IN SILICO ANALYSIS AND HOMOLOGY MODELING OF ALPHA-CONOTOXIN FROM SELECTED VERMIVOROUS CONUS SPECIES

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Abstract

Cone snails are members of the vast Conoidean group of venomous marine gastropods found in a variety of tropical and subtropical ocean ecosystems. They use their venom, like other venomous species, as a defensive mechanism as well as a tool for capturing their prey. As part of their neurochemical and biochemical strategy for catching prey, these species produce peptides that target specific ion channels and receptors, and they appear to have produced conotoxin, an unusual combination of pharmacologically active peptides. These conotoxins contain more than 100 components, resulting in a variety of active mono peptides used pharmacologically. However, studies on the structure of these peptides are still limited. leaving us with a gap in understanding their action, selectivity, and potency. Therefore, in silico and homology modeling studies on one (1) family of alpha-conotoxin from selected vermivorous Conus species were discussed in this study. The majority of the alpha-conotoxins were highly basic in nature, according to physicochemical characterization, with one alpha-conotoxin sequence (α -conotoxin Lt28.1) indicating acidic in nature. The index of instability ranges from stable α -conotoxin RgIA (14.62) to unstable α -conotoxin Imll (126.91). Additionally, the aliphatic index for the protein sequences studied ranges from 29.15 to 97.50, indicating that it is thermostable over a wide temperature range. Furthermore, GRAVY values for alphaconotoxins range from -0.910 (most hydrophilic; α-conotoxin SrIA/SrIB) to 0.731 (most hydrophobic; alphaconotoxin Lp1.1). Moreover, toxin 8 was discovered to be the common domain among the species. A random coil dominates other secondary structures in terms of percentage score of amino acid distribution for secondary structure prediction, followed by α -helix, β -strand, and β -turns. Finally, the predicted models for α-conotoxin Lp1.4, α-conotoxin ArIA, α-conotoxin VxXXC, α-conotoxin VxXXA, and α-conotoxin LvIA are of high quality, with \geq 90% coverage in their favored regions.

Index Terms: *Conus*, Alpha-Conotoxin, in Silico Analysis, Homology Modeling, Ramachandran Plot, Cone Snails, Marine Gastropods

1. INTRODUCTION

Cone snails are members of the vast Conoidean group of venomous marine gastropods, including *Conidae, Turridae*, and *Terebridae*. They can be found in a wide range of tropical and subtropical ocean ecosystems, from shallow coral reefs to deep-sea environments [1]. Similar to other venomous species, cone snails utilize their venom as a defensive mechanism and a tool for capturing their prey [2], [3], [4], [5]. These species produce peptides that target specific ion channels and receptors as part of their neurochemical and biochemical strategy for catching prey [6].

The genus *Conus* has approximately 900 species of venomous marine cone snails, and as a result of the widespread occupation of their biological niche, they appear to have generated an unusual combination of pharmacologically active peptides known as conotoxin [7], [8], [9], [10]. These conotoxins contain more than 100 components, leading to various active monopeptides used pharmacologically wherein each *Conus* species uses a distinct combination of peptides to paralyze its prey rapidly. The disulfide bond frameworks responsible for its potency contain *alpha*-helices, *beta*-sheets, and *beta*-turns with exquisite selective of receptor subtype and resistance to proteases, making it a strong candidate for neurological tools and drug development [11].

Moreover, conotoxins, according to [12] are classified based on their precursor's signal sequence, defining the gene superfamily (A-Q, S, T, V, Y); cysteine structures, describing the cysteine pattern (I-XXVI); and pharmacology, determining its pharmacological target (α , γ , ϵ , δ , κ , μ , ρ , σ , τ , χ , ω). Among these, alpha-conotoxin is given more focus due to its ability to block receptors such as nicotinic acetylcholine receptors (nACHR), the well-known target of other animal toxins such as neurotoxins from snake venom. Alpha-conotoxin is the most prominent family of nACHR antagonists; it has rich peptides isolated from venomous marine snails composed of 12-19 amino acids [13], [14]. However, studies on the structure of these peptides are still limited, providing us with a gap in understanding their action, selectivity, and potency.

The goal of the drug discovery process is to find novel medicinal compounds that can bind to a recognized disease-causing target. While the most critical task in the traditional drug development approach is identifying a good therapeutic target [15]. According to [16], one of the major drawbacks of the experimental method used to characterize protein was its high cost and time consumption. As a result, these methods were incompatible with high throughput techniques. These issues, however, can be solved using computational (*in silico*) approaches, which are frequently used in the drug discovery process nowadays. Furthermore, researchers can use computational tools to learn about the physicochemical and structural properties of proteins, because the amino acid sequence contains the vast majority of the information required to determine and characterize the molecule's function, physical, and chemical properties [16]. In addition, the application of homology modeling has evolved into an improved method in structural

biology, significantly bridging the gap between known protein sequences and empirically determined structures [17].

