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Assessing the Correlation between Water Quality Parameters and *E. coli* Resistance

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ABSTRACT

Access to clean drinking water is essential for human health, but many communities face challenges in obtaining safe water. This study focuses on evaluating the presence of coliform bacteria, including *Escherichia coli* (*E. coli*), in drinking water samples collected during pre- and post-monsoon seasons. A total of 102 samples were analyzed using standard microbiological techniques to assess the prevalence and distribution of multi-drug resistant (MDR) *E. coli*. The study also explores relationships between *E. coli* occurrence and physicochemical water quality parameters using Pearson correlation analysis. Principal Component Analysis (PCA) was employed to identify the underlying patterns and factors influencing antibiotic resistance in *E. coli* strains. The results revealed that calcium, chloride, total dissolved solids, total hardness, and total alkalinity significantly influenced *E. coli* resistance. Additionally, fluoride and pH were found to be critical factors, with fluoride strongly associated with microbial activity, particularly with multi-drug-resistant *E. coli*, while pH affected water chemistry and bacterial dynamics. This study presents a novel and comprehensive approach to assessing drinking water quality through physicochemical analysis, microbial contamination evaluation, and antibiotic susceptibility testing. The findings provide valuable insights into antibiotic resistance dynamics in urban water systems, supporting efforts to develop targeted strategies for mitigating public health risks from waterborne pathogens.

1. Introduction

The consumption of water is a fundamental requirement for the sustenance of human life. There is a pressing need for a supply that is suitable, cost-effective, and secure for consumers. The provision of clean drinking water is expected to result in significant improvements in public health. It is imperative to strive towards attaining the highest level of purity in drinking water quality [1]. Amidst the present circumstances, individuals are facing challenges in accessing potable water for consumption. Ingestion of water contaminated with human or animal faecal matter poses the most significant infectious hazards. Micro-organisms, including bacteria, viruses, etc, have been identified as significant contributors to various health hazards. These microorganisms have the ability to thrive, multiply, and spread within water systems, thereby posing a significant risk to human health [2]. According to the World Health Organization (WHO) approximately 1.7 billion children under the age of five in developing nations succumbed to diarrhoea, primarily as a result of consuming polluted water [3]. In 2018, a global estimate of 525,000 child fatalities was attributed to inadequate water quality, sanitation, and hygiene conditions, with infectious diarrhoea being the primary cause [4]. 1.9 billion people worldwide drink faeces-contaminated water [5]. Waterborne infections affect 37.7 million Indians, with 1.5 million children dying from diarrhoea. According to Elzein et al. (2016), water has the potential to enhance the hydration levels of the internal organs within the human body [6]. The human body's integumentary system is responsible for various functions, including the maintenance of consistent volume and fluid uniformity akin to blood and lymph [7]. Additionally, it plays a crucial role in regulating body temperature and eliminating toxins from the body through urine, sweat, and respiration [8]. These functions are vital to the regulation of skin functions [9].

The *E. coli* is one of the pathogenic bacteria that is gram-negative, non-spore forming, and has a rod-shaped morphology. These bacteria are capable of producing gas in the designated growth medium through fermentation within a period of 48 hours at a temperature of 35 °C [10].

The recognition of *Escherichia coli* as a human pathogen dates back to 1982 [11]. The classification of this entity can be delineated into three distinct categories, namely commensal, diarrheagenic, and extraintestinal groups [12]. The group of bacteria known as faecal coliforms includes *Citrobacter, Enterobacter, Hafnia, Klebsiella, and Escherichia coli*. Among these, *Escherichia coli* is the predominant species that typically thrives in the gastrointestinal tract of endothermic animals. Certain bacterial strains, such as the commensal varieties, are considered benign, whereas others are pathogenic in [13]. Diarrheagenic strains have the potential to cause a range of gastrointestinal illnesses, including diarrhoea, haemorrhagic colitis, haemolytic uremic syndrome, inflammatory colitis, and dysentery. According to Evans & Evans, 1996, extraintestinal strains have the potential to induce urinary tract infections, septicaemia, and neonatal meningitis. Bacteria exhibit a diameter of approximately 0.5 µm, while their length ranges from 1.0 to 3.0 µm. According to research, the survival duration of *E. coli* in water can range from 4 to 12 weeks, contingent upon the prevailing environmental circumstances [14]. The main origin of pathogenic microorganisms in water is faecal matter. To assess water contamination that can affect various water bodies such as rivers, streams, groundwater, surface water, and natural water, the *E. coli* is frequently utilized as an indicator. Additionally, this contamination can have an impact on the diverse activities associated with these water bodies [15]. As per the guidelines provided by the World Health Organization [16], the United States Environmental Protection Agency [17], and the Indian Standard 10500: 2012 [18], the presence of *E. coli* in a water sample of 100 mL should not be detectable.

