Assessment of Success Factors for AI Application in Supply Chain Management with Fuzzy SAW-MOORA Methods

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Abstract

Artificial Intelligence (AI) offers a promising solution for fostering agile and resilient supply chains. Machine learning, natural language processing, and robotics are all potential enablers of supply chain transformation. Such AI technologies can be applied in different supply chain activities. However, selecting the most suitable AI technology is challenging since the features of supply chains changes for different organizations from various sectors. Accordingly, this study aims to present a fuzzy Simple Additive Weighting (SAW)-Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) methodology for assessing thesuccess factors of AI application in Supply Chain Management (SCM). Fuzzy sets approach is applied to represent assessments of experts by handling uncertainty. The combined fuzzy SAW-MOORA methodology offers many benefits such as simplicity, usability, ability to overcome complex situations, flexibility, and simultaneously optimizing two or more conflicting attributes. The criteria, consisting of AI success factors, are weighted with the fuzzy SAW method. Then, AI technologies such as machine learning, autonomous systems, natural language processing, multi-agent systems, etc. are evaluated with the fuzzy MOORA method. To illustrate the effectiveness of the research methodology, an application is also provided.

Keywords
Artificial intelligence, Fuzzy sets, MOORA, SAW and Supply Chain Management.

1. Introduction
Globalization and digital transformation have drastically changed the way supply chains work. The new supply chains can be considered as a part of huge digital networks across different sectors and countries. Organizations aim achieving consistency, traceability and speed while considering their cost constraints, deadlines, and inventory optimization (Riahi et al. 2021). Therefore, Supply Chain Management (SCM) activities become more and more complex.

To keep up with the changing SCM concept, and work well in complex environments, organizations have to creature silient and agile supply chains. In this context, many organizations use Artificial Intelligence (AI) in major parts of their supply chains. AI can be applied in various end-to-end supply chain activities with tools that help in augmentation to automation (Andersen et al. 2018).In recent years, applications based on AI have arisen in various fields. For instance, AI technologies can help organizations removing many levels of manual activities by predicting the trends, optimizing warehousing and logistics set prices, and personalizing promotions (Dash et al. 2019). However, there cannot be a standardized AI technology since the dynamic characteristics of supply chains are case based. They vary with every business and sector. Thus, in this study, Multi-Criteria Decision-Making (MCDM) methodology is utilized to support the decision-making process of AI application in SCM.

The aim of this study is proposing a fuzzy Simple Additive Weighting (SAW)-Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) methodology for assessing success factors of AI application in SCM. Zadeh (1965) proposed the fuzzy sets to overcome the uncertainty in decision-making.In the literature, fuzzy MCDM approaches has been applied in many fields such as ERP system selection, facility location selection, personnel selection and logistics tool selection (Chou et al. 2008; Karande and Chakraborty 2012; Baležentis et al. 2012; Büyüközkan et al. 2012).
This study contributes to literature by applying the fuzzy SAW-MOORA methodology for the first time in AI application in SCM area. In this paper, the success factors for AI applications in SCM are determined based on

literature review, industry reports and expert views. The combined fuzzy MCDM methodology has many benefits such as simplicity, usability, ability to overcome complex situations, flexibility, and of simultaneously optimizing two or more conflicting attributes (objectives) subject to certain constraints(Chou et al. 2008; Karande and Chakraborty 2012).Group Decision Making (GDM) is preferred to eliminate the subjectivity in the decision-making. Then, an application is realized with the participation of experts to illustrate the potential employment of the presented methodology.

The plan of this study is as the following. In the next section, the literature review is provided. The proposed fuzzy SAW-MOORA methodology is presented in the third section. The application for the proposed methodology is offered in the fourth section. Finally, the concluding remarks and suggestions for future studies are listed in the fifth section.

2. Literature Review

AI can be applied through supply chain actions, i.e. from early phases of planning to production, warehouse activities, distribution, communication and logistics; to increasing the customer experience. AI-enabled solutions support the supply chains with an efficient process (quicker results with less cost), precision planning, effectiveness in the process that forms markets, and near-perfect logistics and transport(Andersen et al. 2018).

Development in implementing AI in supply chains definitely advance their performance. However, firms should not rush into AI-enabled supply chains without making sure of the AI pre-requisites and appropriate application plan. Supply chain companies attain much benefits when they have a broad vision, evaluation and monitoring tools, and long- term roadmap(Andersen et al. 2018).

