

Organic compounds based on 1-(prop-2-yn-1-ylamino)-2,3-dihydro-1H-indene-4-thiol as selective human monoamine oxidase B inhibitors. Quantitative analysis of structure-activity relationships and *in-silico* investigations

M. Ahfid El Alaouy^{1, *}, S. El Bahi¹, M. Boutalaka¹, M. Ouabane^{1,2},
A. Sbai^{1,*}, H. Maghat¹, M. Bouachrine^{1,3}, T. Lakhli¹

¹ Molecular chemistry and Natural Substances Laboratory, Faculty of Science, University Moulay Ismail, Meknes, Morocco

² Chemistry- Biologie Applied to the Environment URL CNRT 13, department of chemistry, Faculty of Science, Moulay Ismail University, Meknes, Morocco.

³ EST Khenifra, Sultan Moulay Sliman University, Benimellal, Morocco

*Corresponding author, Email address: a.sbai@umi.ac.ma

**Corresponding author, Email address: mo.elalaouy@edu.umi.ac.ma

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Abstract: After Alzheimer's disease, Parkinson's disease is the most prevalent neurodegenerative condition. Because it is fatal and affects a large proportion of the world's population over the age of 60, the development of new drugs to treat it is crucial. To achieve this objective, we used the 3D-QSAR technique to design effective hMAO-B inhibitors from a 1-(prop-2-yn-1-ylamino)-2,3-dihydro-1H-indene-4-thiol chain. The 3D-QSAR models were generated by combining comparative molecular field analysis (CoMFA) and comparative molecular similarity index analysis (CoMSIA). In this study, the different field models obtained proved that the CoMSIA/SEA model is the best model with excellent predictive power over several models ($Q^2 = 0.701$; $R^2 = 0.926$; $R^2_{\text{test}} = 0.69$). A new group of MAO-B inhibitors was predicted based on this fitting model, and the pharmacokinetic properties were studied using ADMET in silico prediction. All examined compounds showed good oral bioavailability. In addition, the docking simulation of the designed compound M4 and the most active compound of the training set K12 were analyzed. The results showed that the newly designed compound M4 remained more stable at the active site of the receptor compared to the compound K12, and we can finally rely on it as a potential pharmacological compound.

Keywords: ADMET; 3D-QSAR; Molecular docking; hMAO-B.

1. Introduction

Two varieties of monoamine oxidase exist (MAO, EC 1.4.3.4): human MAO (hMAO A and hMAO B). MAO is present in small blood vessels in the brain, liver, mucosa of the gastrointestinal tract, and other organs. Monoamine neurotransmitters such as serotonin, dopamine, tyramine, norepinephrine, N-methyl-4-phenyl-1,2,3,6-tetrahydropyridine (MPTP), and flavin adenine dinucleotide are oxidatively deaminated by MAOs (Aydin *et al.*, 2020). HMAO A interacts especially with serotonin and norepinephrine. HMAO B hydrolyzes phenylethylamine monoamine (PEA) and benzylamine. Both isoforms also hydrolyze dopamine, tyramine, and tryptamine. In the presence of oxygen and water, both enzymes react with their respective amines (Aigner *et al.*, 2017), forming

aldehydes, ammonia, and one equivalent of hydrogen peroxide. MAO A and B are involved in a variety of physiological (pathological) processes in humans (Edmondson *et al.*, 2009). Therefore, monoamine-related disorders such as Parkinson's disease (PD), Alzheimer's disease (AD), and depression are treated with MAO inhibitors. Inhibitors are classified according to isoform selectivity, which includes non-isoform selectivity, as well as the type of enzyme inhibition, which includes reversible and non-reversible inhibitors (Aigner *et al.*, 2017). While hMAO A inhibitors such as moclobemide are used to treat depression, selective hMAO B inhibitors such as selegiline (diprenil) are used to treat Parkinson's disease. hMAO-B inhibitors are useful and effective in improving motor fluctuations in patients with (PD) in the treatment (Icht *et al.*, 2022) of early to advanced PD, alone or in combination with other antiparkinsonian drugs. This family of drugs increases dopamine levels and is safer than other treatments for reducing PD symptoms (Fišar, 2016). However, concerns regarding the selectivity of these drugs have been highlighted, and side effects such as hepatotoxicity and the "cottage cheese" effect have hindered their use in medicine. A few non-selective hMAOA/hMAO-B inhibitors, such as caroxazone, have been withdrawn from the market due to potentially dangerous and unlikely side effects. In addition to Parkinson's disease, hMAO-B has been implicated in the pathogenesis of many human diseases, making it a potential target for the treatment of a wide range of conditions, including inflammation, chronic pain, muscular dystrophy, and cancer (Kong *et al.*, 2021a). Concerning (PD), hMAO B inhibitors have been shown to facilitate memory formation in patients with (AD). As a result, there have been increasing efforts to develop and discover drugs that inhibit hMAO B to treat (PD) (Aigner *et al.*, 2017), (AD), and memory problems, and to alleviate cognitive impairment without impairing brain function (Hawkins, 2021). The main objective of this work is to investigate the therapeutic characteristics of 27 derivatives of the compound 1-(prop-2-yn-1-ylamino)-2,3-dihydro-1H-indene-4-thiol as potent selective inhibitors of hMAO B (Awasthi *et al.*, 2020).

Over the past two decades, computer-aided drug design has been an effective method for identifying new drug candidates. This new technique is a tool to reduce the time and resources required for chemical synthesis in the laboratory. In this work, carefully planned QSAR studies provided predictive models and a series of graphical contour maps (Li *et al.*, 2021).

