

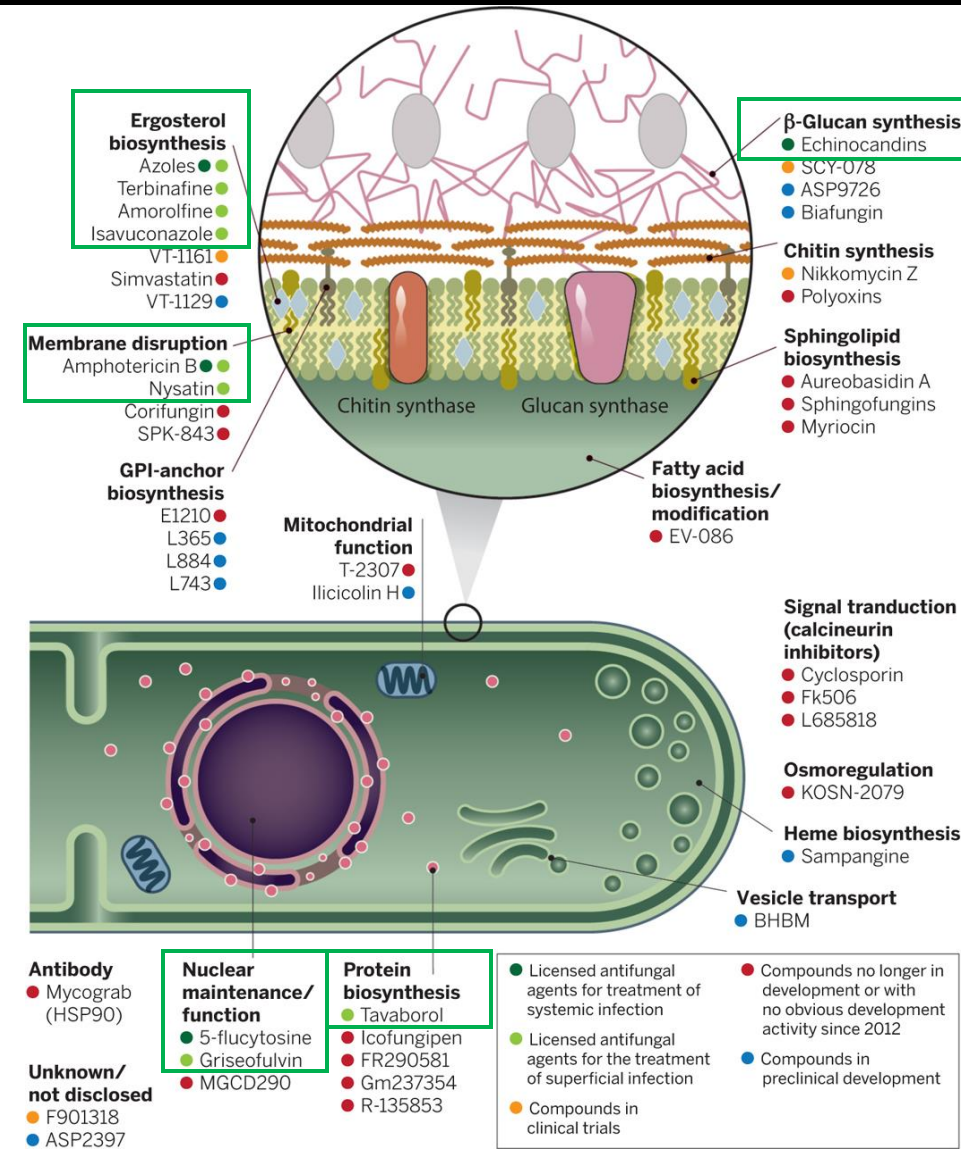


AI-Designed Peptides: A New Weapon Against Fungal Pathogens

Barbara S. Perez
Parmis Abdoli

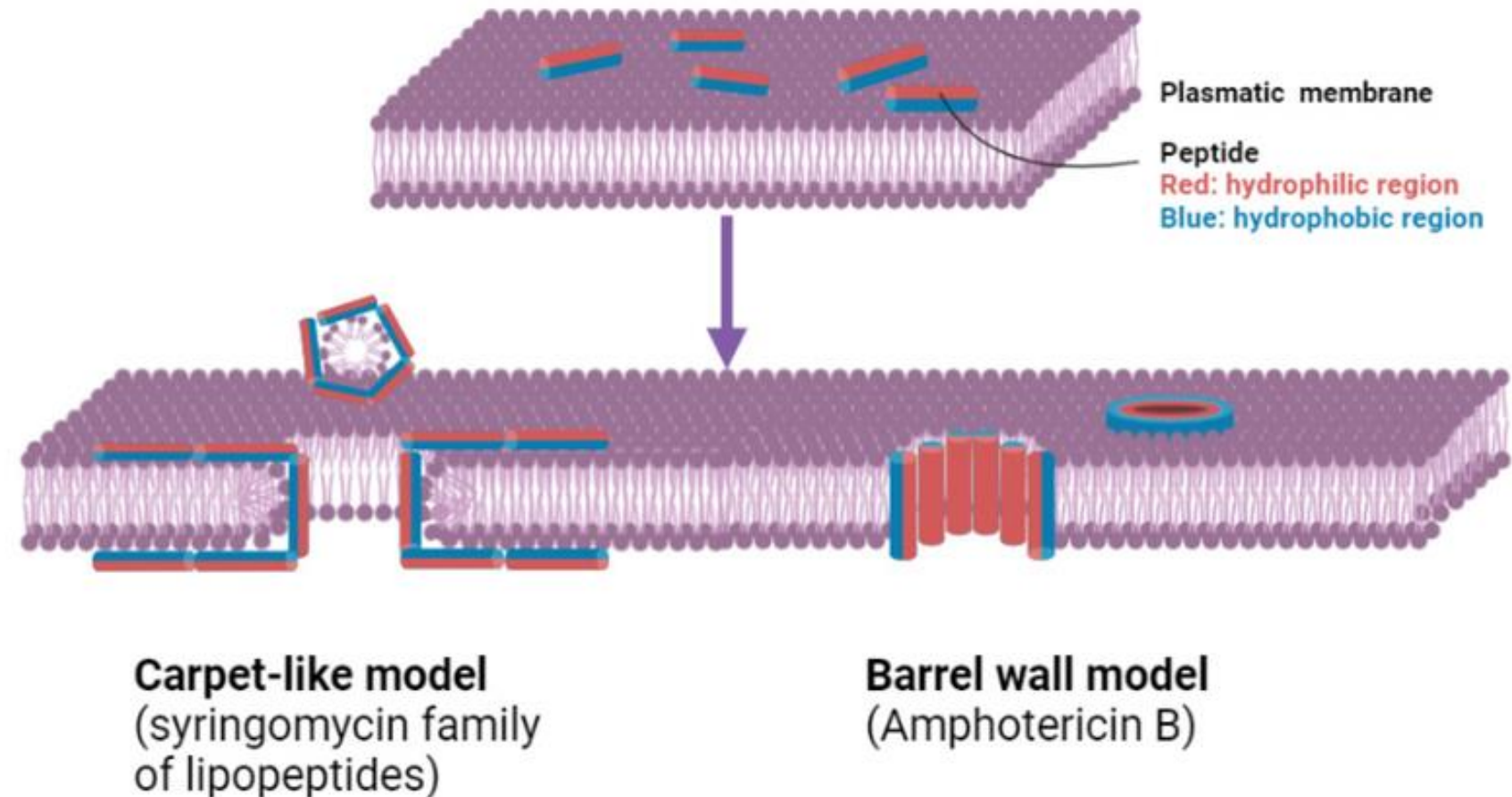
Challenges in antifungal discovery

- Rising morbidity and mortality rates due to antifungal resistance
- Limited therapeutic targets
- Fungal and eukaryotic similarity complicates drug design
- Many candidates fail due to host toxicity



Antifungal peptides as alternative therapeutics





- Short, naturally occurring peptides
- Often disrupt multiple cellular processes
- ML methods increasingly used for peptide discovery



New Results

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Fung-AI: An AI/ML-driven pipeline for antifungal peptide discovery

 Daniel S Berman,  Libby M Lewis, Tom D Curtis, Olivia N Tiburzi, Daniel F Q Smith,  Arturo Casadevall,  Laura J Dunphy

