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**Insight into the structural requirement for  
Anticancer Activity: Pharmacophore  
Generation and 3D QSAR Analysis**

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# INTRODUCTION

- **Cancer:**

- Transforming growth factor  $\beta$  receptor-associated kinase 1 (TAK1) or mitogen activated-protein kinase kinase kinase 7 (MAP3K7)
- It is serine/threonine kinase which forms a key part of canonical immune and inflammatory signaling pathways
- Regulate expression of a large number of genes involved in immune and inflammatory responses, as well as in cell survival, proliferation, and differentiation
- TAK1 inhibitors used in cancers with an inflammatory component, for example, ovarian and colorectal carcinomas, as well as in hematological malignancies

## Computational Chemistry in Anticancer Drug Research

- ➡ Molecular modelling programs have been developed and widely used in the pharmaceutical and biological industry
- ➡ Pharmacophore modelling involves extracting common chemical features (hydrogen-bond acceptors, hydrogen bond donors, hydrophobic regions and positively or negatively charged groups) from 3D structures of a set of known ligands
- ➡ 3D QSAR analysis is performed for generating models which correlates biological activity with physico-chemical properties of the molecules
- ➡ A statistically significant 3D QSAR model helps in better understanding of structure activity relationship of a series of molecules and predicts the activity of yet to be synthesized compounds

# OBJECTIVES AND STRATEGY

- Three-dimensional quantitative structure–activity relationships (3D-QSAR) models are used to analyze favorable and unfavorable pharmacophoric features of molecules which play a crucial role to mimic the interaction of ligands with a particular protein target
- The present paper reports 3D-QSAR analysis of set of 7-aminofuro [2,3-c]pyridine derivatives, reported by Hornberger K. R. *et al.* (2013) and intends to provide the platform to develop new compounds over existing substituted pyridines
- The calculated fields are correlated with experimental biological activity data
- Different color-coded contour maps surrounding the ligands give insights about favorable and unfavorable ligand–receptor interactions, and also used as guides for designing novel leads

# MATERIAL AND METHODS

- ✿ The 3D-QSAR studies were performed using 54 molecules reported by Hornberger *et al.*
- ✿ Out of 54 molecules, **19** molecules were taken for the Test set and **35** molecules for Training set which was selected manually by considering activity variation present
- ✿ The dataset consists of both active and inactive molecules
- ✿ The study was performed using the PHASE 3.4 module of Schrodinger molecular modeling software for 3D-QSAR pharmacophore model developing

# RESULTS AND DISCUSSION

- Different variant CPHs were generated by common pharmacophore identification process
- All CPHs were examined and scored to identify the pharmacophore that yields the best alignment of the active compounds ( $\text{pIC}_{50} > 6.2$ ).
- All CPHs were validated by aligning and scoring the inactive compounds ( $\text{pIC}_{50} < 5.7$ ).
- All top CPHs were used for atom-based 3D-QSAR model generation.
- The CPHs ADHRR.84 and ADHRR.651 yielded 3D-QSAR models with good PLS statistical values.

**Table 1: Score of different parameters of the hypothesis ADHRR-84 and ADHRR-651**

<b>Parameter</b>	<b>Score</b>	
	<b>ADHRR-84</b>	<b>ADHRR-651</b>
Survival	3.880	3.864
Survival- inactive	1.041	1.056
Post hoc	5.860	5.844
Site	0.97	0.95
Vector	1.000	0.999
Volume	0.908	0.911
Selectivity	1.869	1.971
Matches	17	17
Energy	0.00	17
Activity	6.602	6.602
Inactive	2.838	2.808



