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Assessment of Toxicity Characteristics in Leachate from the Textile Industry–Based Sludge Using Leachate Pollution Index

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Abstract The toxicity, Leachate Pollution Index (LPI), and risk assessment of the leachate of hazardous sludge are very rarely and scantly studied. This study evaluates the leachate characteristics of the textile industry–central effluent treatment plant sludge. X-ray fluorescence (XRF) analysis determines the sludge's chemical composition. The Toxicity Characteristic Leaching Procedure (TCLP) is a sample extraction method performed to simulate the leaching through landfills. The leachate samples are tested using inductively coupled plasma-optical emission spectrometry (ICP-OES) techniques for the metal ions. The 30 TCLP tests are performed as per the scheme generated by the Central Composite Design of Experiment (CCDoE). The study provides a novel and flexible framework for developing the Textile-Leachate Pollution Index (T-LPI) using a hybrid fuzzy analytical hierarchical process (FAHP). The metal ions' weights in the leachate (Al, Cu, Cr, Fe, Mn, Ni, Pb, Zn, K, Mg, Ca) are obtained using FAHP infused with inter-valued triangular fuzzy numbers. The membership grade functions are derived for each metal ion, and the Leachate Pollution Index is estimated for 30 experiments. The experimental runs are ranked based on their LPI values. Pearson's correlation coefficient indicates a poor association between the metal ions and their presence from different sources. The Human Health Risk Assessment (HHRA) of metal ions (Al, Cu, Cr, Fe, Pb, Zn, Mn, Ni) present in leachate shows the potential non-carcinogenic impact by Ni, Pb, Zn, Cu, Cr, and Mn. In contrast, Fe and Al have shown no adverse non-carcinogenic effect. The carcinogenic risk by Pb and Cr metal ions in leachate lies in the high- and very high-risk levels. The ranking of hazardous sludge sites can help in the immediate disposal of higher LPI value sludge to treatment storage disposal facilities (TSDF) as compared to the sludge with lower LPI. The study provides insight into the human health risk associated with the consumption (oral intake and skin absorption) of leachate-polluted surface water.

Keywords Common effluent treatment plant · Human Health Risk Assessment · Fuzzy analytical hierarchical process · Leachate Pollution Index · Toxicity

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Abbreviations

ADEI	Average daily exposure by ingestion
ADED	Average daily exposure by dermal contact
AET	Average exposure time

AvgHI	Average Hazard Index values
AvgCR	Average carcinogenic risk
CCDoE	Central Composite Design of Experiment
CETP	Common effluent treatment plant
CPCB	Central Pollution Control Board
CR	Carcinogenic risk
CSF	Carcinogenic slope factor
ESP	Extremely severely polluted
FAHP	Fuzzy analytical hierarchical process
FAM	Fuzzy assessment matrix
FS	Final scores
GDP	Gross domestic product
HCA	Hierarchical cluster analysis
HHRA	Human Health Risk Assessment
HI	Hazard Index
ICP-OES	Inductively coupled plasma-optical emission spectrometry
IVTFN	Inter-valued triangular fuzzy number
IVFSs	Inter-valued fuzzy sets
IVFW	Inter-valued fuzzy weights
LP	Less polluted
LPI	Leachate Pollution Index
LPIDC	Leachate Pollution Index for Developing Countries
MP	Moderately polluted
MSW	Municipal solid wastes
RM	Relation matrix
SP	Severely polluted
SSA	Skin surface area
TCLP	Toxicity Characteristic Leaching Procedure
T-LPI	Textile-Leachate Pollution Index
Tri	Triangular membership function
Trap	Trapezoidal membership function
TSDFs	Treatment, storage, and disposal facilities
VCF	Volumetric conversion factor
XRF	X-ray fluorescence

1 Introduction

The textile industry in India is the largest employing sector, contributing about 2% to the country's gross domestic product (GDP) and sharing about 5% of the global trade, thus generating a huge revenue of $103.4 billion in 2019–2020 (MoT, 2020). The finished fabric is processed through several operations, such as sizing, bleaching, mercerizing, printing, desizing, dyeing, and finishing (Holkar et al., 2016). The commonly used chemicals during fabric processing are hydrogen peroxide, alkalis, dyes, hypochlorite, and organic surfactants (Behera et al., 2021).

The textile industry generates colored chemical effluents, which must be treated for reuse or safe disposal in the environment. The effluent from the industrial cluster is treated in common effluent treatment plant (CETP) using various physio-chemical treatment processes, producing hazardous sludge as one of the end products (Goyal et al., 2019). This hazardous sludge contains organic and inorganic salts, heavy metals and other chemicals used in the textile industry and while treating the effluent in CETP (Paul et al., 2023). The two traditional methods used for sludge disposal are landfilling and incineration. Due to the low calorific value of the sludge, incineration is not a suitable solution for textile sludge (Goyal et al., 2022). Landfilling and open dumping are not recommended for hazardous wastes by the Central Pollution Control Board (CPCB) of India, and the sludge is disposed of in the treatment, storage, and disposal facilities (TSDFs) (Patel & Pandey, 2012). However, during the field survey, it was observed that a large quantity of sludge lies in CETP, waiting for its disposal to TSDFs. Further, this sludge is also being used for landfilling and agricultural purposes in European countries due to its high nutritional value (Zou et al., 2019).

Landfilling and open sludge disposal before its transfer to the TSDF site have the potential to pollute the surrounding air, surface, and groundwater. The landfills containing hazardous sludge produce odour and leachate. This leachate is highly toxic and contains inorganic and organic compounds and heavy metals (Ma et al., 2022). Due to the severe polluting potential of leachate, it is imperative to quantify it and estimate the possible human health risk (Rajoo et al., 2020). A tool is required to enumerate the true pollution potential of industrial sludge leachate. The Textile-Leachate Pollution Index (T-LPI) will aid in sludge management and rank the sites for immediate waste disposal at the TSDF.

The LPI was first formulated in 2005 for municipal solid waste (MSW) (Kumar & Alappat, 2005). The LPI was developed based on the feedback of 80 experts, and 18 parameters were included. Rajoo et al. (2020) have developed the Leachate Pollution Index for Developing Countries (LPIDC) based on the concept that the waste composition of MSW landfills from developed and developing countries varies. Chaudhary et al. (2021) have studied the temporal variation in LPI of four MSW dumping sites in Delhi, India. The LPI was revised, and a different optimal aggregation function was selected (Bisht et al., 2022). The LPI is highly dependent on the type of waste and its composition.

In contrast, industrial sludges, such as textile industry–effluent treatment plant sludge, consist of chemicals used for the treatment process and the chemicals present in effluent before treatment. The chemical composition and the concentration of heavy metals in the leachate from industrial sludges would be very high and different from the MSW. Hence, using the same index to determine the pollution impact of leachate from the MSW and industrial effluent treatment plant sludge would yield an inaccurate pollution potential of the leachate. Therefore, the existing LPI cannot be used to evaluate the pollution potential of leachate from industrial waste accurately. It is essential to develop another, more flexible, and precise pollution index concerning to textile industry–effluent treatment plant sludge.

The present study proposes a novel framework for developing the T-LPI using the hybrid fuzzy model. The study combines the batch experimental data of the TCLP (Toxicity Characteristic Leaching Procedure) leachate test with the linguistics judgments of the decision makers for developing the T-LPI. The study uses the hybrid fuzzy analytical hierarchical process (FAHP) infused with inter-valued fuzzy sets (IVFSs) for calculating the weights of different heavy metals. The different membership functions based on a different set of grades to each membership function are also formed for constructing the relation matrix. It is followed by calculating the final weight for each experiment run.

