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FOOD LOSS FACTORS IN THE COLD SUPPLY CHAIN: A CASE STUDY IN THE POULTRY SECTOR

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Abstract

Food loss is one of the challenges in the cold chain (CC), which can lead to serious problems with human safety, environment, and economies around the world. Recently, reducing food loss has drawn public attention; previous studies mostly gave attention to food loss drivers in the retailer--consumer stages of the supply chain. In this study, we focused on identifying food-loss-factors (FLF) all over the CC, and developed an approach based on multi decision-making methods and fuzzy sets to rank FLFs by those who have more influence on food loss in the poultry sector. The first phase concerns the identification of FLFs based on the literature as well as experts opinions in the poultry field. Then fuzzy Delphi method was implemented to reach the consistency level of >75% among all the group members. In the second phase, fuzzy AHP method was employed for the weighting of FLFs, in order to rank them. For the validation of our contribution, a sensitivity analysis was performed. This research presents a guide for decision makers in the CC to help them make an efficient strategy plan to reduce food loss during logistic activities.

Keywords: cold chain (CC), food loss factors (FLF), MCDM, poultry supply chain, sensitivity analysis.

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1 Introduction

In today's competitive and instable business environment, managing flows in a supply chain has become increasingly complex. Maintaining and optimizing these flows is a challenge for decision-makers, particularly in a cold chain (CC), where products are more sensitive due to their perishable nature. CC refers to the management of temperature-sensitive goods throughout the supply chain, including transportation, storage and handling (Ali, Nagalingam and Gurd, 2018). These goods, such as food, pharmaceuticals and vaccines, require specific conditions to maintain their quality and safety. There is an optimum storage temperature for each product category to protect and extend their shelf life. Hence, any deviation from these temperatures can result in spoilage, loss of potency, or even contamination, which can have severe consequences for public health (Loisel et al., 2021). Chilled and frozen products are two categories of temperature--sensitive products that require different temperature. Chilled products typically have a shelf life of a few days to a few weeks, and they require temperatures between 0°C and 8°C to maintain their quality. Examples of chilled products include fresh meat, seafood, dairy products, and ready-to-eat meals. These products are often transported in refrigerated trucks or vans and stored in refrigerated facilities to maintain their freshness. Frozen products, on the other hand, have a much longer shelf life and can be stored for several months or even years. These products require much lower temperatures, typically between –18°C and –23°C, to maintain their quality and prevent spoilage. Examples of frozen products include frozen vegetables, fruits, meats, and seafood, as well as ice cream and other frozen desserts. These products are transported in refrigerated trucks or containers and stored in frozen warehouses or freezers. Although the temperature is the most critical factor influencing the perishability of a food product, humidity, carbon dioxide production, respiratory behavior, ethylene production, and sensitivity are also significant factors (Han et al., 2021).

A typical food cold chain generally starts with harvesting, slaughtering, fishing or processing, followed by precooling, then storage and distribution, and finally shipping to retailers (Mercier et al., 2017; Han et al., 2021). Nevertheless, ensuring the timely and healthy distribution of perishable products to customers requires precise management of time and temperature factors. An efficient management of the CC is the key to prevent unnecessary losses and maintaining the appropriate conditions throughout the CC process. If there are any disruptions in this process, such as fluctuations in temperature and/or humidity that exceed the desired ranges, then the entire CC will become ineffective. CC breaks can result between 10% and 40% of shelf life reduction depending on the product type, the duration and the CC break level, which can highly affect the product quality

(Loisel et al., 2021). Hence, those breaks contribute to food loss and affect the overall economic performance of the CC.

The Food and Agriculture Organization (FAO) estimated that approximately 14% of the food produced globally is lost each year before it reaches the retailer or consumer. Food loss in the CC poses a significant challenge to the achievement of sustainable development; it has serious implications for the economy, society, and environment at each stage of the supply chain. From a societal perspective, it results in the inability to ensure food security for a larger population. Environmentally, it has implications for soil and water resources, energy consumption, and the emission of greenhouse gases (GHGs) (Ferretti, Mazzoldi and Zanoni, 2018). Particularly in developing countries, food loss and waste can be attributed to two main factors: cultural influences and limitations in financial, managerial, and technical resources. These constraints impact various stages of the food CC, including harvesting techniques, cooling technologies, and storage facilities (UNEP and FAO, 2022; Alamar et al., 2018). Furthermore, minimizing food loss at earlier stages of the CC is considered as a big challenge that requires coordinated efforts from various stakeholders.

Many previous studies have investigated the causes of food loss in the CC but few have focused on the importance and effects of logistic activities on maintaining food quality during the entire process (Balaji and Arshinder, 2016; Surucu-Balci and Tuna, 2021).

This study aims to identify FLF in the CC, to rank them and to provide a guide for decision-makers to establish an efficient strategic plan to reduce loss and waste all over the chain. We propose a methodological approach based on MCDM and fuzzy sets. The remaining parts of the paper are organized as follows: The description of the problem is presented in Section 2, followed by the theoretical foundations of the proposed approach, the Fuzzy DELPHI, and Fuzzy AHP methods in Section 3. Section 4 will focus on the application of the method. In the last section, we present the results and discussion.

2 Problem description

Losses result primarily from financial, technical, and management limitations affecting production, infrastructure and storage conditions, packaging and marketing systems, and are exacerbated by climatic conditions promoting food deterioration. Numerous factors influence the level of food loss and waste, as each stage of the logistics chain has its specific factors. Subsequently, we will describe a case from the poultry industry and the logistic factors of loss identified.

2.1 Case study

Founded in 1995, CHAHIA specializes in the processing and preservation of poultry meat. Its factory is located in the Sfax region, and is responsible for slaughtering, processing and packing poultry products, mainly of chicken and turkey. Poultry meat is a particularly favorable substrate for microbe development due to its composition. Salmonella and Campylobacter are the poultry bacteria which very often cause human diseases (Hafez and Attia, 2020).