Therefore, in this study, the *in silico* and homology modeling studies on one (1) family of alpha-conotoxin from selected vermivorous *Conus* species were reported. The research compares, analyzes, and structures this family of alpha-conotoxin compounds using several *in silico* approaches such as physical and chemical property prediction, domain scanning, protein secondary structure prediction, and peptide structural analysis. Since the three-dimensional (3D) structure of this protein family was not yet available, model structures for this alpha-conotoxin family were constructed to describe their structural features and to understand their molecular function. Through this research, a thorough understanding of the target molecule's composition and biological properties will serve as the foundation for developing and comprehending its design and effect. Furthermore, the evolution of its structure will benefit its overall structure as well as clinical development via computer-aided techniques.

2. METHODOLOGY

2.1 Protein Sequence Retrieval of the Target Protein

The protein database from the National Library of Medicine, National Center for Biotechnology Information (NCBI), which contains sequences from various sources, including annotated coding sections from GenBank, RefSeq, and TPA with the addition of records from SwissProt, PIR, PRF, and PDB, was used to analyze the structure and functional phenomena of the protein networks of alpha-conotoxin. The protein sequence of *C. imperialis, C. lividus, C. pulicaria, C. vexillum, C. planorbis, C. leopardus, C. regius, C. litteratus, C. arenatus,* and *C. spurius* were retrieved from the Universal Protein Resource (UniProt; http://www.uniprot.org) protein database and was saved in fast all (FASTA) file format for further analysis. Most of the sequences were from the translation of sequences, which is a great resource for understanding protein's post-translational modifications [18].

2.2 Physicochemical Parameters Analysis

Determination of physicochemical parameters used Expasys's ProtParam Tool (https://web.expasy.org/protparam/) to determine the nature of interactions between systems components. These parameters were used to examine the properties of chemicals identified as significant structural [19]. Briefly, Expasys's ProtParam Tool was used to determine several physical and chemical parameters such as molecular weight, isoelectric pl (isoelectric point), instability index (II), aliphatic index (AI), and grand average of hydropathy (GRAVY; [20]). To calculate such parameters, the protein sequence was supplied using an accession number from UniProtKB/Swiss-Prot or UniProtKB/TrEMBL or as an amino acid sequence.

2.3 Domain Analysis

The Protein families (Pfam) database was used to analyze the molecular domain of alphaconotoxin from selected vermivorous *Conus* species utilizing the protein sequence

obtained from the protein database. Pfam 34.0 is a comprehensive collection of multiple sequence alignments and hidden Markov modeling encompassing many common protein domains and families.

2.4 Secondary Structure Prediction

Self-optimized Prediction with Method and Alignment (SOPMA; https://www.npsa-ibcp.fr) was used to predict the secondary structure (*alpha*-helix, *beta*-sheet, and coil) of the alpha-conotoxins. SOPMA correctly predicts 69.5% of amino acids in a database [21] in which the researchers used this tool to visualize the results and the score curves for all predicted states, allowing the researcher to interpret the data accurately. The protein sequences saved in FASTA format from the protein database were submitted to the SOPMA server to yield secondary structure components. It shows the parameters, such as window width, number of states, etc., that are used for the prediction and provides a link to the prediction result file, which gives the result in a text format.

2.5 Homology Modeling of Alpha-Conotoxin and Structure Verification

Homology modeling was utilized in this study to bridge the gap between primary and three-dimensional (3D) structures, allowing the derivation of functional and beneficial properties in the same way as an experimental 3D structure does [22]. This approach allows access to more therapeutic targets as well as a variety of other applications, such as studying protein function, structural roles of proteins in the cell, and protein interactions [23], [24], [25], [26]. Briefly, the alpha-conotoxin's three-dimensional (3D) structure was constructed using the SWISS-Model Server, a bioinformatics tool widely used for protein structure prediction and changing the modeling parameters to produce the needed data according to the research of [27]. Wherein the protein ID would be entered into the SWISS-Model webserver to create a model with enough guery sequence coverage and sequence identity. The most dependable 3D structure was chosen based on the Global Model Quality Estimation (GMQE) [28] and Qualitative Model Energy Analysis (QMEAN) values [29]. The GMQE values are normally between 0 and 1, and the greater the number, the more reliable the projected structure is, whereas a value below 4.0 indicates reliability for QMEAN [29]. The modeled alpha-conotoxin's .pdb file format was uploaded to the European Bioinformatics Institute's PDBsum online server [30]. Lastly, for structure validation, acquiring the Ramachandran plot was used to analyze the quality of the modeled protein.

