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QSPR Analysis of Eye Conjunctivitis Drops Using Regression Model via Degree Based Topological Indices

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Abstract:

Introduction: Topological indices (TIs) are numerical values derived from the structural graph of a molecule, vital in cheminformatics for predicting various properties. In chemical graph theory, graphs represent molecular structures where vertices correspond to atoms and edges to bonds. Degree-based indices, reflecting vertex connectivity, are used to predict properties such as boiling point and molar refractivity. This study analyses eight eye drops—ciprofloxacin, gentamicin, moxifloxacin, norfloxacin, tobramycin, levofloxacin, gatifloxacin, and chloramphenicol—using these indices.

Objectives: To analyse the degree-based topological indices of eight eye drops and predict their physicochemical properties, including boiling point, enthalpy, mass, flash point, molar refractivity, and volume, using a linear regression model.

Methods: Degree-based topological indices were computed through edge partitioning. A Quantitative Structure-Property Relationship (QSPR) model was developed with linear regression to predict the properties of the eye drops. Prediction accuracy was evaluated by comparing predicted values to actual values and analysing the associated errors.

Results: The study found a strong correlation between the topological indices and the physicochemical properties of the eye drops. The linear regression model accurately predicted these properties, with minimal error, demonstrating the effectiveness of using TIs in this context.

Conclusions This research highlights the effectiveness of topological indices and linear regression models in predicting the properties of eye drops. These tools offer valuable insights for drug design and development, paving the way for more effective treatments for eye conditions.

Keywords: chemical graph theory; cheminformatics; correlation; degree based topological indices; QSPR analysis; regression

1. Introduction

A mathematical field known as "graph theory" studies the characteristics and uses of graphs, which are structures made up of vertices (nodes) and edges (connections) that represent pairwise relationships between entities [1]. Graphs are used extensively to represent and analyse networks and their properties in a variety of fields, including computer science, biology, the social sciences, and logistics. Beyond these fields, graph theory plays a crucial role in the pharmaceutical and chemical industries. In drug discovery and chemistry, graphs are utilised to model molecular structures, with atoms depicted as

vertices and chemical bonds as edges. This graphical representation enables researchers to analyse molecular properties, forecast the behaviour of chemical compounds, and identify promising drug candidates.

Molecular graphs are connected, simple, and have no parallel edges. The degree of a vertex, denoted as dv, is the number of edges connected to that particular vertex. If an edge joins vertices v_1 and v_2, then the degree of v_1 is denoted as dv_1, and the degree of v_2 is denoted as dv_2 [2]. In molecular graph theory, hydrogen atoms are often considered to have no direct impact on the graph's topological features. Therefore, a hydrogen-suppressed graph is used, which excludes hydrogen atoms and focuses on the main framework of the molecule.

In chemical graph theory, a topological index (TI) is a number or parameter that is obtained from a molecule's structural graph[3]. It contains information about the molecule's structure, connectivity, symmetry, branching, and cyclicity, among other topological and geometric features. When predicting the physical, chemical, and biological properties of molecules based on their structural traits, topological indices play a crucial role in quantitative structure-activity relationship (QSAR) investigations. They are useful resources for a number of chemical and biochemistry-related subjects, including drug design and materials research. Cheminformatics, also referred to as chemical informatics, is a scientific discipline merging mathematics and chemistry. Within cheminformatics, one area of focus involves QSPR (Quantitative Structure-Property Relationship) and QSAR (Quantitative Structure-Activity Relationship) investigations. These methods utilise mathematical models to establish relationships between the structural characteristics of chemical compounds and their associated physical, chemical, and biological properties or behaviours.

For humans to survive, their eyes are essential. They can become pink or red and irritate when they are impacted by illnesses such as conjunctivitis. Daily tasks may be disrupted, and normal functioning may be prevented. Seeking prompt treatment is crucial to reducing these symptoms and safeguarding eye health. Pink eye, also known as conjunctivitis, can result in a number of discomforts and issues, such as redness, irritation, itching, excessive tearing, discharge (which may be watery or contain pus), and swelling of the eyelids. One can observe the differences between a normal eye and an eye affected by conjunctivitis. When the eyes are affected, they become red and disrupt our healthy, normal routine.

Figures 1 and 2 illustrate a healthy eye and an eye affected by conjunctivitis, respectively. Figures 1–2 are sourced from Google Images.

Figure 1. Healthy Eye

Figure 2. Affected Eye

Various eye drops are recommended by doctors to treat conjunctivitis. Depending on the patient's health and ocular conditions, different eye drops are prescribed. Eight eye drops—Ciprofloxacin,

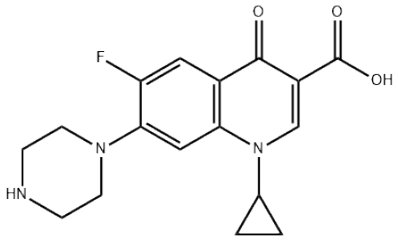
Gentamicin, Moxifloxacin, Norfloxacin, Tobramycin, Levofloxacin, Gatifloxacin, and Chloramphenicol—were selected for examination in this study, as they are commonly used for treating bacterial infections like conjunctivitis.