Further, the statistical analysis is performed, followed by the human health risk assessment for the leachate-contaminated surface water consumption through ingestion and dermal route. The study findings are helpful in solid waste management by ranking sites based on the index for competitive sludge transfer from CETP to TSDF sites. The present study effectively estimates the human health risk associated to the textile-effluent treatment plant sludge.

2 Methodology

The literature survey has helped to identify the types of leachate pollution indices that have been developed and the importance of developing the indices useful for hazardous sludges such as textile industry–central effluent treatment plant sludge. The sludge is collected and processed, followed by the identification of the chemical composition of the sludge. Experiments were performed using the TCLP leachate test, and leachate samples were tested for metal ion concentrations using the ICP-OES analysis. Further, the experimental data is used to develop the Textile-Leachate Pollution Index (T-LPI) and assess the human health risk and the statistical analysis. The detailed outline is given in Fig. 1.

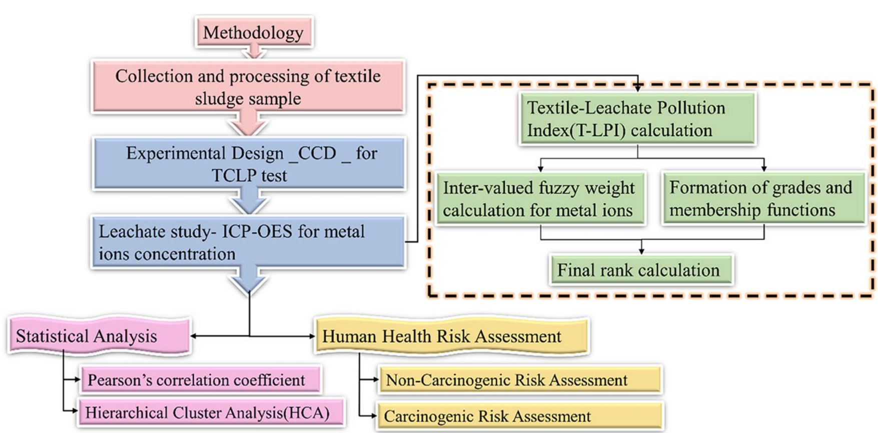

Fig. 1 Framework for the study

2.1 Material and Experimental Design

The textile industry–effluent treatment plant sludge was collected from the Balotra industrial cluster in Rajasthan, India. The sludge is bluish-green and is air-dried for a week before being ground using the ball mill. After that, the sludge is sieved through a 90-µm sieve and is used for the study. The primary metal ions in the sludge are identified using X-ray fluorescence (XRF). The batch experimental study was performed in compliance with the Toxicity Characteristic Leaching Procedure (TCLP) following USEPA Hazardous waste SW 846 test method 1311 (USEPA, 1992). As per the TCLP, the glacial acetic acid was diluted to pH = 2.88 by mixing 5.7 ml of glacial acetic acid in 1 l of Millipore water. The diluted acetic acid is used as the primary leaching agent in this study.

The scheme of experiments for batch experiments in accordance with full factorial Central Composite Design of Experiment (CCDoE) is prepared using the trial version of Design Expert 13. The CCDoE consists of independent variables, levels, and responses as their primary elements. The independent variables refer to factors, namely, (A) weight of sludge (g), (B) time of contact (h), (C) the temperature for performing the batch experiment (°C), and (D) horizontal rotations (rpm). The levels refer to setting the limits for the variables, and the response refers to the measurable output from the experimental runs. The independent factors are coded for the five levels under CCDoE, which are represented in Table 1.

Number of experiments (N) by the CCDoE can be calculated by

$$N = 2^n + n_c + 2n \tag{1}$$

where n = the number of variables independent factors and is the replicates of the center point (Agarwal et al., 2023). The scheme generated using Eq. (1) has 30 sets of experiments, and the details are given in Supplementary Table 1s. The leachate-sludge mixture is filtered using the gravity filtration techniques using Whatman filter paper No. 42 and a 0.22µ syringe filter. The leachate is stored in the 50-ml centrifuge tubes. These tubes were cleaned using diluted nitric acid (HNO3) and washed thrice in deionized water, followed by air-drying before their use. The experiments are performed in duplicate. Diluted nitric acid (0.01M HNO3) is added to filtered leachate to stabilize the metal ions in their soluble state (Rice et al., 2012). The leachate from each experimental run is tested for metal ion concentration using the ICP-OES.

Table 1 The coded level used in the design of the experiment

Independent factors↓ coded levels→	Factor level				
	− 2	− 1	0	1	2
A: weight of sample (g)	5	10	15	20	25
B: time (h)	2	4	6	8	10
C: temperature (°C)	20	30	40	50	60
D: Horizontal rotations (rpm)	100	120	140	160	180

2.2 Statistical Analysis

The data's minimum, maximum, mean, and standard deviation considering all the 30 experiments for the eleven metal ions are computed. Multivariate analysis of the metal ions detected is performed using Pearson's correlation coefficient, and hierarchical cluster analysis (HCA) is performed using the software package Origin Pro 2022. The correlation between the metal ions was tested at the significance level of $p \leq 0.1$. HCA is a commonly used clustering technique that considers the similarities based on the neighborhood method on Pearson correlation distance type.

2.3 Textile-Leachate Pollution Index (T-LPI) Development

2.3.1 *Weight Calculation*

As the different metal ions have a different impact on the overall assessment of leachate toxicity, weights set $M = \{M1, M2, \ldots, Mm\}$ represents the weight coefficient of each metal ion. The weight set has been derived using the hybrid fuzzy analytical hierarchical process (FAHP) infused with inter-valued fuzzy sets (IVFSs) as proposed by Srinivas and Singh (2018). The IVFSs assign an interval to membership functions when conventional fuzzy membership function such as μ: $X \rightarrow [0,1]$ fails to allocate a specific numerical value between [0,1] to each element $x \in X$. Therefore, IVFSs can effectively deal with the uncertainty related to experts' judgments. IVFSs can be represented using Eqs. (2)–(5) as given below:

$$L = \left\{ x, \left[\mu_L^L(x), \mu_L^U(x)\right]\right\}, x \in X \tag{2}$$

$$\mu_L^L, \mu_L^U : X \rightarrow [0,1]\ \forall\, x \in X, \mu_L^L \leq \mu_L^U \tag{3}$$

$$\overline{\mu}_L(x) = \left[\mu_L^L(x), \mu_L^U(x)\right] \tag{4}$$

$$L = \left\{\left(x, \overline{\mu}_L(x)\right)\right\}, x \in (-\infty, +\infty) \tag{5}$$

where $\mu_L^L(x)$ indicates the lower limit and $\mu_L^U(x)$ indicates the upper limit of the degree of membership functions. The step-by-step procedure for applying hybrid FAHP-IVFSs is explained below:

(a) Selection of criteria

The criteria for developing the T-LPI are selected based on the XRF elemental composition of the textile industry CETP sludge and from the results of experimental data. The existing literature and expert opinion have further helped to select suitable criteria for developing T-LPI for hazardous wastes. Further, the selected criteria are linguistically rated by the expert panel of three members. These experts are members of the CPCB, India; academicians; and researchers. The judgment for the different criteria is recorded in the linguistic form through a questionnaire survey and is converted into the quantitative score to generate the pairwise comparison matrices of criteria using Table 2.

