

1 Identification *in silico* and *in vitro* of novel trypanosomicidal drug-like 2 compounds

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23 Abstract

24 Atom-based bilinear indices and linear discriminant analysis (LDA) are used to discover novel
25 trypanosomicidal compounds. The obtained LDA-based quantitative structure-activity
26 relationship (QSAR) models, using non-stochastic and stochastic indices, provide accuracies
27 of 89.02% (85.11%) and 89.60% (88.30%) of the chemicals in the training (test) sets,
28 respectively. Later, both models were applied to the virtual screening of 18 *in house*
29 synthesized compounds to find new pro-lead antitrypanosomal agents. The *in vitro*
30 antitrypanosomal activity of this set against epimastigote forms of *Trypanosoma cruzi* is
31 assayed. Predictions agree with experimental results to a great extent (16/18) of the chemicals.
32 Sixteen compounds show more than 70% of epimastigote inhibition at a concentration 100
33 µg/mL. In addition, three compounds (CRIS 112, CRIS 140 and CRIS 147) present more than
34 70% of epimastigote inhibition at a concentration of 10 µg/mL (79.95%, 73.97% and 78.13%,
35 respectively) with low values of cytotoxicity (19.7%, 7.44% and 20.63%,
36 correspondingly). Taking into account all these results, we could say that these three
37 compounds could be optimized in forthcoming works. Even though none of them resulted
38 more active than nifurtimox, the current results constitute a step forward in the search for
39 efficient ways to discover new lead antitrypanosomals.
40

41 **Keywords:** Atom-based bilinear indices, Anti-epimastigote elimination, Cytotoxicity,
42 *Trypanosoma cruzi*, Trypanosomicidal, *virtual* screening.
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45 **1. Introduction**

46 Chagas disease is an autochthonous illness that affects to 22 countries in the continental
47 Western Hemisphere (1), caused by the protozoa *Trypanosoma cruzi*. The parasite is found in
48 the vector as an epimastigote and in the human host as an intracellular amastigote (2). It is
49 estimated about 15 million people infected with *T. cruzi*, almost 28 million in risk of being
50 infected and 41 200 new cases reported each year (3). It is also estimated that up to 5.4 million
51 people will develop chronic Chagas heart disease (4, 5), while 900 000 will develop
52 megaesophagus and megacolon (5). Although this disease is typically related to poor and/or
53 rural populations, recent trends in migration have brought *T. cruzi* infection to Latin-American
54 cities and far beyond the borders of Latin America(6, 7).

55 Human infection is primarily transmitted by domestic and sylvatic insects of the subfamily
56 Triatominae (Hemiptera, Reduviidae), the kissing bug, whose habitat in the Americas ranges
57 from the US and Mexico in the North to Argentina and Chile in the South (1, 8). Vectorial
58 transmission of *T. cruzi* occurs only in endemic countries in the Western Hemisphere. The
59 haematophagous triatomine deposits containing the parasite are excreted on the host while
60 taking a blood meal; inoculation of the parasite into the bite wound, conjunctivae or mucus
61 membranes can result in *T. cruzi* infection. Recently, oral transmission has been reported in
62 several outbreaks (9). *T. cruzi* infection may be also transmitted to humans congenitally, by
63 blood transfusion and organ transplant in non-endemic countries as well as in Latin America
64 (1, 8). The acute phase of Chagas' disease lasts 6–8 weeks; some patients have fever,
65 lymphadenopathy, splenomegaly and/or oedema, but most cases are asymptomatic or
66 oligosymptomatic. Rarely, patients may develop severe disease, with myocarditis or
67 encephalomyelitis; but without treatment, around 5–10% of these patients die (7, 10). When
68 the acute phase ends, *T. cruzi* infection passes into a clinically silent chronic phase designated
69 the indeterminate form (10). Infected individuals may remain asymptomatic for life. However,
70 over a period of ten to thirty years, 20–35% of patients develop symptomatic chronic Chagas'
71 disease, characterized by cardiac and/or gastrointestinal disorders. The gravest complications
72 include high-grade conduction blocks, ventricular arrhythmias, ventricular aneurysm,
73 thrombo-embolic complications, heart failure, and sudden death. Optimum management may
74 require expensive procedures, such as subspecialist examinations, pacemakers, defibrillators,

75 and even heart transplant. A smaller proportion of patients develop digestive system disease,
76 especially megaesophagus or megacolon (7).