In the literature, AI application in supply chain management has been investigated in the last decade. (Min 2010) examined the potential benefits of AI application in SCM despite AI has been accepted as a decision-aid instrument in those years. Author has linked AI tools (e.g. agent-based systems, genetic algorithm) with associated SCM application fields (e.g. demand planning, negotiation, network design). (Dash et al. 2019) focused on automation of SCM and the listed the examples of AI application in SCM areas such as production, promotion and pricing, delivery and smart manufacturing. (Belhadi et al. 2021) examined supply chain resilience by applying AI based techniques. Authors have found that the most promising AI techniques are fuzzy logic programming, machine learning and big data and agent-based systems. (Fosso Wamba et al. 2021) presented some examples from the sector to highlight the benefits of AI application in SCM. For example, in Netflix, machine learning is used for content production which optimizes resource utilization and enhance customer satisfaction (Fosso Wamba et al. 2021).

(Helo and Hao 2021)conducted an exploratory research on the companies implementing AI-based business models. (Modgil et al. 2021)examined the contribution of AI applications for enhancing supply chain resilience. Authors have found that AI can ensure transparency, provide last-mile delivery and produce personalized solutions. (Riahi et al. 2021)conducted a literature review on AI applications in supply chain and explored the future directions. (Dubey et al. 2021) studied the benefits of AI driven supply chain analytics by using hypothesis testing method.(Sharma et al. 2022) studied the role of AI in SCM by applying citation analysis and trend analysis. Authors have founded the main themes as supply chain network design, supplier selection, inventory planning, demand planning and green supply chain management.

The proposed fuzzy SAW-MOORA methodology has advantages that separate itself from other papers. To the best of the authors' knowledge, it is the first study that apply fuzzy SAW-MOORA methods in this field. Moreover, with the utilization of fuzzy logic the uncertainty of the problem is reflected and by using the GDM approach, the partial judgments of experts are integrated in the decision-making process.

3. Methodology

The methodology of this study consists of three main stages. In the first phase, the problem is defined and the evaluation framework is constructed with the help of a literature review, industry reports, and experts. The evaluation model consists of seven success factors and five key applications of AI. In the second phase, experts evaluated these success factors, and the weights of these factors are calculated by using fuzzy SAW technique. Finally, experts evaluated AI applications, and fuzzy MOORA technique is applied for ranking the alternatives. Figure 1 illustrates the research methodology.

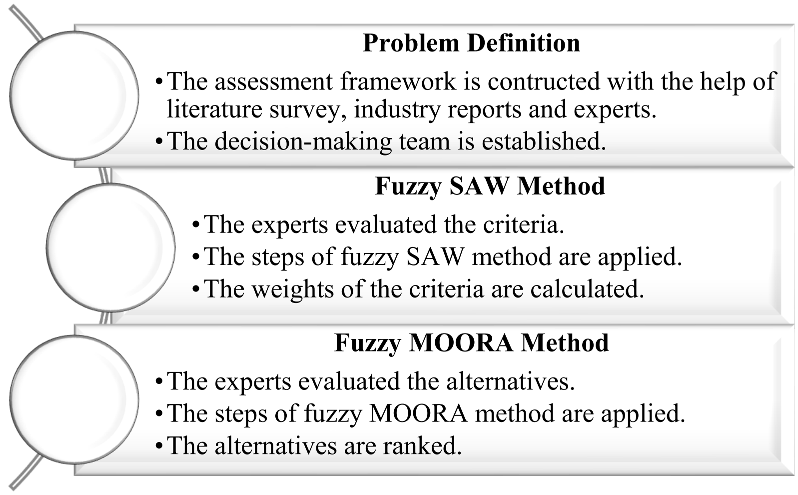

Figure 1. The phases of the methodology

3.1 Fuzzy SAW Method

Chou et al. (2008) introduced the fuzzy SAW technique to solve problems under fuzzy environments. The steps of the fuzzy SAW technique are as follows:

Step 1. DMs evaluate criteria using linguistic terms in Table 1.