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Abstract

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Abstract

Emerging fungal pathogens represent a concerning threat to both global health and food security. In this study, we aimed to address our rising vulnerability to fungal pathogens through the development of the Fung-AI pipeline: an AI/ML-driven approach for antifungal discovery. A generative adversarial network (GAN) was trained to generate novel candidate antifungal peptide sequences. Next, *in silico* antifungal and hemolytic classifiers were built to further prioritize AI-generated peptides for experimental validation. From a pool of ~10,000 candidates, thirteen peptides were selected for testing over two-stages of experimentation. Five peptides were found to display mild antifungal activity against the wheat pathogen, *Fusarium graminearum*, with minimal inhibitory concentrations (MICs) ranging from 250 $\mu\text{g}/\text{mL}$ to 500

Generative adversarial networks (GANs)



As training progresses, the generator gets closer to producing output that can fool the discriminator:



Finally, if generator training goes well, the discriminator gets worse at telling the difference between real and fake. It starts to classify fake data as real, and its accuracy decreases.



Consists of two parts:

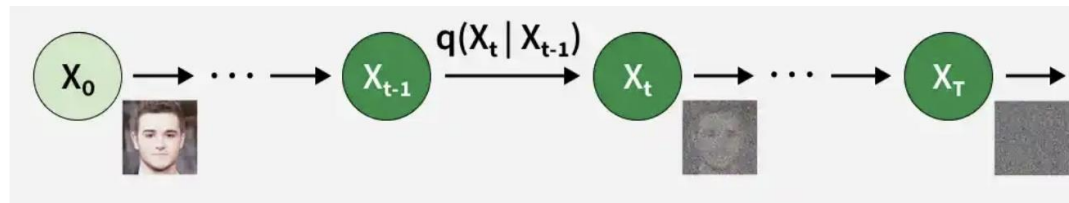
- Generator: creates candidate peptides
- Discriminator: tries to determine if the peptide is real

Common failure: mode collapse

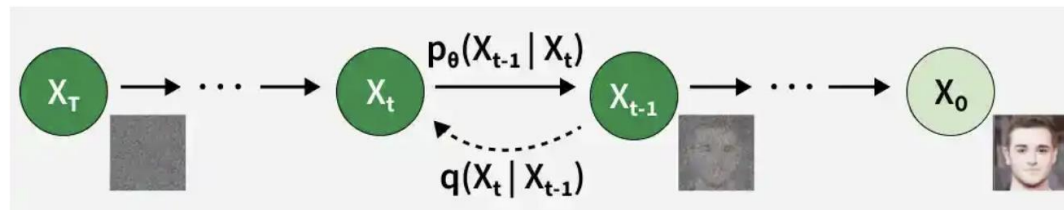
- Authors add an encoder to mitigate this

Diffusion models

Diffusion models are trained to progressively turn random noise into meaningful output.



Forward Diffusion Process



Reverse Diffusion Process

Artificial intelligence using a latent diffusion model enables the generation of diverse and potent antimicrobial peptides

YEJI WANG, MINGHUI SONG, FUJING LIU, ZHEN LIANG, BUI HONG, YUEMEI DONG, HUIAIZHILUAN, XIAOJIE FU, WENCHANG YUAN, [..], AND WENQIANG CHANG

+3 authors Authors Info & Affiliations

> Adv Sci (Weinh). 2025 May;12(20):e2412926. doi: 10.1002/advs.202412926. Epub 2025 Apr 15.