77 On the other hand, the chemotherapy of this parasitic infection remains undeveloped. The
78 treatment is based on old and quite unspecific drugs that have significant activity only in the
79 acute phase of the disease and, when associated with long-term treatments, give rise to severe
80 side effects (11). The currently available chemotherapy for Chagas disease is based on two
81 agents introduced in the market in the 1970s: nifurtimox (a nitrofurantoin derivative) and
82 benznidazole, (a nitroimidazole derivative). They show limited efficacy to the diseases' acute
83 phase and only against some pathogen strains; they are also associated to severe side effects,
84 including cardiac and/or renal toxicity (12). Their efficacy also varies according to
85 geographical areas, mainly because of differences in drug susceptibility of different *T. cruzi*
86 strains (13). Benznidazole efficacy and tolerance are inversely related to the age of the patient,
87 while its side effects are more frequent in elderly patients (14). Furthermore, medication is
88 expensive, for example, nifurtimox regimen requiring 10 mg/kg in three or four doses per day
89 over a 60- to 120-day period (15). Once the disease has progressed to later stages, no
90 medication has consistently proved to be effective (12).

91 As mentioned above it is necessary to search for new effective and less toxic
92 chemotherapeutic and chemo-prophylactic agents against *T. cruzi*. However, the great costs
93 associated with the development of new drugs and the small economic size of the market for
94 antiprotozoals, make this development slow (16). In this context, our research group has
95 recently developed a novel scheme to generate molecular fingerprints based on the application
96 of discrete mathematics and linear algebra theory. The approach [known as **TOMOCOMD**
97 acronym of *TO*polo*gical MO*lecular *COM*puter *DES*ign] (17-19) allows us to perform rational
98 *in silico* molecular design (selection/identification) and Quantitative Structure-
99 Activity/Property Relationship (QSAR/ QSPR) studies. In fact, this scheme has been
100 successfully applied to the prediction of several physical, physicochemical, chemical,
101 pharmacokinetic, toxicological as well as biological properties (20-25). Furthermore, these
102 molecular descriptors (MDs) have been extended to consider three-dimensional (3D) features
103 of small/medium-sized molecules based on the trigonometric-3D-chirality-correction factor
104 approach (26-31).

105 In the present report, atom-based non-stochastic and stochastic bilinear indices are used to
 106 find classification models that allow the discrimination of antitrypanosomal compounds. This
 107 approach permits the rational identification of those candidates to be evaluated, which have
 108 the highest probabilities of being active ones. Following this idea, 18 already-synthesized
 109 compounds were then *in silico* evaluated and, after that, *in vitro* assayed against epimastigote
 110 forms of *Trypanosoma cruzi*. Cytotoxic studies were also conducted, as a selection criterion of
 111 compounds with good activity vs, lowest toxicity.

112

113 2. Results and Discussion

114 2.1. Development and validation of the discriminant functions.

115 The linear discriminant analysis (LDA) has become an important tool for the prediction of
 116 chemical properties. Because of the simplicity of this method, many useful discriminant
 117 models have been developed and presented by different authors in the literature (21, 23, 32-
 118 35). It was the technique used in the generation of a discriminant function in the present work.
 119 Also, the principle of maximal parsimony (Occam's razor) was taken into account as the
 120 strategy for model selection (36). The general dataset was randomly divided into two subsets,
 121 training and test set (which have 346 and 94 compounds, respectively), both of them
 122 containing active and inactive compounds. The best models obtained using atom-based non-
 123 stochastic and stochastic bilinear indices as molecular descriptors, together with their
 124 statistical parameters are given below, respectively:

$$\begin{aligned}
 125 \text{Class} = & -5.103 - 2.9 \times 10^{-8} \text{MK} \mathbf{b}_{13\text{L}}^{\text{H}}(\bar{w}_E) + 6.62 \times 10^{-9} \text{MK} \mathbf{b}_{14\text{L}}^{\text{H}}(\bar{w}_E) + 1.52 \times 10^{-5} \text{MP} \mathbf{b}_{8\text{L}}^{\text{H}}(\bar{w}_E) \\
 126 & - 8.70 \times 10^{-6} \text{MP} \mathbf{b}_{9\text{L}}^{\text{H}}(\bar{w}_E) + 5.30 \times 10^{-7} \text{MV} \mathbf{b}_{9\text{L}}^{\text{H}}(\bar{w}_E) - 3.93 \times 10^{-3} \text{VK} \mathbf{b}_{1\text{L}}^{\text{H}}(\bar{w}_E) \\
 127 & + 7.93 \times 10^{-6} \text{VP} \mathbf{b}_6(\bar{w}) \quad (1)
 \end{aligned}$$