The molecular docking approach was also used to study the interactions of new drugs with protein active site residues, as well as an ADMET predictor, which is critical for the efficacy and safety of the therapeutic drug test (Aoumeur *et al.*, 2021; Koubi *et al.*, 2022). Finally, for the proposed results to be evaluated, the molecules must pass through all these filters (Xin *et al.*, 2021). The results of this study provide essential information for the creation of new inhibitors (Sherry, 2001).

2. Material and methods

2.1 Procedure for splitting and minimizing datasets

In this research paper, we used a series of human monoamine oxidase B inhibitors from the work of Haiyan Kong *et al.* (Kong *et al.*, 2021b). The structures of 1-(prop-2-yn-1-ylamino)-2,3-dihydro-1H-indene-4-thiol derivatives, as well as their activity levels, are shown in Figure 1 and Table 1. For the CoMFA and CoMSIA analyses, the inhibitory activity (IC_{50}) was transformed into negative log units and reported as pIC_{50} . In addition, the dataset was divided into two parts: the training set and the test set, which were used to generate the final 3D-QSAR models and to evaluate the predictive accuracy of these models. In addition, the test set was chosen with the following criteria in mind: the inhibitory structures in the test set should be varied, and their inhibitory actions should be similar to those in the training set (Wang *et al.*, 2021). Sybyl software was used for molecular modeling and 3D QSAR experiments. To develop a stable structure of the inhibitors, a systematic and comprehensive search was first performed.

Then, the Gasteiger-Hückel method was used to add partial atomic charges (Fu *et al.*, 2018). Then, energy reduction was performed using a Tripos force field. The convergence criterion of 0.01 kcal/mol or in 1000 minimization cycles, is all available in SYBYL (Clark *et al.*, 1989).

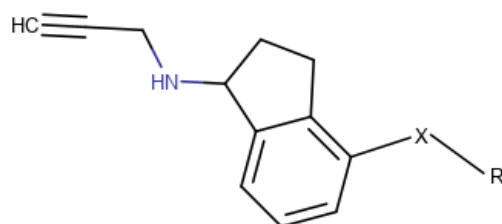
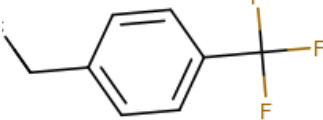
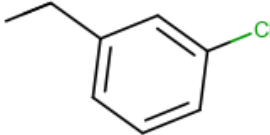
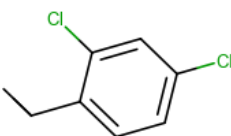
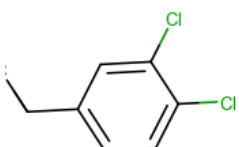
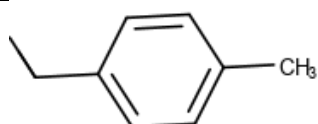
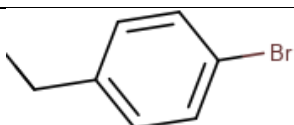
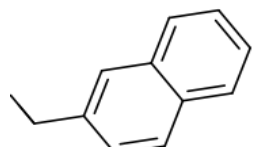
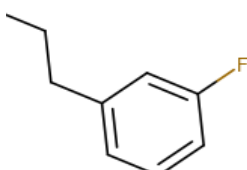
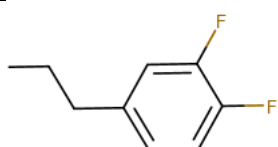
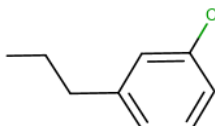
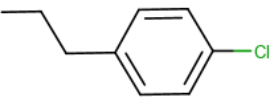
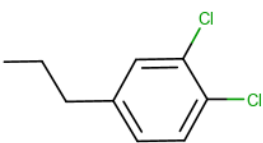
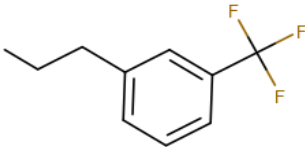
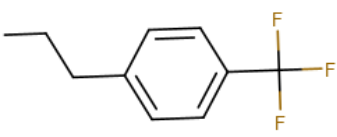
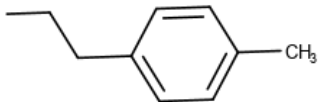
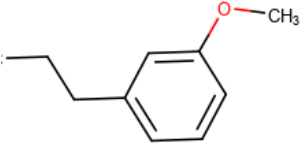
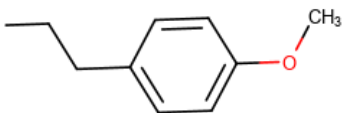
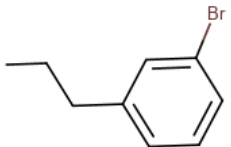
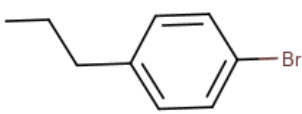
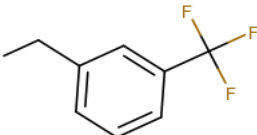
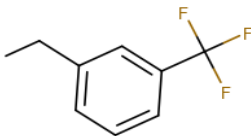


Figure 1. The formula of the studied chemical compounds.

Table 1. Activities and structures of 1-(prop-2-yn-1-ylamino)-2,3-dihydro-1H-indene-4-thiol derivatives.

