DOI: 10.31534/engmod.2023.1.ri.06v
Professional paper
Received: 19.05.2022.

Fuzzy-AHP Modelling of Risk Factors for Tanneries in Bangladesh to Adapt Industry 4.0

Sarajit Kumar Mondal(1*), **Sajal Chandra Banik**(1), **Md. Sanaul Rabbi**(1)

(1*) *Department of Mechanical Engineering, Chittagong University of Engineering & Technology, Chattogram, BANGLADESH*
e-mail: sarajitkm@gmail.com (corresponding author)

(1) *Department of Mechanical Engineering, Chittagong University of Engineering & Technology, Chattogram, BANGLADESH*
e-mails: baniksajal@cuet.ac.bd; rabbi@cuet.ac.bd

SUMMARY

Bangladesh is marching forward in the way of the Industry 4.0 adaption process with its strength of human assets and long productive experiences. Bangladesh's traditional tanneries are under pressure to change their unfavourable working conditions into safe and productive ones. The study aims to determine the main risk factors of tanning industries from a related literature review and analyse these challenges to adapt the Industry 4.0. A Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) based Multi-Criteria Decision Making (MCDM) methodology is developed to analyse and determine the most and the least critical risk factors. In addition, the purpose of this paper is to provide recommendations for mitigating the risk factors associated with the conversion of a tannery to Industry 4.0. Paired comparisons were created among the criteria for collecting 12 experts' judgments from different tanneries at different levels to progress the methodology using Fuzzy-AHP geometric mean process. The results have shown that the main four risk factors for Industry 4.0 are: Lack of Commitment from Top Management and Policy Makers' Support (47% weight); Lack of Ability to Meet up Initial Cost (29% weight); Lack of ICT-Based Knowledge and Training (15%); and Availability of Cheaper Workforce (9% weight). The judgments given by the experts are acceptable since the paired comparisons are tested with the consistency ratio checking mechanism.

KEY WORDS: *Industry 4.0; tanning industry; risk factors; Fuzzy-AHP; paired comparisons; judgments.*

1. INTRODUCTION

There are many manufacturing and production sectors, including the pharmaceutical and apparel industries, prioritizing their entry into the global market for smart products and new digital technologies. Accordingly, Bangladesh's tanning industry/tannery sector has enormous potential for growth and profitability and is virtually as important as the apparel industry. Several large tanning industries have already been upgraded using automated and semiautomated machinery. As a result, the researchers tend to investigate the imposed challenges for possible digital transformation. Furthermore, due to the availability of raw materials and the production of finished products with its exporting capabilities, the Bangladesh Government designated the tanning industry as a priority while leather sector has gradually risen and become the country's second largest export sector. In this regard, it is vital to identify the barriers to the tanning industries in Bangladesh and plan a strategy to overcome the barriers in the way of the Industry 4.0 adaption process.

Industry 4.0 shows a challenge for the manufacturing and processing industries to adopt new technology while paving the way for more skilled and useful production processes. The technology is a vastly challenging system because a factory needs to develop new tactics that classify with its strategy and workflow. The primary worry of the workforce is that they might be replaced by robots or artificial intelligence (AI). It is crucial for manufacturers to gradually shift people's mindsets to integrate technologies and a smart working environment. Many factories have used new technology to improve manufacturing processes, such as 3D printing, RFID, and robotics to track production, advance productivity, and reduce long-term expenses [1]. However, in a labor-intensive industry, fully accumulating all technologies in the processing system is a time factor problem. The rapid use of digital technology in manufacturing and processing can give rise to a number of challenges, including resistance from workers, steep learning curves, and an overload of data. Jones et al. [2] assessed the likelihood that some factories will adopt industry 4.0 technologies. They require sufficient ICT-based expertise and training in order to effectively exploit and integrate digital technologies. The processing and manufacturing system in smart factory is a massive data processing system that engages in productive human-machine interaction.

Industrial Automation is currently undergoing the transition to its fourth industrial revolution, known as Industry 4.0, and is therefore driving the digitization of Cyber Physical Systems (SPS), Internet of Things (IoT), Augmented Reality, Big Data & Analytics, Smart Factory, Internet of Service (IoS), Industrial internet of things (IIoT), Simulation, Autonomous Robots, Cloud Computing, System Integration, Additive Manufacturing, and Cyber-Security [3] According to Pereira et al in [4], the traditional working environment must shift from mass production to mass customization, which will result in major benefits in the future. Products are developed and built in this manner to meet specific criteria at a cheap cost, with the rapid development of new technologies and their application in industries. Rames et al [5] demonstrated in their article that using a Computer Aided Dosing System (CADS) might result in greater quality control and a healthier work environment in the factory. Aside from that, the effects of Industry 4.0's quickly evolving technologies represent the Fourth Industrial Revolution, which poses significant difficulties/challenges for society and policymakers. In [6], [7], Z. & Kocsis and A. Bashar et al are attempting to demonstrate that the high levels of problems and uncertainties connected with enterprises' strategic planning activities are realized by industries as they migrate to Industry 4.0.

This research investigates the available literature on Industry 4.0 in order to identify the main risk factors for adopting new technologies linked to Industry 4.0 in Bangladesh, specifically in the Tanning Industries sector, and to design a fuzzy decision-making model for prioritizing these risk factors. This study also suggests to enhancing productivity, maintaining healthy environments, and improving product quality through the application of intelligent technology. To find the most and least essential risk factors, the study used experts' verbal and numerical judgments, as well as a Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) based on Multi Criteria Decision Making (MCDM) technique.

The formation of the paper has been organized as follows: Section 2 includes a literature review on the adaption of Industry 4.0.; Section 3 presents the research objective and methodology flow chart; Section 4 presents the research methodology; Section 5 covers the results and discussion; in Section 6 the conclusions of the research are given; and Section 7 presents the related references.

2. LITERATURE REVIEW

The production of leather raw materials is increasing day by day in developing countries. On the other hand, it is reducing in developed countries due to declining per capita consumption of red meat. In this situation, more than half of the total supply of raw hides and skins is provided by developing countries [8]. According to Kazi Waliul in [9] Bangladesh has a long history with the leather industry. Bangladesh's leather sector has grown to become the nation's second-largest source of foreign money after RMG, exporting 10% of the world's leather demand. H. L. Paul et al. [10] investigated the quality of bovine and ovine, caprine (buffalo and cow; sheep and goat) skins used for finely textured leathers of universal fame that are exported in the outer world from Bangladesh. However, when Md. Sadat S et al [11] investigated problems in tanneries and discovered that some unconscious/inefficient and old traditional processing methods cause dangerous pollution. The central effluent treatment plant (CETP) volume of 30,000m^3 capacity is not running at full ability. Given that, sludge is gathered in an open yard and untreated water is regularly delivered into the neighboring Dhaleshwari River. Sadat identified problems with workers` safety and observed a lack of funds for further development in a lot of small and medium-sized factories in this sector.

Similarly, Chan Hong indicated in his ADB reports [12] that the CETP in Savar Tannery Estate is only partially operational, contaminates the adjacent Dhaleshwari River, and poses severe health risks for workers in the tanning industry. He also mentioned other obstacles encountered by small and medium-sized tanneries, including inadequate financing possibilities, a lack of skilled labor and training opportunities, a lack of new technology, reliance on imported chemicals, an inefficient procurement system for raw materials, and deficiencies in solid waste management.