3. RESULTS AND DISCUSSIONS

3.1 Retrieved Target Protein Sequences

The protein sequences of alpha-conotoxins from vermivorous cone snails were retrieved and saved in FASTA format from the UniprotKB database and used for further analysis. Table 1 summarizes the retrieved protein sequences with their accession number, species name, length, and protein name. As shown in the results, the sequence from *C. imperialis*' alpha-conotoxin *ImII* and *ImI* was the shortest, with only seventeen (17) amino acids, whereas α -conotoxins *VxXXB* from *C. vexillum*, was the longest, with 95 amino acids.

SPECIES	ACCESSION NUMBER	LENGTH	PROTEIN NAME	
C. Jacon and us	A1X8B6	68	Alpha-conotoxin Lp 1.4	
C. leoparaus	Q6PTD5	68	Alpha-conotoxin Lp1.1	
C. arenatus	POC8R2	39	Alpha-conotoxin ArIA	
C. spurius	P85886	69	Alpha-conotoxin SrIA/SrIB	
	J7JU64	68	Alpha-conotoxin VxXXIVA	
C	P0C1W7	47	Alpha-conotoxin VxXXC	
C. vexilium	P0C1W6	95	Alpha-conotoxin VxXXB	
	P0C1W5	92	Alpha-conotoxin VxXXA	
C. pulicarius	C6ZJQ2	69	Alpha-conotoxin Pu14.1	
Cimporialia	Q8I6R5	17	Alpha-conotoxin ImII	
C. Imperialis	P50983	17	Alpha-conotoxin ImI	
C lividuo	L8BU87	37	Alpha-conotoxin LvIA	
C. Ilviaus	H9N3R7	31	Alpha-conotoxin Li1.12	
C. planorbis	Q0N4U8	76	Alpha/Kappa conotoxin Pl14a	
	A0A068B0Z6	41	Alpha-conotoxin Lt1.3b	
C. litteratus	Q2I2R5	64	Alpha-conotoxin Lt14.1	
	F6JWU7	85	Alpha-conotoxin Lt28.1	
C manifest	POC1D0	32	Alpha-conotoxin RgIA	
C. regius	P85013	66	Alpha-conotoxin RgIIA	

Table 1: Retrieved Protein Sequences Using Uniprotkb

3.2 Physicochemical properties of the alpha conotoxins

The physicochemical properties of the retrieved alpha-conotoxins from the ten (10) selected vermivorous *Conus* species were determined and studied using Expasy's Protparam Tool and results are summarized in Table 2. The parameters include accession number, molecular weight, isoelectric pl, instability index (II), aliphatic index (AI), and grand average of hydropathicity (GRAVY).

The computed pl for the majority of the alpha-conotoxins was larger than seven (pl > 7), with one alpha-conotoxin sequence (α -conotoxin *Lt28.1*) having a pl less than seven (pl < 7), as shown in Table 2. The isoelectric pl and charge are important features for solubility, subcellular localization, and interaction of the proteins [31]. Results show that most alpha-conotoxins were found to be extremely basic in nature, with only one (1) alpha-conotoxin sequence (α -conotoxin *Lt28.1*) identified with less than seven (7) pl value, indicating that the protein is considered acidic [31].

The alpha conotoxins' instability index (II) reveals a wide range of proteins with stable and unstable values. The results show that nine (9) alpha-conotoxins out of the nineteen (19) identified proteins have a stable instability index (II) value, namely α -conotoxins *RgIA* (14.62), *VxXXA* (24.02), *Lp1.1* (26.33), *Iml* (28.68), *RgIIA* (33.24), *Pu14.1* (33.36), *Lp1.4* (36.97), *LvIA* (37.65), and *Lt14.1* (38.32). While ten (10) alpha-conotoxins have an unstable instability index (II) value, namely α -conotoxins *Lt1.3b* (41.86), *SrIA/SrIB* (46.65), *VxXXB* (48.67), *VxXXIVA* (51.71), *VxXXC* (53.59), *Li1.12* (66.50), *ArIA* (68.28), *Lt28.1* (73.31), and *ImII* (126.91), including alpha/kappa-conotoxin *Pl14a* (62.84). According to [32], the dipeptide composition-based Instability Index (II) is the protein's major structure-dependent approach for *in vivo* protein stability predictions. A protein with an instability index of less than 40 is considered stable; a value greater than 40 indicates that the protein may be unstable [33].