(b) Consistency check

The experts' judgments are collected in the linguistic form in the questionnaire and are converted to a crisp scale using the conversion scale given in Table 2. The pairwise comparison matrices have been developed for the different metal ions based on the expert's opinion and checked for consistency using method given by Saaty (2004). Let $z_1, z_2, \ldots, z_n$ denote the set of metal ions; the pairwise comparison matrix (Z) of size $n \times n$ can be defined as follows:

$$Z = \left[z_{ij}\right] = \begin{array}{c} \\ z_1 \\ z_2 \\ z_3 \\ z_4 \end{array} \begin{array}{c} \begin{array}{cccc} z_1 & z_2 & z_3 & z_4 \end{array} \\ \begin{bmatrix} 1 & z_{12} & \cdots & z_{1n} \\ {}^{1}/_{z_{12}} & 1 & \cdots & z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ {}^{1}/_{z_{1n}} & {}^{1}/_{z_{2n}} & \cdots & 1 \end{bmatrix} \end{array} \tag{6}$$

Table 2 Linguistic scale and its crisp score

Linguistic terms	Scale
Equally toxic	1
Slightly less toxic	2
Less toxic	3
Less moderately toxic	4
Moderately toxic	5
Less strongly toxic	6
Moderately strongly toxic	7
Strongly toxic	8
Extremely toxic	9

where $i = j, z_{ij} = 1$ and $i \neq j, z_{ij} = \frac{m_i}{m_j}$ $(i,j = 1,2,3,\ldots,n)$. In the above matrix "Z," z_{ij} represents relative toxicity of metal ion "i" (m_i) over metal ion j (m_j) while m_i and m_j are the crisp values assigned to the linguistic expert's responses. For finding the consistency of decision matrix "Z," steps 1, 2, and 3 are followed as described below.

Step 1. Find the squared power of matrix "Z," and its row sum is calculated. Normalize this row sum array to find the vector E_o.
Step 2. Repeat step 1, with the squared matrix and find ($Z^2 \times Z^2$), followed by calculating the vector arrayE_1. If the difference between $E_o - E_1$ is close to "zero," then E_1 is the eigenvector "E." Calculate the eigen value $\lambda_{\max}$ using Eq. (7).

$$AE = \lambda_{\max} E \tag{7}$$

Step 3. Calculate the consistency index (CI) using Eq. (8) and the consistency ratio (CR) for each decision matrix by using Eq. (9).

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1} \tag{8}$$

$$\mathrm{CR} = \mathrm{CI}/\mathrm{RCI} \tag{9}$$

where RCI is the random consistency index derived from Saaty (2004). If CR ≤ 0.1, experts are not required to reconsider and revise their judgments.
Step 4. Computation of interval-valued triangular fuzzy numbers (IVTFN)

After the consistency of the decision matrices is satisfied, IVTFNs are calculated using the Eqs. (10)–(15) as given by Srinivas and Singh (2018). Each IVTFN number consists of three components: pessimistic, moderate, and optimistic assessment of expert viewpoint for each metal ion.

$$\widetilde{L}_{ij} = \left[\left(\acute{a}_{ij}, a_{ij}\right);\ b_{ij};\ \left(c_{ij},\ \acute{c}_{ij}\right)\right] \tag{10}$$

$$\acute{a}_{ij} = \text{Min}\left(L_{ijk}\right),\ \forall\ k = 1, \ldots, \gamma \tag{11}$$

$$a_{ij} = \text{Min}\left(L_{ijk}\right) + \frac{\left(\prod_{k=1}^{\gamma} L_{ijk}\right)^{\frac{1}{k}} - \text{Min}\left(L_{ijk}\right)}{2} \tag{12}$$

$$b_{ij} = \left(\prod_{k=1}^{\gamma} L_{ijk}\right)^{\frac{1}{k}} \tag{13}$$

$$c_{ij} = \text{Max}\left(L_{ijk}\right) - \frac{\text{Max}\left(L_{ijk}\right) - \left(\prod_{k=1}^{\gamma} L_{ijk}\right)^{\frac{1}{k}}}{2} \tag{14}$$

$$\acute{c}_{ij} = \text{Max}\left(L_{ijk}\right) \tag{15}$$

where $\acute{a}_{ij} \leq a_{ij} \leq b_{ij} \leq c_{ij} \leq \acute{c}_{ij}$; L_{ijk} represents the relative weight that expert k has given to the toxicity of metal ions i over metal ion j, and γ is the total number of experts considered in the study. The single pairwise comparison matrix $\left(\tilde{\tilde{Z}}^{*}\right)$ is derived consisting of IVTFN as given in Eq. (16).

Step 5. Estimation of inter-valued fuzzy weight (IVFW) and de-fuzzification

The IVFW for the decision criteria from the IVFN are evaluated by Eq. (17) and Eq. (18). The de-fuzzified weights for each criterion are estimated using Eq. (19).

$$\tilde{\tilde{Y}}_i^{*} = \left[\tilde{L}_{ij} \otimes \cdots \otimes \tilde{L}_{in}\right]^{\frac{1}{n}} = \left(\acute{y}_{1i}, y_{1i}\right);\ y_{2i};\left(y_{3i},\ \acute{y}_{3i}\right) \tag{17}$$

$$\tilde{\tilde{M}}_i^{*} = \tilde{Y}_i \otimes \left(\tilde{Y}_i \otimes \cdots \otimes \tilde{Y}_n\right)^{-1} = \left(\acute{m}_{1i},\ m_{1i}\right);\ m_{2i};\left(m_{3i},\ \acute{m}_{3i}\right) \tag{18}$$

$$M_i^{*} = \frac{\acute{m}_{1i} + m_{1i} + 2m_{2i} + m_{3i} + \acute{m}_{31}}{6} \tag{19}$$

2.3.2 *Fuzzy Relation Matrices and Grade Functions*

The membership functions in the fuzzy set theory are described as $\mu_{ij}(x)$, where x is the actual value of a given metal ion concentration. The membership function $\mu_{ij}(x) = \mu_R(U_i, G_j)$ has two components, G_j represents evaluation class, while U_i is the membership function of the metal ion i (Singh et al., 2017). In the relation matrix (RM), $\mu_{ij}(x)$ represents the value of membership function for the given metal ion$i$ ($i \in [1, m]$ for m number of metal ions) for the evaluation class j ($j \in [1, n]$ for n number of an evaluation class) as is expressed in Eq. (20).

$$\tilde{\tilde{Z}}^{*} = \begin{bmatrix} (1,1);\ 1;\ (1,1) & \left(\acute{a}_{12}, a_{12}\right); b_{12}; \left(\acute{c}_{12}, c_{12}\right) & \cdots & \left(\acute{a}_{1n}, a_{1n}\right);\ b_{1n}; \left(\acute{c}_{1n}, c_{1n}\right) \\ \left(\frac{1}{\acute{c}_{1n}}, \frac{1}{c_{1n}}\right); \frac{1}{b_{1n}}; \left(\frac{1}{a_{1n}}, \frac{1}{\acute{a}_{1n}}\right) & (1,1);1;(1,1) & \cdots & \left(\acute{a}_{2n}, a_{2n}\right);\ b_{2n}; \left(c_{2n}, \acute{c}_{2n}\right) \\ \vdots & \vdots & \ddots & \vdots \\ \left(\frac{1}{\acute{c}_{1n}}, \frac{1}{c_{1n}}\right); \frac{1}{b_{1n}}; \left(\frac{1}{a_{1n}}, \frac{1}{\acute{a}_{1n}}\right) & \left(\frac{1}{\acute{c}_{2n}}, \frac{1}{c_{2n}}\right); \frac{1}{b_{2n}}; \left(\frac{1}{a_{2n}}, \frac{1}{\acute{a}_{2n}}\right) & \ldots & (1,1);\ 1;\ (1,1) \end{bmatrix} \tag{16}$$

$$\text{RM} = \begin{bmatrix} \mu_{11}(x) & \mu_{12}(x) & \cdots & \mu_{1n}(x) \\ \mu_{21}(x) & \mu_{22}(x) & \cdots & \mu_{2n}(x) \\ \mu_{31}(x) & \mu_{32}(x) & \cdots & \mu_{3n}(x) \\ \vdots & \vdots & \vdots & \vdots \\ \mu_{m1}(x) & \mu_{m2}(x) & \cdots & \mu_{mn}(x) \end{bmatrix} \tag{20}$$