CHAHIA's supply chain consists of three main operations: slaughter, processing and distribution. Chicken carcasses are cleaned and packed directly after the slaughter process or they undergo transformation into frozen meals or ready-to-cook products. After the treatment process, the products are ready for shipping. All the products are shipped in well-equipped and refrigerated vehicles, which ensure the distribution of products to all customers, everywhere in Tunisia (CHAHIA's franchises, supermarkets, and restaurants). CHAHIA demonstrates infallible rigor and high standards, which enable it to provide products that meet the strictest international standards, particularly in terms of hygiene, quality and food safety, by adopting continuous strategies of improvement and optimization of its flows. Therefore, reducing food losses and waste represent a principal goal for the company. In this context, we propose a methodological approach, which aims to identify, evaluate and rank food loss factors from a logistics perspective within CHAHIA.

2.2 Identification of FLF

Studies have been conducted previously to determine food loss drivers among logistic activities. Based on the literature (Surucu-Balci and Tuna, 2020; Balaji and Arshinder, 2016; Moraes et al., 2020; Surucu-Balci and Tuna, 2021; Raak et al., 2016; Sharma, Abbas and Siddiqui, 2021), we have focused on identifying FLFs in a CC, taking into account logistic activities. Then, for the validation of the identified FLF, we consulted the opinion of experts from CHAHIA. As a result, we identified 18 factors associated with five logistic activities:

- FLF related to transportation,
- FLF related to storage,
- FLF related to inventory management,
- FLF related to packaging,
- FLF related to communication.

Table 1 summarizes categories of factors and their related sub-factors.

Table 1: Logistic factors and sub-factors of food loss in a CC

FLF (F_i)	SF_{ij}	**Sub-factors**	**Description**	**References**
F1: Transportation	***SF11***	Inappropriate transport conditions	Include transportation mode, vehicle type (with/without cooling system depending on product proprieties and distance), use of dedicated materials, transport unit to be used	Surucu-Balci and Tuna (2021); Magalhaes et al. (2021)
	SF12	Delays	Due to the correlations between freshness of chicken meat and quality degradation, any delay may cause a decrease in the quality	Magalhaes, Ferreira and Silva (2021)
	SF13	Lack of transportation equipment	Transport agility will certainly depend on the company fleet availability	UNEP and FAO (2022); Ndraha et al. (2018)
	SF14	Poor transport management	Short-term decisions, including vehicle routing planning, and medium-term decisions, including distribution network planning, can influence the quality of the transported products	Balaji and Arshinder (2016); Ndraha et al. (2018)
	SF15	Inadequate transport infrastructure	Poor physical infrastructure: road conditions, the design and the state of the transport network may causes damage to the transported goods, which leads to waste	Sharma, Abbas and Siddiqui (2021); Bhattacharya, Nand and Prajogo (2021); Moraes et al. (2020)
F2: Storage	***SF21***	Inadequate cold storage infrastructure	Conditions of cold storage; the control and monitoring system of equipment, regular maintenance of cooling systems and the hygiene of equipment affect the quality of stored products	Sharma, Abbas and Siddiqui (2021); Raak et al. (2016); UNEP and FAO (2022)
	SF22	Poor storage conditions (improper storage)	Storing perishable product in incorrect, poorly-cooling conditions, can lead to huge loss	Bhattacharya, Nand and Prajogo (2021); Ndraha et al. (2018); Chauhan et al. (2021)
	SF23	Poor handling system	Accidents during loading and unloading (crushing, damage) cause the quality deterioration of products	Balaji and Arshinder (2016); Ndraha et al. (2018); Chauhan et al. (2021)
	SF24	Lack of handling equipment	The handling process is very sensitive in the CC, the handling equipment should fulfill the requirements to ensure a successful handling and reduce damage of products in transit	Moraes et al. (2020); Surucu-Balci and Tuna (2021)
F3: Inventory Management	***SF31***	Lack of strict inventory policy	Ensuring a steady flow of inventory availability in case of demand change is a big advantage for the company	Surucu-Balci and Tuna (2021); Bhattacharya, Nand and Prajogo (2021); Balaji and Arshinder (2016); Magalhaes et al. (2021)
	SF32	Low demand forecasting	Forecasting problems lead to an undersupply or oversupply and will negatively affect the overall supply chain	Surucu-Balci and Tuna (2021)

Table 1 cont.

FLF (F_i)	SF_{ij}	Sub-factors	Description	References
	SF33	Poor inventory management	Lack of an efficient stock control (not having an accurate real-time information on the state of the inventory, the ability of keeping an optimal stock level) lead to inefficient processes and increase the amount of loss (costs, time, opportunities)	Raut et al. (2019); Magalhaes et al. (2021)
F4: Packaging	***SF41***	Damaged packaging	When the package gets damaged during the process of the CC, it will no longer protect the product from contamination sources (physical, chemical, and biological)	Raak et al. (2016); Moraes et al. (2020)
	SF42	Unsuitable packing material	Choosing the perfect packaging material for a specific product is a big challenge for CC (high-quality with the minimum costs) improper material causes quality deterioration	Chen and Chen (2018); Fang et al. (2017) ; Raak et al. (2016); UNEP and FAO (2022)
	SF43	Damages during packaging	Confusing and incorrect labeling of expiry dates on packaging, improper packaging (inadequate to the size of the product), lack of control in the packaging process to prevent damages to the product	Raak et al. (2016); UNEP and FAO (2022)
F5: Communications	***SF51***	Lack of communication	Lack of exchange of ideas and information sharing among CC actors	Surucu-Balci and Tuna (2021); Kaipia, Dukovska-Popovska and Loikkanen et al. (2013)
	SF52	Lack of coordination	Lack of coordination can result in misunderstandings, inaccurate supply and demand forecasting which lead to waste. CC actors should coordinate to achieve a common goal	Surucu-Balci and Tuna (2021); Moraes et al. (2020)
	SF53	Poor collaboration	Effective collaboration with CC partners requires sharing valuable information in real time (collaboration with logistic service providers helps to diminish food loss)	Sharma, Abbas and Siddiqui (2021); Kaipia, Dukovska-Popovska and Loikkanen (2013)

3 The Proposed Approach

This study adopts an approach based on MCDM to analyze, evaluate and classify FLFs in a CC. Figure 1 presents a flowchart of the methodology of research.