**Table 2: 3D-QSAR statistical parameters for ADHRR-84 hypothesis**

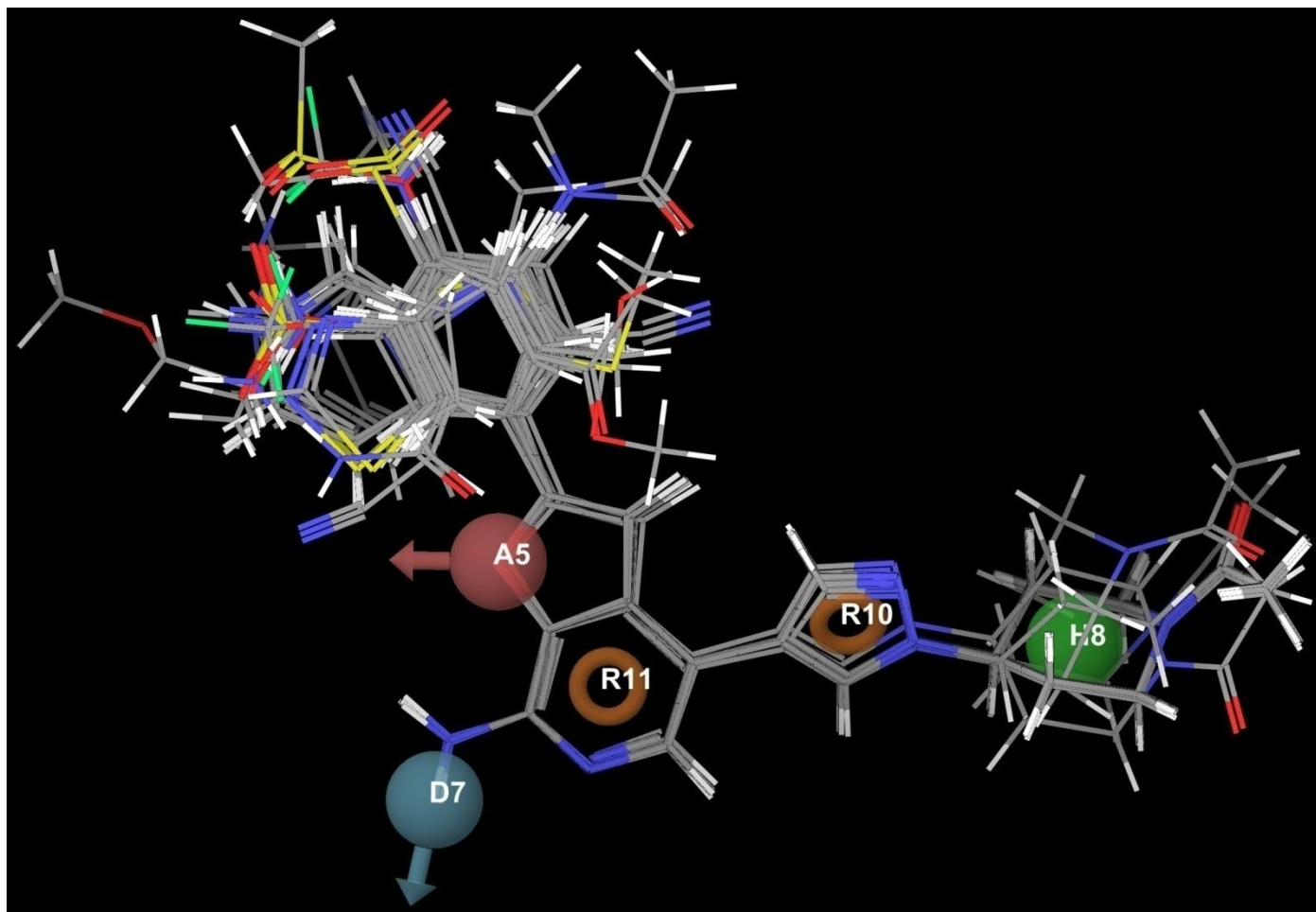
<b>PLS factors</b>	<b>SD</b>	<b>r<sup>2</sup></b>	<b>F</b>	<b>P</b>	<b>RMSE</b>	<b>q<sup>2</sup></b>	<b>Pearson-R</b>
<b>1</b>	0.4993	0.6342	57.2	1.059e-008	0.4367	0.5568	0.7895
<b>2</b>	0.3043	0.8682	105.4	8.297e-015	0.4071	0.6146	0.8027
<b>3</b>	0.2168	0.9352	149.1	1.679e-018	0.3423	0.7276	0.8684
<b>4</b>	<b>0.1705</b>	<b>0.9612</b>	<b>185.9</b>	<b>1.043e-020</b>	<b>0.297</b>	<b>0.7949</b>	<b>0.9093</b>