The membership function shape and their value at each grade for all the metal ions concerning textile effluent plant sludge are decided based on the toxicity and previous literature (Bisht et al., 2022) and are represented in Table 8. Each criterion is classified into four membership grades $G = \{G_1$: less polluted, G_2: moderately polluted, G_3: severely polluted, and G_4: extremely severely polluted$\}$. For instance, the membership function for criterion Al which is a heavy metal and its acceptable limit in drinking water is 0.03 mg/l. However, the leachate from the textile sludge is studied, and the concentration of metal ions in the leachate is exceptionally high. Therefore, the opinion of three experts is considered for developing the membership functions and grade classification. Hence, the concentration for Al between 0 and 22 mg/l is classified into four grades based on expert opinion. The Al concentration is classified into 0–4 mg/l for less polluted, 2–10 mg/l for medium polluted, 8–22 mg/l for severely polluted, and 20–22 mg/l for extremely severely polluted which is considered. For the Al, membership functions considered are triangular for grade 1 (i.e., 0, 0, 4), trapezoidal for grade 2 (i.e., 2, 4, 8, 10), trapezoidal for grade 3 (i.e., 8, 10, 20, 22), and triangular for grade 4 (i.e., 20, 22, 22) and are represented in Fig. 2. Similarly, for all the metal ions considered in this study, the membership functions according to grades based on concentrations are defined in Table 3.

LP less polluted, *MP* moderately polluted, *SP* severely polluted, *ESP* extremely severely polluted, **Tri* triangular membership function, ***Trap* trapezoidal membership function

The membership functions for all the metal ion criteria (U_1, U_2, $U_3 \ldots U_m$) have been assessed for the four classification grades. The Al membership function value concerning the four grades can be evaluated using Eqs. (21)–(24).

$$\mu_{\mathrm{LP}}(\mathrm{Al}) = \begin{cases} -1 - 0.25\ \mathrm{Al}, & 0.0 \le x < 4 \\ 0 & \text{otherwise} \end{cases} \tag{21}$$

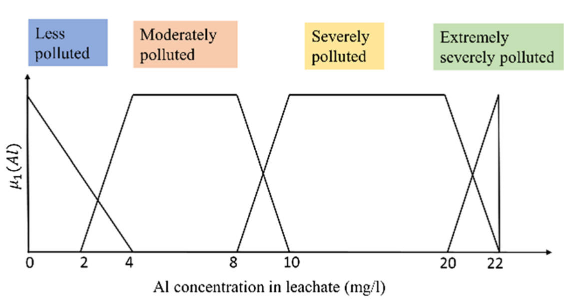

Fig. 2 Membership grade function for Al

$$\mu_{\mathrm{MP}}(\mathrm{Al}) = \begin{cases} 0.5\ \mathrm{Al} - 1, & 2 \le \mathrm{Al} \le 4 \\ 1 & 4 \le \mathrm{Al} \le 8 \\ 5 - 0.5\ \mathrm{Al}, & 8 \le \mathrm{Al} \le 10 \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

$$\mu_{\mathrm{SP}}(\mathrm{Al}) = \begin{cases} 0.5\ \mathrm{Al} - 4, & 8 \le \mathrm{Al} \le 10 \\ 1 & 10 \le \mathrm{Al} \le 20 \\ 11 - 0.5\mathrm{Al}, & 20 \le \mathrm{Al} \le 22 \\ 0 & \text{otherwise} \end{cases} \tag{23}$$

$$\mu_{\mathrm{ESP}}(\mathrm{Al}) = \begin{cases} 0.5\mathrm{Al} - 10, & 20 \le x \le 22 \\ 1 & x \ge 22 \\ 0 & \text{otherwise} \end{cases} \tag{24}$$

2.3.3 Final Rank Calculations

After the evaluation of the fuzzy relation matrix and the IVFWs, the fuzzy assessment matrix (FAM) is derived. The FAM unifies the combined impact of RM and IVFWs for comparison of different experiment sets. The FAM is derived using Eq. (25).

$$\mathrm{FAM} = M_i^* * \mathrm{RM} = \left[\mathrm{M}_1, \mathrm{M}_2, \ldots, \mathrm{M}_m\right] * \begin{bmatrix} \mu_{11}(x) & \mu_{12}(x) & \cdots & \mu_{1n}(x) \\ \mu_{21}(x) & \mu_{22}(x) & \cdots & \mu_{2n}(x) \\ \mu_{31}(x) & \mu_{32}(x) & \cdots & \mu_{3n}(x) \\ \vdots & \vdots & \vdots & \vdots \\ \mu_{m1}(x) & \mu_{m2}(x) & \cdots & \mu_{mn}(x) \end{bmatrix} \tag{25}$$

$$\mathrm{FAM} = \left[F_j\right]_{1\times n} \tag{26}$$

where F_j are the elements of FAM for each set of experiment corresponding to all possible grades. The final score (FS) at station k is derived using Eq. (27).

$$\mathrm{FS}_k = \frac{\sum_{j=1}^{n} F_j \alpha_j}{\sum_{j=1}^{n} F_j} \tag{27}$$

where α_j are the values assigned to each grade of T-LPI ranging from 0.25 to 1 based on their comparative importance, as given by Singh et al. (2017). The values for each grade [α_1, α_2, α_3, α_4=0.25, 0.5, 0.75, 1] are used for driving the de-fuzzified score for each experimental run. The final score is used for driving the T-LPI and ranking it according to the experimental data. A lower score indicates the less polluted leachate at the considered experiment conditions.

Table 3 Grade classification of metal ions and their membership functions

Linguistic description of leachate quality	Al	Cu	Cr	Fe	Mn	Ni	Pb	Zn	K	Mg	Ca
Less polluted (LP)	Tri (0, 0, 4)	Trap (0, 0, 0.5, 1)	Tri (0, 0, 0.2)	Trap (0, 0, 0.5, 1)	Tri (0, 0, 2)	Tri (0, 0, 1)	Tri (0, 0, 0.1)	Trap (0, 0, 5, 15)	Tri (0, 0, 200)	Trap (0, 0, 200, 1000)	Trap (0, 0, 400, 1000)
Moderately polluted (MP)	Trap (2, 4, 8, 10)	Trap (0.5, 1, 3, 3.5)	Trap (0.1, 0.2, 0.9, 1)	Trap (0.5, 1, 3, 3.5)	Trap (1.5, 2, 4, 4.5)	Trap (0.5, 1, 1.5, 2)	Trap (0.05, 0.1, 0.95, 1)	Trap (5, 15, 20, 25)	Trap (100, 200, 400, 500)	Trap (200, 1000, 4200, 5000)	Trap (400, 1000, 4400, 5000)
Severely polluted (SP)	Trap (8, 10, 20, 22)	Trap (3, 3.5, 9.5, 10)	Trap (0.9, 1, 1.9, 2)	Trap (3, 3.5, 5.5, 6)	Trap (4, 4.5, 9.5, 10)	Trap (1.5, 2, 4.5, 5)	Trap (0.95, 1, 1.95, 2)	Trap (20, 25, 30, 35)	Trap (400, 500, 900, 1000)	Trap (4200, 5000, 9200, 10,000)	Trap (4400, 5000, 11,400, 12,000)
Extremely severely polluted (ESP)	Tri (20, 22, 22)	Tri (9.5, 10, 10)	Tri (1.9, 2, 2)	Tri (5.5, 6, 6)	Tri (9.5, 10, 10)	Tri (4.5, 5, 5)	Tri (1.95, 2, 2)	Tri (30, 35, 35)	Tri (900, 1000, 1000)	Tri (9200, 10,000, 10,000)	Tri (11,400, 12,000, 12,000)