N°	X	R	IC ₅₀ (μM)	pIC ₅₀
K ₁	S		6.4	5.194
K ₂	S		3.19	5.496
K ₃	S		1.9	5.721
K ₄	S		1.48	5.83
K ₅	S		2.65	5.576
K ₆	S		2.43	5.614

*K ₇	S		9.68	5.014
*K ₈	S		23.27	4.633
K ₉	S		3.76	5.424
*K ₁₀	S		2.84	5.546
K ₁₁	S		1.56	5.806
K ₁₂	S		1.31	5.882
*K ₁₃	S		4.95	5.303
K ₁₄	S		4.3	5.366
*K ₁₅	S		3.24	5.489
*K ₁₆	S		82.4	4.084

K ₁₇	S		10.84	4.965
K ₁₈	S		3.85	5.414
K ₁₉	S		3.72	5.429
K ₂₀	S		16.13	4.792
K ₂₁	S		25.78	4.588
*K ₂₂	S		28.73	4.541
K ₂₃	S		62.01	4.207
*K ₂₄	S		30.51	4.515
K ₂₅	S		85.26	4.069
K ₂₆	O		6.41	5.193
K ₂₇	NH		5.11	5.291

2.2 Alignment of the inhibitors

The alignment procedure is one of the most critical steps in the CoMFA and CoMSIA analysis. In this research paper, the strongest inhibitor of K12 was used as a template. The other inhibitors were aligned with the model using the "Align Database" function. The result is shown in (Figure 2) (Wang *et al.*, 2021).

2.3 CoMFA and CoMSIA studies

The two 3D-QSAR technologies, CoMFA and CoMSIA (Paolini *et al.*, 2019) were used in this research paper to better understand the local physical and chemical aspects of ligand-receptor interactions. Comparative Molecular Field Analysis (CoMFA) (Giansanti *et al.*, 2022) is one of the most useful 3D-QSAR approaches since its inception in 1988 (Tabti *et al.*, 2022a). A 3D cubic lattice is constructed with a mesh distance of 1 and spans 4 Å in all directions to include aligned particles.

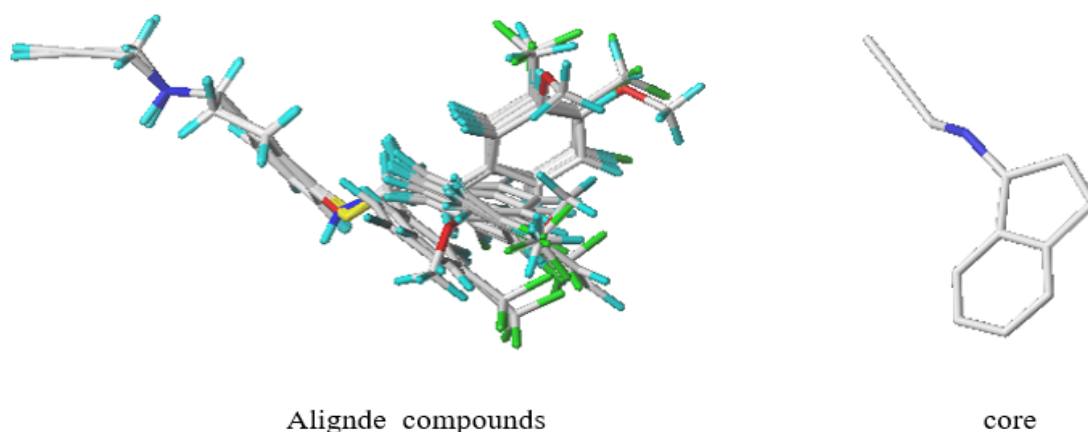


Figure 2. Overlay and alignment of the 27 molecules using Molecule K12 as a model.

CoMFA fields were generated by calculating citric field energies and electrostatic fields with a distance-dependent insulator at each grid point (Samin & Azim, 2019) using an sp³ carbon probe with a charge +1. Field (CoMSIA) Calculates the similarity indices in the region surrounding each of the previously aligned molecules in the data set (El Khatabi *et al.*, 2021). CoMSIA, like CoMFA (Shagufta *et al.*, 2007), uses a probe atom to calculate five distinct similarity index fields (steric, electrostatic, hydrophobic, hydrogen bond donor, and acceptor) (Tabti *et al.*, 2022b). The incorporation of these additional fields is not intended to increase the predictive power of the models, but to distribute distinct features to spatial locations where they are important for determining contact convergence (San Juan, 2007).

2.4 Partial least square (PLS) statistical analysis

PLS was used to generate 3D-QSAR models using CoMFA and CoMSIA descriptors as independent variables and inhibitory activities as dependent variables. Column filtration was used to filter the CoMFA and CoMSIA columns before PLS analysis. In the first step, a cross-validation analysis was performed using the Analyze (LOO) technique to determine the optimal number of components (ONC) and the coefficient of determination for cross-validation q^2 (Umair *et al.*, 2021; Kasmi *et al.*, 2022). In the second step, a cross-validation analysis was performed based on the correlation coefficient (r^2), Fisher values, and standard error of estimation (SEE), which are basic statistical properties (Wang *et al.*, 2021).