Nuchjarin Intalar et al. [13] determined many digital transformation risks for Industry 4.0 in Thailand, mainly for the conventional manufacturing factories managed without digital technologies. It was a case study of a safety shoe manufacturer, CPL Group Public Company Limited, implementing industry 4.0 technologies to improve its production system after 40 years. Moktadir et al. [14] determined that lack of technological infrastructure is the greatest barrier to implementing Industry 4.0, while "environmental side effects" is the least significant barrier. The leather industry in Bangladesh might prolong the adaptation to Industry 4.0 due to both of these problems.

Vaibhav S et al. [15] identified twenty hurdles to a sustainable Industry 4.0 based on a survey of the relevant literature. The data was acquired from Indian footwear companies and processed with the Fuzzy-DEMATEL technique. According to the findings, the most significant hurdles are a lack of new organizational policy, a lack of consumer feedback and cooperation toward I4.0 and sustainable practices, and a lack of infrastructure. They also believed that the research on thriving economies' footwear factories would support the development of an effective Industry 4.0 implementation strategy. Md Asadul Islam et al. [16] presented some significant risk factors for the production environment in their studies to adapt the Industry 4.0 in Bangladesh, such as poor infrastructure, availability of cheaper labor, expensive technology installation, lack of top management commitment, and lack of knowledge and training.

According to the government's budget speech, the leather and leather goods sector directly employs 0.6 million people and indirectly employs another 0.3 million people, and it is a major source of export revenues in Bangladesh. To acquire the productive capacity of the sector and enhance its exports, a guideline for the development of leather and leather goods products has been established in 2019. In Bangladesh, there are around 220 tannery units, according to the data in [10]. There are 113 large and medium-sized units, and the other units are primarily unregistered small and cottage-style dwellings. Approximately 60000 employees are currently employed in the tanning sector, with the majority working laboriously in an uncomfortable atmosphere. To overcome this situation, the government of Bangladesh is committed to adapting advanced technology in tanneries, which provides an unrivaled opportunity to execute sustainable practices in a world-class setting. In addition to the above speech and review articles, it is evident that implementing Industry 4.0 in the tanning sector could come with some significant risks as a new technological adaptation. Obstacles might accumulate in the context of Bangladesh as indicated below:

(i) Lack of Commitment from top management & Policy Makers' Support to Go Industry 4.0, (Criteria R1),

(ii) Lack of ICT Based Knowledge & Training regarding Industry 4.0, (Criteria R2),

(iii) Lack of Ability to Meet up Initial Cost (Infrastructure & Smart Machineries Cost) (Criteria R3) and

(iv) Availability of Cheaper workforce (Criteria R4).

Other challenges mentioned by experts in the context of Bangladesh include river water and land pollution risk, raw hides and skins procurement management problems, workers' safety and privacy, poor storing system, transporting, harmful chemical handling, poor treatment facilities, employee turnover risks, legal, militancy risks, labor unrest risks, political unrest risks, climate change risks, health safety risks, risks due to local politics, administration risks. All of these local risks can be mitigated by decision-makers in the interest of the country as a whole.

3. RESEARCH OBJECTIVES AND FLOW CHART

The research objectives are as follows:

- To determine the main risk factors to Industry 4.0 adaption from the related review studies of Tanneries in Bangladesh.
- To develop a questionnaire for comparing two challenges and get the opinions of experts from the tanning industries who will take part in the interviews.
- To construct a Fuzzy-AHP decision model based on the data (Importance weights) collected from tannery specialists, as well as the prioritization of risks, and to suggest the solutions to overcome the risk factors for the adaptation of Industry 4.0.

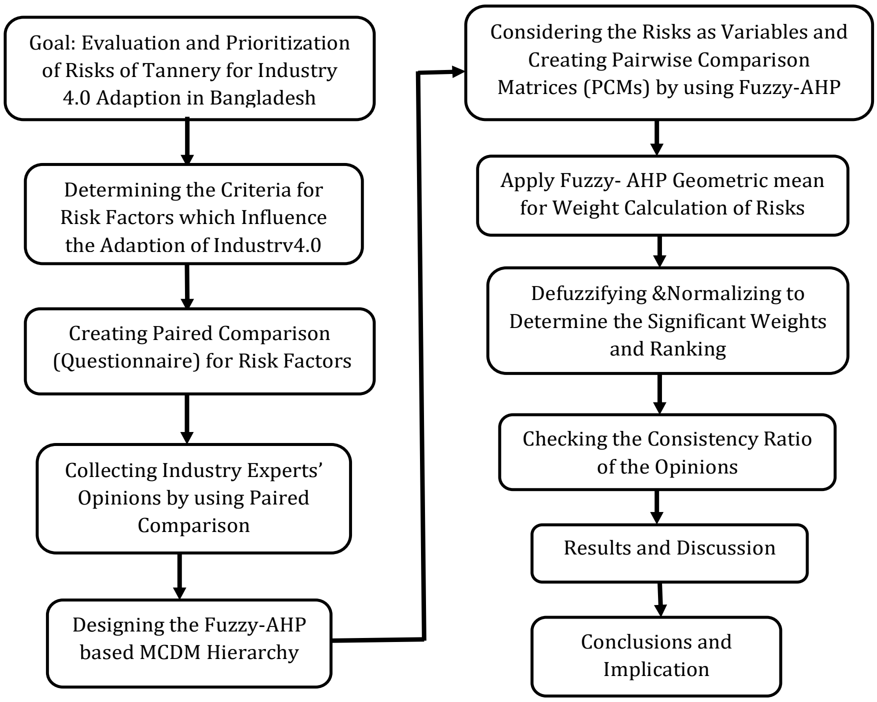

Fig. 1 *Flow Chart of Fuzzy-AHP modeling for Industry 4.0 adaption in the Tanning industry*

4. RESEARCH METHODOLOGY

4.1 EQUATIONS OF FUZZY SET

The mathematical form of some common nomenclatures in Fuzzy set by Lotfi A Zadeh [17] is considered in this paper for the Fuzzy-AHP method. The membership function of a Fuzzy set represents the belongingness of an object that ranges from zero to one. Fuzzy numbers are established as the name of the fuzzy set theory. A fuzzy set $\widetilde{A}$ in a discrete and finite universe of discourse X is defined by:

$$\tilde{A}=\mu_{\tilde{A}}(x_1)/x_1 + \mu_{\tilde{A}}(x_2)/x_2 + ------ = \sum_X \mu_{\tilde{A}}(x_i)/x_i = \{(x_i, \mu_{\tilde{A}}(x_i)) \mid x_i \in X\}$$

Where, $x_1, x_2, x_3, -, -, -, -$ are the elements of X and $\mu_{\tilde{A}}$: X → [0, 1] is called membership function $\mu_{\tilde{A}}(x_i) / x_i$ is termed as the grade of membership of an element x in X with respect to $\tilde{A}$.