2.4 Human Health Risk Assessment (HHRA)

The residents of the textile industry cluster are divided into four categories based on their age, mainly infants (<1 year), children (1–10 years), teens (11–20 years), and adults (21–72 years). The USEPA HHRA is adopted in this study to measure the health hazard associated with the leaching from textile sludge (USEPA, 1989). The human health risk is evaluated as carcinogenic and non-carcinogenic health hazards considering oral intake and exposure through dermal contact. Each age group and non-carcinogenic risk assessment for each heavy metal is computed. The ingestion risk is associated with the direct intake of polluted water by human beings, and dermal contact by bathing and swimming is considered the direct exposure of polluted water to the skin. The average daily exposure by ingestion (ADEI) and average daily exposure by dermal contact (ADED) was calculated using Eq. (28) and Eq. (29) in terms of milligrams per kilogram per day.

$$\mathrm{ADEI}_i^j = \left(C_i^j \times \mathrm{InR} \times \mathrm{ExF} \times \mathrm{ExD}\right) / (\mathrm{BWt} \times \mathrm{AET}) \tag{28}$$

$$\mathrm{ADED}_i^j = C_i^j \times \mathrm{SSA} \times \mathrm{DK}_i \times F \times \mathrm{ExF} \times \mathrm{ExT} \times \mathrm{ExD} \times \mathrm{VCF}\big) / (\mathrm{BWt} \times \mathrm{AET}) \tag{29}$$

where C_i^j is the concentration of ith metal ions in leachate from *j*th experimental run in milligrams per liter, InR stands for ingestion rate (kg/day); ExF is the exposure frequency measured in terms of days per year; ExD is the exposure duration (year); ExT is the leachate exposure time in hours per day; BWt is the bodyweight of residents of different age group in kilograms; AET is the average exposure time in days; SSA is the exposed skin surface area in cm^2; DK_i is the dermal permeability coefficient in centimeters per hour; *F* is the fraction of skin in contact to lecahte and is considered as unitless; VCF is the volumetric conversion factor (l/1000 cm^3). The input parameter values are adopted from the previous literature and are represented in Supplementary (Table 2s) (Mukherjee et al., 2020, 2019; USEPA, 1989).

2.4.1 Non-carcinogenic Risk Assessment

The non-carcinogenic risks of heavy metals are assessed by Hazard Index (HI). The Hazard Index for the ith metal ion is estimated using Eq. (30)

$$\mathrm{HI}_i^j = \left(\mathrm{ADEI}_i^j / \mathrm{RfDing}_i\right) + \left(\mathrm{ADED}_i^j / \mathrm{RfDder}_i\right) \tag{30}$$

where RfDing_i and RfDder_i represent the reference dose for the *i*th heavy metal ions for oral intake and skin absorption, respectively. The reference dose (RfDing_i and RfDder_i) for Al heavy metals was obtained from Tong et al. (2021), and the other heavy metals were taken from Mukherjee et al. (2020). Dermal permeability coefficient ($\mathrm{DK_i}$) for Pb, Cr, Zn, and Cu is obtained from Zeng et al. (2015); Al, Mn, Fe, and Ni are obtained from Tong et al. (2021) and Wang et al. (2017) as given in Supplementary (Table 3s). $\mathrm{HI}_i > 1$ indicates the non-carcinogenic adverse impact on human health are likely to occur while $\mathrm{HI}_i < 1$, shows no adverse effect on human health (USEPA, 2004). However, the Average Hazard Index (AvgHI_i) was calculated by averaging the HQ_i for all the experimental runs for different age groups.

2.4.2 Carcinogenic Risk Assessment

The Carcinogenic risk (CR_i) associated with the *i*th heavy metals for *j*th experimental run is estimated using Eq. (31).

$$\mathrm{CR}_i^j = \left(\mathrm{ADEI}_i^j \times \mathrm{CSF}_i^{\mathrm{ing}}\right) + \left(\mathrm{ADED}_i^j \times \mathrm{CSF}_i^{\mathrm{der}}\right) \tag{31}$$

where $\mathrm{CSF}_i^{\mathrm{ing}}$ and $\mathrm{CSF}_i^{\mathrm{der}}$ are the ingestion and dermal exposure carcinogenic slope factors for the heavy metals. The ingestion slope factor values of 0.5 and 0.0085 for Cr and Pb $(\mathrm{mg/kg/day})^{-1}$ and the dermal contact slope factor values for Cr and Pb are 13.158 and 0.073 $(\mathrm{mg/kg/day})^{-1}$, respectively. The slope factor values are adopted from the USEPA (2018). The different carcinogenic risk levels are as follows: $\mathrm{CR} < 10^{-6}$ corresponds to very low risk, $10^{-6} < \mathrm{CR}_i < 10^{-5}$ corresponds to low risk, $10^{-5} < \mathrm{CR}_i < 10^{-4}$ moderate risk, $10^{-4} < \mathrm{CR}_i < 10^{-3}$ indicates high, and $\mathrm{CR}_i > 10^{-3}$ corresponds to very high cancer risk (Ma et al., 2022; Şimşek et al., 2022; USEPA, 1989). The average CR_i is calculated by averaging the CR_i values for all the experimental runs for different age groups.

3 Results and Discussions

3.1 Statistical Analysis

The chemical composition, mainly the metal ions present in the textile industry–central effluent plant sludge, is determined from the XRF analysis which is given in Table 4. The metal ion concentration in the leachate is found using the ICP-OES technique. The statistical analysis of the concentrations of metal ions found in the 30 experimental runs is represented in Table 4 and Fig. 3. The average metal concentration of the sludge increased as the following order Cr < Pb < Fe < Mn < Ni < Cu < Al < Zn and alkali metal ions K < Ca < Mg. Some of the heavy metal ions, such as Al and Cu, and alkali metal ions, such as K, Mg, Ca, have shown higher standard deviations due to differences in the experimental conditions for the TCLP test. The mean concentrations of all the metal ions considered in the study are higher than the admissible concentrations as defined by well-known standards (BIS (2012); WHO (2011)).