$$128 \quad N = 346 \quad \lambda = 0.42 \quad Q_{\text{Total}} = 89.02 \% \quad \text{MCC} = 0.76$$

$$129 \quad D^2 = 5.975 \quad F = 65.73 \quad p < 0.001$$

$$\begin{aligned}
 130 \text{Class} = & -4.531 + 9 \times 10^{-2} \text{VPs} \mathbf{b}_0^{\text{H}}(\bar{w}) + 12.29 \times 10^{-2} \text{VKs} \mathbf{b}_1^{\text{H}}(\bar{w}) - 4.22 \times 10^{-2} \text{VKs} \mathbf{b}_7(\bar{w}) \\
 131 & - 4.69 \times 10^{-2} \text{VKs} \mathbf{b}_{1\text{L}}^{\text{H}}(\bar{w}_E) - 1.63 \text{PKs} \mathbf{b}_9^{\text{H}}(\bar{w}) + 9.09 \times 10^{-1} \text{PKs} \mathbf{b}_{6\text{L}}^{\text{H}}(\bar{w}_E) \\
 132 & - 2.47 \times 10^{-2} \text{MPs} \mathbf{b}_{2\text{L}}^{\text{H}}(\bar{w}_E) \quad (2)
 \end{aligned}$$

$$133 \quad N = 346 \quad \lambda = 0.45 \quad Q_{\text{Total}} = 89.60 \% \quad \text{MCC} = 0.77$$

$$134 \quad D^2 = 5.357 \quad F = 58.95 \quad p < 0.001$$

135 where, *Class* refers to antitrypanosomal activity, N is the number of compounds, λ is the
 136 Wilks' statistic, Q_{Total} is the accuracy of the model for the training set, MCC is the Matthews'
 137 correlation coefficient, D^2 is the square Mahalanobis distance, F is the Fisher ratio and p -value
 138 is its significance level.

139 Both equations appeared statistically significant at $p < 0.001$. The best non-stochastic model
 140 (Eq. 1), which includes non-stochastic indices, present a good overall accuracy of 89.02% for
 141 the training set (see Table 1). In addition, this model showed an adequate Matthews'
 142 correlation coefficient of 0.76; MCC quantifies the strength of the linear relation between the
 143 molecular descriptors and the classifications and, usually, it may provide a much more
 144 balanced evaluation of the prediction than, for instance, the percentages (accuracies). Together
 145 with the accuracy other parameters such as sensitivity, specificity, and false-positive rate (also
 146 known as 'false-alarm rate'), are among the most commonly used parameters in medical
 147 statistics. While the sensitivity is the probability of correctly predicting a positive case, the
 148 specificity (also known as 'hit rate') is the probability that a positive prediction be correct
 149 (37). The non-stochastic model shows, for the training set, a good value of sensitivity of
 150 85.83%, a specificity value of 83.06% and a false-positive rate of only 9.29% (See Table 1).
 151 Nevertheless, the most important criterion, for the acceptance or not of a discriminant model,
 152 is based on statistics for the external prediction set, which is known as *the predictive power* of
 153 the model. For the test set, the non-stochastic model showed an accuracy of 85.11%, MCC of
 154 0.67, a good value of sensitivity of 91.30% and a specificity value of 63.64%, with a 16.90%
 155 of false-positive rate.

156 **Table 1.** Prediction performances for LDA-based QSAR models for training and test sets.

Models	Matthews Corr. Coefficient (C)	Accuracy 'Q _{Total} ' (%)	Specificity (%)	Sensitivity 'hit rate' (%)	False positive rate (%)
Training set					
Eq. 1	0.76	89.02	83.06	85.83	9.29
Eq. 2	0.77	89.60	82.81	88.33	9.73
Test set					
Eq. 1	0.67	85.11	63.64	91.30	16.90
Eq. 2	0.74	88.30	68.75	95.65	14.08

157

158 On the other hand, the best stochastic model (Eq. 2) presents a good overall accuracy of
 159 89.60%, with a good MCC value of 0.77 for the training set. These values are slightly better
 160 than those obtained with the non-stochastic model. The achieved values for sensitivity and

161 specificity were 88.33% and 82.81%, respectively, as well as a false-positive rate of only
162 9.73%. For the test set the results of the stochastic model were an accuracy of 88.30%, MCC
163 of 0.74, sensitivity of 95.65%, and specificity of 68.75%; these values are acceptable. All the
164 values are reported in Table 1. The results of the classification for compounds in both, training
165 and test, sets achieved with Eqs. 1 and 2 can be seen in the Supporting Information (Tables
166 S1-S4).

