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Pharmaceutical Supply chain Risk Assessment During COVID-19 Epidemic

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Abstract: The global health products supply chain is negatively influenced by the COVID-19 pandemic. Moreover, the risks in the pharmaceutical supply chain (PSC) have increased. Assessment and mitigation risks in PSC are essential issues to control and counter these risks. In this study, a 2-Tuple ARAS-BWM approach, which combines ARAS and BWM methods under linguistic 2-Tuple environment, is proposed to evaluate and address various risks to the best mitigation strategies in the pharmaceutical industry in Tunisia during COVID-19. Noted that the main risk identified in the PSC is related to supply and suppliers and its best mitigation strategy is reducing risk.

Keywords: Pharmaceutical supply chain, risk assessment, COVID-19, risk mitigation strategy, 2-Tuple BWM, ARAS, 2-Tuple linguistic environment.

1. INTRODUCTION

Supply chain management (SCM) is an important process in the business environment, business ecosystems, business networks, and keiretsu relationships. This process helps to achieve higher performance and to improve service customers (Bechtel et al. (1997)). In fact, good SCM keeps companies that find the right suppliers, reduce costs and deliver the right quantities with the right quality of products to the consumer faster (Mavi et al. (2016)). Supply chain risk management (SCRM) has been of growing interest for the past years in order to identify, prioritize and mitigate risk sources as well as to develop predictive enterprise risk management (Ho et al. (2015)). Supply chain risks give rise to operational fluctuations being the flow of products, price variability, and demand uncertainties. It is also caused by environmental risks which are usually related to different factors related to social, economic, governmental, and climate factors, including the threat of terrorism. Therefore, managing risk is essential in any sector to achieve the targeted goals. On the other hand, the COVID-19 epidemic outbreaks can be considered one of the different types of disasters, and it will become a pandemic leading to a global crisis if it is not effectively controlled. It is the most recent and most dangerous pandemic in 2020 that has caused much strain on the healthcare system and especially on the healthcare supply chain (Zamiela et al. (2021)). Moreover, the pharmaceutical supply chain (PSC) is seen as a crucial element of the health care system and especially in managing risks (Aigbavboa et al. (2020), Jlassi et al. (2021), Faghhi-Rooobia et al. (2021), Sibevei et al. (2022)).

This research proposes an innovative multi-criteria decision approach for analyzing the overall impact of COVID-19 on the pharmaceutical supply chain risk (PSCR) and managing PSCR by addressing each type of risk according to the best mitigation strategy. The proposed approach is based on the combination of the multicriteria decision methods ARAS and BWM under 2-Tuple linguistic environment. The 2-Tuple BWM obtains weights priority of all risk criteria whereas the 2-Tuple ARAS ranks each type of risk to the best mitigation strategy.

The remainder of this paper is organized as follows: in section 2, a literature review on pharmaceutical supply chain risk management (PSCR) is presented. In section 3, the 2-Tuple BWM–ARAS proposed approach for assessing and ranking PSCR during COVID-19 is introduced. In section 4, an application of the proposed approach to the supply chain of pharmaceuticals is given. Finally, a conclusion and potential research opportunities are presented.

