputs [41, 42]. ANN is an effective tool in risk assessment due to its ability to handle the large amounts of data gained from previous lessons, its quick predictions of risk and classifications, and its ability to monitor ongoing risks and implement mitigation strategies which enable organisations or businesses to operate more efficiently and reduce their overall risk exposure [9]. A multilayer perception (ANN MLP) was implemented to evaluate the risk factors associated with five SC projects that were chosen in Iraq. MLP is a feed-forward neural network that produces output from the input data [43]. Due to the existence of multiple layers of neurons, ANN-MLP uses back-propagation for training as a supervised learning technique. Figure 4 shows the steps that the authors followed to develop the ANN-MLP model.

Step 1: Determine the structure of ANN-MLP

The ANN-MLP involves three layers: An input layer, a hidden layer, and an output layer. According to Hung [43], the neurons in ANN-MLP are organised into layers, and each neuron connects with another neuron in the same layer or with the next layer. Also, it can produce an output from every neuron based on the input signal.

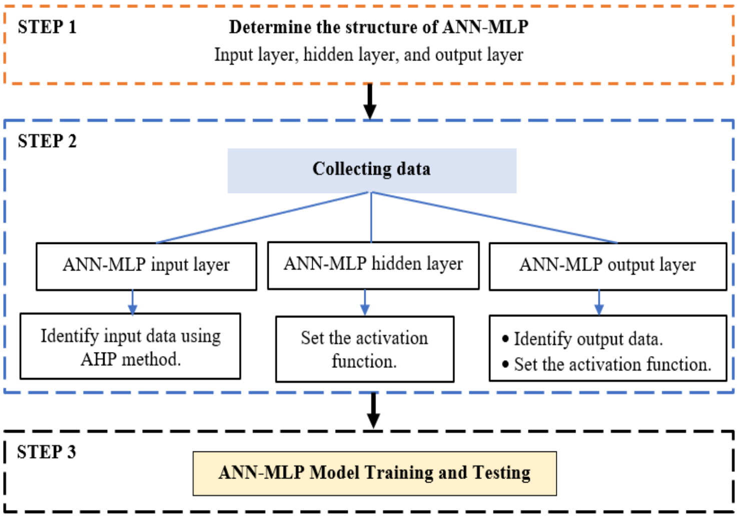

Fig. 4. Developed ANN-MLP model steps.

The input layer receives input data and converts it into a signals network compatible with the problem characteristics and with an equal number of variables and neurons. The hidden layer is located between the input and output layers, where all the required computational operations are carried out. The number of layers and neurons in the hidden layer can change based on the complexity of the data. In the output layer, the data is processed, and the problem's nature and characteristics are known. Fig. 5. illustrates the structure of the ANN-MLP.

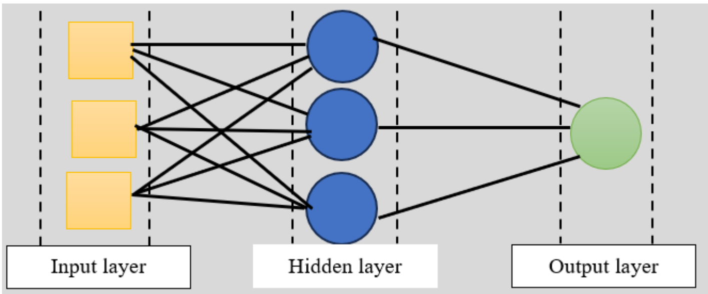

Fig. 5. ANN-MLP structure.

Step 2: Collecting data for ANN-MLP

In this step, the input and output data were collected. The input data involved 16 sub-risk factors (RF1 to RF16) and five sustainable construction projects in Iraq. The risk factors (RFV) values were obtained for ANN input via the AHP method. Afterwards, a hyperbolic tangent activation function was identified for the hidden layer due to its features, such as the accuracy of the results and its allowance for centring the data on the output layer, covering the full range of inputs from -1 to 1 to produce its output [42].The last layer is the output layer which involves one neuron representing project risk (PR) for each completed project, while the activation function (Identity) is selected for the output layer. The output data can be calculated using Eq. (10).

$$\text{Project Risk (PR)} = \frac{Project\ Profit}{Project\ cost} \times 100 \tag{10}$$

Table 10 illustrates the ANN-MLP input and output data for 16 sub-risk factors and 5 SC-completed projects.

Table 10. ANN model input data and output data (in percentages).