Both ***ciprofloxacin(***$C_{17}H_{18}FN_3O_{3)}$ and ***moxifloxacin(***$C_{21}H_{24}FN_3O_{4)}$ are fluoroquinolone antibiotics that are effective against a wide range of Gram-positive and Gram-negative bacteria. They function by blocking the bacterial enzymes DNA gyrase and topoisomerase IV, which are necessary for DNA replication and cell division. ***Norfloxacin***($C_{16}H_{18}FN_3O_3$), another fluoroquinolone, shares a similar mechanism but is typically used against Gram-negative bacteria and some Gram-positive strains. ***Gentamicin***($C_{21}H_{43}N_5O_7$) and ***tobramycin***($C_{18}H_{37}N_5O_9$) are aminoglycoside antibiotics that disrupt bacterial protein synthesis by binding to the 30S ribosomal subunit, targeting a range of Gram-negative and some Gram-positive bacteria[4]. ***Levofloxacin(***$C_{18}H_{20}FN_3O_{4)}$, also a fluoroquinolone, is effective against both Gram-positive and Gram-negative bacteria through its inhibition of DNA synthesis. ***Gatifloxacin(***$C_{19}H_{22}FN_3O_{4)}$, another member of the fluoroquinolone class, similarly interferes with bacterial DNA replication. ***Chloramphenicol(***$C_{11}H_{12}Cl_2N_2O_{5)}$**,** distinct from the others, inhibits protein synthesis by binding to the 50S ribosomal subunit, and it has a broad spectrum of activity against many Gram-positive and Gram-negative bacteria, including some resistant strains. By focusing on different bacterial pathways to reduce symptoms and aid in recovery, each of these drugs is essential in the management of bacterial eye infections.

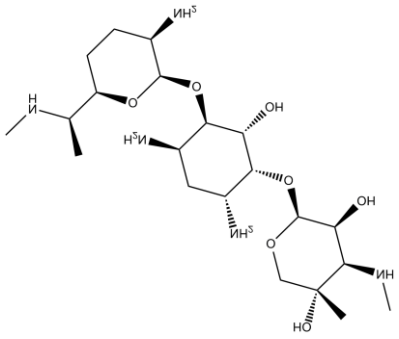
Figure 3 displays the chemical structures of these eight eye drops. The source of these structures is ChemBook.

Several recent studies have explored the use of topological indices and quantitative structure-property relationship (QSPR) modelling in analysing novel drugs for various medical conditions [5–17]. These studies collectively demonstrate the utility of topological indices and QSPR modelling in pharmaceutical research for predicting molecular properties and understanding drug behavior. Inspired by these studies, there is a growing interest in applying topological indices and QSPR modelling to analyse the properties of eye drops.

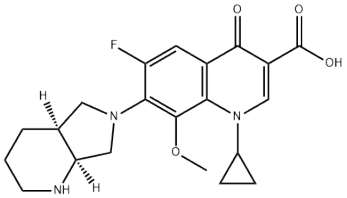
In this work, physicochemical properties are predicted using a variety of degree-based topological indices. Of the several indices that are now available, seven degree-based topological indices have been selected for examination. The Forgotten Index (F(G), the First Zagreb Index (M_1(G), the Second Zagreb Index (M_2(G), the Randic Index R(G), the Augmented Zagreb Index AZI(G), the Harmonic Index H(G), and the Atom-Bond Connectivity Index ABC(G) are among them. By examining and measuring the topological features of the molecules being studied, these indices offer important new perspectives on their physicochemical qualities.



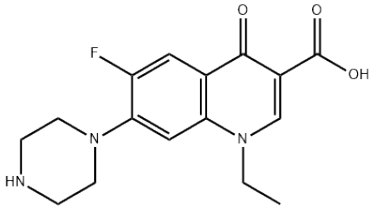
a) Ciprofloxacin



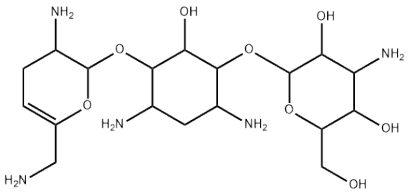
b) Gentamicin



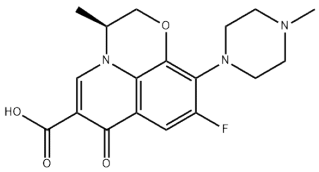
c) Moxifloxacin



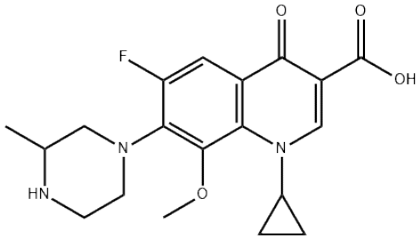
d) Norfloxacin



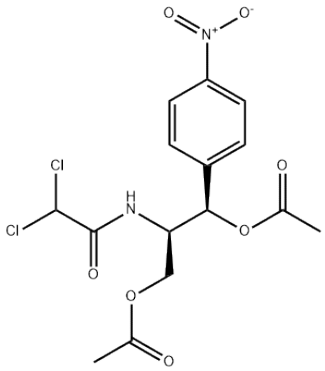
e) Tobramycin



f) Levofloxacin



g)Gatifloxacin



h)Chloramphenicol

Figure 3. Molecular Structures of Eye drops

2. Objectives

The main objective of this paper is as follows

- ❖ Convert the molecular structures of selected eye drops into molecular graphs.
- ❖ Determine the edge partition for eight selected eye drop formulations.
- ❖ Calculate seven degree-based topological indices from the molecular graphs.
- ❖ Identify the physicochemical properties of the active ingredients in the drugs.
- ❖ Analyze the correlation between topological indices and physicochemical properties of the drugs.

❖ Conduct Quantitative Structure–Property Relationship (QSPR) analysis using a regression model, comparing predicted values with actual experimental data.