Step 2. Let $I_t$be the degree of importance of each DM, where $0 \leq I_t \leq 1$, $t = 1,2,...,k$, and $\sum_{t=1}^{k} I_t = 1$, $\widetilde{\omega t}$be the fuzzy weight of the DMs. I_t is computed as:

$$I_t = \frac{d(\widetilde{w_t})}{\sum_{t=1}^{k} d(\widetilde{w_t})}, t = 1,2, ..., \tag{1}$$

where $d(\widetilde{w_t})$yields the fuzzy weight's defuzzified value using the signed distance.

Table 1. Linguistic scale for fuzzy SAW-MOORA(Beg and Rashid 2013)

Linguistic term	Abb.	Fuzzy Numbers
None	N	(0,0,0.17)
Very Low	VL	(0,0.17,0.33)
Low	L	(0.17,0.33,0.5)
Medium	M	(0.33,0.5,0.67)
High	H	(0.5,0.67,0.83)
Very High	VH	(0.67,0.83,1)
Perfect	P	(0.83,1,1)

Step 3. Aggregated fuzzy weights of individual attributes $(\widetilde{W_j})$ are computed.The aggregated fuzzy attribute weight, $\widetilde{W_j} = (a_j, b_j, c_j)$ of criterion *Cj* assessed by the committee of *k* DMs is computed as:

$$\widetilde{W_j} = (I_1 \otimes \widetilde{W_{j1}}) \oplus (I_2 \otimes \widetilde{W_{j2}}) \oplus \ldots \oplus (I_k \otimes \widetilde{W_{k1}}) \tag{2}$$

where $a_j = \sum_{t=1}^{k} I_t a_{jt}$, $b_j = \sum_{t=1}^{k} I_t b_{jt}$, $c_j = \sum_{t=1}^{k} I_t c_{jt}$.

Step 4. The fuzzy weights of criteria are defuzzified. The defuzzification of $\widetilde{W_j}$ is denoted as $d(\widetilde{W_j})$and computed as:

$$d(\widetilde{W_j}) = \frac{1}{3}(a_j + b_j + c_j), j = 1,2, \ldots, n \tag{3}$$

Step 5. Normalized weight of criterion *Cj*is denoted as W_j and computed as:

$$W_j = \frac{d(\widetilde{W_j})}{\sum_{j=1}^{n} d(\widetilde{W_j})}, j = 1,2, \ldots, n \tag{4}$$

where $\sum_{j=1}^{n} W_j = 1$ and the weight vector W=$(W_1, W_2, \ldots, W_n)$ is constructed.

3.2 Fuzzy MOORA Method

Karande and Chakraborty (2012) proposed the fuzzy MOORA method to solve problems under fuzzy environments. The steps of the fuzzy MOORA technique are as follows:
Step 1. To construct fuzzy decision matrix, DMs evaluate alternatives using linguistic terms in Table 1.
*Step 2.*The fuzzy decision matrix is normalized by using the following equations:

$$\boldsymbol{r_{ij}^{l}} = \frac{x_{ij}^{l}}{\sqrt{\sum_{i=1}^{m}\left[\left(x_{ij}^{l}\right)^{2}+\left(x_{ij}^{m}\right)^{2}+\left(x_{ij}^{n}\right)^{2}\right]}} \tag{5}$$

$$\boldsymbol{r_{ij}^{m}} = \frac{x_{ij}^{m}}{\sqrt{\sum_{i=1}^{m}\left[\left(x_{ij}^{l}\right)^{2}+\left(x_{ij}^{m}\right)^{2}+\left(x_{ij}^{n}\right)^{2}\right]}} \tag{6}$$

$$\boldsymbol{r_{ij}^{n}} = \frac{x_{ij}^{n}}{\sqrt{\sum_{i=1}^{m}\left[\left(x_{ij}^{l}\right)^{2}+\left(x_{ij}^{m}\right)^{2}+\left(x_{ij}^{n}\right)^{2}\right]}} \tag{7}$$

where $\boldsymbol{x_{ij}^{l}}$, $\boldsymbol{x_{ij}^{m}}$ and $\boldsymbol{x_{ij}^{n}}$ denotes the lower, middle and upper values of membership function for i^{th} alternative and j^{th}criterion.