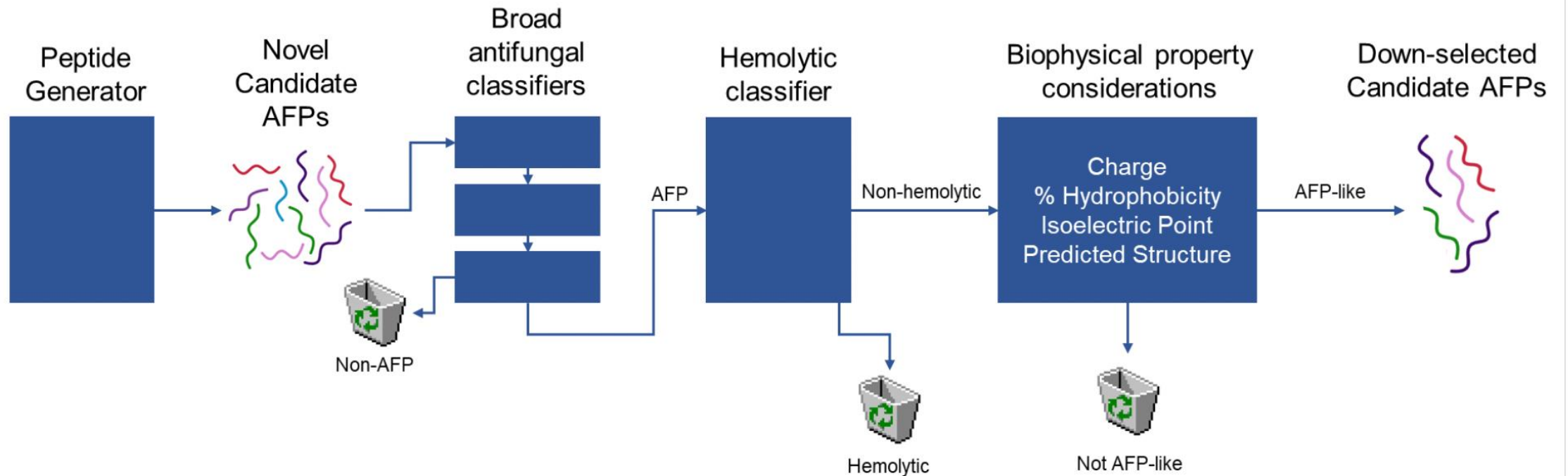
CPL-Diff: A Diffusion Model for De Novo Design of Functional Peptide Sequences with Fixed Length

Zhenjie Luo¹, Aoyun Geng¹, Leyi Wei^{2,3}, Quan Zou^{4,5}, Feifei Cui¹, Zilong Zhang¹