2.1 Topological Indices Preliminaries

If an edge between u and v is considered to be uv, then the additive degree based Topological indices (TI) have the generic form [18].

$$TI=TI(A)=\sum_{uv\in E(A)} F(d_u, d_v)$$

The Forgotten index was originally introduced by Furtula and Gutman [19] in 2015 and is defined as

$$F(G)=\sum_{v_1v_2\in E(G)}[(dv_1)^2+(dv_2)^2] \quad (1)$$

The first and second Zagreb indices are part of the earliest topological indices, introduced by Gutman and Polansky[20] in 1986. They are used to describe the pi-electron properties of molecules.

$$M_1(G)=\sum_{v_1v_2\in E(G)}(dv_1+dv_2) \quad (2)$$

$$M_2(G)=\sum_{v_1v_2\in E(G)}(dv_1\times dv_2) \quad (3)$$

The Randić index, created by Milan Randić[21], assesses molecular graph connectivity for QSAR predictions of biological activity based on molecular structure.

$$R(G)=\sum_{v_1v_{2\in E(G)}}\frac{1}{\sqrt{dv_1\times dv_2}} \quad (4)$$

The Augmented Zagreb index[22], an extension of the Zagreb indices, incorporates the squares of vertex degrees to enhance molecular structure characterization in chemoinformatics.

$$AZI(G)=\sum_{v_1v_2\in E(G)}\left(\frac{dv_1dv_2}{dv_1+dv_2-2}\right)^3 \quad (5)$$

In 2012, Zhong[23] introduced the harmonic index, a measure capturing molecular graph connectivity, while in 1998, Estrada et al. defined the ABC index[24], describing atom-bond connectivity in molecules, both offering insights into molecular structure and properties.

$$H(G)=\sum_{v_1v_2\in E(G)}\frac{2}{(dv_1+dv_2)} \quad (6)$$

$$ABC(G)=\sum_{v_1v_2\in E(G)}\sqrt{\frac{dv_1+dv_2-2}{dv_1\times dv_2}} \quad (7)$$

The molecular structures of drugs are converted into molecular graphs. The calculation of topological indices for all eight drugs was conducted using vertex connectivity and edge partitioning, as outlined in Table 1, which includes the number of edges (|E(G)|), number of vertices (|V(G)|), and edge partition (Ei,j) where

$$E_{i,j}=\{e=v_1v_2\in E(G)/dv_1=i \text{ and } dv_2=j\}$$

for each drop.

Table 1. Edge Partition of Eight Drugs

Drugs	|V(G)	$E_{1,2}$	$E_{1,3}$	$E_{1,4}$	$E_{2,2}$	$E_{2,3}$	$E_{3,3}$	$E_{4,2}$	$E_{4,3}$	|E(G)|
Ciprofloxacin	24	----	4	----	5	10	8	----	----	27
Gentamicin	33	2	6	2	2	13	8	1	1	35
Moxifloxacin	29	1	4	----	4	13	11	----	----	33
Norfloxacin	23	1	4	----	4	9	7	----	----	25
Tobramycin	32	2	8	----	----	14	10	----	----	34
Levofloxacin	26	----	6	----	3	10	10	----	----	29
Gatifloxacin	27	1	5	----	3	11	10	----	----	30
Chloramphenical	20	1	6	----	2	7	4	----	----	20

3. Methods

3.1 Computation of Topological indices

Let G_1 be the molecular graph of Ciprofloxacin as shown in Figure 4. G_1 consists of 24 vertices and 27 edges. The edge partition of G_1 is $|E_{1,3}|=4$, $|E_{2,2}|=5$, $|E_{2,3}|=10$ and $|E_{3,3}|=8$. The topological indices(TI) is calculated by using definitions(1-7) and the results are :

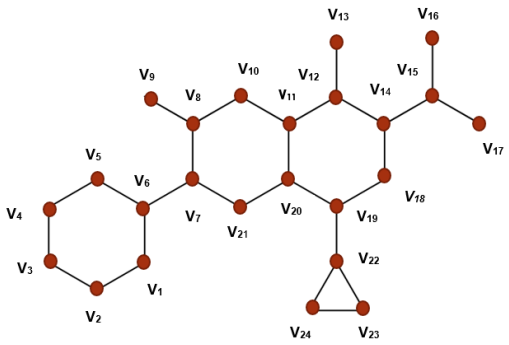


Figure 4. Moleculer Graph(G_1) of Ciprofloxacin

1. $F(G_1)=4(1^2+3^2)+5(2^2+2^2)+10(2^2+3^2)+8(3^2+3^2)=\mathbf{354}$
2. $M_1(G_1)=4(1+3)+5(2+2)+10(2+3)+8(3+3)=\mathbf{134}$
3. $M_2(G_1)=4(1\times3)+5(2\times2)+10(2\times3)+8(3\times3)=\mathbf{164}$
4. $R(G_1)=4\left[\frac{1}{\sqrt{1\times3}}\right]+5\left[\frac{1}{\sqrt{2\times2}}\right]+10\left[\frac{1}{\sqrt{2\times3}}\right]+8\left[\frac{1}{\sqrt{3\times3}}\right]=\mathbf{11.5586}$
5. $AZI(G_1)=4\left[\frac{1\times3}{1+3-2}\right]^3+5\left[\frac{2\times2}{2+2-2}\right]^3+10\left[\frac{2\times3}{2+3-2}\right]^3+8\left[\frac{3\times3}{3+3-2}\right]^3=\mathbf{224.625}$
6. $H(G_1)=4\left[\frac{2}{1+3}\right]+5\left[\frac{2}{2+2}\right]+10\left[\frac{2}{2+3}\right]+8\left[\frac{2}{3+3}\right]=\mathbf{11.1667}$
7. $ABC(G_1)=4\sqrt{\frac{1+3-2}{1\times3}}+5\sqrt{\frac{2+2-2}{2\times2}}+10\sqrt{\frac{2+3-2}{2\times3}}+8\sqrt{\frac{3+3-2}{3\times3}}=\mathbf{19.2059}$

Using the same method as previously stated and Definitions 1 through 7, topological indices of various medications can be computed. A calculation of the TIs for every medicine is provided in Table 2. The computed TIs for different medications are shown graphically in Figure 5. Origin Software was used to draw the graph.