*Step 3.*The weighted normalized decision matrix is calculated by using:

$$v_{ij}^{l} = w_j r_{ij}^{l} \tag{8}$$
$$v_{ij}^{m} = w_j r_{ij}^{m} \tag{9}$$
$$v_{ij}^{n} = w_j r_{ij}^{n} \tag{10}$$

Step 4. The overall ratings of beneficial and non-beneficial criteria for each alternative are calculated.
For beneficial criteria, the overall ratings of an alternative are calculated as:

$$s_i^{+l} = \sum_{j=1}^{n} v_{ij}^{l} \mid j \in J^{max} \tag{11}$$
$$s_i^{+m} = \sum_{j=1}^{n} v_{ij}^{m} \mid j \in J^{max} \tag{12}$$
$$s_i^{+n} = \sum_{j=1}^{n} v_{ij}^{n} \mid j \in J^{max} \tag{13}$$

For non-beneficial criteria, the overall ratings of an alternative are calculated as:

$$s_i^{-l} = \sum_{j=1}^{n} v_{ij}^{l} \mid j \in J^{min} \tag{14}$$
$$s_i^{-m} = \sum_{j=1}^{n} v_{ij}^{m} \mid j \in J^{min} \tag{15}$$
$$s_i^{-n} = \sum_{j=1}^{n} v_{ij}^{n} \mid j \in J^{min} \tag{16}$$

*Step 5.*The overall performance index (S_i) for each alternative is calculated by using the vertex method as:

$$S_i(s_i^{+}, s_i^{-}) = \sqrt{\frac{1}{3}\left[\left(s_i^{+l}-s_i^{-l}\right)^2+(s_i^{+m}-s_i^{-m})^2+(s_i^{+n}-s_i^{-n})^2\right]} \tag{17}$$

5. Application

In this section, an application is provided to obtain an in-depth knowledge of critical success factors and technologies for the application of AI in SCM. Four experts assessed the critical success factors and the alternatives. All experts have enough know-how in AI technology and supply chain domain. Experts are selected grounded on their expertise and knowledge and experts' weights are assumed to be equal. The critical success factors are determined based on experts' views, literature survey and industry reports' investigation. These factors are listed in Table 2.

Table 2. The critical success factors

Critical Success Factors (CSFs)	References
Access to real-time data (CSF1)	(Syazwan et al., 2015; Andersen et al., 2018)
Access to multi-source data (CSF2)	(Andersen et al., 2018; Dora et al., 2021)
Support consumer-driven objectives (CSF3)	(Andersen et al., 2018; Dora et al., 2021; Thoo et al., 2011; Syazwan et al., 2015)
Continuous, self-monitored and self-learning process (CSF4)	(Andersen et al., 2018; Dora et al., 2021)
Networked decision-making and scalable tools (CSF5)	(Andersen et al., 2018; Syazwan et al., 2015)
User-AI interaction opportunity (CSF6)	(Andersen et al., 2018; Dora et al., 2021)
Organization culture and environment (CSF7)	(Dora et al., 2021; Thoo et al., 2011)

The five alternatives are determined based on the report of Big Innovation Center (BIC)(Andersen et al., 2018)and the authors' own elaboration. They can be listed as:

- **Machine Learning (A1):** It enables machines to learn how to perform tasks without being explicitly told how.
- **Autonomous Systems (A2):** It is a network or collection of networks that are all managed by a single organization.
- **Semantic Web (A3):**It enables computers to understand and reason about the content of web pages so that browsers can make smarter decisions.
- **Natural Language Processing (A4):** It enables machines to interact in ordinary human languages rather than in machine-oriented programming languages.
- **Multi-Agent Systems (A5):**It enables AI systems to cooperate with each other.

In the following section, these alternatives (i.e., AI applications) are assessed considering the seven criteria (i.e., success factors) provided in Table 2.

5.1 Calculation of Success Factors' Weights

First, expertsevaluate the critical success factors.The assessment of the factors is presented in Table 3.

Table 3.Assessment of critical success factors

	DM1	DM2	DM3	DM4
CSF1	VH	VH	M	VH
CSF2	VH	VL	VH	H
CSF3	VH	P	VP	VH
CSF4	VH	H	VH	P
CSF5	VH	VH	VH	VH
CSF6	VH	VH	H	VH
CSF7	H	H	VH	H

Then, (1)-(4) are applied to find the weights of the criteria. The weights of the criteria are provided in Table 4. At the end of the fuzzy SAW method, the most important critical success factor for AI application in SCM is found as "Support consumer-driven objectives(CSF3)".The second important criterion is found as "Access to multi-source data (CSF2)" where the third criterion is ranked as "Continuous, self-monitored and self-learning process (CSF4)".