2. LITERATURE REVIEW

2.1 MCDM method for solving PSCR problem

Many studies focused on PSCR using different methodologies such as Multi-Criteria Decision Making (MCDM) methods. Enyinda et al. (2009) used AHP method for managing global pharmaceutical supply chain outsourcing risk. Four criteria (regulatory risk; business risk; technical risk; and intellectual property risk) are proposed in this paper by the decision maker to assess four alternative policy options (risk reduction, risk acceptance, risk avoidance, and risk transfer). The AHP method was also used by Kamath et al. (2012) to deal with the same objective. The most important risk to be managed in this paper are inventory risk, regulatory risk, financial risk, and counterfeit risk. Jaberidoost et al. (2015) used the group AHP and SAW methods to evaluate risk assessment in pharmaceutical industry in Iran. The group AHP approach is used to prioritize pharmaceutical supply chain and the SAW technique is used to obtain a ranking of 86 risks after the calculation of their final score. El Mokrini et al. (2016), on the other hand, used fuzzy AHP-PROMETHEE approach for risk assessment in order to measure the level of risk related to outsourcing logistics. The fuzzy AHP method is applied for determining criteria priority, the fuzzy PROMETHEE is used
for computing the outranking flows and the PROMETHEE TRI is applied for ranking and assigning risk to categories. In addition, Mavi et al. (2016) proposed a hybrid MCDM method. They used Shannon entropy method to find criteria weights and fuzzy TOPSIS to rank suppliers. As an example, Enyinda (2018) proposed the AHP methods and sensitivity analysis to identify, evaluate and manage various categories of risks in pharmaceutical supply chain. Moktadir et al. (2018) used the Delphi method to select the pertinent risks associated to five pharmaceutical companies in Bangladesh. Then, they applied the AHP method to analyze the risks and determine their weights. In addition, Aigbavboa et al. (2020) used Delphi method to select the most critical risks associated with the outsourcing of pharmaceutical outbound value chains in Nigeria. As a matter of fact, Paul et al. (2020) used a Bayesian Belief Network (BBN) model to evaluate the transportation disruption risk in supply chains in the pharmaceutical industry in Bangladesh. Jlassi et al. (2021) also proposed the fuzzy AHP method to identify the most important risk in Tunisian pharmaceutical supply chain in the time of Covid-19. One of relevant studies in the context is a research conducted by Osorio Gómez et al. (2021) where operational risk is assessed in a pharmaceutical company in Colombia, particularly in the transport and storage of finished products for export using Ontologies and Fuzzy Quality Function Deployment (FQFD) methods to reach the results that the chain expects. In another work, Faghih-Roohia et al. (2021) proposed a hybrid approach to evaluate risk for selecting shipping lanes for pharmaceutical products. A FMEA table is presented for risk evaluation of pharmaceutical product shipments and logistics and an intuitionistic fuzzy hybrid TOPSIS method is used for ranking and scoring risk categories.

The pharmaceutical industry plays a critical role in the medical and health care systems, as the COVID-19 crisis has proved. For this reason, managing risk becomes an important mechanism in PSC. In our paper, we propose to address these challenges in PSC using BWM and ARAS methods under a linguistic 2-Tuple environment.

2.2 The 2-Tuple BWM method

The 2-Tuple BW technique is proposed by Labella et al. (2021) for managing linguistic information and decreasing the number of pairwise comparison in decision-making problems. In fact, it is an extension of the BWM in which the human evaluations are given by crisp numbers (Rezaei (2015)). The main objective of the later is to obtain optimal weights of criteria by optimization model based on pairwise comparisons vectors.

According to the literature review, the BWM is more commonly used in PSCM (Vimal et al. (2022), Chauhan et al. (2022)) whereas its extension has yet to be studied in this field. Our paper focuses on the importance of using the 2-Tuple BWM in this discipline. This method was combined, in this contribution, with a novel extended MCDM technique which is based on the ARAS method.

2.3 The ARAS method

Zavadskas and Turskis (2010) are the first authors whose propose the ARAS technique in 2010. This method aims to select the best alternative among others according to a set of criteria. It has been touched diverse disciplines (Liu et al. (2021)) such as the industrial sector, agricultural sector, services sector, and information industry sector. Additionally, the ARAS method was extended to 13 types of different information environments from 2010 to 2020 (triangular fuzzy set environment, trapezoidal fuzzy set environment, gray numbers, rough set, hesitant fuzzy linguistic term set, probability multivalued neutrosophic set, interval-valued type-2 hesitant fuzzy set, interval-valued pythagorean fuzzy set, intuitionistic fuzzy set, z-number, picture fuzzy set, interval type-2 fuzzy environment, hesitant fuzzy sets) to deal with the uncertainty and subjectivity of humans disciplines (Liu et al. (2021)). In 2022, the ARAS method was extended to the state of hierarchical linguistics term (ELH) for handling multi granular linguistic data in the group decision-making problem without loss of information (Daoud Ben Amor et al. (2022)).