Table 2. Topological indices for Eight Drugs

Drugs	F(G)	$M_1(G)$	$M_2(G)$	R(G)	AZI(G)	H(G)	ABC(G)
Ciprofloxacin	354	134	164	11.5586	224.625	11.1667	19.2059
Gentamicin	478	174	208	15.4945	273.9397	14.6190	25.3378
Moxifloxacin	444	166	207	13.9904	282.7969	13.5334	23.3272
Norfloxacin	320	122	147	11.0240	205.2344	10.6	17.8322
Tobramycin	452	168	202	15.0818	268.9063	14.2666	24.5124
Levofloxacin	394	146	180	12.3799	238.1563	11.8333	20.7581
Gatifloxacin	402	150	185	12.9179	189.1563	12.4	21.3558
Chloramphenical	244	94	106	9.3622	139.0625	8.8	14.6367

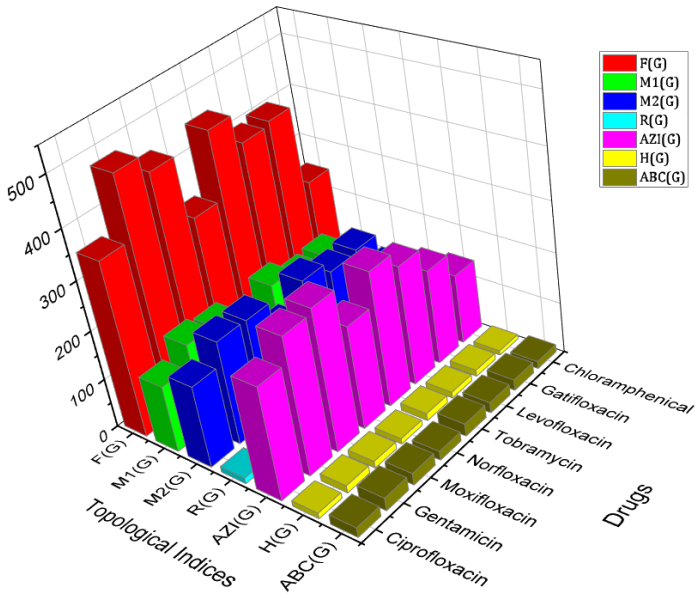


Figure 5. Topological indices of eight drugs

3.2 Physical Properties of Drugs

Various physical properties can be considered. For this study, seven properties were selected for eight drugs: Boiling Point (BP), Enthalpy (En), Average Mass (AM), Flash Point (FP), Molar Refractivity (Re), Polarizability (Po), and Average Mass (AM). These properties were chosen to analyze the QSPR model.

The boiling point of a substance, such as a drug, refers to the temperature at which it changes from a liquid to a gas phase under normal atmospheric pressure. This property is crucial for drug formulation and stability, impacting storage conditions and manufacturing processes.

Enthalpy in drugs refers to the total heat content of the drug system under constant pressure. It is crucial in pharmaceuticals for understanding drug stability, reaction kinetics, and formulation processes.

Mass refers to the quantity of matter contained in a drug substance. It influences various pharmaceutical properties, including dosage formulation, stability, and manufacturing processes. ***Flash point*** is the temperature at which a drug substance emits vapors that can ignite when exposed to an open flame or spark..

Molar refractivity quantifies the ability of a drug molecule to refract light, providing insights into its molecular structure and intermolecular interactions. ***Polarizability*** measures the ability of a drug molecule to undergo distortion by an electric field, reflecting its susceptibility to electrostatic interactions ***Volume*** represents the amount of space occupied by a drug substance.

Table 3 displays the physicochemical properties of eight drugs.

Table 3. Physical Properties of Eight Drugs

Drugs	BP	En	AM	FP	Re	Po	MV
Ciprofloxacin	581.8	91.5	331.341	305.6	83.3	33	226.8
Gentamicin	669.4	112.6	477.595	358.6	122.6	48.6	366.9
Moxifloxacin	636.4	98.8	401.431	338.7	101.8	40.4	285
Norfloxacin	555.8	88.1	319.331	289.9	80.7	32	237.4
Tobramycin	775.4	128.7	467.514	422.8	111.7	44.3	305.9
Levofloxacin	571.5	90.1	361.367	299.4	91.1	36.1	244
Gatifloxacin	607.8	95	375.394	321.4	94.6	37.5	270.8
Chloramphenicol	644.9	100	323.129	343.8	72.6	28.8	208.8

3.3 Regression Models

A regression model is a statistical technique used to analyse the relationship between a dependent variable and one or more independent variables. Its goal is to predict the dependent variable's value based on the data from the independent variables. Here, linear regression model is used to predict drug properties and determine the dependent variable. This model forecasts the characteristics of drugs based on the data.

$$R=\alpha+\beta[TI] \tag{8}$$

In the regression model, α and β are constants, R symbolize the physical properties of the drug, while TI represents the topological indices. Linear regression is utilized to establish a model for the topological indices, with the topological index of the molecular structure of eight eye conjunctivitis drops serving as the independent variable. Meanwhile, the physical characteristics are treated as the dependent variable in this model.

Statistical parameters and regression models for seven degree-based topological indices are calculated and presented in Tables 4 to Table 10. MS Excel was used to construct the linear regression models.

If the p-value is 0.05 or less, it is deemed statistically significant; if it exceeds 0.05, it is not considered significant. A p-value significantly below 0.05 is often characterized as highly significant.