167 Therefore, the *robustness* of the model refers to the stability of its parameters (predictor
168 coefficients) and, consequently, to the stability of its predictions when a perturbation is
169 applied to the training set and the model is regenerated from the “perturbed” training set.
170 Here, we develop the leave-group-out (LGO) and *Y-scrambling* procedures (3, 38) as very
171 important tools in order to detect what is sometimes referred to as “internal predictivity” and
172 possible chance correlation in the models obtained, respectively (For details, see section 1 of
173 Supporting Information). First, a LGO strategy was performed and the calculation of
174 accuracies in the new training sets and test set compounds permitted us to carry out the
175 assessment of the models. The results of this validation process are illustrated in Figure S1
176 (see Supporting Information). It can be observed from this plot that the models present a high
177 stability to disturbances within the database. The results of the stochastic model were better
178 than those obtained with the non-stochastic model. After that, the *Y-scrambling* test was
179 carried out. The results of our randomization experiments are shown in Figure S2 (see
180 Supporting Information) and indicate that, when the random group size is increased, the
181 globally good accuracy of the model decreased gradually. This outcome indicates that the
182 values of good overall classification are not because of chance correlation or structural
183 redundancy in the training set.

184 **2.2 *In silico* and experimental identification of novel antitrypanosomals.**

185 The entire algorithm, described in the sections above, was made up with the main objective of
186 exploring the applicability of the QSAR models, obtained with the atom-based bilinear
187 indices, for the identification of ‘hits’ (pro-lead compounds) from large databases. Therefore,
188 an *in silico* screening of novel compounds was performed, looking for the biological activity
189 concerning this work. In order to carry out this, a pool of approximately 200 compounds
190 available from our academic collaborators never described in the literature as
191 antitrypanosomal agents was chosen. Later, the *in silico* assays were performed by using all

Table 2. Compounds evaluated in the present study, their classification ($\Delta P\%$) according to the obtained models, their antitrypanosomal activity and cytotoxicity at three different concentrations (100, 10, and 1 $\mu\text{g/mL}$) and antitrypanosomal activity of nifurtimox (reference).