2.5 ADMET and Drug-likeness prediction

It is believed that current or potential drugs have similar distributions of physical and chemical properties. Therefore, by evaluating the simple molecular properties of current or proposed drugs, it is possible to develop simple bases/candidates that set acceptable limits for these properties (El Masaoudy *et al.*, 2023). ADMET analysis was used, which is necessary to verify the pharmacokinetic similarities of the newly developed hMAO-B inhibitors. The electronic tool SwissADMET (Daina *et al.*, 2017), Lipinski Five Judgment, and Egan and Weber (Veber *et al.*, 2002) have been used in this context, as these bases have been used in drug similarity screening studies. Compounds and properties such as lipid susceptibility, water solubility, (BBB) permeability, cytochrome P450-1A2 (CYP1A2 enzyme), human gastrointestinal absorption (HIA), and permeability were also investigated. Skin (log Kp) and toxicity using the pkCSM web server. If a compound violates two or more rules, it may not be orally active (Pires *et al.*, 2015).

2.6 Molecular docking

The CB-Dock (guided blind docking for cavities detection) server (<http://clab.labshare.cn/cb-dock/php/index.php>; accessed February 21, 2022) was used by the researchers in this paper to analyze the structural interaction mechanisms between ligands and receptors, determine the most energetically efficient binding mode, and calculate centers and volumes using a novel Curvature-based cavity detection method. The server works in tandem with AutoDock Vina and was carefully optimized to achieve a higher success rate in the developed models (Flores-Castañón *et al.*, 2022). Only a protein file in PDB format and a ligand file in MOL², MOL, or SDF format were used as inputs for the analysis. Five suitable dockets are found by CB-Dock, which checks the input files after they are sent and converts them to pdbqt format using OpenBabel (O'Boyle *et al.*, 2011). Based on the lowest value detected by Vina (Rose *et al.*, 2018), the value with the lowest binding energy was determined.

3. Results and discussion

3.1 CoMFA analysis

The statistical results of the CoMFA model are presented in Table 2. Compared to the electrostatic (E) and static (S) models, the CoMFA (S + E) model has a strong ability to predict activity, and the calculated statistical parameters are as follows: Q² was 0.619 (>0.5), correlation coefficient (R²) 0.994, F-value 196.82, standard error (SEE) 0.056 and 3 as the optimal number of components. The test set molecules were also consistent with the CoMFA (S + E) model, with the R²_{test} = 0.52.

Table 2. Possible CoMFA results.

	Q ²	N	SEE	R ²	F	R ² _{test}
Steric (S)	0.729	4	0.047	0.996	276.64	0.38
Electrostatic (E)	0.017	2	0.303	0.813	5.425	0.48
S + E	0.619	3	0.056	0.994	196.82	0.52

3.2 CoMSIA analysis

On the statistical parameter values used throughout the development process, we chose eight models. The findings of the various ways in which the five variables were combined to create the various CoMSIA models are displayed in Table 3. For the (COMSIA/S + E + A) model, judging from the parameters in Table 3, the PLS analysis shows that Q² was 0.701 (>0.5), the correlation coefficient R² was 0.926, the F-value was 15.61, and the standard error estimate (SEE) was 0.19 with an optimal number of components of 4. The (COMSIA/S + E + A) model was also validated by external test vehicles with

$R^2_{\text{test}} = 0.69$. These statistical findings indicate that this model has a very strong predictive potential compared to other models. According to these results, we can say that this model is the most relevant model with strong predictive power and can provide important statistical keys to predict human monoamine oxidase B inhibitors. The actual and predicted activities of the CoMFA/S+E and COMSIA/S+E+A models of hMAO-B inhibitors are presented in **Table 4**.

Table 3. The different possibilities of combining fields (COMSIA/S+E+A).

	Q^2	N	SEE	R^2	F	R^2_{test}
S	0.643	3	0.176	0.936	18.42	0.499
E	0.608	2	0.223	0.898	11.025	0.716
S+E	0.669	3	0.219	0.902	11.469	0.686
H	0.608	7	0.145	0.957	27.94	0.25
H+S+E	0.606	3	0.129	0.966	35.47	0.42
S+E+A	0.701	4	0.19	0.926	15.61	0.69
S+A	0.716	4	0.187	0.928	16.77	0.54
A+E	0.642	4	0.199	0.919	14.21	0.42

Table 4. Experimental and predicted pIC_{50} of the CoMFA/S + E and CoMSIA/S + E + A models

N°	pIC_{50} (M)	CoMFA/SE		CoMSIA/SEA	
		Predicted	Residuals	Predicted	Residuals
K ₁	5.194	5.191	0.003	5.165	0.029
K ₂	5.496	5.517	-0.021	5.401	0.095
K ₃	5.721	5.733	-0.012	5.732	-0.011
K ₄	5.83	5.871	-0.041	5.767	0.063
K ₅	5.576	5.556	0.02	5.589	-0.013
K ₆	5.614	5.603	0.011	5.567	0.047
*K ₇	5.014	5.759	-0.745	5.385	-0.371
*K ₈	4.633	5.929	-1.296	5.962	-1.329
K ₉	5.424	5.386	0.038	5.412	0.012
*K ₁₀	5.546	5.677	-0.131	5.814	-0.268
K ₁₁	5.806	5.88	-0.074	5.969	-0.163
K ₁₂	5.882	5.817	0.065	5.878	0.004
*K ₁₃	5.303	5.856	-0.553	6.016	-0.713
K ₁₄	5.366	5.357	0.009	5.522	-0.156
*K ₁₅	5.489	5.666	-0.177	5.884	-0.395
*K ₁₆	4.084	5.255	-1.171	5.008	-0.924
K ₁₇	4.965	4.99	-0.025	4.84	0.125
K ₁₈	5.414	5.391	0.023	5.178	0.236
K ₁₉	5.429	5.43	-0.001	5.356	0.073
K ₂₀	4.792	4.788	0.004	4.865	-0.073
K ₂₁	4.588	4.516	0.072	4.528	0.06
*K ₂₂	4.541	4.125	0.416	4.661	-0.12
K ₂₃	4.207	4.197	0.01	4.092	0.115
*K ₂₄	4.515	3.885	0.63	4.438	0.077
K ₂₅	4.069	4.153	-0.084	4.505	-0.436
K ₂₆	5.193	5.151	0.042	5.142	0.051
K ₂₇	5.291	5.33	-0.039	5.349	-0.058