The complement of a fuzzy set A is a fuzzy set $\widetilde{A}$ in X whose membership function reads as follows:

$$\mu_{\tilde{A}}(x) = 1 - \mu_A(x) \, \forall x \in X \tag{1}$$

A fuzzy set $\tilde{A}$ is convex if and only if for any $x_1, x_2 \in X$, and any parameter lambda, $\lambda \in [0,1]$ the following condition of the membership function of $\widetilde{A}$ satisfies the inequality:

$\lambda_{\tilde{A}}\{\lambda x_1 + (1-\lambda)x_2\} \geq min\{\mu_{\tilde{A}} x_1, \mu_{\tilde{A}}(x_2)\}$; $0 \geq \lambda \leq 1$ where, *min* denotes the minimum operator. So, a convex fuzzy set is described by a membership function whose values are strictly monotonically increasing and then strictly monotonically decreasing with increasing values for elements in the universe of discourse X.

The height of a fuzzy set $\widetilde{A}$ is calculated by the equation as follows:

$$hgt(\tilde{A}) := sup_{x \in X} \mu_{\tilde{A}}(x) \tag{2}$$

It is the least upper bound of the membership function $\mu_{\tilde{A}}$. Consequently, it indicates the largest grade of membership of a fuzzy set. Where, *sup* denotes the supremum, which is known to exist because 1 is an upper bound.

A normal fuzzy set $\widetilde{A}$ signifies that there is at least one *x* in *X* such that $\mu_{\tilde{A}}(x) = 1$.

Fuzzy set $\widetilde{A}$ of which the basic set is nonempty with a height strictly between zero and one, i.e. 0 < $hgt(\tilde{A})$ < 1, are denoted un-normal.

By using Eq. (1) and Eq. (2) a nonempty/subnormal fuzzy set $\widetilde{A}$ can always be normalized by the division of $\mu_{\tilde{A}}(x)$ by $sup_{x \in X}\, \mu_{\tilde{A}}(x)$ for all $x \in X$.

Therefore, the equation of the normalized fuzzy set $A^{'}$ is:

$$A' = Norm(\tilde{A}) = \sum \frac{\mu_{\tilde{A}}(x)}{hgt(\tilde{A})} / x \tag{3}$$

The support of a fuzzy set $\widetilde{A}$ is represented by the membership function in such a way that $\mu_{\tilde{A}}(x) > 0$. It is given as below:

$$supp\ (\tilde{A}) := \{x \in X \mid \mu_{\tilde{A}}\ (x) > 0\}$$

There are various types of fuzzy numbers. In this research, a triangular fuzzy number (TFN) is used which is represented through [*l m u*] (as shown in Figure 2 and Figure 3) and membership function μ_M defined as follows:

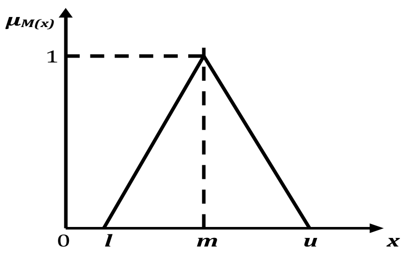

Fig. 2 *Membership function of Fuzzy Triangular Number*

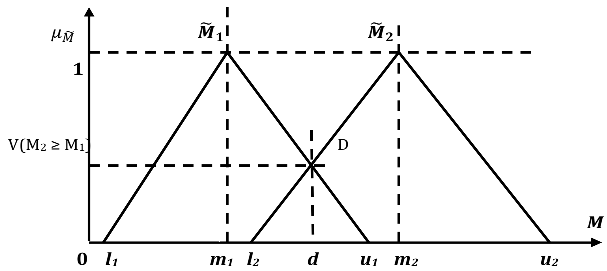

Fig. 3 *The Intersection between TFNs, source [18]*

A Triangular fuzzy number is denoted by $\widetilde{M}=(l, m, u\ )$ where l, m, u are real numbers and $l < m < u$. The membership function $\mu_{\widetilde{M}}(x)$can be described by the following equation:

$$\mu_{\widetilde{M}}(x) = \begin{cases} \frac{x}{m-l} - \frac{l}{m-l}, & x \in [l, m] \\ \frac{x}{m-u} - \frac{u}{m-u}, & x \in \ [m, u] \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

In this research, the fuzzy triangular output set is converted to a crisp output value using the Mamdani inference process, the center of gravity (COG) defuzzification method. This method computes the y coordinate of the center of gravity of the area under the fuzzy set $B^{'}$:

$$y' = \text{cog}(B') = \frac{\sum_{j=1}^{F} \mu_{B'}(y_j) y_j}{\sum_{j=1}^{F} \mu_{B'}(y_j)} \quad \textbf{(5)}$$

Where, F, is the number of elements y_j in uninterrupted state Y.

4.2 FUZZY ANALYTICAL HIERARCHY PROCESS (FAHP)

Saaty, in his research [19], introduced the Analytical Hierarchy Process (AHP) as an MCDM methodology that uses paired comparisons to determine the ratio scales according to the judgments of experts for the criteria. It is difficult to determine the weightings of criteria when utilizing the traditional AHP method. It doesn't consider cognitive human judgment aspects. Classic Fuzzy AHP is an extension of Saaty's theory, and several researchers have found that its algorithms and applications provide more accurate decision-making descriptions than classical AHP and AHP TOPSIS methods [20]. In the Fuzzy-AHP method, the pairwise comparisons of both criteria and the alternatives are formed through the linguistic variables, which are illustrated by triangular fuzzy numbers and thus assist in capturing this vagueness [21]. Linguistic terms are subjective groups for the variable of language. A linguistic variable is a variable whose values are words or sentences in a natural or artificial language. The fuzzy triangle scale employed here is shown in Table 1. Fuzzy-AHP algorithms are prevalent, so this work uses Fuzzy Extent Analysis (FEA) with the geometric mean method [22], which is triangular fuzzy numbers (TFNs). Researchers use various types of fuzzy numbers. In this research, a triangular fuzzy number represented by [l m u] and the membership function μ_M are used. Figure 2 represents the membership function of each set of numbers. As seen in Figure 3, the membership functions are such that the sets overlap. The AHP technique is an expert-experience-based analysis that supports the adjustment of various evaluators in an institutional or organizational hierarchy. Using a relative importance scale ranging from 1 to 9, the number of participants improves the degree of decision-making.

The Fuzzy-AHP technique addresses difficult decision-making problems by capturing fuzzy set information or unclear information. To solve these problems, the method creates a hierarchical model with the main goal (criterion) on the top, criteria, and sub-criteria below that, and possible alternatives at the bottom level. The attributes are compared in pairs to evaluate their relative importance in the levels. The method calculates the eigenvectors, and the final weight vectors are obtained for each criterion toward the main goal [20]. In this research only, the goal and the criteria level of the hierarchy are considered.

4.3 FUZZY CONVERSION WEIGHT SCALING

A Fuzzy AHP is a set of values that assist decision-makers in dealing with uncertainty. The method utilized here is referred to as weight scaling. To complete this step, one must first make a pairwise comparison using a scale with a full number preferring the criterion and then use Table 1 [23] to make a reciprocal judgment to determine which criterion is the least important.