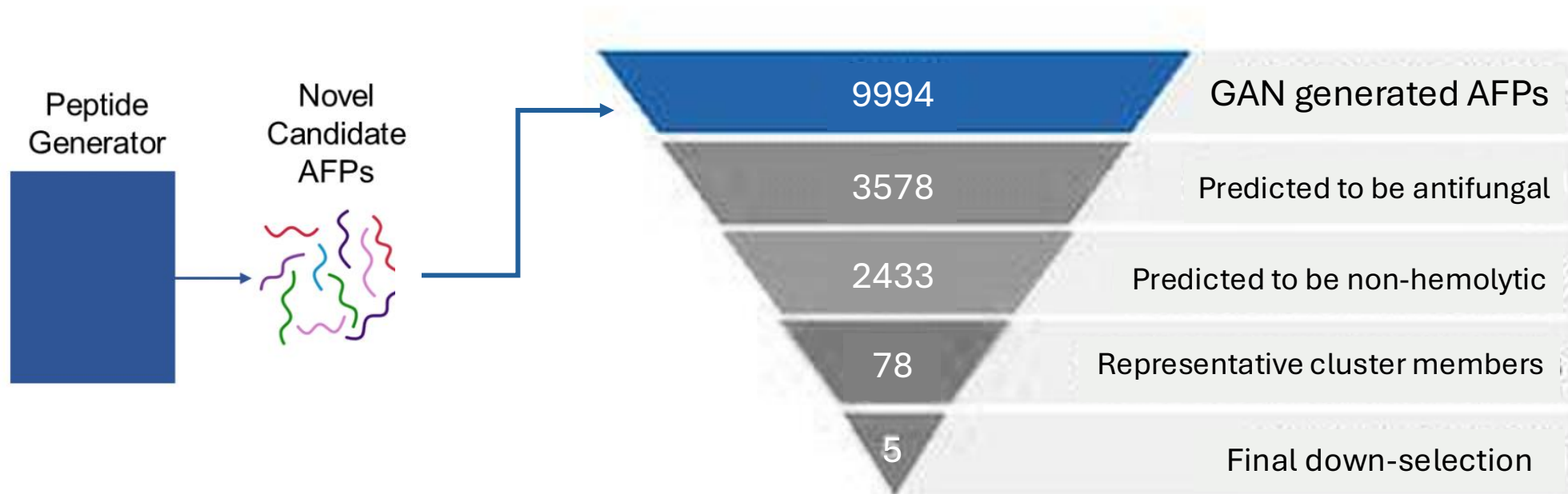
Affiliations + expand

PMID: 40231709 PMID: PMC12120732 DOI: 10.1002/advs.202412926

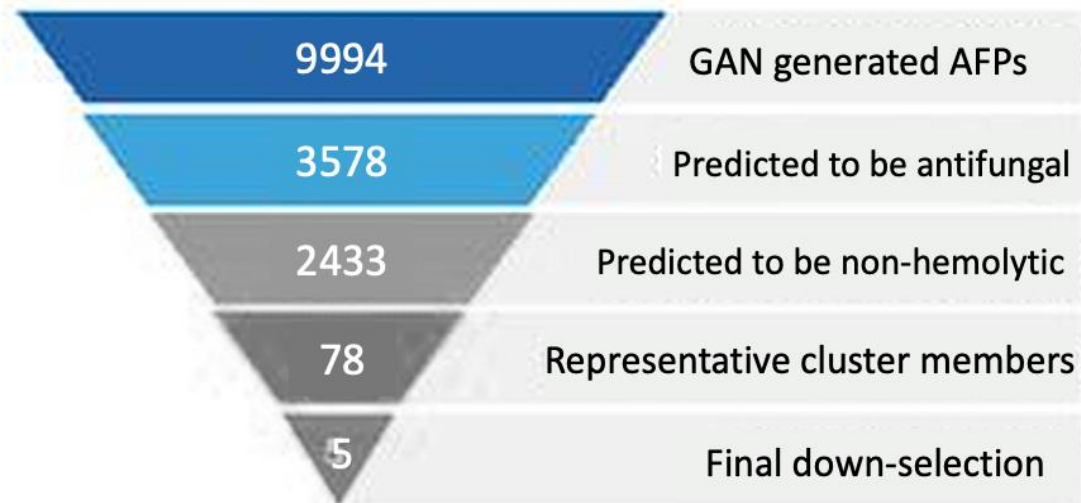
Fung-AI pipeline



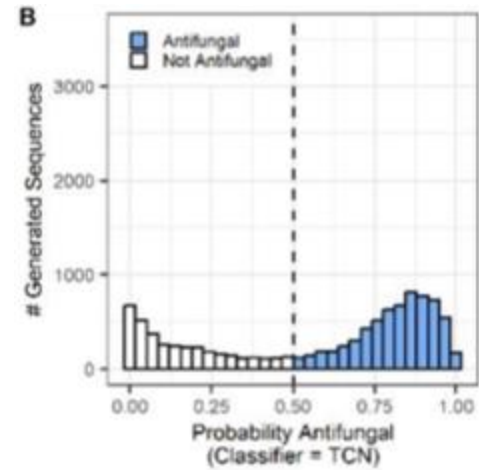
Generated peptide pool