Compound	Exp. ^a	ΔP	ΔP	%AE (SD) ^d			%CI(SD) ^e		
		Eq. 1 ^b	Eq. 2 ^c	100 $\mu\text{g/mL}$	10 $\mu\text{g/mL}$	1 $\mu\text{g/mL}$	100 $\mu\text{g/mL}$	10 $\mu\text{g/mL}$	1 $\mu\text{g/mL}$
CRIS 105	A	94.5	97.5	72.10 ±0.28	38.20 ±2.61	14.83 ±5.16	27.58 ±1.45	0.00 ±4.35	0.00 ±2.18
CRIS 109	A	96.0	97.3	84.21 ±0.75	56.20 ±1.39	0.00 ±2.05	49.21 ±0.60	10.88 ±1.36	11.66 ±1.70
CRIS 110	A	96.3	97.3	82.14 ±0.72	54.15 ±0.89	8.56 ±0.47	65.85 ±1.68	33.48 ±4.61	7.14 ±2.05
CRIS 111	A	96.2	97.8	83.80 ±1.47	41.73 ±1.25	23.94 ±1.02	42.91 ±0.47	8.68 ±0.72	0.00 ±1.64
CRIS 112	A	96.4	97.8	87.24 ±0.29	79.95 ±2.17	15.42 ±1.34	57.99 ±4.88	19.70 ±0.85	0.00 ±1.15
CRIS 116	A	97.9	98.5	70.84 ±2.38	53.18 ±1.88	6.98 ±4.25	24.31 ±1.52	9.71 ±1.57	7.85 ±1.30
CRIS 119	A	98.0	98.6	73.77 ±1.66	30.71 ±0.88	19.65 ±2.57	63.22 ±1.32	25.69 ±1.32	11.22 ±2.28
CRIS 130	A	97.9	98.6	76.45 ±2.31	46.09 ±2.53	0.00 ±2.68	50.21 ±0.82	12.60 ±1.18	0.00 ±2.14
CRIS 131	I	99.8	99.3	35.56 ±2.35	21.71 ±1.81	4.24 ±0.82	20.54 ±1.63	27.56 ±1.45	7.14 ±1.20
CRIS 135	A	94.6	97.6	81.13 ±2.55	35.48 ±4.16	10.69 ±1.35	35.18 ±1.54	11.71 ±1.33	0.00 ±0.85
CRIS 140	A	96.1	97.3	77.46 ±2.69	73.97 ±1.79	33.25 ±1.78	64.19 ±1.10	7.44 ±1.47	0.00 ±1.97
CRIS 141	A	96.2	97.8	75.64 ±0.80	54.38 ±0.55	8.27 ±1.05	99.46 ±0.21	99.90 ±0.07	34.66 ±1.91
CRIS 142	A	99.8	99.0	74.82 ±1.65	22.23 ±5.23	2.51 ±1.67	31.41 ±4.48	19.24 ±1.72	5.72 ±0.65
CRIS 143	A	99.8	99.1	80.35 ±3.25	39.01 ±2.11	7.80 ±3.28	71.14 ±3.60	23.14 ±4.10	4.67 ±0.80
CRIS 147	A	99.8	99.1	99.29 ±0.74	78.13 ±0.78	23.44 ±2.00	37.23 ±0.79	20.63 ±2.12	6.28 ±2.62
CRIS 148	A	99.8	98.9	82.26 ±1.32	31.77 ±0.78	12.56 ±4.04	26.79 ±2.42	26.74 ±5.06	6.71 ±1.06
CRIS 149	A	99.8	99.0	75.00 ±2.96	48.56 ±0.87	14.34 ±1.95	41.32 ±2.76	10.10 ±1.32	0.00 ±1.93
CRIS 153	I	99.9	99.5	20.31 ±0.56	18.75 ±0.54	21.41 ±0.52	20.63 ±1.20	20.70 ±0.56	3.50 ±1.63
Nifurtimox	A	99.98	98.39	100 ±1.49	85.45 ±2.43	38.21 ±2.17	11.68	0.6	0.32

^aObserved activity: A (active), I (inactive)

^bResults of the classification of compounds obtained from Model 1, $\Delta P\% = [P(\text{active}) - P(\text{inactive})] \cdot 100$

^cResults of the classification of compounds obtained from Model 2, $\Delta P\% = [P(\text{active}) - P(\text{inactive})] \cdot 100$

^dAnti-epimastigotes percentage and standard deviation (SD)

^eCytotoxicity percentage and standard deviation (SD)

the models developed inside this report, in order to identify bioactive chemicals that present trypanocidal activity.

Here, 18 new organic compounds were selected as putative antitrypanosomal by the LDA-based QSAR models. However, it is generally acknowledged that QSARs are valid only within the same domain for which they were developed. In fact, even if the models are developed on the same chemicals, the applicability domain (AD) for new chemicals can differ from model to model, depending on the specific molecular descriptors. Therefore, the leverage values (h) and standardized residuals related to these 18 compounds were calculated, the leverage values of these new compounds and were lower than the value of *warning leverage* ($h^* = 0.06$); the corresponding leverage plot is shown in Fig. S3 (For details, see Section 2 of supporting information). According to this, these chemicals lie in the applicability domain of the model, consequently their predictions are reliable. This proves the good valuation for the classification of this set of compounds as new antitrypanosomal, and so, this model can be used with high accuracy for the prediction of new compounds within its AD.

After that, the *in vitro* assays of the previously synthesized compounds (Figure 1) were carried out to corroborate the *in silico* predictions. We proceeded to test the compounds in an epimastigote inhibition (*in vitro*) assay (39). The $\Delta P\%$ values of the compounds in the dataset, using all the discriminant functions and the chemical structures are depicted in Table 2 and Figure 1, respectively. A good agreement (16/18) is observed between the experimental antitrypanosomal activity and theoretical predictions for this set of compounds. Sixteen compounds showed more than 70% of epimastigote inhibition at a concentration of 100 $\mu\text{g/mL}$ (see Table 2). Also, three compounds (CRIS 112, CRIS 140 and CRIS 147) demonstrated more than 70% of epimastigote inhibition at a concentration of 10 $\mu\text{g/mL}$ (79.95%, 73.97% and 78.13%, respectively). Even though none of them resulted more active than nifurtimox, the current results constitute a step forward in the search for efficient ways to discover new lead antitrypanosomals.