The identification of *E. coli* in water sources is a crucial concern for indicating the presence of faecal contamination from humans and animals. The implementation of a monitoring technique aimed at detecting *E. coli* bacterial cells is a crucial step towards enhancing water quality and safeguarding public health. It is imperative for humans to mitigate the transmission of infectious diseases caused by *E. coli* in order to minimize associated risks. Inadequate and delayed treatment of the condition may result in fatality, as it is associated with the manifestation of severe health complications such as renal failure and bloody diarrhoea. Drinking water quality is a critical concern for public health, as contaminated water can lead to various waterborne diseases. Therefore, it is essential to assess the microbial quality of drinking water sources to ensure its safety for consumption. This study aimed to investigate the presence of coliform

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bacteria in drinking water samples collected from different areas of Jaipur, Rajasthan, during the pre- and post-monsoon seasons along with determination of the antibiotic susceptibility profiles of the bacterial isolates and correlation observation of multidrug resistant *E. coli* in Jaipur, Rajasthan.

The objective of this study is to assess the presence of coliforms in drinking water samples collected from different areas of Jaipur, Rajasthan, and determine their antibiotic susceptibility profile. The specific aims of the research are as follows:

- To determine the prevalence and concentration of viable count analysis in drinking water samples collected during pre-and post-monsoon periods in Jaipur, Rajasthan.
- To isolate and identify coliform bacterial isolates from the positive samples obtained from the culture in *E. coli* (EC) broth.
- To perform antibiotic susceptibility testing of the coliform isolates using the Kirby-Bauer disc diffusion method on Mueller-Hinton agar.
- To analyse the resistance patterns of the coliform isolates to a set of antibiotics commonly used in clinical practice.
- To identify potential relationships between the occurrence of *E. coli* and various physicochemical water quality parameters using Pearson correlation analysis
- To observe the underlying patterns and factors contributing to the antibiotic resistance traits of *E. coli* strains in the water supply using Principal Component Analysis (PCA).

2. Experimental Methods

2.1 Sample Collection

A total of 102 drinking water samples were collected during pre-and post-monsoon from different areas of Jaipur, Rajasthan in sterilised sample bottles in a standard manner. The samples were then brought up to the laboratory in an ice bath for immediate analysis.

2.2 Test for Coliforms

All collected drinking water samples were cultured into *E. coli* (EC) broth and incubated at 44.5 ± 0.2℃ in a water bath for ~48h. After this, a loopful culture from EC broth which showed positive for gas production was streaked onto Eosin Methylene Blue agar and incubated at 37 °C for 24 h. The flat, dark centred with or without green metallic sheen appeared colonies were cultured on nutrient agar and incubated at 37 °C for 24 h to obtain a pure culture.

A viable count of *E. coli* bacteria is conducted to quantify the quantity of actively growing bacterial cells in the form of colony-forming units (CFU). A CFU is a macroscopic aggregation of millions of bacteria originating from a single bacterial cell that is visible under a microscope. The plate count technique involves the serial dilution of a water sample to enumerate the quantity of bacterial cells present within the sample. The digital colony counter is a device utilized for the purpose of enumerating the quantity of bacterial colonies present on a petri dish.

2.3 Antibiotic Susceptibility Test

The susceptibility profile of bacterial isolates to a set of antibiotics were tested by the Kirby-Bauer disc diffusion method on Mueller-Hinton agar (Hi Media) following the standard operational procedures of CLSI. Antibiotics (all from Hi media) used in the study included, Amoxicillin (Amx^{30}), Ampicillin (A^{25}), Cefixime (CFM^{5}), Chloramphenicol (C^{30}), Ciprofloxacin (Cf^{30}), Cloxacillin (Cx^{30}), Co-trimoxazole (Co^{25}), Doxycycline Hydrochloride (DO^{30}), Erythromycin (E^{15}), Gentamicin (G^{10}), Imipenem (IPM^{10}), Kanamycin (K^{30}), Methicillin (M^{30}), Nalidixic acid (Na^{30}), Neomycin (N^{30}), Nitrofurantoin (Nf^{30}), Oxacillin (Ox^{5}), Polymyxin-B (Pb^{300}), Rifamycin (R^{30}) and Tetracycline (T^{30}). About 0.1 mL of overnight grown fresh culture were spread over the MH agar plate followed by aseptically placing an antibiotic disc and then incubated for 24h at 37ºC. The result of resistance and sensitivity was recorded and interpreted by measuring the diameter of zones of inhibition using calibrated zone scales and comparing it with the standard zone size interpretative chart as per Clinical Laboratory Standards Institute (CLSI) and the European Committee on Antimicrobial Susceptibility Testing (EUCAST).