Moreover, the aliphatic index value of the nineteen (19) alpha-conotoxins was determined in order to assess the thermostability of each alpha-conotoxin. The aliphatic index for alpha-conotoxin *VvXXC* has the lowest value, 29.15, while alpha-conotoxin *VxXXIVA* has the highest, 97.50, as shown in Table 2. The aliphatic index is the relative volume filled by aliphatic side chains [alanine (Ala), valine (Val), isoleucine (IIe), and leucine (Leu)], and it could be viewed as a positive factor in globular proteins' increased thermostability [34]. This means that the higher the aliphatic index, the more thermally stable the protein.

Finally, the protein's grand average hydropathy, or GRAVY, is determined by dividing the total amount of hydropathy values of all amino acids by the number of residues in the sequence [34]. The GRAVY value of a protein determines whether it is hydrophobic (+) or hydrophilic (-), with most proteins ranging from -2 to +2. As shown in the results (Table 2), eleven (11) of the nineteen (19) identified proteins have positive values, suggesting that these alpha conotoxins are hydrophobic, whereas eight (8) of the nineteen (19) proteins have negative values, suggesting that these alpha conotoxins are hydrophobic, whereas eight conotoxins are hydrophilic.

Table 2: Determined Physicochemical Characteristics of the Nineteen (19) Alpha-
Conotoxins from Ten (10) Selected Vermivorous Conus Species Using the
Expasys' Protparam Tool

C. leopardus	.66	9.30	36.97 (stable)		
c. leoparaus	.61		50.57 (50050)	81.91	0.340
Alpha-conotoxin Lp1.1 7154		9.37	26.33 (stable)	92.06	0.731
C. arenatus Alpha-conotoxin ArIA 4437	.04	10.59	68.28 (unstable)	52.56	-0.910
C. spurius Alpha-conotoxin SrIA/SrIB 7587	.92	8.93	46.65 (unstable)	73.09	0.201
Alpha-conotoxin VxXX/VA 6697	.00	9.96	51.71 (unstable)	97.50	0.078
Alpha-conotoxin VxXXC 5286	.11	8.81	53.59 (unstable)	29.15	-0.389
Alpha-conotoxin VxXXB 10545	5.20	8.79	48.67 (unstable)	69.79	-0.277
Alpha-conotoxin VxXXA 10112	2.86	8.59	24.02 (stable)	76.20	0.035
C. pulicarius Alpha-conotoxin Pu14.1 7509	.98	9.20	33.36 (stable)	83.33	0.281
Alpha-conotoxin Imll 2096	.50	10.41	126.91 (unstable)	45.88	-0.712
Alpha-conotoxin Iml 1938	.29	9.01	28.68 (stable)	45.88	-0.300
Alpha-conotoxin LvIA 3841	.33	7.91	36.97 (stable) 26.33 (stable) 68.28 (unstable) 46.65 (unstable) 51.71 (unstable) 53.59 (unstable) 48.67 (unstable) 24.02 (stable) 33.36 (stable) 126.91 (unstable) 28.68 (stable) 37.65 (stable) 66.50 (unstable) 41.86 (unstable) 38.32 (stable) 38.32 (stable) 14.62 (stable) 14.62 (stable) 14.62 (stable) 33.24 (stable)	60.81	-0.297
Alpha-conotoxin Li1.12 3081	.73	8.56		75.81	0.713
C. planorbis Alpha/Kappa 8297 conotoxin Pl14a	.84	10.02	62.84 (unstable)	66.71	0.088
Alpha-conotoxin Lt1.3b 4243	.73	8.52	41.86 (unstable)	47.80	-0.407
C. litteratus Alpha-conotoxin Lt14.1 6878	.28	8.38	38.32 (stable)	79.38	0.341
Alpha-conotoxin Lt28.1 9391	.21	4.40	71.31 (unstable)	96.35	0.311
Alpha-conotoxin RgIA 3725	.38	9.93	14.62 (stable)	49.06	-0.831
Alpha-conotoxin RglIA 7038	.18	9.00	33.24 (stable)	87.12	0.305

3.3 Domains and secondary structures of the alpha conotoxins

Table 3 summarizes the molecular domains of the nineteen (19) alpha conotoxins identified from the ten (10) vermivorous *Conus* species. According to the results, nine (9) of the nineteen alpha conotoxins contain a domain belonging to the protein family (Pfam) 07365 and known as *toxin_8*, whereas ten (10) have no domains in their sequence. The identified specific domain, *toxin_8*, is the sole member of the superfamily cl06417 (Pfam Database) [35]. This alpha-conotoxin domain-containing family also includes multiple alpha-conotoxin precursor proteins from various *Conus* species. Moreover, alpha-conotoxins are peptide neurotoxins found in the venom of various cone snail species that block nicotinic acetylcholine receptors (nAChRs). The discovery of domains in putative and conserved proteins raises the likelihood of proteins sharing the same domain function [36]. Conserved domain footprint identification on protein sequences is frequently the initial step in *in-silico* protein function analysis. Protein domains can be arranged into an evolutionary classification and considered units in the molecular evolution of proteins. The set of protein domains identified thus far appears to describe only a few thousand super families, with members of each superfamily descended from the same ancestor [37].