First, a literature review is conducted to determine the main parameters of our study (such as the main objective, the FLF, the sub-factors linked to each factor, etc.). Based on previous studies, we have identified food factors related to logistics activities in the CC (Table 1). Second, an interview is designed to collect data. We have selected a group of experts in the poultry sector, who were asked to compare and rate the importance and causal relationship among FLF. It was divided into two parts: 1) experts were asked to compare different food loss factors; 2) experts were asked to compare different FLF sub-factors. Interviews were conducted by the fuzzy Delphi method. Subsequently, to estimate relative weights of the factors and sub-factors, the fuzzy AHP was selected for its reliability and validity. Finally, a linear program was formulated for the sensitivity analysis.

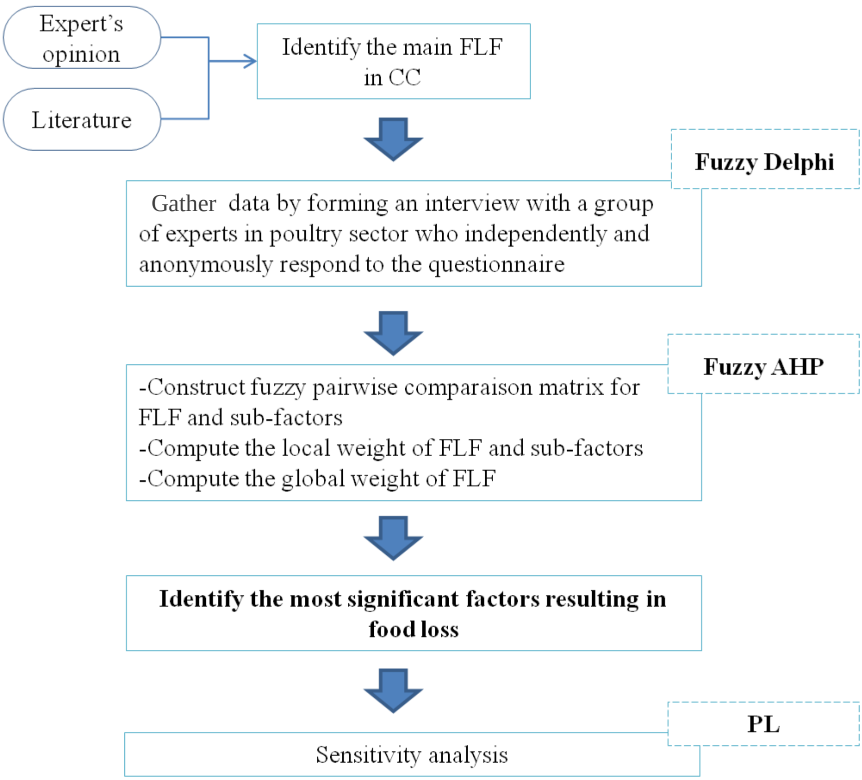

Figure 1: The methodological process

3.1 Identification of parameters

We have based our study on previous studies (Balaji and Arshinder, 2016; Moraes et al., 2020; Surucu-Balci and Tuna, 2021) to identify all food loss factors related to the CC. These factors were categorized according to the logistics functions: factors related to Transport, factors related to Warehousing, factors related to Stock management, factors related to Packaging and factors related to Communication. For more validation, we consulted experts who proposed some hypotheses based on their experiences and expertise in the field of temperature-controlled food supply chains.

3.2 The Fuzzy Delphi Method (FDM)

The Delphi method is an expert opinion survey method with three features: anonymous response, iteration, and controlled feedback. This approach was developed by Dalkey and Helmer (1963). It aims to collect the judgments of experts through a series of questionnaires conducted iteratively to reach a consensus. However, in many real-life situations, expert judgments cannot be properly reflected in quantitative terms. In addition, some ambiguity will result due to differences in the meanings and interpretations of expert opinions. Since human beings use linguistic terms, such as “good” or “very good” to reflect their preferences, the concept of combining fuzzy set theory and the Delphi method was proposed by Murray, Pipino and Gigch (1985). The concept of integrating fuzzy sets was used to improve the vagueness of the classic Delphi method. FDM is the modified and improved version of this method. Thus, this method was proposed on the basis of taking human language preferences into account in the decision-making process. It has been used in many areas, such as program planning, policy determination, needs assessment, and resource utilization.