	RFV	P1	P2	P3	P4	P5
ANN Input data	**RF1**	429.40	423.89	420.17	411.92	400.60
	RF2	360.88	341.70	365.98	342.49	333.78
	RF3	322.32	319.28	308.73	312.90	321.80
	RF4	283.91	278.21	267.50	251.43	251.43
	RF5	226.07	209.46	233.79	213.36	206.19
	RF6	187.95	187.95	181.40	177.75	173.24
	RF7	170.46	163.55	170.46	165.22	167.94
	RF8	133.69	128.89	117.90	111.83	110.99
	RF9	122.20	122.20	129.35	117.99	129.35
	RF10	112.20	99.04	93.66	96.92	92.58
	RF11	107.06	102.02	104.82	107.06	102.02
	RF12	96.92	95.49	93.97	96.92	96.92
	RF13	87.07	78..02	82.76	87.07	83.85
	RF14	82.85	78.02	82.85	78.02	82.85
	RF15	63.82	61.45	60.92	63.82	61.45
	RF16	51.22	44.79	48.40	51.10	51.22
ANN Output Data	**PR**	2.00	3.00	6.50	7.00	8.50

The example shown in Table 10 shows how the RFV was calculated for Project 1 and risk factor 1 (RF1) using the AHP approach in Eq. (1). Table 11 shows how the RFV value of 429.43 in Table 9 above was calculated for Project 1 and Risk Factor Value (Eq. (1)):

Table 11. Sample showing calculation for project 1 and risk factor 1 using Eq. (1).

Project	Project 1				
	PO	**RS**	**RD**	**EC**	**RFV**
RF1	4.973	6.881	4.931	2.545	429.43

For example, the PR for Project P1 is calculated using ANN Eq. (1). PR for P1 = (2000/100,000) x 100% = 2%.

Step 3: ANN training and testing

In this step, the training and testing process began once the data were collected. The primary goal of training and testing is to reduce the error function. The training mechanism changes the network weight and biases to small random values, after which the output of each neuron in the input layer is calculated to feed the next layer. The training process can be repeated until the desired output is achieved [43].

Five projects were utilised in this study for ANN training and testing and were divided into two sets. The first set consisted of four projects (80% of the sample) which were used for training, and the second set consisted of one project (20% of the sample) used for testing. To select the best ANN-MLP model, the error in the output model can be identified by calculating the Sum Square of Error (SSE) using Eq. (11).

$$SSE = \frac{1}{2}\sum_{i=1}^{p}(y_i - d_i)^2 \tag{11}$$

where p = The total number of projects selected, y_i = The predicted output, and di = The actual output.

As such, it is possible to identify the most suitable ANN model based on its SSE value, as it is considered a measurement to assess the ANN-MLP model. The SSE value ranges from 0.01 to 0.31; the closer the SSE value is to 0.01, the better the outcomes. For this study, several trials were conducted to get the best results. We obtained the most suitable model with the lowest SEE value: 0.012 for training and 0.01 for testing. Also, Fig. 6. Illustrates that RF1 occupied the top rank among the risk factors in terms of impact. RF3 and RF4 followed this. In contrast, RF16 had the lowest impact among the five sustainable construction projects.

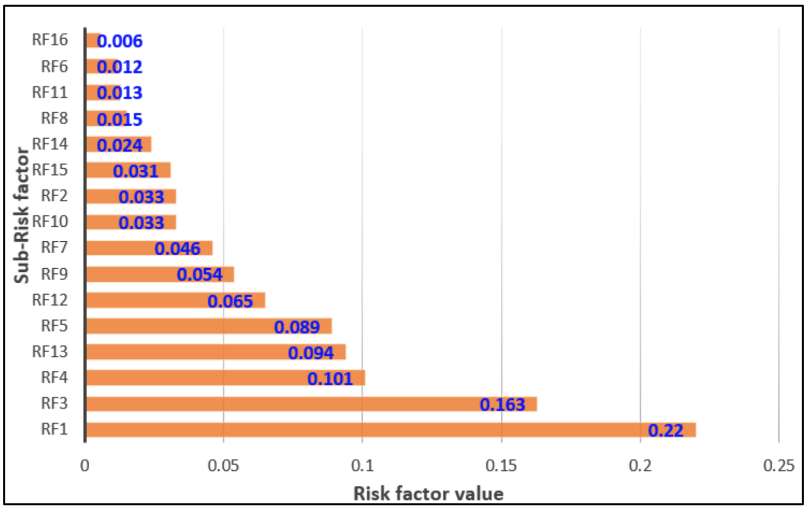

Fig. 6. Sub-risk factor ranking using ANN.