**Table 3: 3D-QSAR statistical parameters for ADHRR-651 hypothesis**

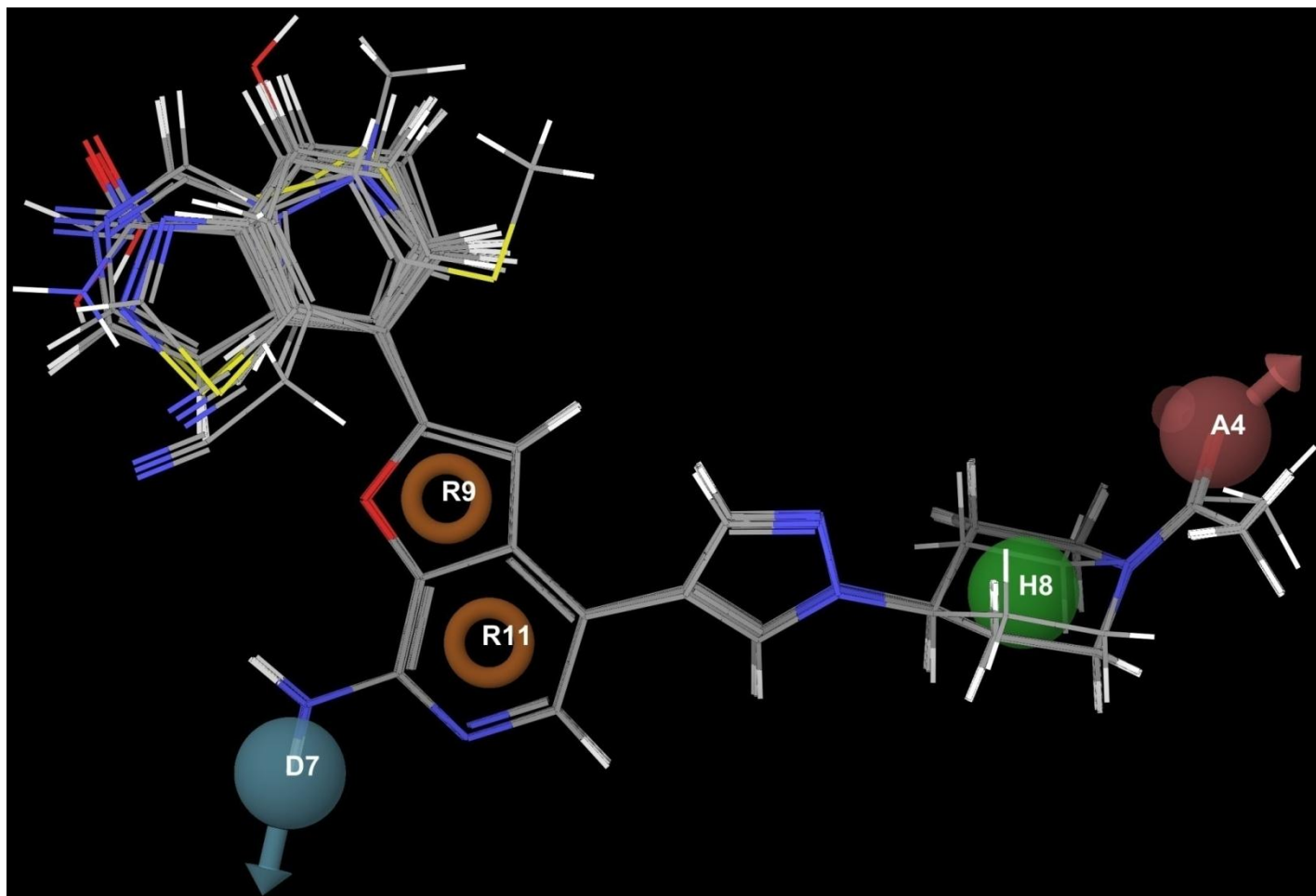
<b>PLS factors</b>	<b>SD</b>	<b>r<sup>2</sup></b>	<b>F</b>	<b>P</b>	<b>RMSE</b>	<b>q<sup>2</sup></b>	<b>Pearson-R</b>
<b>1</b>	0.5489	0.5578	41.6	2.569e-007	0.4776	0.4697	0.7878
<b>2</b>	0.3230	0.8515	91.8	5.566e-014	0.3918	0.6431	0.8247
<b>3</b>	0.2004	0.9446	176.3	1.463e-019	0.3436	0.7256	0.8884
<b>4</b>	<b>0.1431</b>	<b>0.9727</b>	<b>266.8</b>	<b>5.552e-023</b>	<b>0.2895</b>	<b>0.8051</b>	<b>0.9258</b>