3.3 Y-randomization test

To avoid random association, we performed random operations on the training set compounds and evaluated the power of the model by performing ten tests in different ways. **Table 5** shows the low

values of Q^2_{cv} (LOO) (rand) and R^2_{rand} . The results confirm that the obtained model is not due to a random association.

3.4 Interpretation of model CoMSIA contour

The 3D fields of the best model (COMSIA/S+E+A) for the most active compound are shown in **Figure 3**. The steric field (A): Green colors indicate a favorable bulky group while yellow colors indicate an unfavorable bulky group to increase activity. There is a large green contour map near the meta and ortho substituents, which means that the addition of a bulky group (large substituents) at this position increases the biochemical activity, this can be explained by the higher activity of compound K2 ($pIC_{50}=5.496$) with the $-OCH_3$ radical in the meta position compared to compound K8 ($pIC_{50}=4.633$) with the $-Cl$ radical in the same position.

Table 5. Values of randomization test results

Model	R	R^2	Q^2
Original	0.844	0.713	0.556
Random 1	0.432	0.187	-0.448
Random 2	0.235	0.055	-0.869
Random 3	0.422	0.178	-0.775
Random 4	0.334	0.111	-0.763
Random 5	0.766	0.587	0.196
Random 6	0.572	0.327	-0.172
Random 7	0.468	0.219	-0.835
Random 8	0.330	0.109	-2.180
Random 9	0.419	0.175	-0.492
Random 10	0.496	0.246	-0.310
Random Models Parameters			
Average	0.447	0.219	-0.665

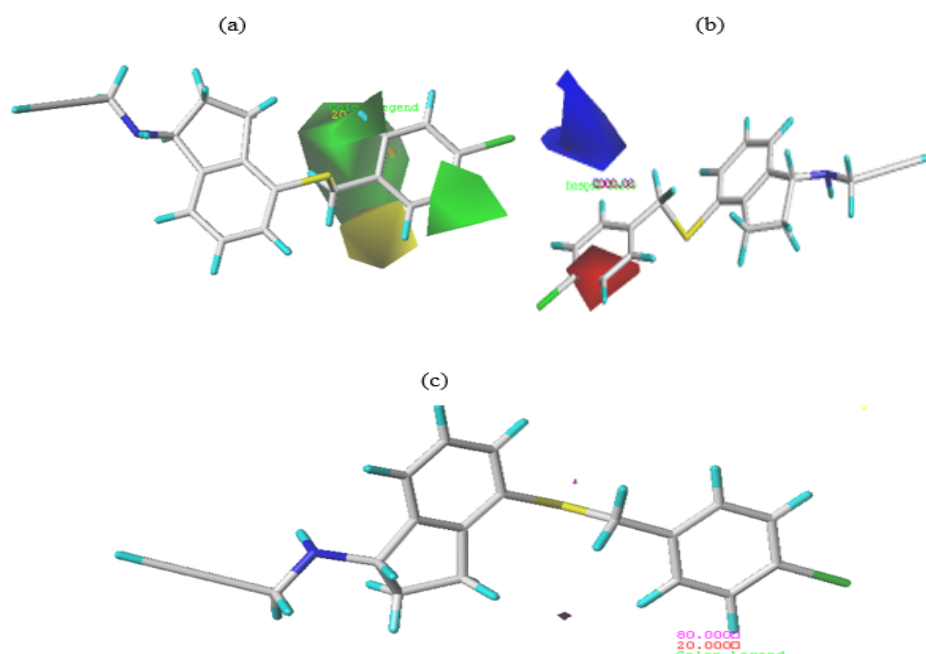


Figure 3. CoMSIA model contour map results. (a) Steric field, (b) electrostatic field, (c) hydrogen bond acceptors field

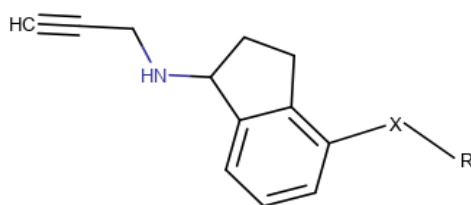
Moreover, the ortho and meta position is more efficient than the para position, which explains the higher activity of compound K19 with the $-CF_3$ root compared to that of compound K20 with the same root in the meta position and similarly for compound K22 with the $-O-CH_3$ root compared to that of

compound K23 with the same root-O-CH₃ in the meta position. Field (B): electrostatic contours where the blue areas are favorable to positive charges and the red areas to negative charges (Abdullahi *et al.*, 2022). We noticed a red contour next to the R substitution in the para position, indicating that the introduction of highly electronegative groups or atoms such as the halogens -Cl, -Br, and -F could increase their activity. This is illustrated by the observation that compound K17 (pIC₅₀=4.965) with -Cl in the para position shows higher activity than compound K25 (pIC₅₀=4.069) with -Br in the same position. Field (C): Magenta regions (80% contribution) indicate desired hydrogen bond acceptor sites, while red regions (20% contribution) indicate unwanted acceptors.