Notations:

α = *intercept* R^2=*Coefficient of determination*

β=Coefficient Constant *F=Fisher's Statistics*
N=Number of drugs *p=Significance Level*
r=Correlation Coefficient

The coefficient of determination, R^2 shows how well a model predicts an outcome, with values between 0 and 1. If the R^2 value is 1, the model predicts the outcome perfectly. If the value is between 0 and 1, the model provides a partial prediction. If the value is 0, the model does not predict the data effectively.The standard error of the estimate measures how accurate these predictions are.

Table 4. Regression Model of F(G)

Regression Models	N	r	R^2	F	p	Significant
BP=75.4753+0.4926[F(G)]	8	0.4475	0.2002	1.5023	0.7770	NOT significant
En=64.9633+0.0923[F(G)]	8	0.5215	0.2719	2.2412	0.0364	Statistically Significant
AM=112.1376+0.6995(F(G)	8	0.8688	0.7548	18.4669	0.1299	NOT significant
FP=240.0489+0.2461[F(G)]	8	0.4476	0.2003	1.5030	0.0226	Statistically Significant
Re=16.7958+0.2021[F(G)]	8	0.9396	0.8828	45.2003	0.2047	NOT significant
Po=6.6565+0.0801[F(G)]	8	0.9394	0.8825	45.0606	0.2055	NOT significant
MV=46.1968+0.5751[F(G)]	8	0.8735	0.7630	19.3187	0.4033	NOT significant

Table 5. Regression Model of $M_1(G)$

Regression Model	N	r	R^2	F	p	Significant
BP=462.0805+1.1667[M_1(G)]	8	0.4465	0.1994	1.4945	0.0163	Statistically Significant
En=62.6838+0.2629[M_1(G)]	8	0.5162	0.2665	2.1800	0.053	NOT significant
AM=95.6709+1.9859[M_1(G)]	8	0.8576	0.7355	16.6863	0.2276	NOT significant
FP=233.1561+0.7062[M_1(G)]	8	0.4467	0.1995	1.4953	0.0330	Statistically Significant
Re=11.9361+0.5744[M_1(G)]	8	0.9287	0.8624	37.6148	0.4176	NOT significant
Po=4.7272+0.2278[M_1(G)]	8	0.9286	0.8622	37.5516	0.4186	NOT significant
MV=33.6941+1.6257[M_1(G)]	8	0.8585	0.7370	16.8164	0.5828	NOT significant

Table 6. Regression Model of $M_2(G)$

Regression Models	N	r	R^2	F	p	Significant
BP=498.7788+0.7525[M_2(G)]	8	0.3753	0.1409	0.9839	0.0101	Statistically Significant
En=70.6178+0.1714[M_2(G)]	8	0.4388	0.1926	1.4308	0.0325	Statistically Significant
AM=133.1748+1.4237[M_2(G)]	8	0.8012	0.6419	10.7564	0.1354	NOT significant
FP=255.3583+0.4556[M_2(G)]	8	0.3755	0.1410	0.9848	0.0204	Statistically Significant
Re=21.2615+0.4205[M_2(G)]	8	0.8859	0.7849	21.8888	0.2320	NOT significant
Po=8.4260+0.1668[M_2(G)]	8	0.8858	0.7846	21.8607	0.2325	NOT significant
MV=62.9169+1.1739[M_2(G)]	8	0.8078	0.6526	11.2716	0.3509	NOT significant

Table 7. Regression Model of R(G)

Regression Models	N	r	R^2	F	p	Significant
BP=377.0028+19.9096[R(G)]	8	0.5907	0.3489	3.2156	0.0387	Statistically Significant
En=44.9280+4.3746[R(G)]	8	0.6660	0.4435	4.7825	0.1317	NOT significant
AM=23.6648+28.1682[R(G)]	8	0.9429	0.8891	48.1190	0.6667	NOT significant

FP=181.6811+12.0495[R(G)]	8	0.5908	0.3490	3.2164	0.0804	NOT significant
Re=-4.7653+7.8237[R(G)]	8	0.9804	0.9613	148.6628	0.5850	NOT significant
Po=-1.9021+3.1030[R(G)]	8	0.9804	0.9613	149.0043	0.5823	NOT significant
MV=-0.4268+22.6798[R(G)]	8	0.9284	0.8619	37.4477	0.6835	NOT significant

Table 8. Regression Model of AZI(G)

Regression Models	N	r	R^2	F	p	Significant
BP=509.9414+0.5288[AZI(G)]	8	0.3684	0.1357	0.9421	0.0069	Statistically Significant
En=72.4448+0.1236[AZI(G)]	8	0.4419	0.1953	1.4560	0.0227	Statistically Significant
AM=167.9579+0.9405[AZI(G)]	8	0.7392	0.5464	7.2268	0.084	NOT significant
FP=262.142+0.3200[AZI(G)]	8	0.3684	0.1357	0.9421	0.0141	Statistically Significant
Re=31.8196+0.2766[AZI(G)]	8	0.8137	0.6620	11.7542	0.1404	NOT significant
Po=12.6042+0.1097[AZI(G)]	8	0.8138	0.6623	11.7683	0.1407	NOT significant
MV=95.42511+0.7587[AZI(G)]	8	0.7291	0.5317	6.8109	0.2074	NOT significant

Table 9. Regression Model of H(G)

Regression Model	N	r	R^2	F	p	Significant
BP=389.7994+19.7966[H(G)]	8	0.5547	0.3077	2.6668	0.0398	Statistically Significant
En=47.5768+4.3632 [H(G)]	8	0.6273	0.3936	3.8938	0.1306	NOT significant
AM=28.4410+29.1052[H(G)]	8	0.9202	0.8467	33.1407	0.6633	NOT significant
FP=189.4196+11.9817[H(G)]	8	0.5548	0.3078	2.6678	0.080	NOT significant
Re=-4.5566+8.1759[H(G)]	8	0.9676	0.9363	88.1766	0.6851	NOT significant
Po=-1.8198+3.2428 [H(G)]	8	0.9677	0.9364	88.3350	0.6828	NOT significant
MV=-8.3786+23.5821[H(G)]	8	0.917	0.8312	29.5385	0.7422	NOT significant