An extension of the ELH-ARAS method to interval rough number was also proposed by Amor et al. (2021). Its main objective is to obtain a ranking of alternatives taking into consideration the imprecision and the uncertainty provided by the decision-makers. In our contribution, the ARAS method was extended to the case of 2-Tuple linguistic environment for solving the problem of PSCRM.

3. THE PROBLEM DESCRIPTION AND THE PROPOSED 2-TUPLE BWM-ARAS APPROACH

The pharmaceutical supply chain industry has been related to many risks due to the intricate structure of its activities. Therefore, risk management is becoming a more focused activity in the healthcare industry and especially in the time of the COVID-19 epidemic. The current study is an original effort into the risks associated with PSC in Tunisia. In this section, a novel 2-Tuple BWM-ARAS approach is introduced to evaluate different types of risks in PSC during the COVID-19 crisis. The 2-Tuple BWM is used to calculate the preference degree of each criterion and the 2-Tuple ARAS model is proposed to rank the PSC risk to the best mitigation strategies in the time of COVID-19 pandemic. The following figure (Fig.1) illustrates this approach.

The main steps of this approach are listed as follow:

Figure 1. Proposed approach for managing PSC risk
Step 1: Define the set of the benefit (B), cost (C) criteria \((C_i, (j = 1, \ldots, n))\) and the alternative set \((ALT_i, (i = 1, \ldots, m))\).

Step 2: Construct the initial decision matrix \(y_{i,k}\). The decision maker gives his/her evaluation of the alternative \(ALT_i\) with respect to each criterion \(C_j\) based on multi-granular linguistic term sets. Precisely, the expert can express his/her assessment in different scales that are subsequently transformed into 2-tuple linguistic value.

Step 3: Unifying the heterogeneous information into a singular expression domain using three main steps (Herrera et al. (2005)): The choice of the Basic Linguistic Term Set (BLTS) with a larger number of terms than the number of terms that a person is able to discriminate, the transformation of the input information into fuzzy set and the transformation of a fuzzy set into 2-Tuple linguistic values in the interval of granularity of \(S_T\) \([0, 1]\). The applicability of this step will not be necessary if the expert gives his/her assessment of the alternative \(ALT_i\) according to each criterion \(C_j\) with single linguistic term set, i.e. just one elicitation scale.

Step 4: Compute the based normalized 2-Tuple linguistic decision matrix \(\tilde{y}_{ij,m,n}\) using these two formulas:

\[
\tilde{y}_{ij} = \frac{\Delta^{-1}(\tilde{r}_{ij}, a_{ij})}{\sum_{i=1}^{m} \Delta^{-1}(\tilde{r}_{ij}, a_{ij})}
\]

The cost attributes are normalized by applying two stage procedures:

\[
r'_{ij} = \frac{1}{\Delta(\tilde{v}_{ij}, a_{ij})}; \tilde{v}_{ij} = \frac{\Delta^{-1}(\tilde{r}_{ij}, a_{ij})}{\sum_{i=1}^{m} \Delta^{-1}(\tilde{r}_{ij}, a_{ij})}
\]

Step 5: Select the best \(C_B\) and the worst criteria \(C_w\) of all hierarchical level. The decision maker is then asked to make pairwise comparisons of \(C_B\) over all the other criteria and also to make pairwise comparisons of all the criteria over the \(C_w\) using linguistic values which are transformed into 2-Tuple value respectively \((a_{Bj} = \Delta^{-1}(d_{Bj}, a_{Bj})) = \beta_{Bj}\), \(a_{wj} = \Delta^{-1}(d_{wj}, a_{wj}) = \beta_{wj}\). The obtained 2-Tuple Best-to-Others vector is presented by \(A_B = (a_{B1}, a_{B2}, \ldots, a_{Bj})^T\) and the attained 2-Tuple Others-to-Worst vector is given by \(A_w = (a_{1w}, a_{2w}, \ldots, a_{wj})^T\). Then, find the optimal weights \(W_{2-Tuple\ BW}\) and \(\xi\) in all hierarchical level solving model (3) (Labella et al. (2020)).