- The training set correlation in both CPHs is characterized by PLS factors ( $R^2 = 0.9612$ ,  $SD = 0.1705$ ,  $F = 185.9$ ,  $P = 1.043e-020$ ,  $Q^2 = 0.7949$  for CPH ADHRR.84 and  $R^2 = 0.9727$ ,  $SD = 0.1431$ ,  $F = 266.8$ ,  $P = 5.552e-023$ ,  $Q^2 = 0.8051$  for CPH ADHRR.651).
- The CPH ADHRR.84 yielded a 3D-QSAR model with good value of regression coefficient, low standard deviation, and high variance ratio with good stability
- A pictorial representation of the cubes generated in the present 3D-QSAR is shown in Figs. 1 and 2
- In these generated cubes, the blue cubes indicate favorable features, while red cubes indicate unfavorable features for biological activity

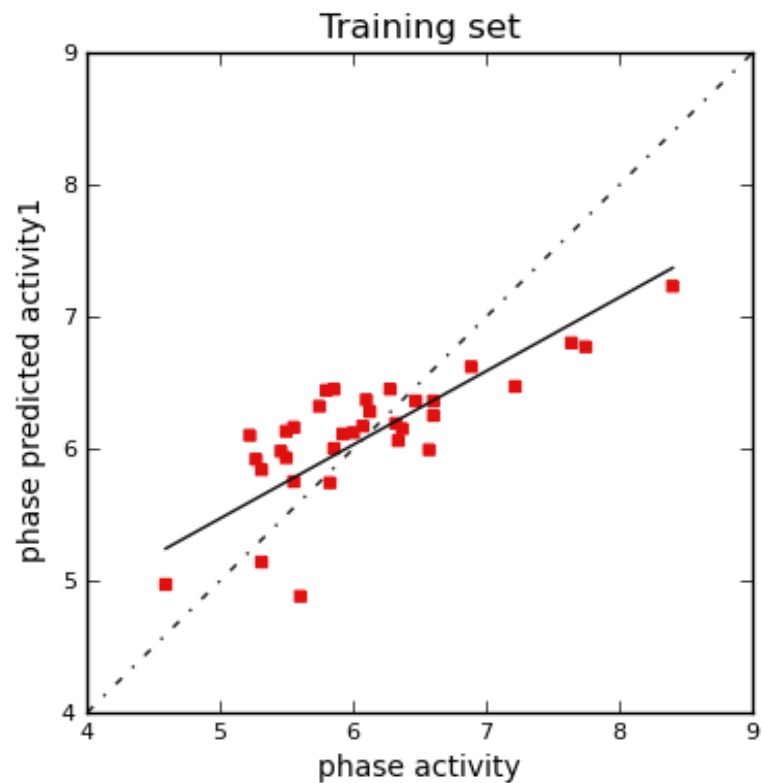
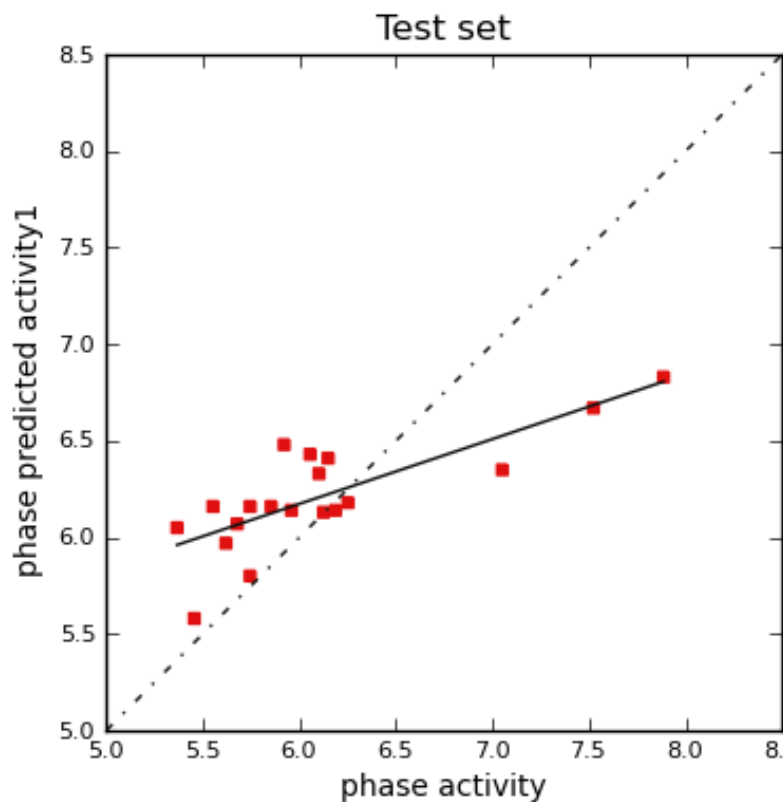
**Figure 1: Alignment of compounds using the 5-point pharmacophore hypothesis**