Table 1 *Fuzzy conversion scale formulated*

Linguistic variable	*Crisp numeric value (Relative scale)*	*Triangular fuzzy number*	*Reciprocal Triangular fuzzy number*
Equally important	*1*	*(1, 1, 1)*	*(1/1, 1/1, 1/1)*
Intermediate value between equally and moderately	*2*	*(1, 2, 3)*	*(1/3, 1/2, 1/1)*
Moderately more important	*3*	*(2, 3, 4)*	*(1/4, 1/3, 1/2)*
Intermediate value between moderately and strongly	*4*	*(3, 4, 5)*	*(1/5, 1/4, 1/3)*
Strongly more important	*5*	*(4, 5, 6)*	*(1/6, 1/5, 1/4)*
Intermediate value between strongly and very strongly	*6*	*(5, 6, 7)*	*(1/7, 1/6, 1/5)*
Very strongly more important	*7*	*(6, 7, 8)*	*(1/8, 1/7, 1/6)*
Intermediate value between very strongly and extremely	*8*	*(7, 8, 9)*	*(1/9, 1/8, 1/7)*
Extremely more important	*9*	*(9, 9, 9)*	*(1/9, 1/9, 1/9)*

Fuzzy judgment matrix $\tilde{\boldsymbol{A}}(a_{ij})$ can be expressed mathematically by TFN via pairwise comparison. Different experts can express different opinions on the same criterion. A Fuzzy-AHP geometric mean method is used to convert the various given judgments into one fuzzy figure for each criterion. To calculate the geometric mean, the following formula can be used:

$$\text{Geometric mean} = \{(x1)\ (x2)\ (x3)\ \text{---------}\ (xn)\}^{1/n} \tag{6}$$

Where x = individual paired weight value of individual expert and n = number of judgments. Crisp numeric values of criteria and ratings of alternatives can be actually indicated by the traditional AHP. When the researcher gets preferences from decision makers for the paired comparisons of criteria with respect to fuzzy aims, TFN_s are used to specify linguistic values with the help of the relative scale of these variable criteria.

Suppose a triangular fuzzy number $\tilde{\boldsymbol{A}}(a_{ij})$ is expressed as $[l_{ij}, m_{ij}, u_{ij}]$, i and j = 1, 2, -, -, - n, where l_{ij} , m_{ij} , u_{ij} are lower bound, the mean bound and upper bound of the triangular fuzzy set. Here it is assumed that $l_{ij}<m_{ij}<u_{ij}$, when $i \neq j$.

$$a_{ij}=[l_{ij}, m_{ij}, u_{ij}]$$

$$a_{ij}^{-1}=[\frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}}]$$

If $i = j$, then $a_{ij} = a_{ii}$ = (1, 1, 1). Therefore, an exact priority vector $w = (w_1, w_2, \text{--}, \text{--}, w_n)$ derived from the judgment matrix must satisfy the inequalities. Chang et al. in [22] introduced the following equation to drive the synthetic weight:

$$a_{ij}^t = \left[a_{ij}^t, a_{ij}^t, a_{ij}^t\right], i, j = 1, 2, -, -, -, n_k;\ t = 1, 2 \tag{7}$$

The triangular fuzzy scale represented in the methodology is used for the matrix creation, as shown in the following Eq. (8):

$$\widetilde{\boldsymbol{A}} = \begin{bmatrix} (1,1,1) & \left(a_{12}^l, a_{12}^m, a_{12}^u\right) & \dots & \left(a_{1n}^l, a_{1n}^m, a_{1n}^u\right) \\ \left(\frac{1}{a_{12}^u}, \frac{1}{a_{12}^m}, \frac{1}{a_{12}^l}\right) & (1,1,1) & \cdots & \left(a_{2n}^l, a_{2n}^m, a_{2n}^u\right) \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \left(\frac{1}{a_{1n}^u}, \frac{1}{a_{1n}^m}, \frac{1}{a_{1n}^l}\right) & \left(\frac{1}{a_{2n}^u}, \frac{1}{a_{2n}^m}, \frac{1}{a_{2n}^l}\right) & \cdots & (1,1,1) \end{bmatrix} \tag{8}$$

Once the matrix is prepared for comparison and it is considered if (*l, m, u*) is the importance of the criteria-1 over criteria-2, then the importance of the criteria-2 over criteria-1 will be (*u, m, l*) $^{-1}$ according to the above Eq. (8) as shown in Table 1. Table 1 also has shown the conversion of all judgments under efficiency into TFNs.

'T' is a TFN given by the t^{th} expert, by the formula k^{th}:

$$M_{ij}^{k} = \frac{1}{\tau} \otimes \left(a_{ij}^{1} + a_{ij}^{2} + \cdots\cdots + a_{ij}^{\tau}\right) \tag{9}$$

Applying the theory in a fuzzy comparison matrix, it can calculate the value of fuzzy synthetic extent with respect to the i^{th} object used in Fuzzy-AHP geometric mean method as follows:

$$S_{j}^{k} = \sum_{j=1}^{n} M_{ij}^{k} \otimes \left[\sum_{\mathrm{i}=1}^{\mathrm{n_k}} \sum_{\mathrm{j}=1}^{\mathrm{n_k}} \mathrm{M_{ij}^{k}}\right]^{-1};\ i,j = 1,2,-,-,n_k \tag{10}$$

The output of this sum$(\sum_{j=1}^{n} M_{ij}^{k})$ in Eq. (10) is the fuzzy another function of n extent solution values for a particular matrix is equated as follows:

$$\sum_{j=1}^{n} M_{ij}^{k} = \left(\sum_{j=1}^{n} l_{ij}, \sum_{j=1}^{n} m_{ij}, \sum_{j=1}^{n} u_{ij}\right) \tag{11}$$

The total sum of these $\left[\sum_{i=1}^{nk} \sum_{j=1}^{nk} M_{ij}^{k}\right]^{-1}$, will lead to the fuzzy addition operation of $M_{ij}^{k}(j = 1,2,\cdots,n)$ values such as those, the inverse of the vector in Eq. (10) can be shown as follow:

$$\left[\sum_{i=1}^{n_k} \sum_{j=1}^{n_k} M_{ij}^{k}\right]^{-1} = \left(\sum_{j=1}^{n} l_{ij}, \sum_{j=1}^{n} m_{ij}, \sum_{j=1}^{n} u_{ij}\right)^{-1} \tag{12}$$

and the reciprocal form of Eq. (11) can be written as:

$$\left[\sum_{i=1}^{n_k} \sum_{j=1}^{n_k} M_{ij}^{k}\right]^{-1} = \left(\frac{1}{\sum_{j=1}^{n} u_{ij}}, \frac{1}{\sum_{j=1}^{n} m_{ij}}, \frac{1}{\sum_{j=1}^{n} l_{ij}}\right) \tag{13}$$

4.4 WEIGHT CALCULATION FOR TANNERY RISK FACTORS IN INDUSTRY 4.0 ADAPTION

The research developed a Fuzzy-AHP MCDM approach for assessing the barriers associated with tanneries adopting Industry 4.0 technologies. In determining the weightings of criteria for risk factors at stage, the four main challenges/risk factors of tanning industries are Lack of Commitment from top management (Criteria R1), Lack of ICT Based Knowledge & Training (Criteria R2), Lack of Ability to Meet up Initial Cost (Criteria R3), and Availability of Cheaper workforce (Criteria R4).