\[
\begin{align*}
\text{Min } & \zeta \\
\text{s.t.} & \sum_{j=1}^{n} w_j = 1, \\
& \frac{w_j}{w_{j'}} - \Delta^{-1}(d_{Bj}, a_{Bj}) \leq \xi, \\
& \frac{w_j}{w_{j'}} - \Delta^{-1}(d_{wj}, a_{wj}) \leq \xi, \\
& w_j \geq 0, j = 1, 2, \ldots, n.
\end{align*}
\]

Afterwards, calculate and verify the consistency ratio \(CR(n, a_{BW})\) of the pairwise comparisons given by expert using this formulas (Labella et al. (2020)):

\[
CR(n, a_{BW}) = \frac{\xi(n,a_{BW})}{RACI(n,a_{BW})}
\]

where \(RACI(n, a_{BW})\) is defined as an average value of consistency \(\epsilon\) derived by selecting randomly \(N\) configurations of possible Linguistic Best-Worst Pairwise Comparison Matrix for a given number of criteria and the reference comparison:

\[
RACI(n, a_{BW}) = \frac{1}{N} \sum_{k=1}^{N} \epsilon^k(n, a_{BW})
\]

And \(\epsilon^k(n, a_{BW})\) is the consistency of the \(k\)-th sample LBWPCM with the Best-Worst preference \(a_{BW}\).

Step 6: Calculate the weighted of the based normalized 2-Tuple linguistic decision matrix \(\tilde{r}_{ij}\) for all the criteria using this formula:

\[
\tilde{r}_{ij} = \Delta^{-1}(\tilde{r}_{ij}, a_{ij}) \star W_{2-Tuple\ BW}
\]

With \(W_{2-Tuple\ BW}\) is the weights obtained in step 4.

Step 7: Determined the 2-Tuple values of optimality function for the \(i^{th}\) alternative.

\[
S'_i = \sum_{j=1}^{n} \tilde{r}_{ij}, i = 0, \ldots, m
\]

Step 8: Calculate the utility alternative degree. The degree of the alternative utility is determined by a comparison of the variant, which is analysed, with the ideally best one \(S_0\).

\[
K'_i = \frac{S'_i}{S_0}, i = 0, \ldots, m
\]

Where \(S_i\) and \(S_0\) are the optimality 2-Tuple criterion values. In this order, a ranking of the alternatives is deduced according to the utility values.

4. AN ILLUSTRATIVE APPLICATION

The COVID-19 pandemic has affected significantly many companies and industries which forced them to transform their global supply chain model. In fact, it also has a substantial influence on the available healthcare facilities and treatment systems in almost all countries. Therefore, risks that influence the pharmaceutical companies could affect the health system quality and disrupt the supply of medicines. The main goal of this contribution is to evaluate several risks in the pharmaceutical supply chain and to rank them to the best mitigation strategies (reduce risk (\(ALT_1\)), accept risk (\(ALT_2\)), avoid risk (\(ALT_3\)), and transfer risk (\(ALT_4\)) by giving quantified empirical results. Based on the literature review like in figure 2, some important risks affecting the PSC are presented as supply and supplier risks, inventory risks, counterfeit risks, and financial risks. Hence, we opted for the application of our proposed approach. In our case, the decision-maker gives their evaluation of the \(ALT_i\) with respect to each criterion \(C_j\) and sub-criterion \(SC_j\) based on multi granu-
For the same example, we do not need to do the unification phase because in this level the expert chooses to give his evaluation with the largest linguistic term set $S^9$.