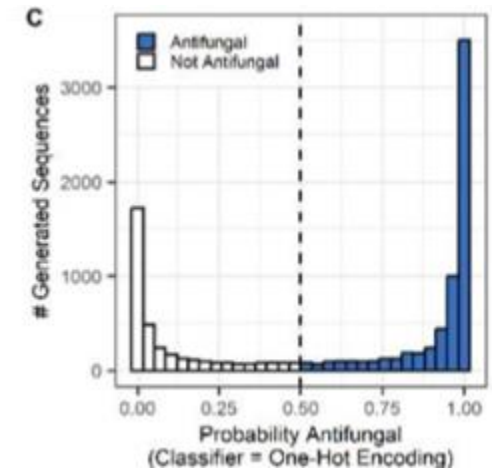
Antifungal classification



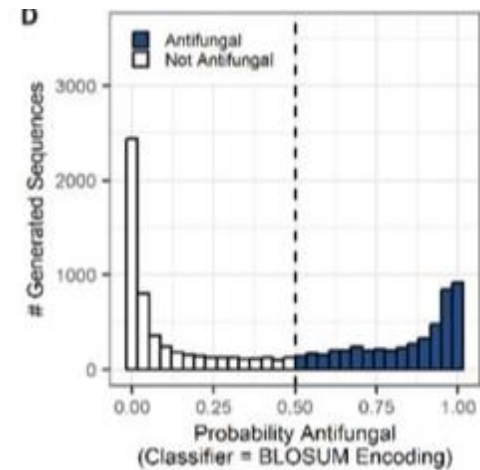
Temporal Convolutional Network



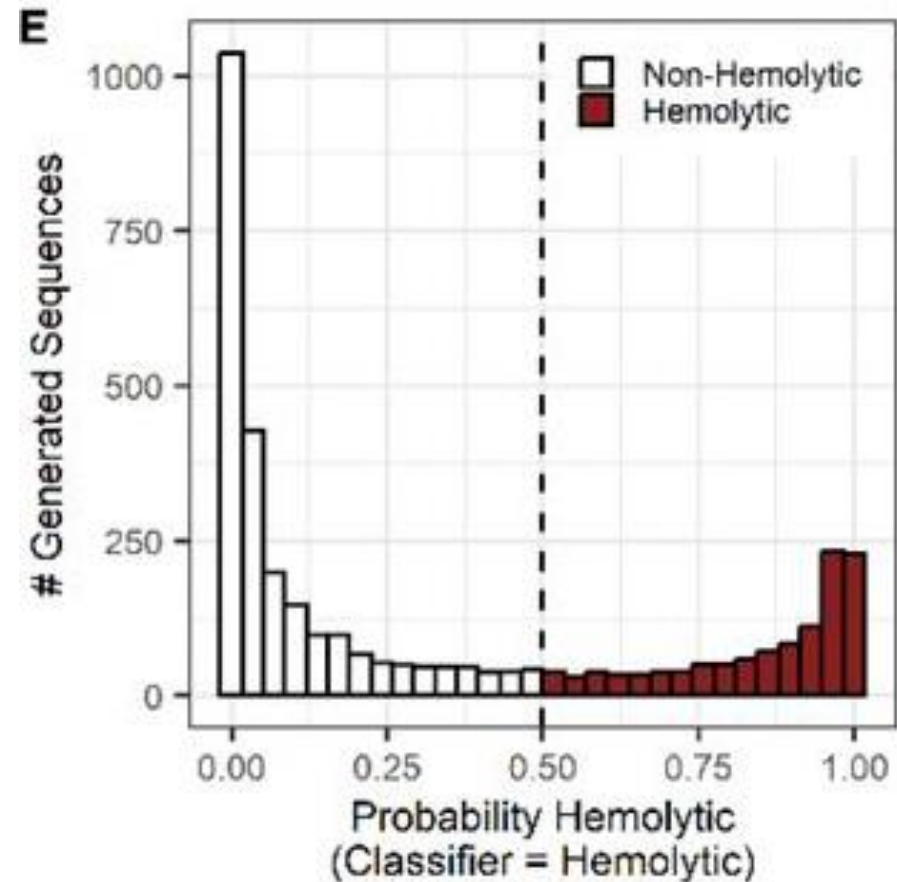
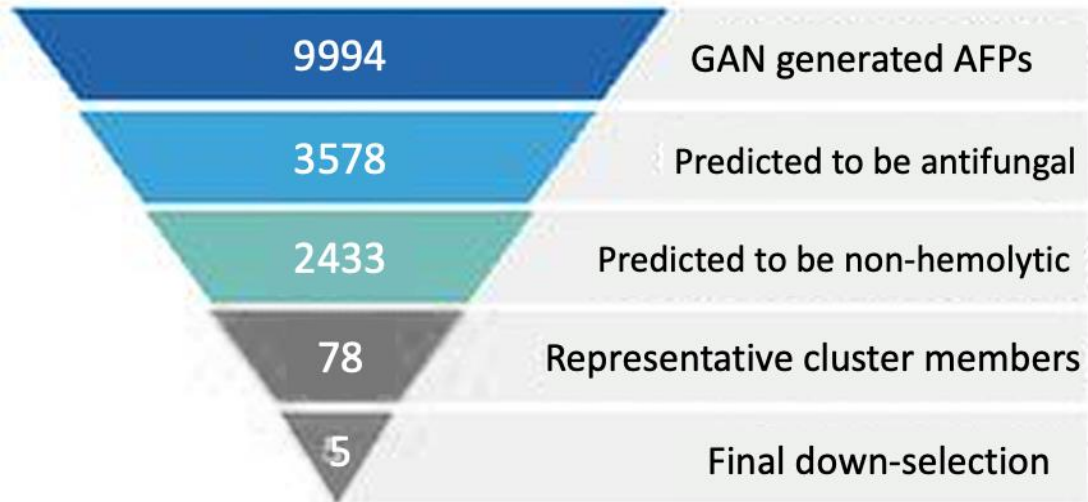
One-Hot Encoding