The researchers developed pairwise comparisons among the risk factors, and a survey questionnaire is provided for tannery professionals in three companies to collect responses in linguistic terms, along with a relative importance scale (from 1 to 9). Expert opinions were obtained from 12 tannery executives from 3 (three) Bangladeshi industries who actively participated in interviews. Surveys are conducted at each tannery to determine which experts best meet the knowledge requirements in the areas like engineering, design, executive business development, quality control, processing, production management, and more. The entire team was well-versed in their respective fields. The Fuzzy-AHP method used 12 pairwise single-value matrices for 12 experts, with the collected verbal phrases (opinions) and their respective weights as the input variables.

In Table 2, the same observations made by the experts for each pair of comparisons have been put into a single matrix, along with the number of experts who made that set of observations. According to the preferences of the experts for four criteria, six combinations/pairwise comparisons are created, including R1 preferred with respect to R2, R1 w. r. t. R3, R1 w. r. t. R4; R2 w. r. t. R4; R3 w. r. t. R2, and R3 w. r. t. R4. These combinations are left measures in Table 2, and when viewed in the opposite direction, these comparisons are right measures in the same table. Here is an illustration of the comparison between R1 and R2 in Table 2 for 12 experts and their conclusions: 1 expert opined, R1 is strongly lacking in comparison to R2, 4 experts opined, Moderately plus lacking, 6 experts opined, Moderately lacking and 1 expert opined, Between equally and moderately lacking in comparison to R2. Similarly, other paired comparisons between left and right measures can be explained by the judgments of 12 experts in a single-value matrix.

Table 2 *Twelve Experts' judgments according to Linguistic variables and Relative importance scale*

Relative Scale / *Criteria Preferred ⇩*	*Extremely Strong 9*	*Very Very Strong 8*	*Very Strong 7*	*Strong Plus 6*	*Strong 5*	*Moderate plus 4*	*Moderate 3*	*Weak Advantage 2*	*Equal 1*	*Weak Advantage ½*	*Moderate 1/3*	*Moderate plus 1/4*	*Strong 1/5*	*Strong Plus 1/6*	*Very Strong 1/7*	*Very Very Strong 1/8*	*Extremely Strong 1/9*	*w. r. t. Criteria*	*Total No. of Experts*
Criteria R1	*0*	*0*	*0*	*0*	*1*	*4*	*6*	*1*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*R2*	*12*
Criteria R1	*0*	*0*	*0*	*0*	*0*	*1*	*2*	*7*	*2*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*R3*	*12*
Criteria R1	*0*	*0*	*1*	*0*	*5*	*6*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*R4*	*12*
Criteria R2	*0*	*0*	*0*	*0*	*0*	*0*	*3*	*9*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*R4*	*12*
Criteria R3	*0*	*0*	*0*	*0*	*0*	*0*	*7*	*5*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*R2*	*12*
Criteria R3	*0*	*0*	*0*	*0*	*0*	*4*	*8*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*R4*	*12*
Reciprocal Re. scale	*1/9*	*1/8*	*1/7*	*1/6*	*1/5*	*1/4*	*1/3*	*1/2*	*1/1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*		

Then, for the use of the Fuzzy-AHP row-wise geometric mean technique, which is a participatory and data-oriented analysis system, the elements of the single-valued comparison matrix/observation in Table 2 are needed to convert into triangular fuzzy numbers (*l, m, u*) with the help of conversion scale in Table 1. The non-normalized fuzzy triangular 4×4 pairwise matrix shown in Table 3 is calculated from the converted fuzzy triangular matrix using geometric mean Eq. (6) where '*n*' is the number of experts. For four risk criteria, a 4×4 fuzzy triangular matrix is created which includes 16 elements. The scale value of four diagonal elements is 1 because one criterion is compared with the same criterion. The scale values of 6 out of 12 pairwise comparisons are determined by experts' opinions. Consequently, the weight values of the remaining 6 pairwise comparisons are reciprocal to those 6 pairwise comparison values. The configurations are shown in Table 3 as a fuzzy triangular matrix formulated by Eq. (8) in subsection 4.3.

Table 3 *Pairwise Fuzzy triangular matrix obtained from triangular judgment matrix by using FAHP*

Risk Factors	*Criteria R1*			*Criteria R2*			*Criteria R3*			*Criteria R4*		
CriteriaR1	*1*	*1*	*1*	*2.28943*	*3.33105*	*4.35137*	*1.23008*	*2.01973*	*2.73471*	*3.58315*	*4.59931*	*5.61012*
Criteria R2	*0.22981*	*0.30021*	*0.43679*	*1*	*1*	*1*	*0.28184*	*0.39469*	*0.66742*	*1.18921*	*2.21336*	*3.22371*
CriteriaR3	*0.36567*	*0.49512*	*0.81296*	*1.49831*	*2.53367*	*3.548152*	*1*	*1*	*1*	*2.28943*	*3.30193*	*4.30887*
CriteriaR4	*0.17825*	*0.21742*	*0.27908*	*0.31020*	*0.45180*	*0.840896*	*0.23208*	*0.30285*	*0.43679*	*1*	*1*	*1*
TFNs	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*

The row-wise Fuzzy geometric mean value denoted by matrix A1 in Table 4, is determined using Eq. (6), where '*n*' represents the number of criteria. Matrix A2 is the column-wise summation of matrix A1 in Table 4. The fuzzified weight of each criterion is obtained by using fuzzy synthetic Eq. (10). The center of the area of a fuzzy triangular matrix in Eq. (5), the arithmetic mean of FTN, is used in the de-fuzzification process. So, the average value of TFN is obtained as the de-fuzzified weight W_i. The summation of de-fuzzified crisp numeric weights W_i is not equal to 1. So, the crisp numeric weights should be normalized. In Table 4, the normalized weights of risk factors and their rankings are displayed.

Table 4 *Fuzzy Geometric Mean, Fuzzy weight, De-fuzzified Crisp weight and Normalized Weight calculation*

Row wise Fuzzy Geometric Mean $\tilde{r}_i$ *= A1*			*Fuzzy Weight of each Criteria* $\widetilde{W}_i$ *= (A1*(1/A2))*			*De-fuzzified Crisp Weights* W_i	*Normalised Weight for Criteria*	*Ranking*
1.78230	*2.35853*	*2.85843*	*0.28351*	*0.47976*	*0.77172*	*0.51166*	***0.4670709***	*1*
0.52681	*0.71562*	*0.98459*	*0.08380*	*0.14557*	*0.26582*	*0.16506*	***0.1506772***	*3*
1.05829	*1.42661*	*1.87762*	*0.16834*	*0.29019*	*0.50692*	*0.32182*	***0.2937720***	*2*
0.33657	*0.41531*	*0.56583*	*0.05354*	*0.08448*	*0.15276*	*0.09693*	***0.0884799***	*4*
Column Wise Sum (A2) =						*Sum =*		
3.703974	*4.916069*	*6.286478*	*l*	*m*	*u*	*1.09547404*	*Sum = 1*	

These Normalized weights for risk variables in tanneries can be used for analyzing results and discussing whether judgments are adequately synthesized and prioritized for each criterion. Weightings of risk factors can also be used in further calculations.