2.4 Pearson Correlation Coefficient

The correlation coefficient is a measure of the relationship between two variables [19]. It ranges between -1 and 1, denoted by a symbol (r). If the two variables are in a perfect linear relationship, the correlation coefficient will be either 1 or –1. The sign shows the correlation between variables as positive or negative [20]. When there is no linear relationship between the variables, the correlation coefficient's value is 0 [21]. A statistical technique used to calculate the linear relationship and dependence between two variables is the Pearson correlation. The absolute value r of 0.1 is classified as small, the absolute value 0.3 is classified as medium, and the absolute value 0.5 is classified as high, according to Cohen [22]. The Pearson correlation coefficient (r) was used in this study to evaluate the correlation between the physicochemical parameters of water quality and *E. coli*. There was a low positive or negative linear correlation when the correlation coefficient was between ±0.1 and ±0.3, a medium positive or negative linear correlation when it was between ±0.3 and ±0.7, and a high positive or negative linear correlation when it was between ±0.7 and ±1.0. The statistical analysis was performed using MATLAB 2024a software.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \overline{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

where,

$r = correlation\ coefficient$

$x_i = values\ of\ the\ x - variable\ in\ a\ sample$

$\bar{x} = mean\ of\ the\ values\ of\ the\ x - variable$

$y_i = values\ of\ the\ y - variable\ in\ a\ sample$

$\bar{y} = mean\ of\ the\ values\ of\ the\ y - \ variable$

2.5 Principal Component Analysis (PCA)

The principal component analysis (PCA) is a multivariate statistical technique employed to diminish the dimensionality of a dataset comprising a substantial number of observations, thereby facilitating an enhanced comprehension of the variables involved [23]. PCA operates on a mathematical algorithm rooted in linear algebra, delineating the relationships within a dataset structured with variables as columns and observations or samples as rows. The primary objective of PCA is to construct a transformed matrix utilizing coefficients of principal components to encapsulate the maximal amount of information, subsequently facilitating the visualization of the data via a two-dimensional plot in MATLAB software [24]. The PCA algorithm facilitates the reduction of data dimensions to a manageable number of variables, thereby enhancing interpretability. Subsequently, it generates fundamental visualizations, such as score plots and loading plots, which are instrumental in examining the correlations within a broadly clustered dataset [24,25]. Variables that are correlated in this manner are referred to as principal components [26].

3. Results and Discussion

The Durham's tubes are the tiny, inverted glass tubes in the EC broth in Fig. 1. A gas bubble forming within the Durham's tubes is a sign that there is gas present. This gas generation indicates contamination in the water samples and is a positive indicator of the presence of coliform bacteria. The faecal coliform bacteria are first detected in the drinking water samples by the growth and gas generation shown in Fig. 1. This detection is crucial because coliform bacteria are signs of faecal pollution, which may endanger consumer health if found in drinking water. The existence of coliform bacteria would have been confirmed, and their sensitivity to antibiotics would have been determined, by further investigation and testing.

Fig. 1 Growth of faecal coliform in EC broth showing gas production in Durham's tubes

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The growth of *E. coli* on eosin-methylene blue agar medium is illustrated in Fig. 2. The visual depiction portrays an increase of *E. coli* colonies on the agar medium, thereby signifying the existence of this microorganism in the water specimens. The detection of *E. coli* colonies serves as a significant marker for the existence of faecal contamination and the probable health hazards linked with the water samples.

Fig. 2 Growth of *E. coli* on eosin-methylene blue agar medium showing green metallic sheen

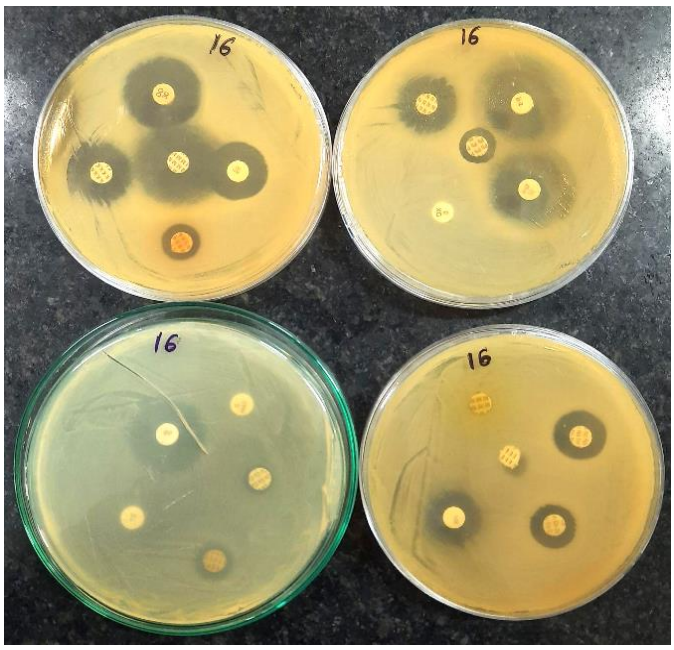

Fig. 3 Antibiotic susceptibility test of *E. coli* on Mueller-Hinton agar medium by Kirby-Bauer disc method