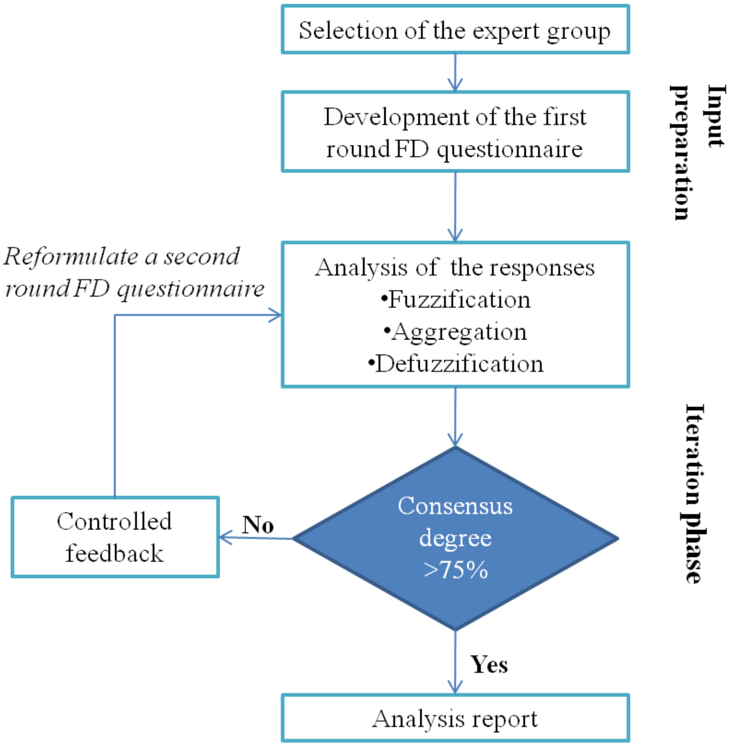

Figure 2: Flowchart of the Fuzzy DELPHI method

The FDM process starts with gathering information (data collecting) to prepare the questionnaire and then to select a group of experts to be included in the decision-making process. The analysis phase starts with transforming the matrix from the linguistic form to the triangular fuzzy numbers form using the values presented in Appendix 1 (Table 6) (*fuzzification*), followed by aggregation and *defuzzification*. In the context of this study, a triangular fuzzy number is characterized by a triplet of real numbers (l, m, u); to be able to obtain a triangular fuzzy aggregate matrix for each factor, we used formulas proposed by Vahidnia et al. (2008) (1, 2, and 3). Then, the outcomes of the analysis are used to indicate the need for the iteration phase. Between each round, we analyze and synthesize the (re)evaluations of the experts, and include them in a new version of the questionnaire aiming to accomplish a level of consensus greater than 75%. Consensus is not the achievement of unanimity within a group, but of a degree of agreement shown by all members. Thus, the consensus level of the opinions of experts is interpreted as follows: strong (between 75 and 100%), moderate (60 to 74.9%), weak (50 to 59.9%), and none if it is less than 50%.

$$l_{ejs} = \left(\prod_{k=1}^{p} l_{ejsk}\right)^{\frac{1}{p}}, \forall\, e, j = 1, .., n \text{ and } \forall\, s = 1, \dots, l \tag{1}$$

$$m_{ejs} = \left(\prod_{k=1}^{p} m_{ejsk}\right)^{\frac{1}{p}}, \forall\, e, j = 1, .., n \text{ and } \forall\, s = 1, \dots, m \tag{2}$$

$$u_{ejs} = \left(\prod_{k=1}^{p} u_{ejsk}\right)^{\frac{1}{p}}, \forall\, e, j = 1, .., n \text{ and } \forall\, s = 1, \dots, u \tag{3}$$

To ensure the validation of the outcomes (aggregated matrix), we calculate the Consistency Index (CI) (4-8):

$$CI = \frac{\lambda_{max} - n}{(n-1)} \tag{4}$$

with:

$$\lambda_{max} = \max_{\mathrm{j}}\left(\sum_{j=1}^{n} \frac{L_j + U_j}{2 \times M_j}\right) \tag{5}$$

$$L_j = \frac{\sum_{i=1}^{n} l_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{z} l_{ij}} \tag{6}$$

$$U_j = \frac{\sum_{i=1}^{n} u_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} u_{ij}} \tag{7}$$

$$M_j = \frac{\sum_{i=1}^{n} m_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} m_{ij}} \tag{8}$$

where *n* is the total number of factors.

After calculating *CI*, we calculate the consistency ratio (*CR*) which represents the ratio of *CI* to random consistency index *CIA* (9):

$$RC = \frac{CI}{CIA} \tag{9}$$

CIA is a random index given by Saaty (1980), defined according to the number of criteria as presented in Table 2. *RC* must be less than 0.1 for the aggregated matrices to be valid and consistent.

Table 2: Random consistency index

N	1	2	3	4	5	6	7	8	9	10
CIA	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.45

Source: Saaty (1980).

FDM was used to gather the opinions of the experts within the framework of a questionnaire, considering the aggregation of the answers obtained until a predetermined level of consensus is reached.

3.3 The Fuzzy Analytical Hierarchical Process (FAHP)

According to Saaty (1980), AHP is intended to solve unstructured problems. This approach relies on pairwise comparisons to eliminate subjectivity and reduce inconsistencies. It does not fully reflect human thinking when the conventional mathematical set theory is used, but with the inclusion of fuzzy sets it takes into account imprecision and uncertainty. We have based this work on Chang's approach which introduced triangular fuzzy numbers for peer comparison (Chang, 1996). The FAHP method is used as a multi-level tool for decision--making, to give precise weights reflecting the importance of each factor and sub-factor studied, and then to classify them based on their priority weighting. The steps of the procedure are as follows:

Step 1. Set up a hierarchical structure. In this study we establish a hierarchical architecture by surveying experts' opinions through the FDM and screening the important FLF relevant to the target problem.

Step 2. Sum up each row of the fuzzy comparison matrix $\widetilde{\boldsymbol{A}}$:

$$\breve{A} = (\widetilde{a_{ij}})_{n\times n} = \begin{bmatrix} (1,1,1) & \cdots & (l_{1n}, m_{1n,}, u_{1n}) \\ \vdots & \ddots & \vdots \\ (l_{1n}, m_{1n,}, u_{1n}) & \cdots & (1,1,1) \end{bmatrix} \tag{10}$$

where $\widetilde{a_{ij}} = (l_{ij}, m_{ij}, u_{ij})$ and $\widetilde{a_{ij}}^{-1} = \left(\frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}}\right)$ for $i, j = 1, \ldots, n$ and $i \neq j$.

Step 3. Normalize the sums:

$$\widetilde{S} = \sum_{j=1}^{n} \widetilde{a_{ij}} \times \left[\sum_{i=1}^{n}\sum_{j=1}^{m} \widetilde{a}_{ij}\right]^{-1} \tag{11}$$

Step 4. Compute the degree of possibility of $\check{s}_i \geq \check{s}_j$ from the following equation:

$$V(\check{s}_i \geq \check{s}_j) = \begin{cases} 1 & m_i > m_j \\ \dfrac{u_i - l_j}{(u_i - m_i) + (m_j - l_j)} & l_j < u_i\,;\; i,j = 1,\dots n; j \neq i \\ 0 & otherwise \end{cases} \quad (12)$$

where $\check{s}_i = (l_i, m_i, u_i)$ and $\check{s}_j = (l_j, m_j, u_j)$.