SPECIES	ACCESSION NUMBER	PROTEIN NAME	DOMAIN
C lass and us	A1X8B6	Alpha-conotoxin Lp 1.4	toxin_8
C. leoparaus	Q6PTD5	Alpha-conotoxin <i>Lp1.1</i>	toxin_8
C. arenatus	P0C8R2	Alpha-conotoxin ArIA	toxin_8
C. spurius	P85886	Alpha-conotoxin SrIA/SrIB	toxin_8
	J7JU64	Alpha-conotoxin VxXX/VA	N
Cuavilium	POC1W7	Alpha-conotoxin VxXXC	N
C. vexilium	POC1W6	Alpha-conotoxin VxXXB	N
	P0C1W5	Alpha-conotoxin VxXXA	N
C. pulicarius	C6ZJQ2	Alpha-conotoxin Pu14.1	toxin_8
C. imperialis	Q8I6R5	Alpha-conotoxin ImII	N
	P50983	Alpha-conotoxin <i>ImI</i>	N
C lividue	L8BU87	Alpha-conotoxin LvIA	toxin_8
C. IIViaus	H9N3R7	Alpha-conotoxin Li1.12	toxin_8
C. planorbis	Q0N4U8	Alpha/Kappa conotoxin <i>Pl14a</i>	N
C. litteratus	A0A068B0Z6	Alpha-conotoxin Lt1.3b	toxin_8
	Q212R5	Alpha-conotoxin <i>Lt14.1</i>	
	F6JWU7	Alpha-conotoxin Lt28.1	N
C regiue	P0C1D0	Alpha-conotoxin RgIA	N
c. regius	P85013	Alpha-conotoxin RgIIA	toxin 8

Table 3: Domain Analysis of the Nineteen (19) Alpha-Conotoxins from Ten (10)
Selected Vermivorous Conus Species Using the Pfam Database

The secondary structure elements alpha (α) helix, extended strand, and random coils of nineteen (19) alpha-conotoxins from the ten (10) selected vermivorous cone snails are shown in Table 4. *Conus pulicarius* α -conotoxin *Pu14.1*, *Conus leopardus* α -conotoxin *Lp1.1*, and *Conus spurius* α -conotoxin *SrIA* had the most α -helix present, with 38 (55.07%), 37 (54.41%), and 36 (52.94%) respectively. However, *Conus imperialis* α -conotoxin *ImI* lacks a α -helix in its sequence. *Conus imperialis* α -conotoxin *ImI* and α -conotoxin *VxXXA* of *Conus vexillum* have the largest number of β -strands, 6 (35.29%)

and 22 (23.91%), respectively, and the lowest number is α -conotoxin RgIA of Conus *regius*, which has no β -strand in the sequence. In contrast, α -conotoxin *Lt1.3b* of *Conus* litteratus and a-conotoxin LvIA of Conus lividus have the most random coils in their sequences, with 27 (65.85%) and 24 (64.86%), respectively, whereas α-conotoxin Lp1.1 of Conus leopardus has the fewest, with just 12 (17.65%). Furthermore, in terms of the number of β -turns in each sequence, α -conotoxin *ImI* and α -conotoxin *ImII* of *Conus imperialis* have the same number of β -turns (4 (23.53%), however, both α -conotoxins of Conus leopardus do not have any indicated β -turns present in their sequences. The α helical structure is made up of the amino acids methionine (M), alanine (A), leucine (L), glutamate (E), and lysine (K), while the β -helical structure is made up of tryptophan (W), tyrosine (Y), phenylalanine (F), valine (V), isoleucine (I), and threonine (T). Additionally, the amino acids glycine (G) and proline (P) help to make the required turns (Lee et al., 2004). These results suggest that the protein's secondary structure is exclusively influenced by the number of amino acids [38]. The amino acid distribution percentage score indicates that random coils dominate other secondary structures, followed by ahelix, β-strand, and β-turns. This result is in line with the results of [39], who discovered that the most common secondary structural elements are α -helices, β -sheets, and random coils. However, according to [40], alpha-helices are the most common secondary structure, accounting for 30% of the structure of a typical globular protein, which contradicts the stated results because random coils dominate most alpha-conotoxins. The properties of amino acids account for random coils' dominance over other elements. The molecular properties of the polypeptide chain, according to [41], determine the characteristics of a protein's random coil state.