Table 10. Regression Model of ABC(G)

Regression Model	N	r	R^2	F	p	Significant
BP=415.6167+10.2899[ABC(G)]	8	0.5251	0.2757	2.2844	0.0278	Statistically Significant
En=52.8259+2.2890[ABC(G)]	8	0.5994	0.3593	3.3645	0.0921	NOT significant
AM=52.5476+15.7920[ABC(G)]	8	0.9093	0.8268	28.6396	0.4319	NOT significant
FP=205.0449+6.2279[ABC(G)]	8	0.5252	0.2758	2.2852	0.0567	NOT significant
Re=1.5790+4.4666[ABC(G)]	8	0.9627	0.9269	76.0472	0.8889	NOT significant
Po=0.6183+1.7713[ABC(G)]	8	0.9627	0.9267	75.9046	0.8903	NOT significant
MV=1.1532+12.7953[ABC(G)]	8	0.9009	0.8116	25.8500	0.9834	NOT significant

3.4 Standard Error , Correlation Coefficient & Comparison among the actual values and computed Values .

In this section, the correlation coefficient between the topological indices and the physicochemical properties of drugs is determined, as shown in Table 11. Additionally, the comparison between calculated and real values of these properties is conducted.

Table 11. Correlation between Physical Properties and Topological indices

TI	BP	En	AM	FP	Re	Po	MV
F(G)	0.4475	0.5215	0.8687	0.4476	**0.9396**	0.9394	0.8735
$M_1(G)$	0.4466	0.5162	0.8576	0.4467	**0.9287**	0.9286	0.8585
$M_2(G)$	0.3753	0.4388	0.8012	0.3755	**0.8859**	0.8858	0.8078
R(G)	0.5907	0.6660	0.9429	0.5908	**0.9804**	**0.9804**	0.9284
AZI(G)	0.3684	0.4419	0.7392	0.3684	0.8137	**0.8138**	0.7291
H(G)	0.5547	0.6273	0.9202	0.5548	0.9676	**0.9677**	0.9117
ABC(G)	0.5251	0.5994	0.9093	0.5252	**0.9627**	**0.9627**	0.9009

The Standard Error of Estimate (SEE) is crucial in regression analysis as it evaluates the model's ability to predict future values. It quantifies the average deviation of observed data points from the regression line, indicating the model's precision. A lower SEE signifies a better fit, as it demonstrates that the model's predictions closely align with the actual values.A higher Standard Error of Estimate (SEE) indicates that the model's predictions are less accurate and that the observed data points deviate more from the regression line. This suggests that the model may not fit the data well and that there is greater variability between the predicted and actual values.Table 12 displays the standard Error Estimation (SEE) .

Table 12. Standard Error between Topological indices and Physical Properties

TI	BP	En	AM	FP	Re	Po	MV
F(G)	**74.8642**	12.6457	33.3773	41.1541	6.1636	2.4478	26.8321
$M_1(G)$	68.0440	12.6929	34.6625	41.1752	6.6781	2.6504	28.2652
$M_2(G)$	70.4872	13.3174	40.3322	42.6536	8.3513	3.3138	32.487
R(G)	61.3620	11.0555	22.4423	37.1323	3.5463	**1.4049**	20.4830
AZI(G)	70.6995	13.2949	45.3957	42.7845	10.4669	4.1496	37.7212
H(G)	63.2747	11.5413	26.3893	38.2893	4.5446	1.8009	22.6478
ABC(G)	64.7188	11.8630	28.0515	39.1635	4.8690	1.9327	23.9233

4 Results

4.1 Comparison between Calculated and real values of physical Properties of drugs

Tables 13 to Table 18 present the comparison of actual and computed values for all physical properties of the eye conjunctivitis drops.

Table 13. Comparison between Calculated and real Values of Boiling Point

Drugs	BP	F(G)	$M_1(G)$	$M_2(G)$	R(G)	AZI(G)	H(G)	ABC(G)
Ciprofloxacin	581.8±50.0	249.86	618.42	622.19	607.13	628.72	610.86	613.24
Gentamicin	669.4±55.0	310.94	665.09	655.30	685.49	654.80	679.21	676.34
Moxifloxacin	636.4±55.0	294.19	655.75	654.55	655.55	659.48	657.71	655.65
Norfloxacin	555.8±50.0	233.11	604.42	609.40	596.49	618.47	599.64	599.11

Tobramycin	775.4±60.0	298.13	658.09	650.78	677.28	652.14	672.23	667.85
Levofloxacin	571.5±50.0	269.56	632.42	634.23	623.48	635.88	624.06	629.22
Gatifloxacin	607.8±55.0	273.50	637.09	637.99	634.19	609.97	635.28	635.37
Chloramphenical	644.9±55.0	195.67	571.75	578.54	563.40	583.48	564.01	566.23

Table 14. Comparison between Calculated and real Values of Enthalpy

Drugs	En	F(G)	$M_1(G)$	$M_2(G)$	R(G)	AZI(G)	H(G)	ABC(G)
Ciprofloxacin	91.5±3.0	97.64	97.91	98.73	95.49	100.21	96.30	96.79
Gentamicin	112.6±6.0	109.08	108.43	106.27	112.71	106.30	111.36	110.82
Moxifloxacin	98.8±3.0	105.94	106.33	106.10	106.13	107.40	106.63	106.22
Norfloxacin	88.1±3.0	94.50	94.76	95.81	93.15	97.81	93.83	93.64
Tobramycin	128.7±6.0	106.68	106.85	105.24	110.90	105.68	109.82	108.93
Levofloxacin	90.1±3.0	101.33	101.07	101.47	99.09	101.88	99.21	100.34
Gatifloxacin	95.0±3.0	102.07	102.12	102.33	101.44	95.82	101.68	101.71
Chloramphenical	100.0±3.0	87.48	87.40	88.79	85.88	89.63	85.97	86.33