Step 5. Calculate the degree of possibility over all fuzzy numbers:

$$V(\check{s}_i \geq \check{s}_j \mid j = 1,\dots,n; j \neq i) = min_{j\in(1,\dots n),j\neq i}\; V(\check{s}_i \geq \check{s}_j), \\ i = 1,\dots,n \quad (13)$$

Step 6. Define the priority vector W of the fuzzy comparison matrix $\tilde{A}$:

$$w_i = \frac{V(\check{s}_i \geq \check{s}_j \mid j = 1,\dots,n; \neq i}{\sum_{k=1}^{n} V(\check{s}_k \geq \check{s}_j \mid j = 1,\dots,n; \neq k} \quad (14) \\ i = 1,\dots n$$

3.4 Sensitivity analysis

Sensitivity analysis can be used to find the factors which contribute most to significant variations in results, when the model variation reaches its maximum, as well as the interactions between these factors. In addition, it allows to assess the stability and validity of the solution with respect to changes in parameters (Selmer, 2018). For sensitivity analysis of the FAHP results, we propose a linear model. We have developed a linear mathematical program (LP) to explore the impact of variations of one factor (or more) on the results and to ensure the validation of the results obtained. This model is based on the assumption that the objective function seeks to maximize the performance of each factor.

Settings:

$\boldsymbol{n}$: Number of factors;

$\boldsymbol{m}$: Number of sub-factors;

$\boldsymbol{W_i}$: Weight of factor i;

$\boldsymbol{W_{ij}}$: Weight of sub-factor j which belongs to the factor i;

$\boldsymbol{a}$: Total number of sub-factors to select, value set by the experts;

$\boldsymbol{b_i}$: Minimum number of sub-factors to select in each factor i, value set by the experts;

Variables:

$\boldsymbol{X}$: Number of sub-factors j selected belonging to the factor i;

$$\boldsymbol{Y_{ij}}: \begin{cases} 1 \ \ if\ subfactor\ j, belongs\ to\ factor\ i, is\ selected \\ 0 \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad if\ not \end{cases}$$

$$Max\ Z(Y) = \sum_{i=1}^{n}\sum_{j=1}^{m} W_{ij} \times Y_{ij} + \sum_{i=1}^{n} W_i \times X_i \tag{15}$$

$$\sum_{j=1}^{m} Y_{ij} - X_i = 0 \qquad\qquad \forall\ i = 1, \dots n \tag{16}$$

$$\sum_{i=1}^{n} X_i = a \tag{17}$$

$$\sum_{j=1}^{m} Y_{ij} \geq b_i \qquad\qquad \forall\ i = 1 \dots n \tag{18}$$

$$y_{ij} \in \{0,1\} \qquad \forall\ i = 1 \dots n \text{ and } \forall j = 1 \dots m \tag{19}$$

$$X_i \in IN \qquad\qquad \forall\ i = 1 \dots n \tag{20}$$

The objective function (15) of the proposed model seeks to maximize the performance of the factors based on the results of the FAHP presented as priority weights. Constraint (16) makes it possible to select the most efficient sub-factor taking into account their factor priorities, while constraint (17) specifies the total number of sub-factors selected according to the decision maker. Constraint (18) requires the minimum number of sub-criteria selected in each factor. Constraint (19) specifies that the variables $\boldsymbol{y_{ij}}$ are binary, and constraint (20) specifies that the variables are integers.

4 Application of the proposed approach to the poultry sector

The proposed approach is implemented in the poultry industry, a sector of high consumption significance within the Tunisian economy. Therefore, it will assist decision-makers in this sector in making effective decisions regarding losses during logistic activities.

4.1 Application of the Fuzzy Delphi Method

To apply FDM, we prepared a questionnaire represented as a pairwise comparison matrix. The first part consist in pairwise comparison of the FLFs, while the second part, in pairwise comparison of the FLF sub-factors (Appendix 1). Then, we choose a group of experts based on their position in CHAHIA and the years of experience in the poultry sector. We conducted the questionnaire via email:

the respondents were asked to complete the matrices with the linguistic values. The matrices as well as the profiles of the four selected experts are presented in Appendix 1. The questionnaire for a first round was open and exploratory. In the first step, we started by consolidating the assessment matrices of experts given in the first round; the desired level of consensus (above 75%) has not been reached yet. Hence, we conducted the questionnaire again, this time asking experts to review their original opinions and to answer some specific questions based on the feedback. The level of consensus found in the second round was favorable (above 75%), and there was no need for another round. The assessment matrix from the second round of categorizing factors will be used later in the aggregation phase. Similarly, for each factor, the questionnaire was conducted for three rounds until the desired consensus level was reached. In the second step, and after transforming each matrix into fuzzy triangular numbers, we have found a total number of six aggregated matrices (one aggregated matrix of factors category and five aggregated matrices of the factors) by applying aggregation formulas (1, 2 and 3) (cf. Appendix 2).

These matrices will be used as a database for the fuzzy AHP method to find the corresponding weights. To ensure the consistency of these aggregated matrices we have applied formulas (4-9) for the calculation of the Consistency Index *CI* and the Consistency Ratio *CR*.

Table 3: Consistency calculation results

Factors	**CI**	**CR**	**Notes**
Category of factors	**0.003**	**0.003**	**< 0.1**
F1	**0.017**	**0.015**	
F2	**0.060**	**0.053**	
F3	**0.028**	**0.025**	
F4	**0.027**	**0.024**	
F5	**0.053**	**0.048**	

Table 3 summarizes the calculation results of *CI* and *RC* of the aggregated matrices. Since *CR* is less than 0.1 for the category of factors and for all factors, the judgments are valid and consistent.