SPECIES	PROTEIN NAME	ALPHA-HELIX	BETA-STRAND	RANDOM COIL	BETA TURN
C. leopardus	Alpha-conotoxin Lp 1.4	30 (44.12%)	13 (19.12%)	25 (36.76%)	
	Alpha-conotoxin Lp1.1	37 (54.41 %)	13 (19.12%)	12 (17.65%)	
C. arenatus	Alpha-conotoxin ArIA	13 (33.33%)	2 (5.13%)	20 (51.28%)	4 (10.26%)
C. spurius	Alpha-conotoxin SrIA/SrIB	36 (52.94%)	8 (11.76%)	22 (32.35%)	2 (2.94%)
	Alpha-conotoxin VxXXIVA	21 (35.00%)	8 (13.33%)	28 (46.67%)	3 (5.00%)
C	Alpha-conotoxin VxXXC	5 (10.64%)	8 (17.02%)	25 (53.19%)	9 (19.15%)
C. vexilium	Alpha-conotoxin VxXXB	15 (15.79%)	15 (15.79%)	50 (52.63%)	15 (15.79%)
	Alpha-conotoxin VxXXA	15 (16.30%)	22 (23.91%)	40 (43.48%)	15 (16.30%)
C. pulicarius	Alpha-conotoxin Pu14.1	38 (55.07%)	8 (11.59%)	22 (31.88%)	1 (1.45%)
C. imperialis	Alpha-conotoxin Imll	4 (23.53%)	4 (23.53%)	5 (29.41%)	4 (23.53%)
	Alpha-conotoxin ImI	0	6 (35.29%)	7 (41.18%)	4 (23.53%)
C 1: : I	Alpha-conotoxin LvIA	8 (21.62%)	3 (8.11%)	24 (64.86%)	2 (5.41%)
C. lividus	Alpha-conotoxin Li1.12	4 (12.90%)	5 (16.13%)	18 (58.06%)	4 (12.90%)
C. planorbis	Alpha/Kappa conotoxin Pl14a	34 (44.74%)	13 (17.11%)	26 (34.21%)	3 (3.95%)
C. litteratus	Alpha-conotoxin Lt1.3b	9 (21.95%)	4 (9.76%)	27 (65.85%)	1 (2.44%)
	Alpha-conotoxin Lt14.1	29 (45.31%)	3 (4.69%)	28 (43.75%)	4 (6.25%)
	Alpha-conotoxin Lt28.1	27 (31.76%)	9 (10.59%)	42 (49.41%)	7 (8.24%)
a i	Alpha-conotoxin RgIA	13 (40.62%)	0	19 (59.38)	0
C. regius	Alpha-conotoxin RallA	32 (48,48%)	13 (19,70%)	17 (25,76%)	4 (6.06%)

 Table 4: Predicted Secondary Structure of the Nineteen (19) Alpha-Conotoxins

 from Ten (10) Selected Vermivorous Conus Species Using Sopma Tool

Prediction of secondary structures is thought to be useful in conventional drug discovery. Identifying the secondary structure correctly can aid in sequence alignment [42], as the secondary structure is the polypeptide backbone of local conformation proteins. The α -

helix (H) and β -strand (E) secondary structure states are both regular, whereas the coil region is an irregular secondary structure type (C) [43]. Furthermore, in molecular recognition mechanisms, interactions between peptide substrates and receptors, and protein folding, it is assumed that irregular protein secondary structures represent key structural domains [44]. Lastly, according to [45], the secondary structural pattern of neurotoxins is utilized to assess whether an amino acid is in a helix, strand, or coil. Agreeing with their observations, random coil outperforms the other forms in secondary structure prediction of the snake venom neurotoxins studied, with C-turn being the least conformational shape.

3.4 Homology modeling of alpha-conotoxins and structure verification

Figure 1 (*Parts 1* and 2) exhibit the predicted three-dimensional (3D) structure of the seventeen (17) alpha-conotoxin based on protein sequences acquired from the protein database. This was built using the SWISS-Model tool and is based on the Global Model Quality Estimation (GMQE) and Qualitative Model Energy Analysis (QMEAN) data. The GMQE values are generally between 0 and 1, and the higher the number, the more reliable the projected structure is, whereas a score less than 4.0 suggests reliability for QMEAN. SWISS-Model requires more than 30 amino acids to generate a model. Thus, *Conus imperialis*' alpha-conotoxins, namely α -conotoxin *ImII* and *ImI*, are the only proteins that cannot build a 3D model due to their short lengths of seventeen (17) amino acids.