As demonstrated in Fig. 4, Pearson's correlation analysis is performed to examine the positive and negative association between the metal ions. The color symbolizes the correlation coefficient, red denotes the positive, white suggests no correlation, and blue indicates the negative correlation. The bubble size shows the correlation coefficient value (r). The significant positive correlations at $p \leq 0.1$ are observed between Al and Cr (0.35), Cu and K (0.39), Mn and Ca (0.58), Mn and Mg (0.49), K and Mg (0.34), Fe and Ni (0.32), and Mg and Ca (0.74). The positive correlation signifies a common source of origin and identical behavior (Yakamercan et al., 2021). Significant negative correlations at $p \leq 0.1$ were observed between Al and Cu (− 0.38), Fe and Ca (− 0.42), Fe and Mg (− 0.37), Ni and Ca (− 0.36), and Fe and Mn (− 0.39). The Pb does not show any significant correlation with other metal ions. A negative correlation indicates the existence of different sources, mainly chemicals and dyes (Jiang et al., 2022). However, in the study, the low Pearson correlation coefficient value for the heavy metal ions and

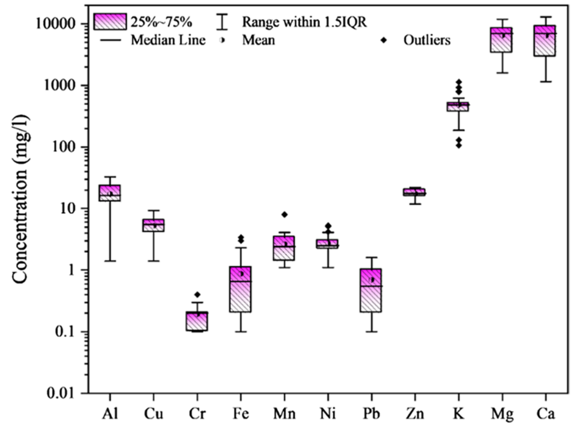

Fig. 3 The variation of heavy metal and alkali metal ions in textile sludge TCLP leachate

Table 4 Metal ion concentration found in the XRF, TCLP test leachate, and the corresponding permissible limits

Elements	XRF (%)	TCLP (mg/l)			Desirable drinking water limit as per the WHO	Drinking water specifications as per BIS (10500:2012)-acceptable limits (mg/l)
		Minimum	Maximum	Mean ± SD (mg/l)		
Al	3.598	1.4	32.7	17.297 ± 8.44		0.03
Cu	0.495	1.4	9.3	5.253 ± 2.049	2	0.05
Cr	0.090	0.1	0.4	0.193 ± 0.083	0.05	0.05
Fe	3.616	0.1	3.4	0.873 ± 0.846	0.4	0.3
Mn	0.078	1.1	8	2.657 ± 1.44	0.04	0.1
Ni	0.011	1.1	9.1	2.75 ± 1.04	0.07	0.02
Pb	0.006	0.1	1.6	0.697 ± 0.50	0.01	0.01
Zn	0.686	11.8	22	17.48 ± 2.75	4	5
K	0.639	106	1135	484.9 ± 217.09	12	-
Mg	12.612	1592	11857	6483 ± 2827.67	150–300	-
Ca	55.621	1153	12962	6433.9 ± 3565.29	150–300	75

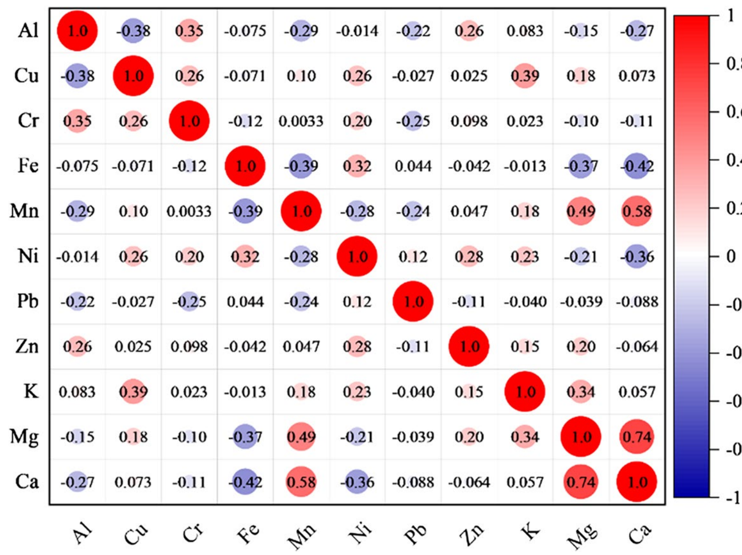

Fig. 4 Pearson's correlation analysis of metal ions presents in leachate from textile sludge

K signifies different sources for their existence. The high correlation between Mg and Ca indicates common sources of their existence.

In this study, the HCA was used to cluster the metal ions and identify their possible source. The HCA clusters are formed using the experimental observations and applying the nearest neighborhood method on the Pearson correlation distance type. The HCA dendrogram is shown in Fig. 5. The heavy metal and alkali metal ion content based on the dendrogram can be divided into one cluster with four groups, and a singleton is formed. Al and Cr have less distance and are clustered in one group; Fe, Ni, and Zn are clustered in the second group; Cu and K are clustered in the third group, while Mn, Mg, and Ca are clustered in the fourth group. The Pb is a singleton joining at the end to form one cluster.

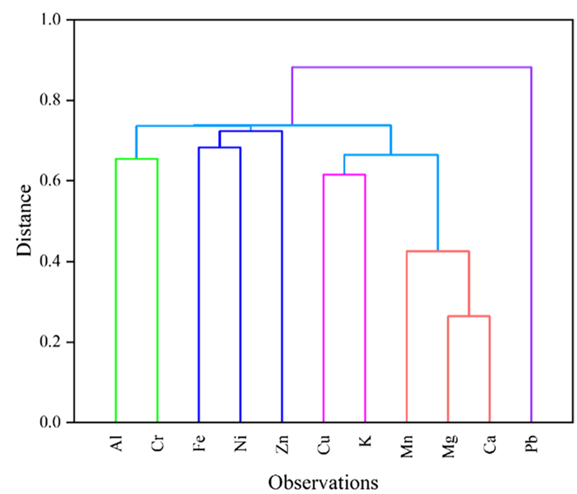

Fig. 5 Dendrogram for the metal ions found in leachate

3.2 Textile-Leachate Pollution Index (T-LPI)

The stakeholder opinion is gathered through the questionnaire in linguistic form and converted to numerical form using the Table 2. Three pairwise comparison matrices are constructed, and the consistency of each matrix is checked by Eqs. (6)–(9). Finally, the IVFWs are calculated applying Eqs. (10)–(15) and the single pairwise matrix is constructed. The defuzzied weights for the metal ions are presented in Table 5 and Fig. 6. The weights are evaluated on the scale of 0–1, with 0 being "least important" and 1 being "extremely important." It is evident from the findings that the relative weight scores are as follows: Al > Pb > Ni > Fe > Cr > Cu >Mn > K > Zn > Mg > Ca. The main reason for the higher score of Al is due to excessive presence of Al in sludge as alum is used extensively in coagulation and flocculation procedure while treating the textile industry effluent.

Table 5 The fuzzy weights matrix $\left(M_i^*\right)$ for the metal ions obtained using the IVTFN

Metal ions	Fuzzy weight using IVTFN	De-fuzzified weights	Rank
Al	(0.162, 0.16, 0.11, 0.175, 0.175)	0.1502	1
Cu	(0.094, 0.086, 0.092, 0.089, 0.089)	0.0912	6
Cr	(0.115, 0.118, 0.101, 0.111, 0.109)	0.1086	5
Fe	(0.121, 0.13, 0.102, 0.123, 0.123)	0.1153	4
Mn	(0.083, 0.076, 0.091, 0.078, 0.078)	0.0838	7
Ni	(0.154, 0.148, 0.111, 0.136, 0.132)	0.132	3
Pb	(0.14, 0.138, 0.124, 0.168, 0.178)	0.147	2
Zn	(0.042, 0.041, 0.073, 0.039, 0.038)	0.051	9
Mg	(0.024, 0.027, 0.06, 0.02, 0.019)	0.0344	10
Ca	(0.022, 0.027, 0.06, 0.02, 0.019)	0.0338	11
K	(0.043, 0.05, 0.076, 0.04, 0.039)	0.0526	8

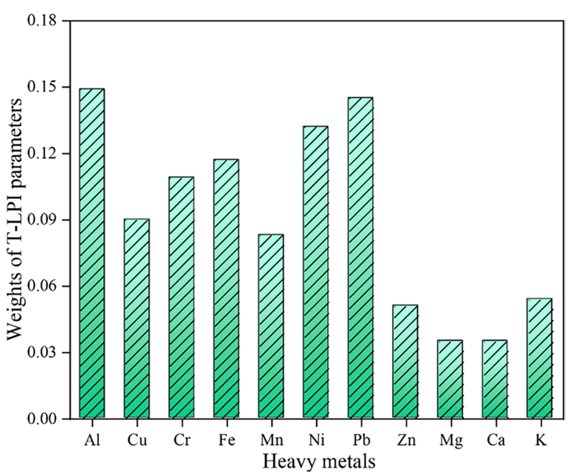

Fig. 6 The de-fuzzified IVFWs of the metal ions present in leachate

Therefore, the higher amount of Al concentration is found in all 30 TCLP test results.