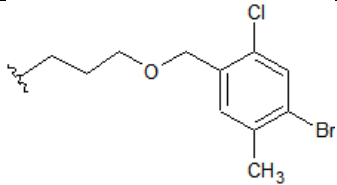
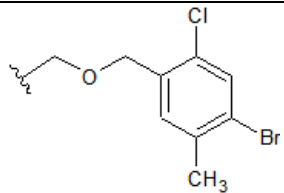
3.5 Newly designed compounds

In this work, key factors influencing inhibitory activity were identified, and substitutions were fitted to appropriate regions using the best contour mapping model (COMSIA/S+E+A) to predict novel compounds with significant activity.

Table 6. The structures and their predicted pIC₅₀ of the newly developed inhibitors by the model (COMSIA/S+E+A)



	X	R	pIC ₅₀ (Pred) CoMSIA/SEA
M ₁	S		6.005
M ₂	C		7.904
M ₃	C		8.052
M ₄	C		8.055
M ₅	O		7.863

M ₆	O C		7.459
M ₇	C		8.24

3.6 Analysis of drug-likeness and in-silico ADMET prediction

All new candidate compounds M1, M2, M3, M4, M5, M6, and M7 were shown to meet Lipinski's rule of five for oral bioavailability. In addition, the MW and logS values of all proposed molecules indicate that they have satisfactory adsorption capacity and are moderately soluble in water. In addition, all molecules showed excellent compatibility with the most important drug similarity rules, except for molecules M3, M5, M6, and M7, which have poor similarity with the drug similarity rules due to a slight increase in the logP value to some extent. Lipinski, Ghose, Veber, Egan, Muegge and showed a score of 55%, indicating good bioavailability(Khamouli *et al.*, 2022). This indicates that these substances have strong drug-like properties. All the newly generated compounds obtained a synthetic access score between 3.49 and 3.75, which means that these compounds can be easily synthesized (Table 7).

Table 7. Prediction of drug similarity and bioavailability of the newly designed compounds.

Compounds	Lipinski	Ghose	Veber	Egan	Alerts PAINS	Alerts Brenk	Lead likeness	Bioavailability score	Synthetic Accessibility
M1	Yes	Yes	Yes	Yes	0	1	1	0.55	3.59
M2	Yes	Yes	Yes	Yes	0	1	2	0.55	3.52
M3	Yes	Yes	Yes	Yes	0	1	2	0.55	3.68
M4	Yes	Yes	Yes	Yes	0	1	2	0.55	3.49
M5	Yes	Yes	Yes	Yes	0	2	2	0.55	3.61
M6	Yes	Yes	Yes	Yes	0	1	3	0.55	3.75
M7	Yes	Yes	Yes	Yes	0	1	2	0.55	3.58

The solubility and absorption of a drug, for example, is a critical physical and chemical property that influences whether it can be a successful therapeutic candidate. Molecular weight (MW) (≤ 500 Da), polarity (TPSA < 140 Å²), elasticity ($0 < \text{volatility} < 9$) and logP less than 5. In contrast, molecules with the total polar area (TPSA) < 140 °C Rotational bonds (NROTb) < 10 , show good bioavailability. Table 8 lists the physical and chemical characteristics of the novel compounds.

Table 8. Lipinski properties of newly designed inhibitors.

	Log P	HBD	HBA	TPSA	Nrotb	MR	MW
M1	4.805	1	1	37.33	5	100.59	321.489
M2	4.72	1	2	21.26	7	107.27	398.34
M3	5.42	1	2	21.26	7	112.24	412.36
M4	4.726	1	2	21.26	7	107.27	398.34
M5	5.174	1	3	21.26	7	109.0	434.75
M6	5.606	1	3	30.49	9	118.61	462.81
M7	5.30	1	2	21.26	7	112.28	432.78

From the results of ADMET (**Table 9**), it appears that all chemicals are less permeable to Kp. The gastro-intestinal index (GI), which is reported as high and indicates that all substances are highly absorbed in intestinal HIA, explains the absorption of the molecule in the gut. To treat Parkinson's disease, we need to focus on drug permeability across the blood-brain barrier (BBB) ([Khamouli et al., 2022](#)) whose main function is to restrict the passage of most compounds from the blood into the brain. This is important for the design of drugs that cross the BBB. It has been predicted that all compounds cross the blood-brain barrier (BBB) and thus may be suitable for the treatment of Parkinson's disease. P-glycoprotein (P-gp), it is a drug flow vector that transports toxins and vital foreign substances away from cells, and acts as a biological barrier to protect cells from the negative effects of drugs. In addition, all compounds are a substrate for P-gp, because it alone metabolizes 50% of all medications, CYP3A4 was the most significant enzyme within the CYP enzyme family. In addition, the negative AMES toxicity test also indicates that the studied derivatives (M1, M2, M3, M4, M5, M6, and M7) are not toxic.

Table 9. ADMET prediction of the newly designed compounds.