Fig 1: Homology models of the seventeen (17) alpha-conotoxin from ten (10) selected vermivorous *Conus* species using SWISS-Model Tool (*Part 1*). (a) Alpha-conotoxin *Lp1.4*, (b) Alpha-conotoxin *Lp1.1*, (c) Alpha-conotoxin *ArIA*, (d) Alpha-conotoxin *SrIA/SrIB*, (e) Alpha-conotoxin *VxXXIVA*, (f) Alpha-conotoxin *VxXXC*, (g) Alpha-conotoxin *VxXXB*, (h) Alpha-conotoxin *VxXXA*, and (i) Alpha-conotoxin *Pu14.1*



Fig 1: Homology models of the seventeen (17) alpha-conotoxin from ten (10) selected vermivorous *Conus* species using SWISS-Model Tool (*Part 2*). (j) Alpha-conotoxin *LvIA*, (k) Alpha-conotoxin *Li1.12*, (l) Alpha/Kappa conotoxin *Pl14a*, (m) Alpha-conotoxin *Lt1.3b*, (n) Alpha-conotoxin *Lt14.1*, (o) Alpha-conotoxin *Lt28.1*, (p) Alpha-conotoxin *RgIA*, and (q) Alpha-conotoxin *RgIA*

A critical component of drug discovery is the structure-based design of small-molecule inhibitors of protein-ligand and protein-protein interactions. The structural similarity of the secondary structure parts can be used to determine the underlying protein interactions [46], and the application of homology modeling generates reliable structural models. The receptor binding assay is one example; when the receptor binds to the ligand, signal transduction events occur, which govern numerous biological processes essential for cell development and function. As a result, identifying chemicals that precisely bind to cellular receptors to inhibit (antagonists) or boost (agonists) a biological function is a key emphasis in drug discovery [47]. However, according to [48], while it was thought that the receptor binding method could be used as a primary screen to accelerate and simplify the identification of new drug candidates, experience has shown that ligand binding is most useful for drug discovery when combined with functional, phenotypic assays.

3.5 Validation of alpha-conotoxins models

According to [16], homology modeling was the most accurate computational method for generating reliable structural models, and it was used in many biological applications. The

models' reliability was estimated using model quality assessment tools. Following the refinement process, the stereochemical quality of the predicted model and the accuracy of the protein model were assessed using Ramachandran map calculations computed with the PROCHECK program. Ramachandran plot is a basic two-dimensional graphic representation of all conceivable protein structures. Each amino acid residue in a polypeptide can have a unique collection of angles; it can be represented as a point on a Ramachandran plot with associated angles [49].

Ramachandran plots were generated from the PDBsum web server and were shown in Figure 2 (*Parts 1 to 3*), where the red regions in the graph indicate the most favored regions. Glycine residues are represented by triangles and other residues are represented by squares. The results revealed, as shown in Table 5, that the modeled structure for alpha-conotoxins *Lp 1.4, ArIA, VxXXC, VxXXA, LvIA*, and *RgIIA* have a percentage of 90%, 95.2%, 100%, 100%, 91.7%, and 100%, respectively, under their favored regions. Such Ramachandran plot figures indicate that the predicted models are of high quality. Furthermore, the remaining alpha-conotoxins have a percentage of less than 90% in their favored regions, indicating that the predicted models are of low quality.

Table 5: Ramachandran Plot Calculation And Analysis Of The Models Of TheNineteen (19) Alpha-Conotoxins From Ten (10) Selected Vermivorous ConusSpecies From The Swiss Model And Computed With The Procheck Program