The membership functions corresponding to four classification grades for all the pollutants considered have been derived as given in Table 3. The membership function value of criteria U_i (metal ions) for each grade G_j corresponding to different experimental run (S_i) for the different metal ions and the fuzzy relation matrix is constructed as given in Eq. (20). It is worth mentioning that the data set of thirty experimental data can be considered the 30 different sites and the ranking of sites for earlier disposal of sludge can be performed. The membership function value for the four metal ions with respect to grade classifications is represented in Table 6. For instance, the Al concentration for the S_1 is 19.1 mg/l which belongs to severely polluted grade, i.e., G_3. The membership function value for the G_3 between 10 and 20 mg/l is 1.

The IVFWs obtained for the metal ions are used to calculate the FAM by substituting the weights in the fuzzy relation matrix in Eq. (25). The FAM for the four metal ions Al, Cu, Cr, and Fe is given in Table 7. For instance, FAM matrix calculations for

Table 6 Fuzzy relation matrix values for each sampling data (S_i), for each heavy metal

Metal ions	Fuzzy relation matrix
Al	$\begin{array}{c c} & \begin{matrix} S_1 & S_2 & \cdots & S_{30} \end{matrix} \\ \begin{matrix} G_1 \\ G_2 \\ G_3 \\ G_4 \end{matrix} & \begin{bmatrix} 0 & 0.65 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 1 \end{bmatrix} \end{array}$
Cu	$\begin{array}{c c} & \begin{matrix} S_1 & S_2 & \cdots & S_{30} \end{matrix} \\ \begin{matrix} G_1 \\ G_2 \\ G_3 \\ G_4 \end{matrix} & \begin{bmatrix} 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \end{bmatrix} \end{array}$
Cr	$\begin{array}{c c} & \begin{matrix} S_1 & S_2 & \cdots & S_{30} \end{matrix} \\ \begin{matrix} G_1 \\ G_2 \\ G_3 \\ G_4 \end{matrix} & \begin{bmatrix} 0 & 1 & \cdots & 0 \\ 1 & 0 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \end{bmatrix} \end{array}$
Fe	$\begin{array}{c c} & \begin{matrix} S_1 & S_2 & \cdots & S_{30} \end{matrix} \\ \begin{matrix} G_1 \\ G_2 \\ G_3 \\ G_4 \end{matrix} & \begin{bmatrix} 0 & 0 & \cdots & 1 \\ 0 & 0.2 & \cdots & 0 \\ 1 & 0.8 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \end{bmatrix} \end{array}$

the experimental run S_1, S_2, S_3, S_4, S_5, …, S_{30} for the Al ions are given in Eq. (32).

$$\mathrm{FAM} = M_i * \mathrm{RM} = [0.152 * 1, 0.152 * 0.65, 0.152 * 1, 0.152 * 1, 0.152 * 1, \ldots, 0.152 * 1] \tag{32}$$

The elements of the matrix a $F_j * \alpha_j$ and $\sum_{j=1}^{n} F_j$ for the calculations of the final FS matrix is given in Eq. (33) and Eq. (34)

$$F_j * \alpha_j = \begin{array}{c} \\ G_1 \\ G_2 \\ G_3 \\ G_4 \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & \cdots & S_{30} \end{array} \\ \begin{bmatrix} 0.0048 & 0.0599 & \cdots & 0.0288 \\ 0.2457 & 0.0711 & \cdots & 0.2293 \\ 0.5074 & 0.3267 & \cdots & 0.3453 \\ 0 & 0.132 & \cdots & 0.1502 \end{bmatrix} \end{array} \tag{33}$$

$$\sum_{j=1}^{n} F_j = \left[0.999 \ \ 0.8970 \ \ \ldots \ \ 0.999 \right] \tag{34}$$

The final score (FS) is calculated using Eq. (27) and is represented in Table 8. The sample calculation for estimating final score for the FS_1 is shown in Eq. (35). The final scores for the different experimental runs are presented in Table 8.

$$FS_1 = (0.00408 + 0.245778 + 0.507468 + 0)/0.9999 = 0.757 \tag{35}$$

Table 7 Fuzzy assessment matrix for the heavy metal

Metal ions	Fuzzy assessment matrix (FAM)
Al	$\begin{array}{c} \\ G_1 \\ G_2 \\ G_3 \\ G_4 \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & \cdots & S_{30} \end{array} \\ \begin{bmatrix} 0 & 0.09763 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 0.1502 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0.1502 \end{bmatrix} \end{array}$
Cu	$\begin{array}{c} \\ G_1 \\ G_2 \\ G_3 \\ G_4 \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & \cdots & S_{30} \end{array} \\ \begin{bmatrix} 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 0.0912 & 0.0912 & \cdots & 0.0912 \\ 0 & 0 & \cdots & 0 \end{bmatrix} \end{array}$
Cr	$\begin{array}{c} \\ G_1 \\ G_2 \\ G_3 \\ G_4 \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & \cdots & S_{30} \end{array} \\ \begin{bmatrix} 0 & 0.1086 & \cdots & 0 \\ 0.1086 & 0 & \cdots & 0.1086 \\ 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \end{bmatrix} \end{array}$
Fe	$\begin{array}{c} \\ G_1 \\ G_2 \\ G_3 \\ G_4 \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & \cdots & S_{30} \end{array} \\ \begin{bmatrix} 0 & 0 & \cdots & 0.1153 \\ 0.1153 & 0.2306 & \cdots & 0 \\ 0 & 0.9224 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \end{bmatrix} \end{array}$

The de-fuzzified score for the different experiment runs is presented in Table 8. The first five rankings are as follows $FS_{14} > FS_{24} > FS_{13} > FS_5 > FS_7$. The higher de-fuzzified score for FS_{14}, FS_{13}, FS_5, and FS_7 is due to higher Al, Ni, and Pb content in the leachate of the sludge. The higher weights for these three metals contribute to the higher score indicating higher toxicity. The higher score for the FS_{24} is mainly due to high Al, Cr, Ni, and Pb concentrations in the leachate.

The concentration of Al, Ni, and Pb heavy metal ions is mainly responsible for the higher score of the experiment run. Further, the presence of heavy metals in the sludge could contaminate the groundwater and surface water (Dandautiya et al., 2018; Singh et al., 2019). The ingestion of these heavy metals may result in carcinogenic, respiratory, skin, gastrointestinal diseases, birth defects, nervous system disorder (Izah et al., 2016).