4.2 Application of the Fuzzy AHP method

After conducting the response analysis using FDM, we applied the fuzzy AHP method to obtain a priority ranking of FLFs in the CHAHIA CC. We have followed the mathematical procedure of the fuzzy AHP, which is described in the previous section (Saaty, 1990).

Table 4 summarizes the weight values W_i of factors, the weight values W_{ij} of sub-factors, as well as the global weight and the ranking obtained.

Table 4: FAHP results

Factors		Sub-factors		Local ranking	Global weight	Global ranking
Weight W_i	**F_i**	**SF_{ij}**	**Weight W_{ij}**			
0.35	F1	SF11	0.185	3	0.065	7
		SF12	0.095	5	0.033	11
		SF13	0.314	1	0.110	3
		SF14	0.179	4	0.063	8
		SF15	0.227	2	0.080	6
0.2	F2	SF21	0.109	3	0.022	14
		SF22	0.252	2	0.050	9
		SF23	0.075	4	0.015	17
		SF24	0.564	1	0.113	2
0.25	F3	SF31	0.366	2	0.092	4
		SF32	0.091	3	0.023	13
		SF33	0.543	1	0.136	1
0.05	F4	SF41	0.394	2	0.020	16
		SF42	0.170	3	0.008	18
		SF43	0.436	1	0.022	15
0.15	F5	SF51	0.574	1	0.086	5
		SF52	0.273	2	0.041	10
		SF53	0.153	3	0.023	12

According to factor weighting, the most influential FLF category in terms of the amount of loss is **F1** with the weight of 0.35 followed by **F3** with the weight of 0.25, then by **F2** with the weight of 0.2, followed by **F5** with the weight of 0.15 and finally **F4** with the weight of 0.05. Among transport-related sub--factors, the two sub-factors **SF13** (Lack of transport equipment) and **SF15** (Inadequate transport infrastructure) stand out with the highest local ranking. Among sub-factors related to storage, we distinguish the two sub-factors **SF24** (Lack of handling equipment) and **SF22** (Inappropriate storage) with the highest local ranking. Among sub-factors related to inventory management, we distinguish the two sub-factors **SF33** (Poor order management) and **SF31** (Lack of strict inventory policy) with the highest local ranking. Among packaging-related sub-factors, the two sub-factors **SF43** (Damage during packaging) and **SF42** (Inappropriate packaging material) stand out with the highest local ranking. Among sub-factors related to communication, we distinguish the two sub-factors **SF51** (Lack of communication) and **SF52** (Lack of coordination) with the highest local ranking.

4.3 Sensitivity analysis

In reality, parameter values can change since they are only estimations. Indeed, the experts can change their opinion, e.g. on the performance of the factors and/or sub-factors. The main objective of the proposed model is to understand the effect of the changes in the parameter on the structure of the optimal solution. Furthermore, for a better understanding of the relationships between factors and the robustness of the proposed ranking, the model was implemented on LINDO SYSTEMS software. Results of the sensitivity analysis are presented in Appendix 3.

The interval of variation of sub-factors weights, in which the solution does not change, is presented in Figure 3.

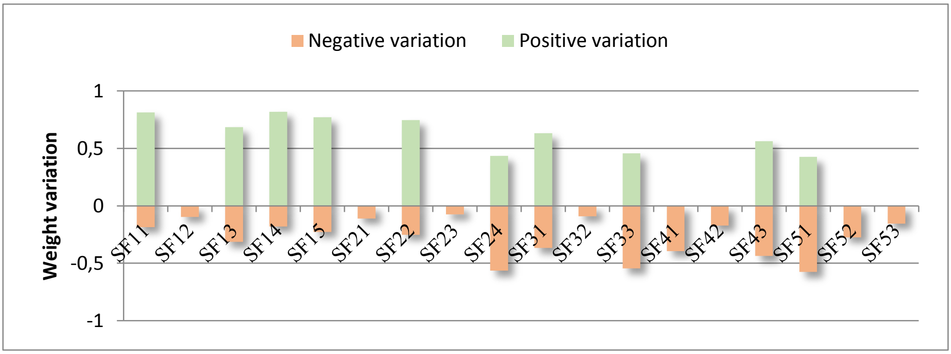

Figure 3: Sensitivity analysis

The values of a and $\boldsymbol{b_i}$ are set by the decision makers. a denotes the number of factors to be selected (CHAHIA decision makers are interested in knowing the sensitivity of the weights of the top 10 most influential FLFs). Obviously, the interval of variation of a is null because if $\boldsymbol{a}$ changes, the structure of the solution changes. $\boldsymbol{b_i}$ refers to the number of sub-factors chosen for each factor i. In our case the decision makers have chosen to identify at least one sub-factor (FLF) which belongs to a logistic function (the factors). Table 15 (Appendix 3) presents the variation intervals of the values of $\boldsymbol{b_i}$ in which the structure of the solution does not change; otherwise it changes.

5 Results and discussion

According to the FAHP results (Table 5), factors related to transport and inventory management are the main causes of food loss in the CC of CHAHIA. These factors are considered significant due to their important role among other logistic activities in the CC. This can also be related to the fact that CCs are highly dependent on good management of temperature controlled stocks and suitable refrigerated transport. In the studied case, CHAHIA's factory is located in the Sfax region, which guarantees the distribution of chicken products and its derivatives throughout the Tunisian territory. Further, the complex nature of the global meat supply chain, with its extensive distribution networks, poses significant challenges in maintaining optimal chilling and freezing conditions. Indeed, any problem related to transport can cause significant loss, which makes this phase more critical for the company.

Otherwise, the results of sub-factors weighting showed that poor inventory management practices, lack of handling equipment and lack of transport equipment are the three factors that greatly influence the food loss in the CC, with associated relative weights greater than 0.1. Thus the absence of a strict inventory policy, the lack of communication and inadequate transport infrastructure occupy the fourth, fifth, and sixth place, respectively, with relative weights greater than 0.08. In fact, decision makers should adopt a new, more rigid, management strategy. They can invest in a more efficient order management system to adequately manage orders, ensure better stock rotation and maintain a perfect balance between offer and demand.