SPECIES			RAMACHANDRAN PLOT		
	NUMBER	NUMBER PROTEIN NAME		DISALLOWED REGION	
Convoloonanduo	A1X8B6	Alpha-conotoxin Lp 1.4	63 (90%)	0 (0%)	
conus reopurdus	Q6PTD5	Alpha-conotoxin Lp1.1	66 (85.7%)	1 (1.3%)	
Conus arenatus	POC8R2	Alpha-conotoxin ArlA	20 (95.2%)	0 (0%)	
Conus spurius	P85886	Alpha-conotoxin SrIA/SrIB	103 (85.8%)	0 (0%)	
	J7JU64	Alpha-conotoxin VxXXIVA	11 (73.3%)	0 (0%)	
Conus vovilium	P0C1W7	Alpha-conotoxin VxXXC	23 (100%)	0 (0%)	
Conus vexinum	POC1W6	Alpha-conotoxin VxXXB	63 (87.5%)	0 (0%)	
	P0C1W5	Alpha-conotoxin VxXXA	23 (100%)	0 (0%)	
Conus pulicarius	C6ZJQ2	Alpha-conotoxin Pu14.1	17 (73.9%)	0 (0%)	
Conus lividus	L8BU87	Alpha-conotoxin LvIA	11 (91.7%)	0 (0%)	
	H9N3R7	Alpha-conotoxin Li1.12	35 (83.3%)	1 (2.4%)	
Conus planorbis	Q0N4U8	Alpha/Kappa conotoxin <i>Pl14a</i>	12 (57.1%)	1 (4.8%)	
Conus litteratus	A0A068B0Z6	Alpha-conotoxin Lt1.3b	46 (82.1%)	1 (1.8%)	
	Q2I2R5	Alpha-conotoxin Lt14.1	5 (35.7%)	0 (0%)	
	F6JWU7	Alpha-conotoxin Lt28.1	12 (63.2%)	1 (5.3%)	
Conus regius	P0C1D0	Alpha-conotoxin RgIA	14 (77.8%)	0 (0%)	
conus regius	P85013	Alpha-conotoxin RgIIA	23 (100%)	0 (0%)	



Fig 2: Ramachandran plots of the seventeen (17) alpha-conotoxin predicted models (*Part 1*). (a) Alpha-conotoxin *LvIA*, (b) Alpha-conotoxin *VxXXIVA*, (c) Alpha-conotoxin *RgIA*, (d) Alpha-conotoxin *RgIIA*, (e) Alpha-conotoxin *VxXXB*, and (f) Alpha-conotoxin *VxXXA*



Fig 2: Ramachandran plots of the seventeen (17) alpha-conotoxin predicted models (*Part 2*). (g) Alpha-conotoxin *VxXXC*, (h) Alpha-conotoxin *ArIA*, (i) Alpha-conotoxin *SrIA/SrIB*, (j) Alpha/Kappa conotoxin *Pl14a*, (k) Alpha-conotoxin *Lp1.1*, and (l) Alpha-conotoxin *Lt14.1*



Fig 2: Ramachandran plots of the seventeen (17) alpha-conotoxin predicted models (*Part 3*). (m) Alpha-conotoxin *Lt1.3b*, (n) Alpha-conotoxin *Lp 1.4*, (o) Alpha-conotoxin *Lt28.1*, (p) Alpha-conotoxin *Pu14.1*, and (q) Alpha-conotoxin *Li1.12*

4. CONCLUSIONS AND FUTURE WORKS

The purpose of this study was to use in silico technologies to produce, evaluate, and compare the structure of alpha-conotoxin from selected vermivorous Conus species. Physicochemical qualities were utilized to calculate molecular weight, isoelectric pl, instability index, aliphatic index, and grand average of hydropathy, among other physical and chemical factors. Furthermore, property prediction, domain scanning, secondary structure prediction, homology modeling, and structural analysis were all included. The results revealed that the majority of the alpha-conotoxins were highly basic in nature, with one alpha-conotoxin sequence (Alpha-conotoxin Lt28.1) indicating acidic in nature. The instability index varies from stable Alpha-conotoxin RgIA (14.62) to unstable Alphaconotoxin ImII (126.91). Additionally, the aliphatic index for the protein sequences included in this study ranges from 29.15 to 97.50, indicating that it is thermostable over a wide temperature range. Moreover, GRAVY values for alpha-conotoxins range from -0.910 (most hydrophilic; alpha-conotoxin SrIA/SrIB) to 0.731 (most hydrophobic; alphaconotoxin Lp1.1). Furthermore, the common domain found among the species was toxin 8. The percentage score of amino acid distribution for secondary structure prediction shows a random coil dominates other secondary structures, followed by alphahelix, beta-strand, and beta-turns. Lastly, the models for Alpha-conotoxin Lp1.4, Alphaconotoxin ArIA, Alpha-conotoxin VxXXC, Alpha-conotoxin VxXXA, and Alpha-conotoxin LvIA are of high quality, as these proteins have a percentage of \geq 90% in their favored regions.

This study proposes doing a more extensive investigation on the alpha conotoxins of vermivorous *Conus* species for their molecular properties, as studies on them are unusual. Furthermore, more research is needed to better understand the structure and method of blocking neuromuscular transmission by selective binding to muscle nicotinic acetylcholine receptors (nAChR). Finally, researchers who intend to continue this type of research might use the same methods to examine the alpha-conotoxin found in piscivorous and molluscivorous cone snails, in order to gain a deeper understanding of this family of *Conus* venom for the optimum application in drug discovery.

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