After this preliminary *in vitro* test, the unspecific cytotoxicity was determined against macrophages at the concentrations that were used in the previous assay (39, 40). At this time, three compounds (CRIS 105, CRIS 116 and CRIS 148) that showed more than 70% of epimastigote inhibition, at a concentration of 100 $\mu\text{g/mL}$ (Table 2), also presented acceptable values of cytotoxicity (27.58%, 24.31% and 26.79%, respectively). The three compounds with more than 70% activity at a concentration of 10 $\mu\text{g/mL}$ (CRIS 112, CRIS 140 and CRIS 147) showed low values of cytotoxicity (19.7%, 7.44% and 20.63%, correspondingly). Taking into account all these results, we can say that some compounds of this group can be optimized in

forthcoming works, but we consider that compound CRIS 140 is the best candidate (see Figure 1).

Here we would like to give a brief consideration about the possible structure-activity relationship for this set of compounds. According with the experimental results if we select for example compound CRIS140 with CRIS149 and CRIS153 we can see that the hybridization sp^3 of the carbon which the pyridyl ring is attached seem to be better than sp^2 hybridization for the trypanosomicidal action. Similar situation can be seen if we compare compounds CRIS112 and CRIS131; in both cases carbons with sp^3 hybridization present more % of AE than those which have sp^2 hybridization in the same position.

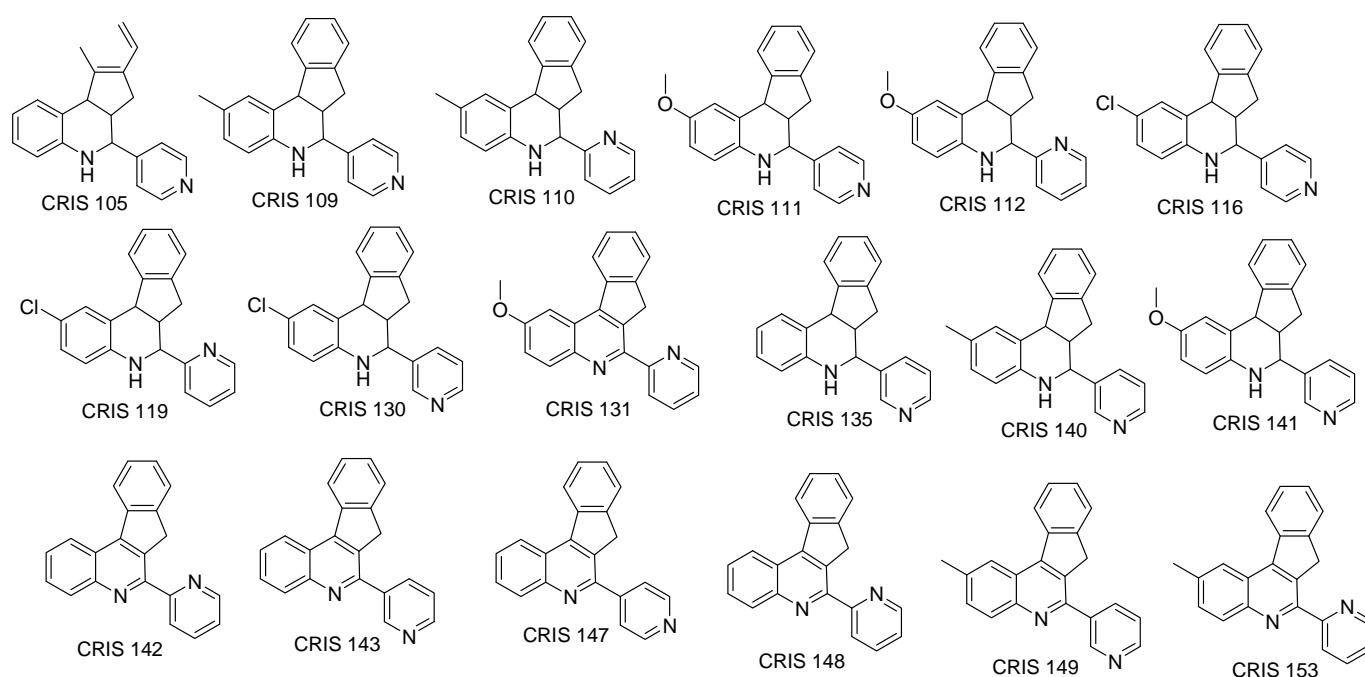


Figure 1. Molecular structures of experimentally evaluated compounds.