A total of 49 bacterial isolates from 102 drinking water samples were identified as *E. coli* by morphological and cultural (green metallic sheen on EMB) characteristics. The antimicrobial susceptibility profile of bacterial isolates to a set of antibiotics showed resistance against rifampicin (85.71%), oxacillin (81.63%), methicillin (81.63%), cefixime (57.14%), erythromycin (55.1%), tetracycline (51.02%), cloxacillin (51.02%), ampicillin (48.97%), amoxicillin (46.93%), nalidixic acid (44.89%), kanamycin (38.77%), ciprofloxacin (34.69%), nitrofurantoin (32.65%), chloramphenicol (18.36%), gentamicin (18.36%), co-trimoxazole (14.28%), imipenem (10.2%), doxycycline hydrochloride (6.12%) and neomycin (2.04%) while 100% of the isolates were susceptible to polymyxin-B (Fig. 4).

The multiple antibiotic resistance index (MARI) was derived using a mathematical formula as described earlier and expressed as MAR_{Index} = a/b, where 'a' defined the number of antibiotics to which the isolates were resistant and 'b' the total number of antibiotics to which an individual isolated was tested. The MARI analysis revealed that isolates of MDR *E. coli* isolates had very high MARI value (>0.2) which implied a high risk of contamination. The MARI value of *E. coli* isolated from drinking water ranged from 0.15 to 0.70.

The multidrug resistant characteristics of each isolate were phenotypically identified by observing the resistant pattern of the isolates against tested antibiotics as represented in Fig. 3. The study showed number 46 (93.87%) were found to be multidrug resistant. Two of the isolates J96-A3 and J97-B4 showed highest MDR pattern against 14 antibiotics of 6 different classes including, quinolones, β-lactam, sulfonamides, macrolides, tetracycline and aminoglycosides (Fig. 5).

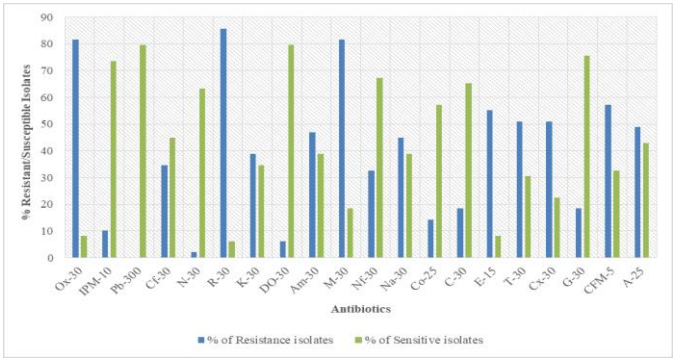

Fig. 4 Antibiotic susceptibility profile of *E. coli* isolates against a set of tested antibiotics

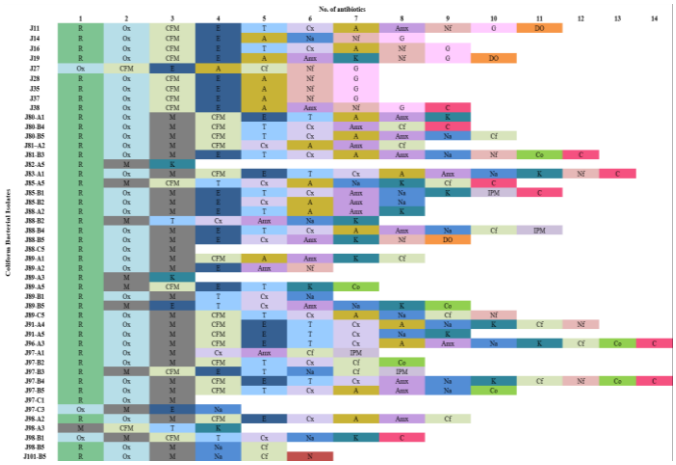

Fig 5 Multidrug resistant pattern of *E. coli* isolates from drinking water of Jaipur, Rajasthan. Key antibiotics: Amoxicillin (Amx^{30}), Ampicillin (A^{25}), Cefixime (CFM^{5}), Chloramphenicol (C^{30}), Ciprofloxacin (Cf^{30}), Cloxacillin (Cx^{30}), Co-trimoxazole (Co^{25}), Doxycycline Hydrochloride (DO^{30}), Erythromycin (E^{15}), Gentamicin (G^{10}), Imipenem (IPM^{10}), Kanamycin (K^{30}), Methicillin (M^{30}), Nalidixic acid (Na^{30}), Neomycin (N^{30}), Nitrofurantoin (Nf^{30}), Oxacillin (Ox^{5}), Polymyxin-B (Pb^{300}), Rifamycin (R^{30}) and Tetracycline (T^{30})