Comp	GI Absorption	BBB permeant	log kp (cm/s)	P-gp substrate	CYP1A2 inhibitor	CYP2C19 inhibitor	CYP2C9 inhibitor	CYP2D6 inhibitor	CYP3A4 inhibitor	AMES toxicity
M1	High	Yes	-5.02	Yes	No	Yes	Yes	Yes	Yes	No
M2	High	Yes	-5.54	Yes	No	Yes	No	Yes	Yes	No
M3	High	Yes	-5.36	Yes	No	Yes	No	Yes	Yes	No
M4	High	Yes	-5.54	Yes	No	Yes	No	Yes	Yes	No
M5	High	Yes	-5.45	Yes	No	No	Yes	Yes	Yes	No
M6	High	Yes	-5.44	Yes	No	No	No	Yes	Yes	No
M7	High	Yes	-5.30	Yes	No	Yes	Yes	Yes	Yes	No

3.7 Docking results

Information on the structural basis and potential interactions between the derivative and receptor binding was gathered by a molecular docking study. We need to determine the active site of human monoamine oxidase hMAO B before we can further investigate the mode and type of interactions in the different complexes. The MAO B substrate binding site is predominantly hydrophobic, surrounded by aromatic and aliphatic residues, except for a conserved lysine (Lys296) that reacts with a water molecule. MAO B tyrosines 398 and 435 are located on opposite sides of the inhibitors and substrates. MAO B tyrosines 398 and 435 are located on opposite sides of the inhibitors and substrates. The covalent bonds between this residue and MAO-B allow the formation of an aromatic "sandwich", which stabilizes the bond with the substrate. There is a small hydrophobic cavity next to the substrate cavity surrounded by residues Phe103, Pro104, Trp119, Leu164, Leu167, Phe168, Leu171, Ile199, Ile 316, and Tyr326. The second cavity is also located between the active site and the surface of the protein ([A. Sbati, 2022](#)). The following residues (Tyr326, Ile199, Leu171, and Phe168) form the boundary between the insertion cavity and the "substrate cavity," and their position affects the substrates and inhibitors capable of binding to MAO-B ([Prilusky et al., 2011](#)). **Figure 4** and **Figure 5** show the results of the molecular docking reaction modes between Receptor for Human Monoamine Oxidase (PDB: 2XFQ) and the most active K12 molecule and the proposed M4 molecule. Compound K12 exhibits alkyl interactions with residues Ile316 (4.79 Å), Ile199 (3.96 Å), Ile198 (5.1 Å), Cys172 (4.92 Å) and Leu171 (4.82 Å). Carbon-hydrogen interaction with residues Ile199 (3.26 Å), Pi-sigma interaction with residue Leu171 (3.94 Å), Pi-alkyl interaction with residue Tyr326 (5.35 Å), Pi-hydrogen-bond-donor interaction with residue Gln206 (3.56 Å), and Pi-Pi stacked interaction with residue Tyr398 (3.89 Å) ([Aoumeur et al., 2021](#)).

The proposed chemical compound M4 displays a conventional hydrogen bonding interaction with the Ile199 (2.7 Å) residue, as shown in **Figure 4**. Pi-alkyl interaction with residues Tyr326(4.57 Å) and Tyr398(4.65 Å). Alkyl interaction with residues Ile316 (3.80 Å), Leu167 (5.49 Å), Leu171 (5.04 Å), Pro104 (4.66 Å), Leu171 (4.19 Å), Cys172 (4.81 Å), Cys397 (4.5 Å), and Arg42 (4.28 Å). Carbon-hydrogen interaction with the Tyr435(3.35 Å) residue.

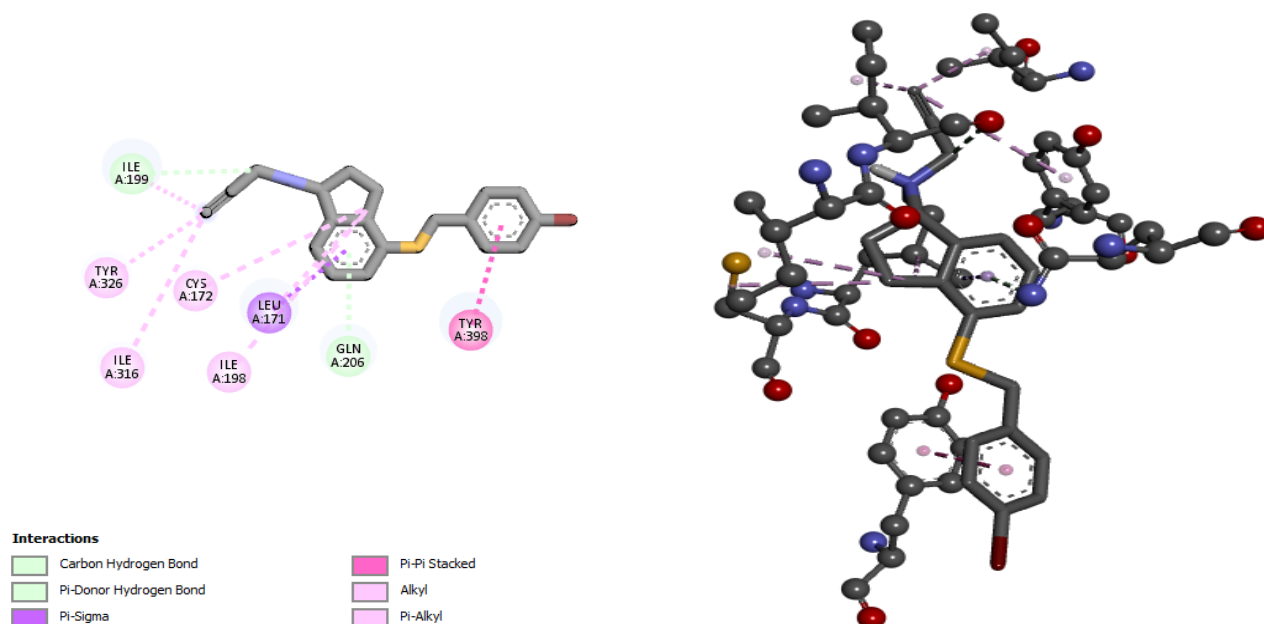


Figure 4. The chemical interactions of K12 compounds at receptor binding sites in 2D and 3D docking.