On the other hand, the same group of chemicals used in this work was recently tested against other protozoan parasite, *Trichomonas vaginalis*, and all compounds were found inactive at all assayed concentrations, with exception of compound CRIS 148 (41). Therefore, we can say that the antitrypanosomal activity, predicted and experimentally corroborated in this work, is quite specific for this group of compounds. However, a *T. cruzi* amastigote susceptibility assay and other tests of activity against other protozoa parasites are needed, in particular with other protozoa that also belong to the trypanosomatida family like *Leishmania* and *Trypanosoma brucei*.

3. Conclusions

The obtained models, developed using atom-based non-stochastic and stochastic bilinear indices, permit us to classify new “physical” or “virtual” chemicals as active or inactive ones, in the chemotherapy of trypanosomiasis, and they will contribute to a more rational discovery of new lead compounds with antitrypanosomal activity. The usage of this method permits a good prediction of the biological property under consideration, thus increasing the likelihood of an *in silico* discovery of new candidate lead compounds and minimizing the use of resources. In the present report, 16 new compounds, subjected to *in silico* screening, were recognized with antitrypanosomal activity. Afterward, several *in vitro* experiments are performed to corroborate the reliability of the classification functions developed in this work and permit us to select the candidates with the best “activity against epimastigote forms/unspecific cytotoxicity” rate. Finally, we can say that the present algorithm constitutes a step forward in the search for efficient ways of discovering new antitrypanosomal compounds, and constitutes an example of how this rational computer-aided method can help to reduce cost and to increase the rate in which novel chemical entities progress through the pipeline.

4. Experimental Section

4.1. Data-set for QSAR Study

The general data-set used in this study was the same that we utilize in previous works (24, 25) and it consists of 440 compounds of great structural variation, 143 of which are actives and 297 are inactive against trypanosome. For active compounds, it is remarkable that the wide variability of drugs and mechanisms of action in the training and prediction sets assures adequate extrapolation power (For details about the data set please see Section 3 of supporting information).

4.2. Computational approach

The theory of the atom-based bilinear indices used in this study was discussed in detail in earlier publications (31, 35). Specifically, the *CARDD* (Computed-Aided Rational Drug Design) module implemented in the *TOMOCOMD* Software (42) was used in the calculation of atom-based non-stochastic and stochastic bilinear indices. In this study, the properties used to differentiate the molecular atoms are those previously proposed for the calculation of the DRAGON descriptors (43-45) i.e., atomic mass (M), atomic polarizability (P), atomic Mulliken electronegativity (K), van der Waals atomic volume (V), plus the atomic electronegativity in Pauling scale (G) (46).

The following descriptors were calculated in this work:

(I) the k^{th} non-stochastic total bilinear indices, not considering and considering H atoms in the molecular pseudograph (G) [$\mathbf{b}_k(\bar{x}, \bar{y})$ and $\mathbf{b}_k^{\text{H}}(\bar{x}, \bar{y})$, respectively].

(II) the k^{th} non-stochastic local (atomic group = heteroatoms: S, N, O) bilinear indices, not considering and considering H atoms in the molecular pseudograph (G) [$\mathbf{b}_{kL}(\bar{x}_E, \bar{y}_E)$ and $\mathbf{b}_{kL}^{\text{H}}(\bar{x}_E, \bar{y}_E)$, correspondingly]. These local descriptors denote putative H-bonding acceptors; in addition, they represent charge as well as dipole moment.

(III) the k^{th} non-stochastic local (atomic group = H-atoms bonding to heteroatoms: S, N, O) bilinear indices, considering H atoms in the molecular pseudograph (G) [$\mathbf{b}_{kL}^{\text{H}}(\bar{x}_{E-H}, \bar{y}_{E-H})$]. These local descriptors denote putative H-bonding donors.

The k^{th} stochastic total [${}^s\mathbf{b}_k(\bar{x}, \bar{y})$ and ${}^s\mathbf{b}_k^{\text{H}}(\bar{x}, \bar{y})$] and local [${}^s\mathbf{b}_{kL}(\bar{x}_E, \bar{y}_E)$, ${}^s\mathbf{b}_{kL}^{\text{H}}(\bar{x}_E, \bar{y}_E)$ and ${}^s\mathbf{b}_{kL}^{\text{H}}(\bar{x}_{E-H}, \bar{y}_{E-H})$] bilinear indices were also computed.