The viable count analysis showed maximum cell count 1.59-13.66 x 10^5 CFU/mL. The findings of the present/absent test for faecal coliform bacteria in the drinking water samples are depicted in Fig. 6. The objective of the test is to ascertain the presence or absence of faecal coliform bacteria in the samples. Among the 102 drinking water samples that were collected, a total of 21 samples were detected to contain faecal coliform bacteria. The presence of colonies suggestive of faecal contamination, potentially encompassing *E. coli*, was detected in the aforementioned 21 samples.

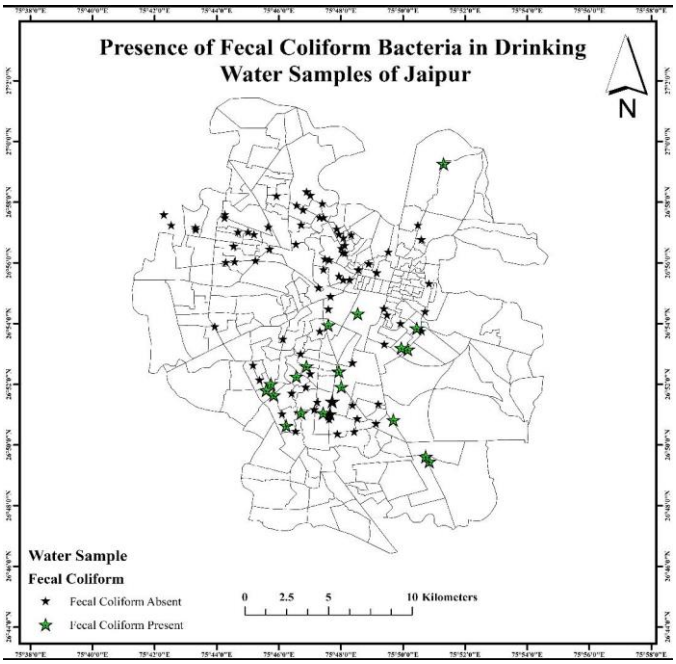

Fig. 6 Present/absent test for fecal coliform bacteria

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The findings depicted in Fig. 4 offer significant insights into the existence or non-existence of faecal coliform bacteria in the potable water specimens. The above information is of utmost importance in evaluating the microbiological standard of the water and detecting plausible health hazards linked with faecal pollution.

The heatmap was used to found the between the presence of *E. coli* like isolates and water quality parameters measured in drinking water samples. Each cell in the heatmap displays a correlation coefficient that provides details how strongly each water quality parameter is associated with the occurrence of *E. coli*-like isolates, as shown in Fig. 7. Positive values indicate a direct correlation, where an increase in the parameter's value tends to coincide with higher occurrences of *E. coli*-like isolates, and negative values indicate an inverse relationship. The colour intensity in the heatmap represents the strength of the correlation, with warmer colours denoting higher positive correlations and cooler colours indicating stronger negative correlations. This analysis is important for identifying important parameters that may influence the prevalence of *E. coli* in water systems, thereby guiding effective management and treatment strategies to ensure water safety and public health.

The correlation analysis shows relationships between the presence of *E. coli* like isolates in drinking water and various water quality parameters. Water quality parameters such as total hardness, total alkalinity, and TDS show stronger correlations with the occurrence of *E. coli*-like isolates which indicative the environmental conditions that favour the growth and presence of bacteria. Water quality parameters like pH and chloride show a less correlation suggesting that they might not be as critical in influencing *E. coli* concentrations under the conditions studied. Understanding these correlations is essential for water quality management, as it helps in identifying specific factors for monitoring and treatment to reduce the risk of waterborne diseases associated with *E. coli* contamination.