In step 4, the expert determined the best (B) and the worst criteria (W) as well as sub criteria for all hierarchical levels. For example, for level 2 and for criterion $C_1$, the sub-criteria $SC_{17}$ is selected as the best criterion and the sub-criterion $SC_{13}$ is regarded as the worst criterion. Then, decision maker gives his preferences of the best criteria compared to all other criteria and his preferences of all other criteria compared to the worst criteria. The evaluation of the expert is given by linguistic term sets which are translated into 2-Tuple linguistic values. For the same example, the 2-Tuple preferences values of the best sub-criterion $SC_{17}$ over all other sub-criteria $SC_1$ and the 2-Tuple preferences values of all the criteria over the worst vector given by expert are listed in Table 2.

Based on the values of the 2-Tuple BWM obtained of all criteria and sub-criteria, we construct five non-linear constrained optimization problems to determine the ideal weights of each criterion and sub-criteria of all hierarchical levels using (3). Solving these models by lingo software, the weight vector of all criteria and sub-criteria for all hierarchical levels is obtained. Equation (8) present the non-linear constrained optimization problem of criterion ($C_1$). By solving (8), we obtain the priority local weights of $C_1$:

$$W_{SC_{1j}}^{2-Tuple-BWM} = [w_{SC_{11}}, w_{SC_{12}}, w_{SC_{13}}, w_{SC_{14}}, w_{SC_{15}}, w_{SC_{16}}, w_{SC_{17}}] = [0.088, 0.088, 0.381, 0.088, 0.215, 0.088, 0.05].$$

The priority local weights of criteria in level 2 are as follow:

$$W_{C_{1j}}^{2-Tuple-BWM} = [w_{C_{11}}, w_{C_{12}}, w_{C_{13}}, w_{C_{14}}] = [0.683, 0.185, 0.05, 0.083].$$

Table 1. 2-Tuple linguistic decision matrix for managing PSCR

| B/C | $SC_{11}$ | $SC_{12}$ | $SC_{13}$ | $SC_{14}$ | $SC_{15}$ | $SC_{16}$ | $SC_{17}$ |
|-----|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| $ALT_1$ | $(S_7^5,0)$ | $(S_8^5,0)$ | $(S_7^6,0)$ | $(S_8^6,0)$ | $(S_7^6,0)$ | $(S_8^6,0)$ | $(S_7^6,0)$ |
| $ALT_2$ | $(S_7^5,0)$ | $(S_8^5,0)$ | $(S_7^6,0)$ | $(S_8^6,0)$ | $(S_7^6,0)$ | $(S_8^6,0)$ | $(S_7^6,0)$ |
| $ALT_3$ | $(S_7^5,0)$ | $(S_8^5,0)$ | $(S_7^6,0)$ | $(S_8^6,0)$ | $(S_7^6,0)$ | $(S_8^6,0)$ | $(S_7^6,0)$ |
| $ALT_4$ | $(S_7^5,0)$ | $(S_8^5,0)$ | $(S_7^6,0)$ | $(S_8^6,0)$ | $(S_7^6,0)$ | $(S_8^6,0)$ | $(S_7^6,0)$ |

The priority local weights of criteria in level 2 are as follow:

$$W_{C_{1j}}^{2-Tuple-BWM} = [w_{C_{11}}, w_{C_{12}}, w_{C_{13}}, w_{C_{14}}] = [0.683, 0.185, 0.05, 0.083].$$

Table 2. Supply and supplier risk assessment using -Tuple BWM approach

| Criteria ($C_i$) | Evaluation of experts with 9 linguistic terms | Value $\beta_{BW}$ and 2-Tuple-BWM |
|------------------|---------------------------------------------|----------------------------------|
| B/W Sub-criteria | $SC_{11}$ | $SC_{12}$ | $SC_{13}$ | $SC_{14}$ | $SC_{15}$ | $SC_{16}$ | $SC_{17}$ |
| Best Sub-criteria | VH | VH | P | MH | P | MH | 7 |
| $SC_B = SC_{17}$ | 7 |
| Worst Sub-criteria | VL | ML | MH | VL | 1 |
| $SC_W = SC_{13}$ | 1 |