4.3. Chemometric method

4.3.1 Linear discriminant analysis

The LDA was performed with software package STATISTICA (47). Forward stepwise was fixed as the strategy for variable selection. The quality of the models was determined by examining Wilk's λ parameter (U-statistic), square Mahalanobis distance (D^2), Fisher ratio (F) and the corresponding p-level [$p(F)$], as well as the percentage in training and test sets of global good classification, Matthews' correlation coefficient, sensitivity, specificity, negative predictive value (sensitivity of the negative category) and false positive rate (false alarm rate) (37). Models with a proportion between the number of cases and variables in the equation lower than 4 were rejected.

Validation external process is necessary to ensure the quality and predictive power of the QSAR models to predict the activity of compounds that were not used for model development. In this study, the original data are divided into two series, the training and test sets. The training set is used to build the QSAR models, and these discriminant functions (DFs) are used to predict the activities of compounds in the test set. The predictivity of a model is estimated by comparing the predicted and observed classes of a sufficiently large and representative test of compounds.

4.4 Biological assay: Determination of 'in vitro' tripanosomicidal activity and cytotoxicity

4.4.1 Parasites and culture procedure

The strain-Y of *T. cruzi* (48) was originally isolated from an acute human case coming from Marília (São Paulo, Brazil) in 1950. Epimastigotes were grown at 28° C in liver infusion

tryptose (LIT) broth with 10% fetal bovine serum (FBS), penicillin and streptomycin as previously described (49).

4.4.2 *Epimastigotes susceptibility assay*

The activity was evaluated with resazurin by a colorimetric method previously described (39). The screening assay was performed in 96-well microplates with cultures in LIT with 10% FBS, which had not reached the stationary phase. Epimastigotes were seeded at 3×10^6 per milliliter in culture tubes. Following a 24 h incubation to allow homogeneous growth, 200 μ L volumes were seeded in the plates in the presence of serial dilutions of reference drugs (concentration range as above) at 28° C for 48 hours, at which time 20 μ L of resazurin solution 3mM was added and returned to the incubator for another 5h. The solution of resazurin was prepared in 1% phosphate buffer solution (PBS) pH 7, and filter-sterilized before use. Growth controls were also included. The oxidation-reduction was quantified at 490 and 595 nm. Each concentration was assayed in triplicate. In order to avoid drawbacks, medium and drug controls were used in each test. The anti-epimastigotes percentage (%AE) was calculated as follows:

$$\%AE = [(ALW - (AHW \times RO) \text{ test well}) / (ALW - (AHW \times RO) \text{ positive growth control})] \times 100$$

where, ALW and AHW represents the absorbances at the lower and the higher wavelength respectively (milieu was subtracted) and RO represents the correction factor ($RO = ALW/AHW$ for resazurin in the milieu).

4.4.3 *Cell culture*

The cell lines used were National Collection of Type Cultures (NCTC) clone 929 and murine J774 macrophages. The NCTC clone 929 cells were grown in Minimal Essential Medium (Sigma) and J774 macrophages were grown in RPMI 1640 medium (Sigma). Both media were supplemented with 10% heat-inactivated FBS (30 minutes at 56°C), penicillin G (100 U/mL) and streptomycin (100 μ g/mL). For the experiments, cells in the pre-confluence phase were harvested with trypsin. Cell cultures were maintained at 37°C in a humidified 5% CO₂ atmosphere.

4.4.4 *Cytotoxicity assays*

The procedure for cell viability measurement was evaluated with resazurin by a colorimetric method described previously (39, 40). The macrophages J774 were seeded (5×10^4 cells/well) in 96-well flat-bottom microplates with 100 μ L of RPMI 1640 medium. The cells were allowed to attach for 24 h at 37°C, 5% CO₂ and the medium was replaced by different concentrations of the drugs in 200 μ L of medium, and exposed for another 24 h. Growth

controls were also included. Afterwards, a volume 20 μ L the 2mM resazurin solution was added and plates were returned to incubator for another 3h to evaluate cell viability. The reduction of resazurin was determined by dual wavelength absorbance measurement at 490 nm and 595 nm. Background was subtracted. Each concentration was assayed in triplicate. Medium and drug controls were used as blanks in each test.

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