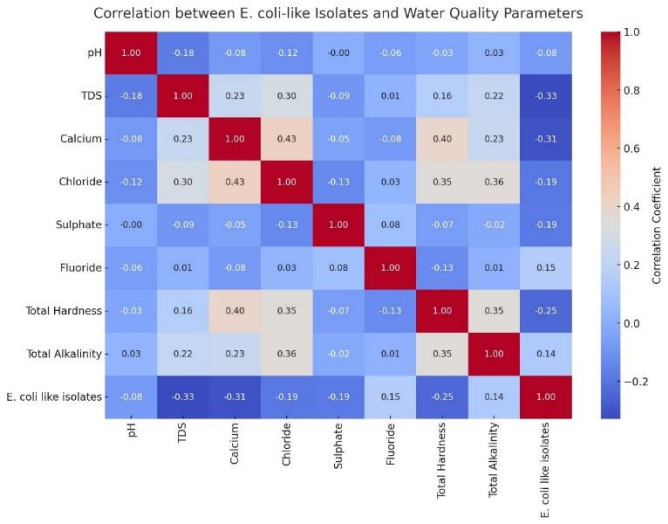

Fig. 7 Correlation between *E.coli* like isolates and water quality parameters

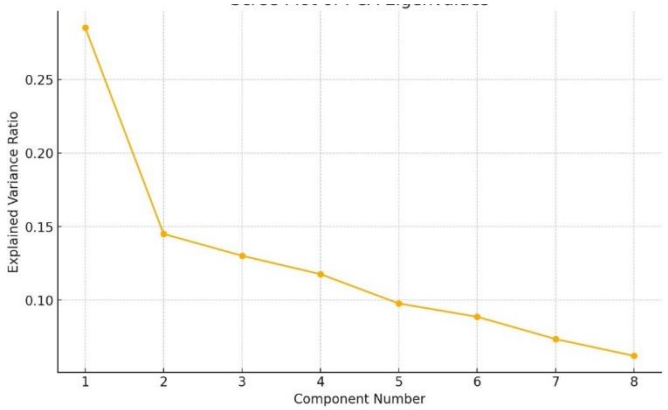

Fig. 8 Scree plot of PCA Eigen values

A strong positive correlation was observed between calcium and hardness, as calcium is a major contributor to water hardness. TDS and other mineral-based parameters such as calcium, chloride, and sulphate also show positive correlations that makes sense as TDS measures the total amount of dissolved substances which include these minerals. The correlation analysis shows in the heatmap provides a quantitative assessment of various water quality parameters related to the presence of *E. coli*-like isolates in drinking water samples. This analysis helps to identify environmental factors that are most likely to influence the prevalence of *E. coli*. Understanding these correlations is crucial for developing targeted water treatment and management strategies. This analytical approach helps in ensuring the safety of drinking water and also supports the optimization of resource allocation in water quality management efforts. The relationship between Eigen values and Eigen vector numbers is plotted in Fig. 8, which gives the scree plot of PCA.

The three coefficients of principal component scores (PC1, PC2, and PC3), derived from the principal component analysis were used as input for prediction, effectively reducing the computational dimension of the model and enhancing its operational efficiency. When three principal components were taken, a stabilization in the observed trends was observed. These components were organized in descending order based on their respective variances. Furthermore, the cumulative contribution of the top three principal components was observed to be 70%, as demonstrated in Figure 8. Therefore, these three principal components were selected for detailed analysis, as presented in Table 1.

Principal components expressions are given in below equations:

Principal Component 1 (PC1):

$$PC1 = (-0.26 \times pH) + (0.356 \times TDS) + (0.466 \times Calcium) + (0.500 \times Chloride) - (0.129 \times Sulphate) - (0.056 \times Fluoride) + (0.452 \times Total\ Hardness) + (0.407 \times Total\ Alkalinity)$$

Principal Component 2 (PC2):

$$PC2 = (-0.617 \times pH) + (0.339 \times TDS) - (0.072 \times Calcium) + (0.095 \times Chloride) + (0.185 \times Sulphate) + (0.616 \times Fluoride) - (0.263 \times Total\ Hardness) - (0.086 \times Total\ Alkalinity)$$

Principal Component 3 (PC3):

$$PC3 = (-0.364 \times pH) + (0.227 \times TDS) - (0.048 \times Calcium) - (0.020 \times Chloride) - (0.720 \times Sulphate) - (0.384 \times Fluoride) - (0.137 \times Total\ Hardness) - (0.360 \times Total\ Alkalinity)$$

PC1 can be interpreted as influenced by mineral content like Calcium and Chloride, whereas PC2 is more influenced by pH and Fluoride content.