Table 5: FLF ranking

SF_{ij}	FLF	Global weight	Rank
SF33	Poor inventory management	**0.136**	**1**
SF24	Lack of handling equipment	**0.113**	**2**
SF13	Lack of transportation equipment	**0.110**	**3**
SF31	Lack of strict inventory policy	**0.092**	**4**
SF51	Lack of communication	**0.086**	**5**
SF15	Inadequate transport infrastructure	**0.080**	**6**
SF11	Inappropriate transport conditions	**0.065**	**7**
SF14	Poor transport management	**0.063**	**8**
SF22	Improper storage	**0.050**	**9**
SF52	Lack of coordination	**0.041**	**10**
SF12	Delays	**0.033**	**11**
SF53	Lack of collaboration	**0.023**	**12**
SF32	Low demand forecast	**0.023**	**13**
SF21	Inadequate cold storage infrastructure	**0.022**	**14**
SF43	Damages during packaging	**0.022**	**15**
SF41	Damaged packaging	**0.020**	**16**
SF23	Poor handling system	**0.015**	**17**
SF42	Unsuitable packing material	**0.008**	**18**

Also, addressing these causes requires investments in infrastructure, implementing standardized handling procedures, ensuring proper temperature control systems, improving logistics and planning processes, enhancing demand forecasting accuracy, implementing robust monitoring systems, and fostering effective communication and collaboration among stakeholders in the CC. This can be achieved through regular meetings, information sharing platforms, or collaborative technologies. By promoting effective communication, potential bottlenecks or issues can be quickly identified and resolved, ensuring smooth operations and minimizing the risk of food loss. It is clear that the packaging-related FLFs have low but not negligible global weights. Damage during packaging, damage to packaging, and improper packaging material are ranked among the bottom four identified FLFs in the overall ranking. It is essential to address these factors to minimize food loss in the CC. Mitigation strategies can include ensuring proper handling practices to prevent damage to packaging during transportation, loading, and unloading processes, as well as conducting regular inspections and audits to identify any packaging-related issues or weaknesses.

Based on the results of the sensitivity analysis, the decision makers have chosen to focus on the top 10 ranking FLFs. Additionally, they have decided to select at least one factor from each logistic function to ensure that they address all the problems within the CC. The specific factors chosen from each logistic function depend on the ranking and weighting obtained from the sensitivity analysis. These factors may vary based on the characteristics and challenges of the CHAHIA CC. The proposed LP model suggests maintaining the same order of factors as in the FAHP ranking while ensuring that at least one factor from each category is addressed. For example, in the revised order provided, SF43 (Damages during packaging) is included to represent the packaging-related FLFs. By addressing these factors, decision makers can implement targeted mitigation strategies to minimize food loss, enhance efficiency, and improve the overall performance of the CC.

6 Conclusion

Food losses result not only in a deterioration of security in all its dimensions, but also in the loss of market opportunities, waste of scarce resources devoted to their production (water, land and energy) and in a considerable ecological footprint. However, a reliable and efficient cold chain not only contributes to reducing these losses, but also to improving the technical and operational efficiency of the food chain. In this paper, as a first step to develop an efficient system in CC management, we proposed to identify and rank the FLF to help decision makers in CHAHIA to prioritize the factors which affect the amount of loss. In a first part we identified the FLF in a CC based on the literature and the opinion of the experts in the poultry sector. Then we conducted a questionnaire in the form of a pairwise comparison. The FDM helped us to reach a satisfactory level of consensus of expert judgments. Indeed the FDM also allows us to have aggregated matrices which were subsequently used as input data for the FAHP method. The classification of the FLFs was established based on the weighting carried out by the FAHP method. Finally, we developed an LP for sensitivity analysis. Sensitivity analysis is used to detect the subjective impact of weight setting. The results obtained proved the validation of our methodological approach. It is important to note that the weight values are valid for the developed application and that we could obtain different results with other groups of experts or in another CC.

Appendix 1

Table 6: Fuzzy triangular values

Scores	Linguistic variable	Symbol	Fuzzy triangular values	Reciprocal value	Symbol
7	Absolument Elevé	AE	(9, 9,9)	$(\frac{1}{9},\frac{1}{9},\frac{1}{9})$	$\frac{1}{AE}$
6	Très Elevé	TE	(7, 9,9)	$(\frac{1}{9},\frac{1}{9},\frac{1}{7})$	$\frac{1}{TE}$
5	Elevé	E	(5, 7,9)	$(\frac{1}{9},\frac{1}{7},\frac{1}{5})$	$\frac{1}{E}$
4	Moyenne	M	(3, 5,7)	$(\frac{1}{7},\frac{1}{5},\frac{1}{3})$	$\frac{1}{M}$
3	Faible	F	(1, 3,5)	$(\frac{1}{5},\frac{1}{3},1)$	$\frac{1}{F}$
2	Très Faible	TF	(1, 1,3)	$(\frac{1}{3},1,1$	$\frac{1}{TF}$
1	Egalité	EG	(1, 1,1)	(1, 1,1)	$\frac{1}{EG}$

Table 7: Profile of experts

Expert	Title	Years of employment within the poultry industry
1	Logistics manager	10
2	Sales manager	6
3	Production manager	8
4	Purchasing manager	12

Appendix 2

Table 8: Aggregated matrix of factors-category

	F1			F2			F3			F4			F5		
F1	1,000	1,000	1,000	2,432	2,817	3,000	2,590	3,708	4,486	6,300	7,937	9,000	0,299	0,439	1,000
F2	0,333	0,355	0,411	1,000	1,000	1,000	0,439	0,531	0,628	5,207	7,297	8,452	1,968	4,213	6,300
F3	0,223	0,270	0,386	1,592	1,884	2,280	1,000	1,000	1,000	2,590	3,708	4,486	0,192	0,232	0,299
F4	0,111	0,126	0,159	0,118	0,137	0,192	0,223	0,270	0,386	1,000	1,000	1,000	5,439	7,454	9,000
F5	1,000	2,280	3,344	0,159	0,237	0,508	3,344	4,304	5,196	0,111	0,134	0,184	1,000	1,000	1,000