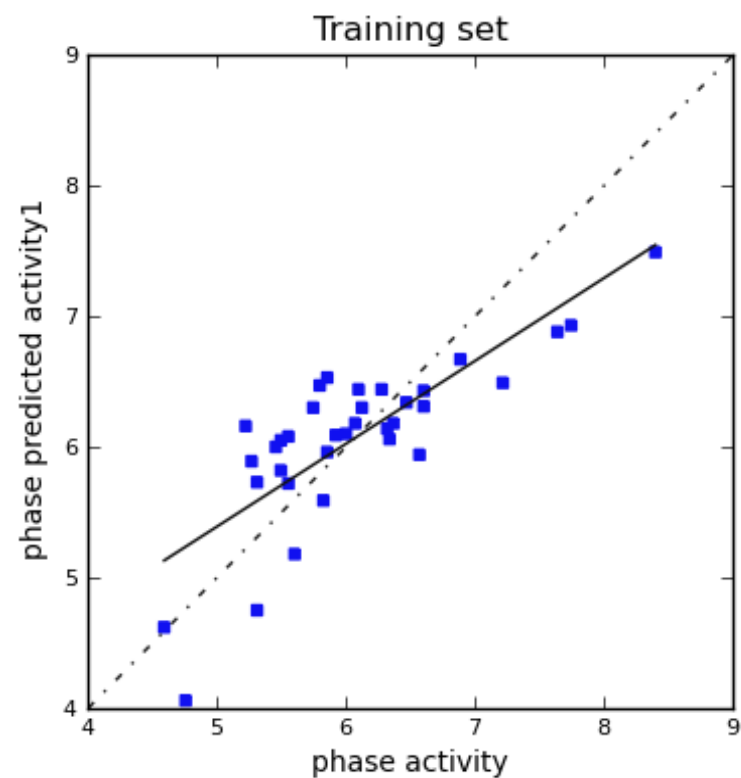
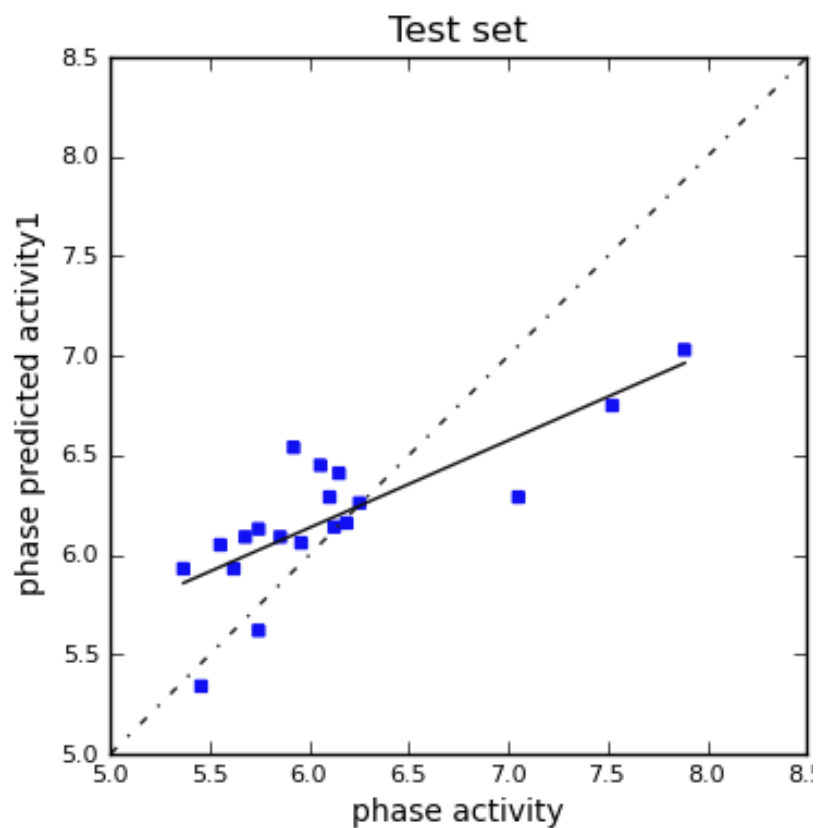
**Figure 2: Alignment of active compounds using the CPH-651**