l linguistic term sets. The expert provides his preferences with five $S^5$, seven $S^7$, and nine $S^9$ linguistic terms. An example of results is introduced in order to explicate the procedure of the proposed approach. For example, for level 2 and for criterion $C_1$, the expert chooses to give his assessment with 9 linguistic term set (table 2) (None (N), Very Low (VL), Medium Low (ML), Low (L), Average (A), Medium High (MH), High (H), Very High (VH), Perfect (P)) which are transformed into 2-Tuple linguistic values in Table 1. The next step consists in unifying the non-homogeneous information into a single linguistic term set.
Model 1 (Sub-criterion) – $C_1$

\[
\begin{align*}
\text{Min } & \xi \\
\left\{ & \frac{w_{17} - 0}{w_{11}} \leq \xi; \frac{w_{17} - 0}{w_{12}} \leq \xi; \\
& \frac{w_{17} + 0.333}{w_{13}} \leq \xi; \frac{w_{17} - 0}{w_{14}} \leq \xi; \\
& \frac{w_{17} + 0.333}{w_{15}} \leq \xi; \frac{w_{17} - 0}{w_{16}} \leq \xi; \\
& \frac{w_{11} - 0}{w_{13}} \leq \xi; \frac{w_{12} - 0}{w_{13}} \leq \xi; \\
& \frac{w_{14} - 0}{w_{13}} \leq \xi; \frac{w_{15} - 0}{w_{13}} \leq \xi; \\
& \frac{w_{16} - 0}{w_{13}} \leq \xi; \frac{w_{17} + 0.333}{w_{13}} \leq \xi; \\
& \sum_{j=1}^{7} w_j \leq 1, \ j = 1, \ldots, 7 \\
& w_j \geq 0.05, \ j = 1, \ldots, 7
\right. 
\end{align*}
\] (8)

In this order, we notice that the most important risk to be managed is supply and suppliers risk with a priority of 0.683 which is followed by organization and strategies issues (0.185). Then, we find financial (0.083), and logistic (0.05). Before going to the next step, we should check the consistency degree ((4), (5)) using Julia software. Following the example above, the consistency ratio for criterion $C_1$ is validated with a value inferior to 0.4445 ($CR_{C_1} = 0.416$).

In the next step, we calculate the normalized 2-Tuple linguistic value using (1) and (2) for obtaining the 2-Tuple normalized decision-making matrix $\overline{W}$. Afterword, we calculate the based linguistic 2-Tuple weighted normalized decision matrix for all the criteria $\overline{R}_{ij}$ by (6). Then, a calculation of the optimality function values ($S_i$) and the utility degree ($K_i$) is done using (7) and (8) to obtain the ranking result of each alternative. Using the same example, the optimality function values and the utility degrees for $C_1$ are presented in Table 3.

Fig.3 represent the ranking of mitigation strategies for the $C_1$. Following the similar calculation, we find the ranking of risks management strategies for the all major decision criteria (Table 4). We notice that the most important risk to be managed has the following rank:

$$ALT_1 > ALT_3 > ALT_4 > ALT_2$$

It means that its best strategy is reduce risk which is followed by avoid risk. Then, we find transfer and accept risk respectively.

Table 3. Solution and ranking results for criteria supply and suppliers issues

| Optimal value | $S_i$ | $K_i$ | Rank |
|---------------|-------|-------|------|
| $ALT_1$       | 0.256224 | 0.05 | 1    |
| $ALT_2$       | 0.199565 | 0.778869 | 2    |
| $ALT_3$       | 0.174751 | 0.682023 | 4    |
| $ALT_4$       | 0.187824 | 0.733045 | 2    |
| $ALT_5$       | 0.179635 | 0.701085 | 3    |

However, the same ranking is obtained for both organization and strategy risk as well as logistic risk.

5. CONCLUSIONS

This paper proposes a new approach for risk evaluation in the pharmaceutical industry in Tunisia in the time of COVID-19. The methodology is based on the combination of two multi-criteria decision-making methods ARAS and BWM under 2-Tuple linguistic environment. In future research, we will assess the PSCR in the context of group decision-makers. Moreover, the consensus reaching process will be also proposed in further study to aggregate the preference degrees of all experts and to find compromise solutions.

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