Table 15. Comparison between Calculated and real Values of Average Mass

Drugs	AM	F(G)	$M_1(G)$	$M_2(G)$	R(G)	AZI(G)	H(G)	ABC(G)
Ciprofloxacin	331.341	359.76	361.78	366.66	349.25	379.22	353.45	355.85
Gentamicin	477.595	446.50	441.22	429.30	460.12	425.60	453.93	452.68
Moxifloxacin	401.431	422.72	425.33	427.88	417.75	433.93	422.33	420.93
Norfloxacin	319.331	335.98	337.95	342.46	334.19	360.98	336.96	334.15
Tobramycin	467.514	428.31	429.30	420.76	448.49	420.86	443.67	439.65
Levofloxacin	361.367	387.74	385.61	389.44	372.38	391.94	372.85	380.36
Gatifloxacin	375.394	393.34	393.56	396.56	387.54	345.86	389.35	389.80
Chloramphenical	323.129	282.82	282.35	284.09	287.38	298.75	284.57	283.69

Table 16. Comparison between Calculated and real Values of Flash Point

Drugs	Re	F(G)	$M_1(G)$	$M_2(G)$	R(G)	AZI(G)	H(G)	ABC(G)
Ciprofloxacin	305.6±30.1	327.17	327.79	330.08	320.96	334.02	323.22	324.66
Gentamicin	358.6±31.5	357.68	356.03	350.12	368.38	349.80	364.58	362.85
Moxifloxacin	338.7±31.5	349.32	350.39	349.67	350.26	352.64	351.57	350.32
Norfloxacin	289.9±30.1	318.80	319.31	322.33	314.51	327.82	316.43	316.10
Tobramycin	422.8±32.9	351.29	351.80	347.39	363.41	348.19	360.36	357.71
Levofloxacin	299.4±30.1	337.01	336.26	337.37	330.85	338.35	331.20	334.32
Gatifloxacin	321.4±31.5	338.98	339.09	339.64	337.34	322.67	337.99	338.05
Chloramphenical	343.8±31.5	300.10	299.54	303.65	294.49	306.64	294.86	296.20

Table 17. Comparison between Calculated and real Values of Molar Refractivity

Drugs	Re	F(G)	$M_1(G)$	$M_2(G)$	R(G)	AZI(G)	H(G)	ABC(G)
Ciprofloxacin	83.3±0.3	88.34	88.91	90.22	85.67	93.95	86.74	87.36
Gentamicin	122.6±0.4	113.40	111.88	108.73	116.46	107.59	114.97	114.75
Moxifloxacin	101.8±0.3	106.53	107.29	108.31	104.69	110.04	106.09	105.77

Norfloxacin	80.7±0.3	81.47	82.01	83.08	81.48	88.59	82.11	81.23
Tobramycin	111.7±0.4	108.15	108.44	106.20	113.23	106.20	112.09	111.07
Levofloxacin	91.1±0.4	96.42	95.80	96.95	92.09	97.69	92.19	94.30
Gatifloxacin	94.6±0.3	98.04	98.10	99.05	96.30	84.14	96.82	96.97
Chloramphenical	72.6±0.3	66.11	65.93	65.83	68.48	70.28	67.39	66.96

Table 18. Comparison between Calculated and real Values of Polarizability

Drugs	**Po**	**F(G)**	**M_1(G)**	**M_2(G)**	**R(G)**	**AZI(G)**	**H(G)**	**ABC(G)**
Ciprofloxacin	33.0±0.5	35.01	35.25	35.78	33.96	37.25	34.39	34.64
Gentamicin	48.6±0.5	44.94	44.36	43.12	46.18	42.66	45.59	45.50
Moxifloxacin	40.4±0.5	42.22	42.54	42.95	41.51	43.63	42.07	41.94
Norfloxacin	32.0±0.5	32.29	32.52	32.95	32.31	35.12	32.55	32.20
Tobramycin	44.3±0.5	42.86	43.00	42.12	44.90	42.10	44.44	44.04
Levofloxacin	36.1±0.5	38.22	37.99	38.45	36.51	38.73	36.55	37.39
Gatifloxacin	37.5±0.5	38.86	38.90	39.28	38.18	33.35	38.39	38.45
Chloramphenical	28.8±0.5	26.20	26.14	26.11	27.15	27.86	26.72	26.54

Table 19. Comparison between Calculated and real Values of Molar Volume

Drugs	**MV**	**F(G)**	**M_1(G)**	**M_2(G)**	**R(G)**	**AZI(G)**	**H(G)**	**ABC(G)**
Ciprofloxacin	226.8±3.0	249.78	251.54	255.44	241.72	265.85	244.96	246.90
Gentamicin	366.9±5.0	321.09	316.57	307.09	330.99	303.26	326.37	325.36
Moxifloxacin	285.0±3.0	301.54	303.56	305.91	296.87	309.98	300.77	299.63
Norfloxacin	237.4±3.0	230.23	232.03	235.48	229.60	251.14	231.59	229.32
Tobramycin	305.9±5.0	306.14	306.81	300.04	321.63	299.44	318.06	314.80
Levofloxacin	244.0±5.0	272.79	271.05	274.22	260.35	276.11	260.68	266.76
Gatifloxacin	270.8±3.0	277.39	277.55	280.09	272.55	238.94	274.04	274.41
Chloramphenical	208.8±3.0	186.52	186.51	187.35	191.91	200.93	189.14	188.43