Table 1 The coefficient of principal component score of variables

Variable	PC1	PC2	PC3
pH	-0.126	-0.617	-0.364
TDS	0.356	0.339	0.227
Calcium	0.466	-0.072	-0.048
Chloride	0.500	0.095	-0.020
Sulphate	-0.129	0.185	-0.720
Fluoride	-0.056	0.616	-0.384
Total Hardness	0.452	-0.263	-0.137
Total Alkalinity	0.407	-0.086	-0.360

Principal component 1 (PC1) appeared as a crucial factor, showing strong positive loadings with total dissolved solids, calcium, chloride, total hardness, and total alkalinity. This component suggests that the general mineral content and hardness of the water are essential in explaining the variance within the dataset. These parameters are often associated with the overall quality of water, influencing everything from taste and safety to chemical reactivity and the efficacy of disinfection processes. Principal component 2 (PC2) shown a significant correlation between microbial activity and the levels of Fluoride in the water. This relationship suggests that fluoride levels can interact with microbial viability or growth, potentially influencing the presence and survival of multi-drug-resistant *E. coli*. The high loading of *E. coli* on this component highlights the importance of microbial indicators in understanding water quality and safety. Principal component 3 (PC3) is influenced by pH, which is a critical factor in water chemistry, affecting solubility, chemical reactions, and biological processes. The involvement of pH in this component points to its role in the stability or reactivity of the water, which could impact microbial dynamics and the effectiveness of water treatment methods.

It is evident from the PCA results that certain chemical properties of water specifically, mineral content (TDS, calcium, chloride, total hardness and alkalinity), fluoride levels, and pH are crucial in understanding the dynamics of multi-drug-resistant *E. coli* in drinking water systems. Since hardness and mineral content significantly influence water quality,

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adjusting these parameters through treatment processes could potentially mitigate the risks associated with harmful bacterial presence. Managing pH levels could be critical in maintaining chemical balance and preventing conditions favourable for the growth of resistant bacteria. These observations can help in developing targeted water treatment strategies and regulatory measures to monitor and control the presence of multi-drug-resistant *E. coli* in drinking water, ensuring public health safety.

4. Conclusion

This study aimed to assess the presence of coliforms in drinking water samples collected from various areas of Jaipur, Rajasthan, and to determine their antibiotic susceptibility profiles. The research objectives were successfully achieved through methodical sample collection and analysis. A total of 102 drinking water samples were collected during the pre- and post-monsoon periods, and subjected to immediate laboratory analysis. Coliform testing was conducted by culturing the water samples in *E. coli* broth, followed by streaking on eosin-methylene blue agar. The presence of *E. coli* colonies indicated faecal contamination, posing potential health risks.

The Kirby-Bauer disc diffusion method was employed to test the antibiotic susceptibility of isolated coliform bacteria, revealing resistance patterns through zone of inhibition measurements. Out of the 102 water samples, 21 tested positives for faecal coliform bacteria, underscoring the presence of contamination and associated health risks. The study provides valuable insights into the microbiological quality of drinking water, highlighting the importance of water treatment and sanitation practices to ensure safe drinking water. The antibiotic susceptibility profiles of coliform bacteria offer key information for the effective treatment of waterborne infections. Pearson correlation analysis was performed to explore the relationship between water quality parameters and *E. coli* isolates, providing critical information for water quality management. This analysis aids in identifying specific factors to monitor and treat, reducing the risk of *E. coli* contamination in drinking water.

The principal component analysis (PCA) revealed that certain chemical properties of water, such as mineral content (calcium, chloride), fluoride levels, and pH, are crucial in understanding the dynamics of multidrug-resistant (MDR) *E. coli* in drinking water systems. PC1 was influenced primarily by mineral content, while PC2 was more influenced by pH and fluoride levels. These findings are essential for future studies and interventions in water quality management, particularly in regions with a growing concern for antibiotic resistance. Additionally, the study highlighted the importance of examining how fluoride treatment impacts microbial populations, particularly resistant strains. These findings provide critical information for policymakers, public health officials, and researchers to develop targeted interventions, surveillance programs, and policies aimed at reducing antibiotic resistance and ensuring the safety of drinking water.

This study also presents a novel and comprehensive approach to assessing water quality through a combination of physicochemical analysis, microbial contamination evaluation, and antibiotic susceptibility testing. It demonstrates important relationships between water quality parameters (pH, total dissolved solids, calcium, chloride, fluoride, total hardness, and total alkalinity) and *E. coli* concentrations, offering unique insights into how environmental factors influence bacterial contamination and resistance. The identification of MDR *E. coli* strains and the use of the multiple antibiotic resistance index (MARI) highlight significant public health risks, particularly in areas where antibiotic resistance is a growing concern. The study provides an understanding of seasonal variations in contamination levels by including both pre- and post-monsoon samples. Ultimately, these findings offer valuable guidance for policymakers and public health officials in managing microbial contamination and mitigating antibiotic resistance risks in drinking water systems.