The study effectively considers the variability in environmental samples related to textile industry sludge. The methodology used for determining the toxicity index is a based analytical hierarchical process using inter-valued triangular fuzzy numbers, which incorporates the uncertainty associated with human judgment. The membership functions developed for the concerned metal ions also incorporate uncertainty. The variability caused by different samples can also be addressed by performing sensitivity analysis using the methodology suggested herein. The large-scale industries, mainly in the textile sector, establish their own decentralized effluent treatment plant and produce sludge as one of their end products. This sludge will not have 100% variability. However, in environmental sludge, samples from different industries can have different chemical compositions. Accordingly, the comprehensive model having membership functions for each metal ion can be prepared using the same methodology. Therefore, the toxicity of variable sludge can be ranked using the methodology explained in the manuscript.

Table 8 Final score for the different experimental runs

Experiment no.	De-fuzzified weights	Rank
FS_1	0.757	10
FS_2	0.657	26
FS_3	0.634	28
FS_4	0.735	14
FS_5	0.781	4
FS_6	0.734	15
FS_7	0.779	5
FS_8	0.755	11
FS_9	0.762	8
FS_{10}	0.654	27
FS_{11}	0.772	6
FS_{12}	0.76	9
FS_{13}	0.797	3
FS_{14}	0.836	1
FS_{15}	0.693	25
FS_{16}	0.731	16
FS_{17}	0.729	18
FS_{18}	0.768	7
FS_{19}	0.729	17
FS_{20}	0.722	21
FS_{21}	0.727	19
FS_{22}	0.724	20
FS_{23}	0.75	13
FS_{24}	0.812	2
FS_{25}	0.63	29
FS_{26}	0.703	24
FS_{27}	0.62	30
FS_{28}	0.721	22
FS_{29}	0.707	23
FS_{30}	0.754	12

4 Human Health Risk Assessment

Human health risk assessment was performed to quantify the risk level of heavy metals in leachate and possible contamination of surface water with it. The estimated Average Hazard Index values ($AvgHI_i$) for Cu, Ni, Fe, Mn, Al, Ni, Pb, Zn, and the Average Carcinogenic Risk ($AvgCR_i$) of Cr and Pb values for the four different age groups considering the ingestion and dermal pathways are presented in Fig. 7a and b, respectively. The hazard index values decreased in the order of Pb > Mn > Ni > Cu > Zn > Cr>Al > Fe. The level of risk is maximum for the infants and children, while risk is almost similar for the teens and adults. This indicates that children and infants are more susceptible to the non-carcinogenic health than adults. The hazard index for Fe and Al for all the age groups is less than 1 which indicates no potential non-carcinogenic impact while other metal ions may produce potential non carcinogenic impact on the human health.

The CR values due to Pb for the all the age group lie in 10^{-4}< CR < 10^{-3} which indicates the high level risk. The CR values for the Cr for all the age groups are greater than CR > 10^{-3} lying in very high carcinogenic risk level. The long-term consumption of leachate-polluted surface water and its dremal contact may result in cancer.

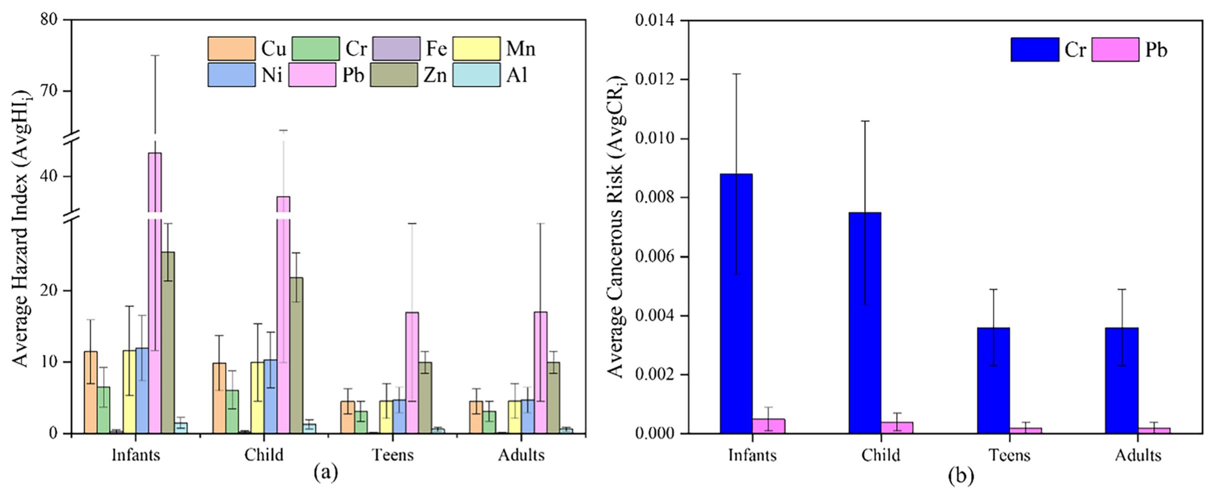

Fig. 7 **a** Average Hazard Index and **b** average carcinogenic risk of the metal ions for different age groups

5 Conclusion

The study provides a novel flexible framework to develop leachate pollution index for hazardous sludges. The study is imperative in distinguishing the different sludges based on their toxicity index and hence useful in establishing the priority among different sludge sites for its sludge disposal at TSDFs. The number of metal ions based on their preliminary investigation can be increased or reduced based on the requirement of the study and the availability of heavy metals in the sludge.

The study is useful for finding the toxicity of different textile sludge and categorizing them based on their toxicity level. These T-LPI scores are essentially helpful in determining the least hazardous sludge. They could provide an alternate sustainable method for its disposal, such as its use in the construction industry or as fertilizer. The higher toxicity scores and knowing about reason for it could also be helpful in finding the probable disposal/usability of sludge. Coagulation and flocculation are a chemical- based effluent treatment process at CETP and could be considered one of the major contributors of heavy metal (Al, Fe) in CETP sludge. Based on the T-LPI score, one can also plan for the best practices in waste management and waste disposal strategies. The hazardous sludge with high T-LPI scores cannot be disposed in open even for few days before their final disposal to TSDF sites. But the sludge with low T-LPI scores can be disposed later after the disposal of sludges with high T-LPI scores. These indices will also be useful in decision making about the sludge disposal. The T-LPI is useful in selecting the effluent treatment site from where the sludge needs to be disposed at first to TSDF based on their toxicity scores.

The statistical analysis and the human health risk assessment of the metal ions present in leachate are performed to find correlation between the metal ions and possible non-carcinogenic, carcinogenic impact of leachate contaminated surface water consumption. The low Pearson correlation coefficient values of the sludge metal ion data indicate the presence of different sources for their existence. The human health risk assessment results indicate the potential non-carcinogenic impact of Pb, Mn, Ni, Cu, Zn, and Cr and the high-level carcinogenic risk of Pb and Cr.

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Author Contribution All authors have contributed as given below with respect to conceptualization, methodology development, data collection, investigation and modeling, original draft preparation, writing, and editing.

SA: conceptualization, methodology, investigation, data collection, data interpretation, analysis, original draft preparation, writing, and editing.

APS: conceptualization, methodology, data collection, data interpretation, investigation and analysis, validation, visualization, writing original draft, review and editing, supervision, and correspondence.

Data Availability All required data supporting the findings are available in the manuscript. If the readers require any additional data, the same would be shared electronically by the authors whenever required.

Declarations

Ethics Approval and Consent to Participate All authors of the manuscript certify that this manuscript fully complies with the ethical standard of this journal.

Consent for Publication Not applicable.

Competing Interests The authors declare no competing interests.

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