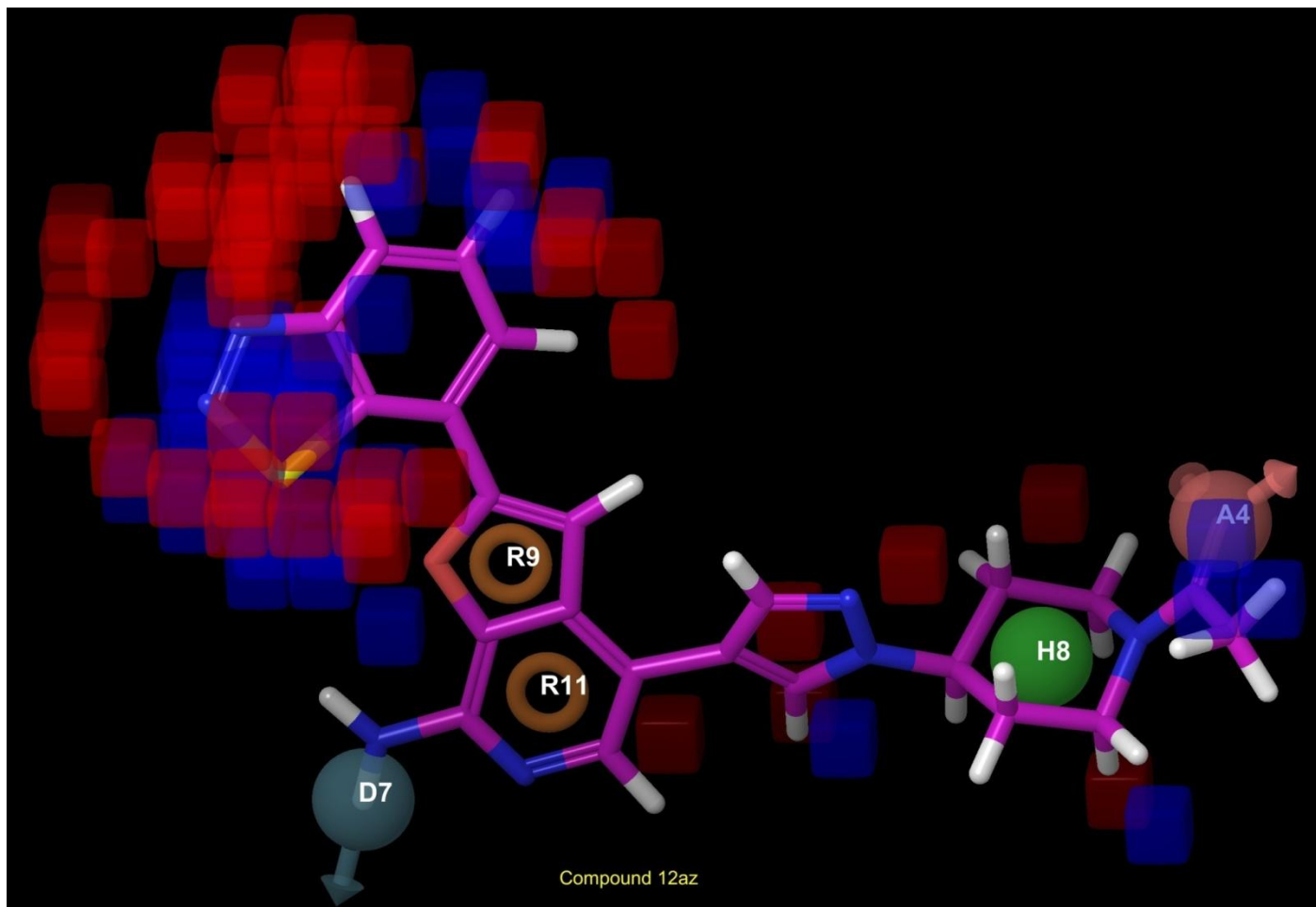
**Figure 3: Plot of experimental versus predicted  $pIC_{50}$  values of compounds for A) CPH-84**