Table 4.The weights of the criteria

	Deffuzzified weights	Normalized weights	Ranking
CSF1	0.750	0.138	5
CSF2	0.625	0.115	7
CSF3	0.888	0.164	1
CSF4	0.819	0.151	3
CSF5	0.833	0.154	2
CSF6	0.792	0.146	4
CSF7	0.708	0.131	6

5.2 Assessment of Alternatives

Experts evaluate the alternatives by using the linguistic scale provided in Table 1. Table 5 provides the assessment of the first expert for the alternatives according to the critical success factors.

Table 5. Assessment of the alternatives according to the first expert

	CSF1	CSF2	CSF3	CSF4	CSF5	CSF6	CSF7
A1	M	L	H	VH	P	VH	L
A2	P	M	L	VH	H	M	L
A3	L	M	M	H	P	P	VL
A4	L	L	VH	H	L	VH	VL
A5	VH	P	M	M	VH	L	L

Then, the assessments of four experts are aggregated and the obtained fuzzy decision matrix is normalized by using (5)-(7). Table 6 presents the normalized decision matrix.

Table 6. Normalized decision matrix

	CSF1			**CSF2**			**CSF3**		
A1	0.213	0.277	0.343	0.166	0.237	0.310	0.208	0.278	0.345
A2	0.178	0.245	0.295	0.163	0.238	0.311	0.071	0.137	0.208
A3	0.212	0.277	0.311	0.201	0.274	0.348	0.172	0.242	0.312
A4	0.214	0.276	0.343	0.164	0.237	0.311	0.278	0.345	0.415
A5	0.131	0.195	0.262	0.200	0.274	0.330	0.137	0.208	0.278

	CSF4			**CSF5**			**CSF6**			**CSF7**		
A1	0.246	0.305	0.367	0.302	0.366	0.382	0.182	0.249	0.316	0.071	0.209	0.348
A2	0.154	0.213	0.275	0.112	0.175	0.239	0.116	0.182	0.250	0.142	0.277	0.419
A3	0.214	0.276	0.320	0.158	0.222	0.271	0.150	0.215	0.266	0.105	0.245	0.383
A4	0.122	0.183	0.245	0.176	0.238	0.303	0.283	0.348	0.399	0.071	0.209	0.348
A5	0.215	0.274	0.337	0.191	0.254	0.319	0.183	0.248	0.316	0.071	0.209	0.348

Then, the normalized matrix is weighted by using the criteria weights obtained in fuzzy SAW and by applying (8)-(10).The overall ratings of alternatives are determined by applying (11)-(16). Finally, the overall performance index (S_i) for each alternative is calculated to rank the alternatives by applying (17). The results of the fuzzy MOORA method are given in Table 7.

Table 7. Ranking of alternatives

	S_i	**Ranking**
A1	0.281	1
A2	0.215	5
A3	0.252	3
A4	0.272	2
A5	0.245	4

According to results in Table 7, the AI technologies can be ranked as:Machine Learning (A1), Natural Language Processing (A4), Semantic Web (A3), Multi-Agent Systems (A5) and Autonomous Systems (A2), respectively.

6. Conclusion

AI praises the existing process, impulses the analytics and technology as well as supplements the talent within the supply chain. Applying AI results in continuous development, occasionally self-improved. AI canbe considered as an aid tool fororganizations to become more smart, agile, resilient, constructa customer-focused supply chain, and be demand-sensitive.

This paper aimed to present the fuzzy SAW-MOORA methodology for assessing AI critical success factors and AI technologies in SCM concept. The critical success factors were weighted with the fuzzy SAW method. Then, technologies such as machine learning, autonomous systems, natural language processing, etc., were assessedby applying the fuzzy MOORA method. The most importantfactor was found as "Support consumer-driven objectives (CSF3)" and the first ranked AI technology was determined as "Machine Learning (A1)".

For future studies, it can be interesting to implement other fuzzy MCDM methods and compare the results with the existing methodology. Besides, other fuzzy set extensions (e.g. intuitionistic fuzzy sets, type-2 fuzzy sets, interval valued fuzzy sets, hesitant fuzzy sets etc.) may be preferred in future research.

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