Table 9: Aggregated matrix of F1

	SF11			SF12			SF13			SF14			SF15		
SF11	1,000	1,000	1,000	1,316	1,495	2,817	0,192	0,340	0,577	1,316	1,968	4,213	0,411	0,508	1,316
SF12	0,355	0,669	0,760	1,000	1,000	1,000	0,137	0,180	0,312	1,000	1,495	1,627	0,863	1,236	2,006
SF13	1,732	2,943	5,207	3,201	5,544	7,297	1,000	1,000	1,000	0,192	0,205	0,253	1,316	1,968	3,201
SF14	0,237	0,508	0,760	0,615	0,669	1,000	3,201	4,213	4,880	1,000	1,000	1,000	0,180	0,312	0,508
SF15	0,760	1,968	2,432	0,531	0,880	1,316	0,312	0,508	0,760	1,968	3,201	5,544	1,000	1,000	1,000

Table 10: Aggregated matrix of F2

	SF21			SF22			SF23			SF24		
SF21	1,000	1,000	1,000	0,355	0,669	1,000	0,577	1,316	1,968	0,159	0,237	0,508
SF22	1,000	1,495	2,817	1,000	1,000	1,000	1,088	1,732	2,590	0,270	0,411	0,669
SF23	0,508	0,760	1,732	0,386	0,577	0,919	1,000	1,000	1,000	0,146	0,209	0,386
SF24	1,968	4,213	6,300	1,495	2,432	3,708	2,590	4,787	6,853	1,000	1,000	1,000

Table 11: Aggregated matrix of F3

	SF31			SF32			SF33		
SF31	1,000	1,000	1,000	1,316	1,968	3,201	0,386	0,760	1,000
SF32	0,312	0,508	0,760	1,000	1,000	1,000	0,169	0,258	0,577
SF33	1,000	1,316	2,590	1,732	3,873	5,916	1,000	1,000	1,000

Table 12: Aggregated matrix of F4

	SF41			SF42			SF43		
SF41	1,000	1,000	1,000	1,316	1,968	4,213	0,508	1,000	1,968
SF42	0,237	0,508	0,760	1,000	1,000	1,000	0,253	0,340	0,760
SF43	0,508	1,000	1,968	1,316	2,943	3,956	1,000	1,000	1,000

Table 13: Aggregated matrix of F5

	SF51			SF52			SF53		
SF51	1,000	1,000	1,000	1,316	2,943	3,956	1,968	3,201	5,544
SF52	0,253	0,340	0,760	1,000	1,000	1,000	0,760	1,732	2,236
SF53	0,180	0,312	0,508	0,447	0,577	1,316	1,000	1,000	1,000

Appendix 3

Max 0.185y11 + 0.095y12 + 0.314y13 + 0.179y14 + 0.227y15 + 0.10y21 + + 0.252y22 + 0.075y23 + 0.564y24 + 0.366y31 + 0.091y32 + 0.543y33 + + 0.394y41 + 0.170y Y52 + 0.153Y53 + 0.35X1 + 0.2X2 + 0.25X3 + + 0.05X4 + 0.15X5

st

Y11 + Y12 + Y13 + Y14 + Y15 − X1 = 0

Y21 + Y22 + Y23 + Y24 − X2 = 0

Y31 + Y32 + Y33 − X3 = 0

Y41 + Y42 + Y43 − X4 = 0

Y51 + Y52 + Y53 − X5 = 0

X1 + X2 + X3 + X4 + X5 = 10

Y11 + Y12 + Y13 + Y14 + Y15 >= 1

Y21 + Y22 + Y23 + Y24 >= 1

Y31 + Y32 + Y33 >= 1

Y41 + Y42 + Y43 >= 1

Y51 + Y52 + Y53 >= 1

$Y_{ij} \in \{0,1\}\ \forall i = 1, \ldots 5 \forall j = 1, \ldots 5$

$X_i \in IN \forall i = 1, \ldots 5$

Table 14: Variation interval of weights

Settings Y_{ij}	Weight W_{ij}	Lindo output		Variation interval of W_{ij}
		Decrease	Increase	
Y11	0.185	0.535	∞	[−0.185; 0.815]
Y12	0.095	∞	0	[−0.095; 0.00]
Y13	0.314	0.664	∞	[−0.314; 0.686]
Y14	0.179	0.529	∞	[−0.179; 0.821]
Y15	0.227	0.577	∞	[−0.227; 0.773]
Y21	0.109	∞	0	[−0.109; 0.00]
Y22	0.252	0.452	∞	[−0.252; 0.748]
Y23	0.075	∞	0	[−0.075; 0.00]
Y24	0.564	0.793	∞	[−0.564; 0.436]
Y31	0.366	∞	∞	[−0.366; 0.634]
Y32	0.091	∞	0	[−0.091; 0.00]
Y33	0.543	0.486	∞	[−0.543; 0.457]
Y41	0.394	0.724	0	[−0.394; 0.00]
Y42	0.170	∞	0	[−0.170; 0.00]
Y43	0.436	∞	∞	[−0.436; 0.564]
Y51	0.574	∞	∞	[−0.574; 0.426]
Y52	0.273	∞	0	[−0.273; 0.00]
Y53	0.153	∞	0	[−0.153; 0.00]

Table 15: Interval of variation of the second members

Variable b_i	**Value given**	**Variation interval of** b_i	
b_1	1	$[-1; 3]$	
b_2	1	$[-1; 1]$	
b_3	1	$[-1; 1]$	
b_4	1	$[-1; 0]$	
b_5	1	$[-1; 0]$	

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