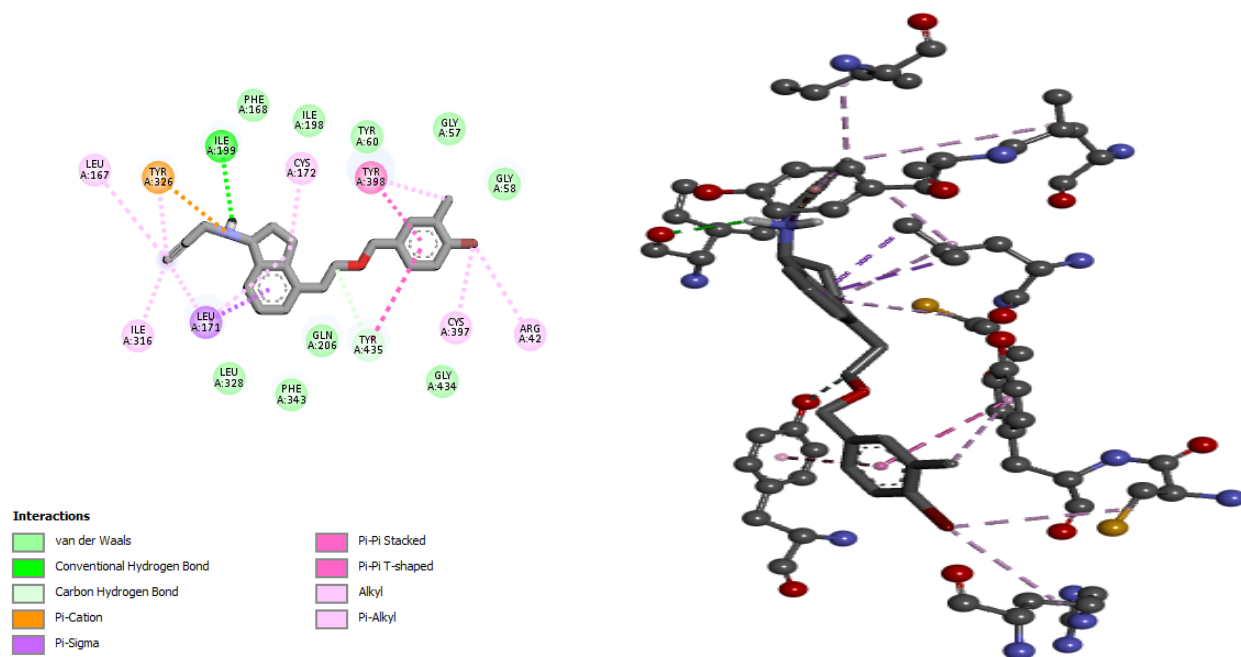


Figure 5. The chemical interactions of M4 compounds at receptor binding sites in 2D and 3D docking.

Interaction of the Pi cation with the Tyr326(4.08 Å) residue. Interaction of the hydrogen bond donor Pi- with the Gln206(3.49 Å) residue. Interaction of Pi-Pi stacked with the Leu177(3.83 Å) residue. Interaction of Pi-sigma with the Tyr398 residue (4.42 Å) and interaction of Pi-Pi shopped with the Tyr435 residue (5.58 Å). We conclude from these results that compound M4 is characterized by a large number of interactions compared to the more active compound K12 in the training set and let us not forget that the interactions between classical hydrogen bonds have a significant impact on the stability

of molecules, thus, based on these results, we conclude that compound M4 is more active in the active pocket (Bouachrine, 2020). Finally, these results support the 3D-QSAR analysis, which means that these new derivatives are more active and efficient.

Conclusion

To generate new candidates for human monoamine oxidase B inhibitors, the researchers performed computational studies (3DQSAR, molecular stabilization, MD, and ADMET simulations), using PLS analysis to predict 1-(prop-2-yn-1-ylamino)-2,3-dimers Hydro-1H-indene-4-thiol as hMAO-B inhibitors (Awasthi et al., 2020). The statistical results showed a high probability of internal and external validation with remarkable statistical power. Then, the best models obtained were tested internally and externally (Apablaza et al., 2017). According to the criteria of PLS analysis, the best model (COMSIA/S + E + A) was selected ($Q^2 = 0.701$, $R^2 = 0.926$, $R^2_{\text{test}} = 0.69$) and the contour maps also provided important information to suggest new inhibitors with better biological efficacy (Bourass et al., 2016). These newly designed molecules were predicted to be orally bioavailable and a good indicator of intestinal absorption of HIA by considering different drug similarity rules (Lipinski, Weber, Ghose, Egan, ADMET prediction), and all newly designed compounds are non-toxic and cross the blood-brain barrier BBB, and docking processes were also considered in the current study, and the newly developed compound M4 participates in a classical hydrogen bonding interaction with ILE A: 199 (Awasthi et al., 2020), playing an important role in the stability of the compound. Thus, the findings of this study can offer an impetus for the progress of hMAO-B inhibitors that can be used to treat Parkinson's disease.

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