**Figure 3: Plot of experimental versus predicted  $pIC_{50}$  values of compounds for B) CPH-651**



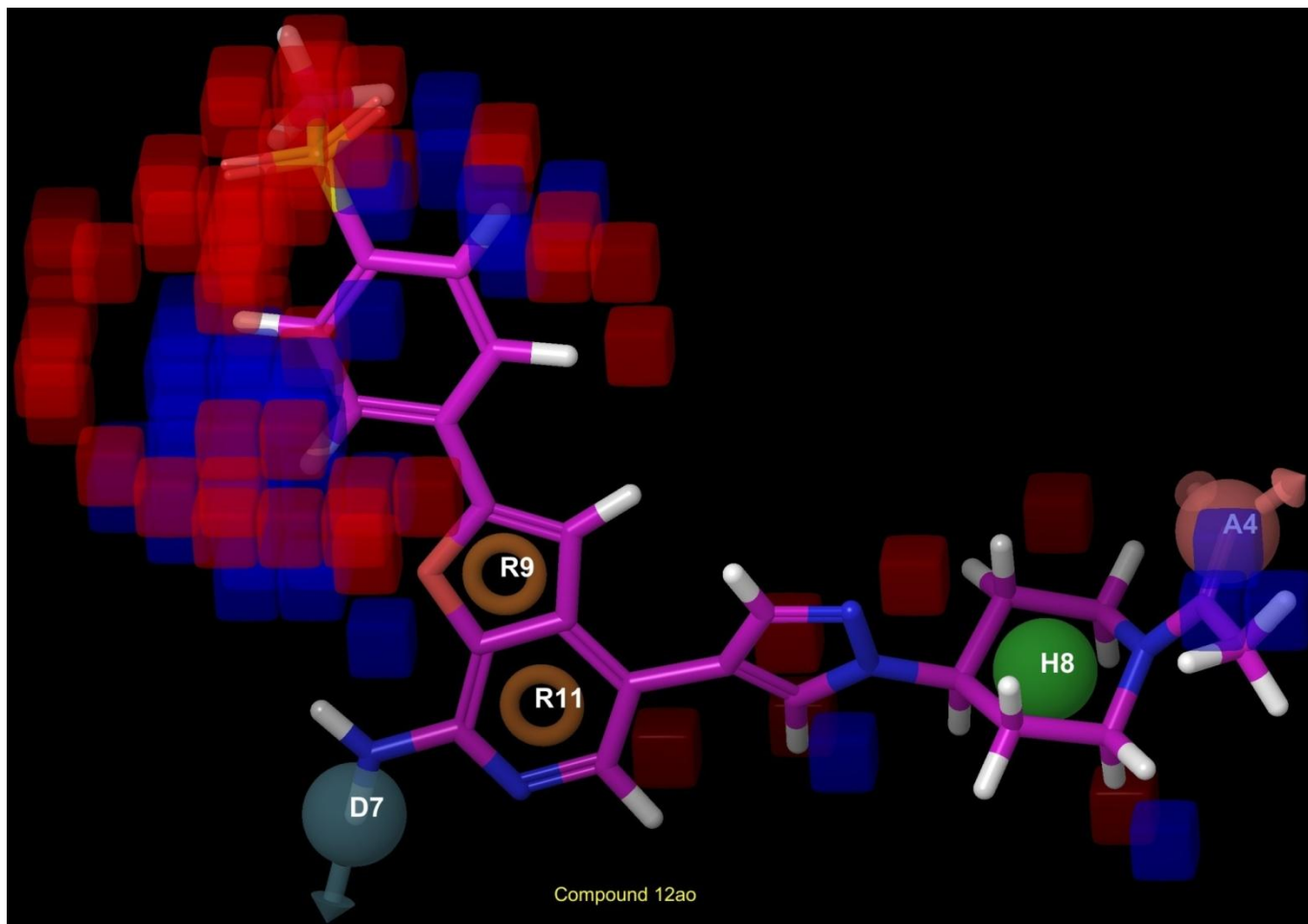
**Figure 4: QSAR visualization of combined effect (blue cubes showing positive potential while red cubes showing negative potential of particular substitution) for CPH-651**



**Compound 12az**



**Figure 4: QSAR visualization of combined effect (blue cubes showing positive potential while red cubes showing negative potential of particular substitution) for CPH-651**



**Compound 12ao**

# CONCLUSIONS

- ✦ The goal of this study is to develop a model that facilitates the design of novel TAK1 inhibitors, for the treatment of cancer.
- ✦ Towards the end, a novel and unique pharmacophore is presented here based on 3D-QSAR modeling of pyrimidine derivatives, which is shown to have general applicability across several leads, clinical and pre-clinical candidates.
- ✦ The present study also explores the structure-activity relationships of TAK1 inhibitors using a pharmacophore based 3D-QSAR model and offers a rationale for their observed activities.
- ✦ Thus the proposed model offers a rationale for observed structure-activity relationships of this series of compounds, which can be incorporated for designing novel inhibitors of TAK1.

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