4.5 CONSISTENCY INDEX (CI) AND CONSISTENCY RATIO (CR) CALCULATION

It is necessary to convert the pairwise triangular fuzzy matrix in Table 3 into a pairwise single value matrix in order to verify the obtained data using consistency ratio checking. This conversion requires defuzzification. Table 5 shows a de-fuzzified non-normalized pairwise matrix derived from the fuzzy triangular matrix in Table 3. This matrix is simply the arithmetic mean of the fuzzy triangular matrix in Table 3.

Table 5 *Non-normalized pairwise matrix obtained from Fuzzy Triangular Matrix*

Criteria Weight	*0.467171*	*0.1515761*	*0.292447*	*0.088806*
Criteria for Risk Factors	*Criteria R1*	*Criteria R2*	*Criteria R3*	*Criteria R4*
Criteria R1	*1*	*3.32394823*	*1.99483815*	*4.597525339*
Criteria R2	*0.32226963*	*1*	*0.44798044*	*2.20876025*
Criteria R3	*0.55791462*	*2.52670931*	*1*	*3.300075038*
Criteria R4	*0.22491916*	*0.53429968*	*0.3239077*	*1*
Column sum	*2.10510341*	*7.38495722*	*3.7667263*	*11.10636063*

As in the traditional AHP method, the normalizing procedure is completed by dividing each column value in Table 5 by the sum of the individual columns. The weights of the criteria are then computed by averaging the row-wise values of the normalized matrix, as shown in Table 6.

Table 6 *Normalized pairwise matrix and criteria weights for consistency checking*

Criteria	*Criteria R1*	*Criteria R2*	*Criteria R3*	*Criteria R4*	*Criteria Weights*
Criteria R1	*0.47503604*	*0.45009715*	*0.52959467*	*0.413954264*	*0.467170532*
Criteria R2	*0.15308969*	*0.1354104*	*0.11893098*	*0.19887345*	*0.15157613*
Criteria R3	*0.26502955*	*0.34214271*	*0.26548252*	*0.297133791*	*0.292447145*
Criteria R4	*0.10684471*	*0.07234973*	*0.08599183*	*0.090038495*	*0.088806193*
					Sum = 1

Now, the normalized matrix (Eigen Vector) is calculated using the same pairwise comparison matrix (Arithmetic mean of FTN/Center of Area) that is not normalized (Table 5). Each value in each column has been multiplied by the weight value from Table 5 for the corresponding criterion. Table 7 shows the calculated normalized matrix, its row-wise weighted sum, the matrix's highest Eigen value, and its Consistency Ratio (*CR*).

Table 7 *Normalized paired comparison matrix (Eigen Vector)*

Criteria for Risk Factor	*Criteria R1*	*Criteria R2*	*Criteria R3*	*Criteria R4*	*Normalized Weight*	*Row wise Weighted Sum Value*	*(Weighted Sum/Weight)*
Criteria R1	*0.467171*	*0.500843*	*0.583385*	*0.408289*	*0.467171*	*1.959687*	*4.194800*
Criteria R2	*0.150555*	*0.150677*	*0.131011*	*0.196152*	*0.151576*	*0.628394*	*4.145734*
Criteria R3	*0.260641*	*0.380717*	*0.292447*	*0.293067*	*0.292447*	*1.226873*	*4.195196*
Criteria R4	*0.105076*	*0.080507*	*0.094726*	*0.088806*	*0.0888062*	*0.369114*	*4.156404*
					Sum = 1		λ_{max} = *4.173034*

Consistency Index (*CI*) = $(\lambda_{max} - n)/(n - 1)$ = 0.057677846

Consistency Ratio (*CR*) = *CI/RI* = 0.064086496 < 0.10

Where λ_{max} is the matrix's maximum eigenvalue and n is the order of the judgment matrix. The Random Index (*RI*) is the consistency index of a pairwise matrix generated at random. The above *CR* equation measures the degree of consistency using the consistency index and random index proposed by Saaty in his research [19]. The number of criteria *n is* equal to 4, and the corresponding *RI* value is 0.90. The consistency ratio *CR* is 0.064086496. Being less than 0.1, it indicates that the given judgments/weights are acceptable because some minor inconsistency in judgments is permissible. It is standard, so it can be assumed that the matrix is reasonably consistent and the research calculation is properly synthesized for Fuzzy-AHP analysis decision-making. All of the associated calculations for determining the weight values of criteria for risk factors and the consistency index and consistency ratio calculations in each step of the Fuzzy-AHP methodology are performed in a Microsoft Excel sheet.

4.6 FINAL WEIGHT VALUES FOR RISK FACTORS AND GRAPHICAL REPRESENTATION

Table 8 below shows the normalized weight of criteria for risk factors and the value of the Fuzzy Weight of each criterion $(\widetilde{W_i})$ side by side.

Table 8 *Normalized weights and Ranking of Criteria for Risk factors of Tannery to Industry 4.0 adaption*

Risk Factors of Tannery for Industry 4.0 Adaption	*Fuzzy Weight of each Criteria* $(\widetilde{W_i})$			*Normalized Weights of Criteria for Risk Factors by Fuzzy-AHP*	*Ranking*
	l	*m*	*u*		
Lack of Commitment from Top Management & Policy Makers' Support, (Criteria R1)	*0.28351*	*0.47976*	*0.77172*	***0.4670709***	*1*
Lack of ICT Based Knowledge & Training (Criteria R2)	*0.08380*	*0.14557*	*0.26582*	***0.1506772***	*3*
Lack of Ability to Meet up Initial Cost, (Criteria R3)	*0.16834*	*0.29019*	*0.50692*	***0.2937720***	*2*
Availability of Cheaper Workforce (Criteria R4)	*0.05354*	*0.08448*	*0.15276*	***0.0884799***	*4*

Figure 4 presents the normalized weights and fuzzy mean bound values of the tanning industries' risk factors for Industry 4.0 adaptation using the weight values from Table 8. The weightings of criteria are calculated using fuzzy values, indicating that the criterion under consideration is significant.