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References

[1] A. Koyun, E. Ahlatcolu, Y. Koca, S. Kara, Biosensors and their principles, in: A Roadmap of biomedical engineers and milestones, IntechOpen, London, UK, 2012, pp.117–142.
[2] A. Sassolas, L.J. Blum, B.D. Leca-Bouvier, Immobilization strategies to develop enzymatic biosensors, Biotechnol. Adv. 30(3) (2012) 489–511.
[3] World Health Organization, Diarrhoeal disease, WHO Fact Sheet FS330, Geneva, 2017.
[4] Central Bureau of Health Intelligence, National Health Profile 2018, Ministry of Health and Family Welfare, Government of India, New Delhi, 2018.
[5] A. Sadana, Binding and dissociation kinetics for different biosensor applications using fractals, Elsevier, USA, 2006.
[6] M. Elzein, A. Alum, M. Abbaszadegan, Biochemical signature assay for use in a biosensor platform to detect bacteria in drinking water biofilms, J. Environ. Sci. Health A 48(8) (2013) 925–932.
[7] N. Hesari, A. Alum, M. Elzein, M. Abbaszadegan, A biosensor platform for rapid detection of *E. coli* in drinking water, Enzyme Microb. Technol. 83 (2016) 22–28.
[8] T. Garcia-Armisen, P. Lebaron, P. Servais, β-D-glucuronidase activity assay to assess viable *Escherichia coli* abundance in freshwaters, Lett. Appl. Microbiol. 40(4) (2005) 278–282.
[9] N.S.K. Gunda, S. Naicker, S. Shinde, S. Kimbahune, S. Shrivastava, S. Mitra, Mobile Water Kit (MWK): a smartphone compatible low-cost water monitoring system for rapid detection of total coliform and *E. coli*, Anal. Methods 6(16) (2014) 6236–6246.
[10] D. Greenwood, R. Slack, J. Peutherer, M. Barer, Medical microbiology: A guide to microbial infections, Churchill Livingstone, 2007.
[11] L.W. Riley, R.S. Remis, S.D. Helgerson, et al., Hemorrhagic colitis associated with a rare *Escherichia coli* serotype, N. Engl. J. Med. 308(12) (1983) 681–685.
[12] O. Tenaillon, D. Skurnik, B. Picard, E. Denamur, The population genetics of commensal *Escherichia coli*, Nat. Rev. Microbiol. 8(3) (2010) 207–217.
[13] F.M. Khan, R. Gupta, S. Sekhri, Analysis of increase in cell counts of Escherichia coli in groundwater of Rajasthan: possible presence of VBNC cells, Res. J. Chem. Environ. 25(6) (2021) 1-8.
[14] M.B. Nevers, A.B. Boehm, Modeling fate and transport of fecal bacteria in surface water, in: The Fecal Bacteria, Eds M.J. Sadowsky, R.L. Whitman, Wiley, USA, 2010, pp.165–188.
[15] R.M. Atlas, Microbial ecology: Fundamentals and applications, Pearson Education India, India, 1998.
[16] World Health Organization, Guidelines for Drinking-water Quality, Fourth Ed., WHO, Geneva, 2011.
[17] United States Environmental Protection Agency, Drinking water standards and health advisories table, USA, 2009.
[18] Bureau of Indian Standards, Indian Standard Drinking Water—Specification (IS 10500:2012), BIS, New Delhi, India, 2012.
[19] I. Cohen, Y. Huang, J. Chen, J. Benesty, Pearson correlation coefficient, in: Noise reduction in speech processing, Springer, Berlin Heidelberg, 2009, pp.1–4.
[20] P. Schober, C. Boer, L.A. Schwarte, Correlation coefficients: appropriate use and interpretation, Anesth. Analg. 126(5) (2018) 1763–1768.
[21] B. Ratner, The correlation coefficient: its values range between +1/−1, or do they?, J. Target. Meas. Anal. Mark. 17(2) (2009) 139–142.
[22] L. Saba, G. Mallarini, A comparison between NASCET and ECST methods in the study of carotids, Eur. J. Radiol. 76(1) (2010) 42–47.
[23] W.Z. Lu, W.J. Wang, X.K. Wang, Z.B. Xu, A.Y. Leung, Using improved neural network model to analyze RSP, NOx and NO_2 levels in urban air in Mong Kok, Hong Kong, Environ. Monit. Assess. 87 (2003) 235–254.
[24] A.J. Bell, T.J. Sejnowski, The "independent components" of natural scenes are edge filters, Vision Res. 37(23) (1997) 3327–3338.
[25] B. Stojanovic, A. Neskovic, Impact of PCA-based fingerprint compression on matching performance, in: Proceedings of TELFOR 2012, IEEE, 2012, pp.693–696.
[26] R.L. Shinde, K.G. Khadse, Multivariate process capability using principal component analysis, Qual. Reliab. Eng. Int. 25(1) (2009) 69–77.

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