4. Discussion on the Case Study Assessments

The AHP results identified the risk factors with the most significant impact on the five SC projects in Iraq. In descending order of impact, these were RF4 (the lack of use of international risk management standards and codes), RF13 (the lack of contract arbitration), RF3 (poor skills amongst SC managers and team), and RF8 (delays to approving the governmental general budget). On the other hand, ANN results showed that the risk factors with the most considerable impact (in descending order) were RF1 (the slow adoption of new technology), RF3 (poor skills of managers and teams), RF4 (the lack of use of international risk management standards and codes), and RF13 (a lack of contract arbitration). For this study, AHP and ANN approaches were used simultaneously to compare the accuracy, time, and cost results. Therefore, an independent sample t-test was applied to compare the differences in results between the AHP and ANN. To make it easier to compute the risk factor value (RFV) of ANN, the authors took the AHP risk factor values (RFV) from Table 8 and assumed the average for each risk factor from the five sustainable construction (SCP) projects where the results later revealed the correctness. Eventually, the independent sample t-test was calculated, as presented in Table 11. It can be noted that the t-value is 0.7415, which is greater than 0.05, meaning there is no significant difference between AHP and ANN (as shown in Table 12).

Table 12. Illustration of the independent sample t-test.

RFV	AHP	ANNs
RF1	170.909	417.2
RF2	114.716	348.97
RF3	333.861	317.006
RF4	424.69	266.5
RF5	141.091	217.77
RF6	232.554	181.66
RF7	194.852	167.54
RF8	287.484	120.67
RF9	115.42	124.28
RF10	51.272	98.88
RF11	83.987	104.57
RF12	104.051	96.044
RF13	424.69	85.19
RF14	62.395	80.92
RF15	130.345	62.29
RF16	87.071	49.35
Mean	**184.96**	**171.18**
Std. deviation	**122.23**	**111.68**
t-test	**0.7415**	

Eventually, the results of this study demonstrated that the artificial neural network (ANN) approach has several distinct benefits as a risk assessment approach in different sectors, particularly the construction sector. For instance, the ANN approach can deal with considerable amounts of data learned from previous historical records. It can also minimise human errors and perform more complex tasks and activities with a high level of accuracy. The results also revealed that ANN approach can drastically reduce the time needed to process data and obtain results compared to other approaches. Moreover, ANN approach is designed to be fault-tolerant and carry out its function correctly despite some of the neurons in the networks being damaged or destroyed. Finally, the approach is characterised by storing the information on the entire network of ANN, not the database, which allows the network to operate even if additional data are added or disappear.

5. Conclusions

A risk assessment is crucial in sustainable construction as it helps organizations determine potential workplace risks and assign the proper steps to mitigate and remove them. This paper investigated risk assessment and its application undertaken in construction projects by reviewing the literature and conducting semi-structured interviews to identify the benefits and drawbacks of traditional and AI-based risk assessments. In addition, a case study of modern SC projects in Iraq has been undertaken to evaluate risk factors associated with these projects and compare the results obtained in terms of accuracy, time, and cost. Accordingly, two separate approaches were applied, namely AHP and ANN approaches. Finally, an independent sample t-test was computed to compare the differences in results between the AHP and ANN.

The findings also showed a slight difference between the two approaches in the ranking of the risk factors. This is because ANN uses a large amount of data from previous lessons or historical records in analysing and predicting the risks. At the same time, AHP approach is based on human intuition which may be inconsistent. Consequently, ANN approach tends to be more accurate than AHP approach. The paper has contributed to knowledge by using traditional risk assessment (AHP) and AI-based risk assessment (ANN) to assess the impact of risk factors in sustainable construction. Also, the study stressed that AI-based risk assessment could provide accurate and efficient results in less time and minimise human errors compared with traditional risk assessment. Therefore, AI could become the future of risk assessment.

6. Limitations and Future Research

This study only focused on four main risk factors and 16 sub-risk factors in sustainable construction projects. It is also necessary to investigate additional risks that impact sustainable construction in developing countries. For future research, Additional research could use both traditional and AI-based risk assessments to complement each other and support the results when evaluating the risk factors in SC. In addition, future research could develop a model using a hybrid method of AI-based risk assessment, such as ANN and fuzzy logic, that automatically identifies the risk factors in SC projects.

Abbreviations

AI	Artificial intelligence
ANN	Artificial Neural Network
AHP	Analytical Hierarchy Process
SC	Sustainable construction
TRA	Traditional risk assessment

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