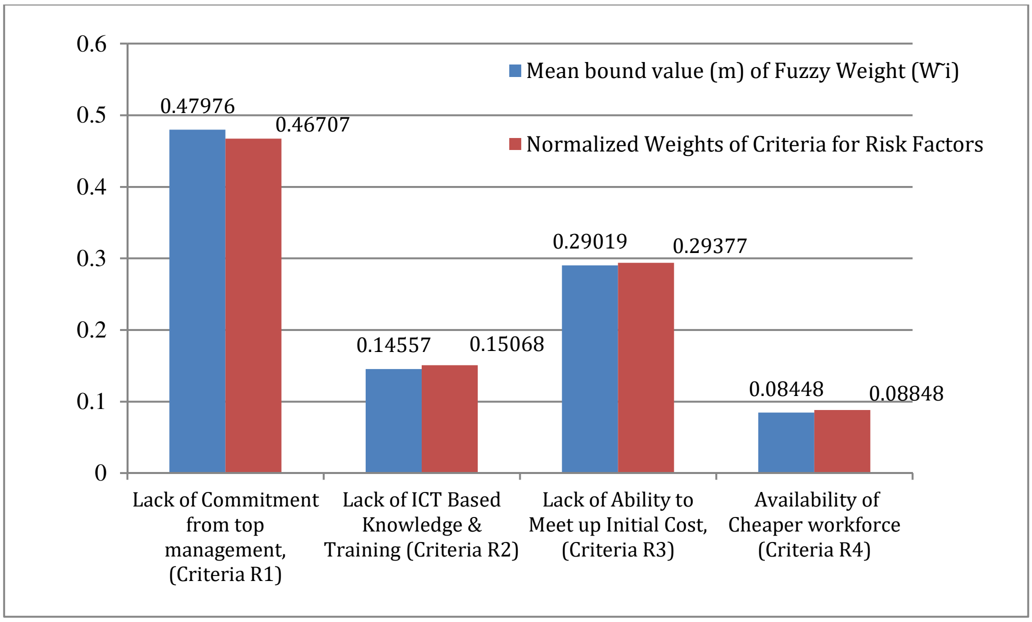

Fig. 4 *The final priority weights of criteria for risk factors of tanneries for Industry 4.0 adaption*

The results show that criterion R1 has the highest priority with a weight value of 0.46707, while R2, R3, and R4 have priorities of 0.15068, 0.29377, and 0.08848, respectively. The Fuzzy mean bound value (m) for criteria R1 has the highest priority, and it is 0.47976, whereas the final normalized weight value of criteria R1 has the highest priority, but the value is 0.46707. Variations also occurred on the second, third, and fourth preferences, where the normalized weights of criteria R2, R3, and R4 have somewhat larger values. Since the fuzzy method naturally includes more uncertainty in its assessments, the normalized weightings of the criteria can be used to analyze and discuss the results and perform additional decision-making calculations.

A Fuzzy mid-bound value (m) is almost a crisp decision application weight that ignores judgment uncertainty. In this circumstance, professional opinions must be presented with confidence. Naturally, verbal values are inconsistent, so imprecision must be considered to reduce unconscious decision-making. If preferences/judgments are uncertain, the fuzzy approach and its normalized weight values of criteria are best for outcomes and discussions.

Furthermore, the Fuzzy-AHP technique allows for the removal of extraneous criteria if all decision makers assign "absolutely not important" values when compared to the other criteria, and then it represents the more essential criteria. This allows the decision-maker to concentrate on the critical criterion [24].

5. RESULTS AND DISCUSSION

Small and medium-sized factories in Bangladesh lack the funds and resources to implement Industry 4.0 in the tannery sector. The first objective of this study was to identify the main risk factors through a literature review and expert opinion. Second, this research used the Fuzzy-

AHP geometric mean method to analyze and rank the identified challenges. The third and final goal was to expose compatible know-how for overcoming existing risk factors. The main risk factors were the most significant challenges for implementing Industry 4.0. The removal of these major barriers would have a positive impact on reducing the obstacles posed by local risk factors. The results showed that *Lack of Commitment from Top Management & Policy Makers' Support (Criteria R1)* is the most unwelcome key risk factor (47% weight), and the leather processing community is missing out on the opportunity of Industry 4.0 adaptation. Furthermore, the government of Bangladesh always encourages organizations to grow in line with Industry 4.0. The second mentionable risk factor (29% weight) was *Lack of Ability to Meet up Initial Cost, i.e., Infrastructure & Smart Machineries Cost (Criteria R3)*. As a least developed country, it is obvious that existing facilities are not built to support the installation of modern machines such as smart machines. Therefore, investing in new technology, raw materials, labor, processes, establishing updated and improved infrastructure, and developing Industry 4.0-based machinery requires significant financial investment. Top management support can also help to reduce financial problems.

Lack of ICT Based Knowledge & Training (Criteria R2) was the third critical risk factor (15% weight). The weight value of the criteria indicated that the workforce involved in processes would be educated, trained, knowledgeable, and kept up to date with new technology. Raising factory workers' awareness of the importance of Industry 4.0 adaptation is essential and should be increased through technical workshops, training programs, on-the-job experience, and conferences. If an honorarium is offered for the training period, and if the trainee can improve living conditions with these honorariums, they will be highly motivated to continue the training that will make them fit for jobs at the new level of Industry 4.0.

Availability of cheaper labor/workforce (Criteria R4) was the fourth notable risk factor (9% weight). This risk factor is not as critical at the moment. Their monthly salary is comparatively satisfactory in comparison to their experience and education, but other incentives and additional facilities are not officially prescribed. The government and industry owners have already agreed to set a minimum wage and a bonus for factory workers in order to assess their contribution.

The elimination of major barriers would reduce the number of local and dependent obstacles. These barriers include river water and land pollution, raw hides and skins procurement management issues, worker personal safety and privacy, poor storing and transporting systems, hazardous chemical handling, inadequate treatment facilities, job loss thinking, insufficient pure drinking water, washroom issues, and so on. Some of the issues are related to worker welfare, and all are mitigated by top management's strong support and the implementation of Industry 4.0. Wastewater, solid waste, hazardous materials, air discharge, and other environmental issues the tanning process poses can be reduced by adhering to international guidelines. After removing the major challenges in the tannery sector, engineering techniques that apply new technology could be used to create a good working environment and reduce tanning industry losses.

6. CONCLUSIONS

In Bangladesh, quality rawhides and skins are available throughout the year. Bangladeshi Tanners have a good opportunity to enter the smart global competitive leather market by developing their factories with new technology and smart products. In addition, the government is interested in introducing this new tanning process to preserve the reputation of Bangladeshi skin with excellent texture. Due to these enormous prospects, the research has moved on to utilize the Fuzzy-AHP geometric mean method to examine tanning industry barriers. The decision-making process identified and prioritized the key risk factors for incorporating Industry 4.0 into the tanning industry. To create this mathematical model, pertinent literature is studied, and judgments from tannery experts are collected as input variables for computing the weight values of criteria. The mathematical study has rated the top four notable challenges of the tanning industry in Bangladesh. Conscious observation is required for decision-makers and corporate executives to manage the entire transition system. The graphical measurements of criteria weight values in Figure 4 represent the ranking of the main four risk factors for Industry 4.0 adaptation in tanneries: Lack of Commitment from Top Management & Policy Makers' Support (Criteria R1), Lack of Ability to Meet Up Initial Cost (Infrastructure & Smart Machineries Cost) (Criteria R3), Lack of ICT Based Knowledge & Training (Criteria R2), and Availability of Cheaper Labor/Workforce (Criteria R4). Local obstacles, on the other hand, are identified through review studies and will be mitigated by the influence of major risk factors. Companies cannot overcome critical challenges on their own. In order to kick-start the Industry 4.0 implementation process, industrial organizations, trade unions, and employer federations must work together to create a positive business environment that supports new technology. Furthermore, the experts' judgments are accepted by the research process because the consistency index and consistency ratio are satisfied, despite the presence of a minor inconsistency in the given judgments. As a result, the fuzzy weight value calculation using expert opinions via the Fuzzy-AHP geometric mean method is adequate for implementing Industry 4.0 technology in Bangladeshi tanning industries.