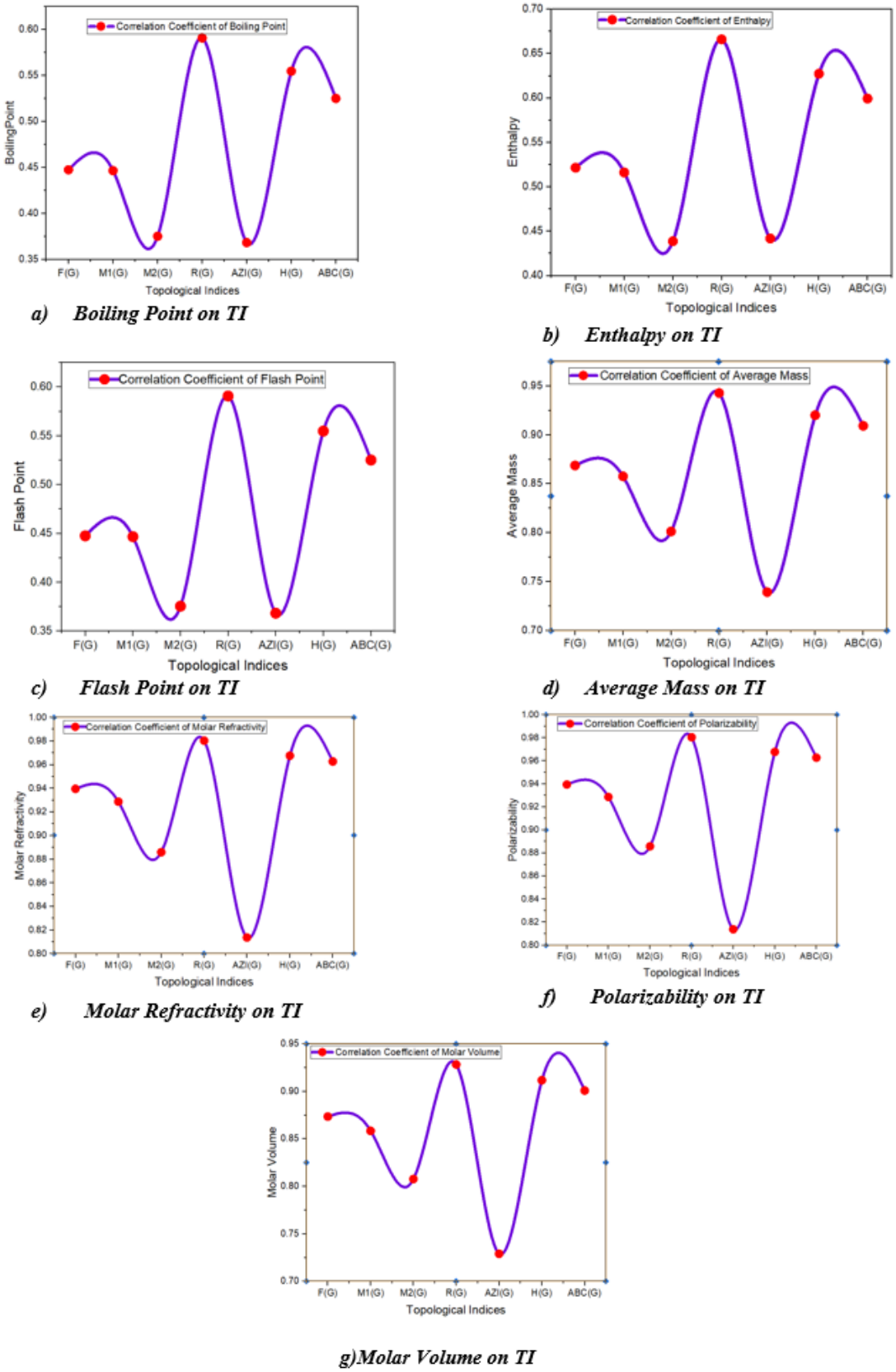


Figure 6. Correlation coefficients of between physical properties and Indices

5 Discussion

In Table 11, the correlation coefficients between various physicochemical properties and topological indices of the drugs are presented. The forgotten index demonstrates a strong correlation of 0.9396 with molar refractivity. The First Zagreb index also shows a significant correlation with molar refractivity (0.9287). The Second Zagreb index exhibits a good correlation with molar refractivity (0.8859), while the Randic index shows a very high correlation with both molar refractivity and polarizability (0.9804). The Augmented Zagreb index has a notable correlation with polarizability (0.8138), and the Harmonic index shows a strong correlation with polarizability (0.9677). The ABC index presents a high correlation with both molar refractivity and polarizability (0.9627). Overall, the Randic index exhibits the highest correlation among the properties studied. However, the augmented Zagreb index has a low correlation coefficient of 0.3684 with the boiling point.

From Table 4 to Table 10, the coefficient of determination R2 indicates how well the outcomes are predicted. Among these tables, Table 7 particularly highlights that the Randic index for the properties of Molar Refractivity and Polarizability are predicted very accurately.

The estimated Standard Error of Estimate (SEE) is shown in Table 12. The findings demonstrate that the Randic index with Polarisability displays an extremely low SEE of 1.4049, suggesting that the predicted values closely match the medications real physicochemical characteristics. Table 18 provides more evidence supporting the tight alignment of the Randic index with Polarisability values with the expected values.

In contrast, the Forgotten index shows a high SEE of 74.8642 for the boiling point, indicating a significant deviation from the actual values of the drugs. Table 13 clearly demonstrates that the boiling point values associated with the forgotten index exhibit a substantial deviation from the predicted values.

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