In the future, the plan is to obtain better results comparing them to similar studies in the field of tannery industries conducted in both domestic and international tannery industries. Also, the technical maturity level should be considered in the model, and the idea will be put forward to the Industry Skill Council (ISC) in Bangladesh.

7. REFERENCES

[1] P. Bertola, J. Teunissen, Fashion 4.0, Innovating Fashion Industry through Digital Transformation, *Research Journal of Textile and Apparel*, Vol. 22, No. 4, pp. 352- 369, 2018. https://doi.org/10.1108/RJTA-03-2018-0023

[2] M.D. Jones, S. Hutcheson, J.D. Camba, Past, Present, and Future Barriers to Digital Transformation in Manufacturing: A Review, *Journal of Manufacturing Systems*, Vol. 60, pp. 936-948, 2021. https://doi.org/10.1016/j.jmsy.2021.03.006

[3] E. Oztemel, S. Gursev, Literature review of Industry 4.0 and related technologies, *Journal of Intelligent Manufacturing*, Vol. 31, pp. 127-182, 2020. https://link.springer.com/article/10.1007/s10845-018-1433-8

[4] T. Pereira, L. Barreto, A. Amaral, Network and information security challenges within industry 4.0 paradigm, *Procedia Manufacturing*, Vol. 13, pp. 1253-1260, 2017. https://doi.org/10.1016/j.promfg.2017.09.047

[5] R.C. Panda, P.G. Rao, Chemical Engineering Applications on Unit Operations of Tanning Industry–Case Studies, *International Journal of Chemical Engineering and Applications*, Vol. 2, No. 2, pp. 112-116, 2011. https://doi.org/10.7763/IJCEA.2011.V2.86

[6] Z. Rajnai, I. Kocsis, Labor market risks of industry 4.0, digitization, robots and AI, *In IEEE 15th International Symposium on Intelligent Systems and Informatics*, (pp. 000343-000346), Subotica, 2017. https://doi.org/10.1109/SISY.2017.8080580

[7] A.B. Bhuiyan, Md. J. Ali, N. Zulkifli, M.M. Kumarasamy, Industry 4.0: Challenges, Opportunities, and Strategic Solutions for Bangladesh, *International Journal of Business and Management Future*, Vol. 4, No. 2, 2020. https://doi.org/10.46281/ijbmf.v4i2.832

[8] United Nations Industrial Development Organization, Vienna, Future Trends in the World Leather and Leather Products Industry and Trade, 2010.

https://leatherpanel.org/sites/default/files/publications-attachments/future_trends_in_the_world_leather_and_leather_products_industry_and_trade.pdf

[9] K.W. Islam, Leather Industry of Bangladesh: Challenges and Opportunities, *Business Inspection BD*, 2022.

https://businessinspection.com.bd/leather-industry-of-bangladesh/#google_vignette

[10] H.L. Paul, A.P.M. Antunes, A.D. Covington, P. Evans, P.S. Phillips, Bangladeshi Leather Industry: An Overview of Recent Sustainable Developments, *Journal of the Society of Leather Technologists and Chemists*, Vol. 97, No. 1, pp. 25-32, 2013.

https://pure.northampton.ac.uk/en/publications/bangladeshi-leather-industry-an-overview-of-recent-sustainable-de

[11] Md. Sadat S. Shibli, Md. Taherul Islam, In Bangladesh, Tanneries in Trouble, *The Asia Foundation*, 2020.

https://asiafoundation.org/2020/05/27/in-bangladesh-tanneries-in-trouble/

[12] S.C. Hong, Developing the Leather Industry in Bangladesh, *ADB Briefs*, No. 102, 2018.

https://www.adb.org/sites/default/files/publication/467956/adb-brief-102-bangladesh-leather-industry.pdf

[13] N. Intalar, K. Chumnumporn, C. Jeenanunta, A. Tunpan, Towards Industry 4.0: digital transformation of traditional safety shoes manufacturer in Thailand with a development of production tracking system, *Engineering Management in Production and Services*, Vol. 13, Issue 4, pp. 79-94, 2021. https://doi.org/10.2478/emj-2021-0033

[14] Md. A. Moktadir, S.M. Ali, S. Kusi-Sarpong, Md. A.A. Shaikh, Assessing challenges for implementing Industry 4.0: Implications for process safety and environmental protection, *Process Safety and Environmental Protection*, Vol. 117, pp. 730-741, 2018.

https://doi.org/10.1016/j.psep.2018.04.020

[15] V.S. Narwane, R.D. Raut, V.S. Yadav, A.R. Singh, Barriers in sustainable industry 4.0: a case study of the footwear industry, *International Journal of Sustainable Engineering*, Vol. 14, Issue 3, pp. 175-189, 2021. https://doi.org/10.1080/19397038.2020.1836065

[16] Md A. Islam, A.H. Jantan, H.B. Hashim, C.W. Chong, Md A. Rahman, Abu B.A. Hamid, Fourth Industrial Revolution In Developing Countries: A Case On Bangladesh, *Journal of Management Information and Decision Sciences*, Vol. 21, Issue 1, 2018.

https://www.researchgate.net/publication/327954073_Fourth_industrial_revolution_in_developing_countries_A_case_on_Bangladesh

[17] L.A. Zadeh, Fuzzy sets, *Information and Control*, Vol. 8, Issue 3, pp. 338-353, 1965.

https://doi.org/10.1016/S0019-9958(65)90241-X

[18] F. Ahmed, K. Kilic, Modification to Fuzzy Extent Analysis Method and its Performance Analysis, Presented at the 6th IEMS Conference, Sevile, Spain, 2015.
https://doi.org/10.1109/IESM.2015.7380193

[19] T.L. Saaty, *The Analytic Hierarchy Process,* New York, NY, McGrawHill, 1980.
https://link.springer.com/chapter/10.1007/978-1-85233-864-0_2

[20] M.J. Sharma, S.J. Yu, Fuzzy analytic hierarchy process–based decision tree in identifying priority attributes for supply chain coordination, *International Journal of Logistics Systems and Management*, Vol. 17, No. 1, pp. 46-65, 2014.
https://doi.org/10.1504/IJLSM.2014.057980

[21] O. Kilincci, S.A. Onal, Fuzzy AHP approach for supplier selection in a washing machine company, *Expert Systems with Applications*, Vol. 38, Issue 8, pp. 9656-9664, 2011.
https://doi.org/10.1016/j.eswa.2011.01.159

[22] D.-Y. Chang, Applications of the extent analysis method on fuzzy AHP, *European Journal of Operational Research*, Vol. 95, Issue 3, pp. 649–655, 1996.
https://doi.org/10.1016/0377-2217(95)00300-2

[23] L. Thames, D. Schaefer, Software-Defined Cloud Manufacturing for Industry 4.0*, Procedia CIRP*, Vol. 52, pp. 12–17, 2016. https://doi.org/10.1016/j.procir.2016.07.041

[24] F. Mulubrhan, A.A. Mokhtar, M. Muhammad, Comparative Analysis between Fuzzy and Traditional Analytical Hierarchy Process, *MATEC Web of Conferences*, Vol. 13, 01006, 2014. https://doi.org/10.1051/matecconf/20141301006

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.