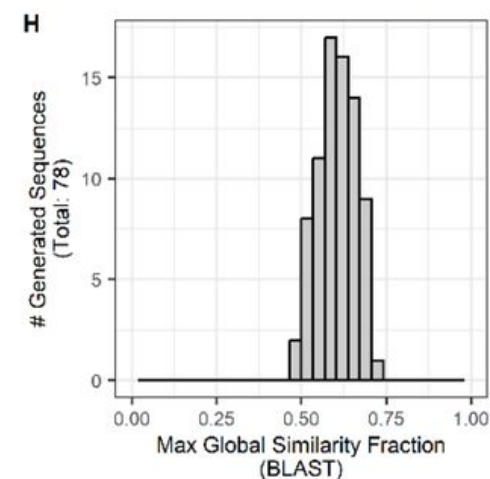
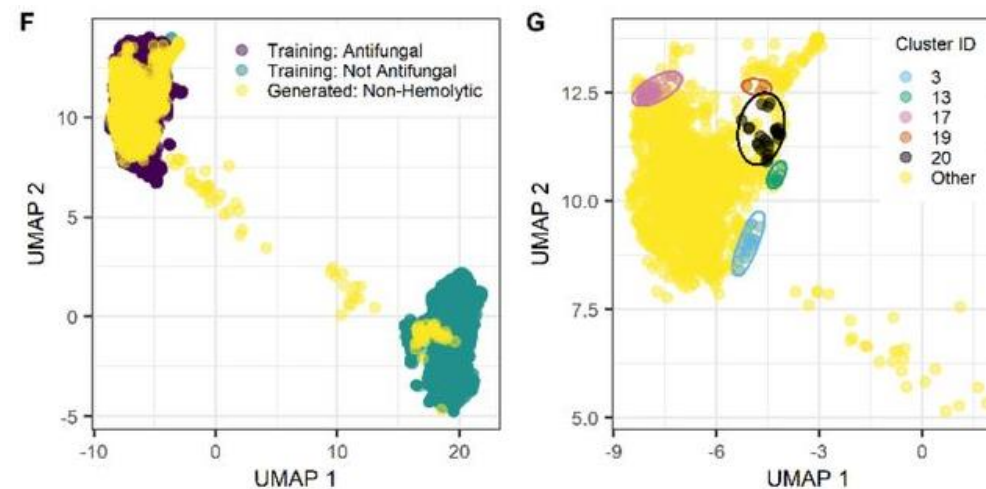
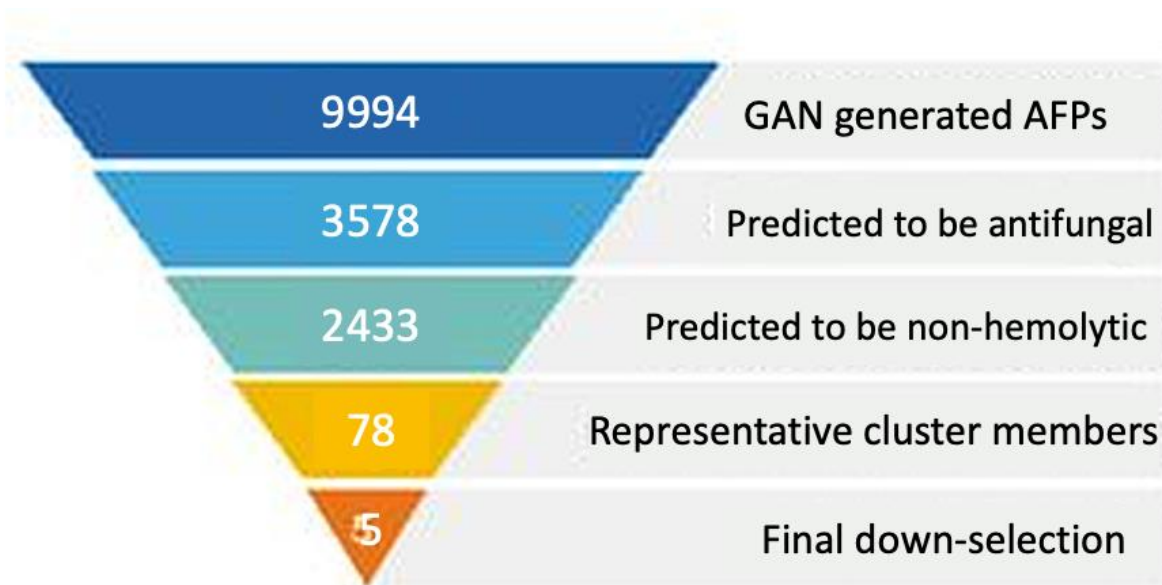
BLOSUM Encoding



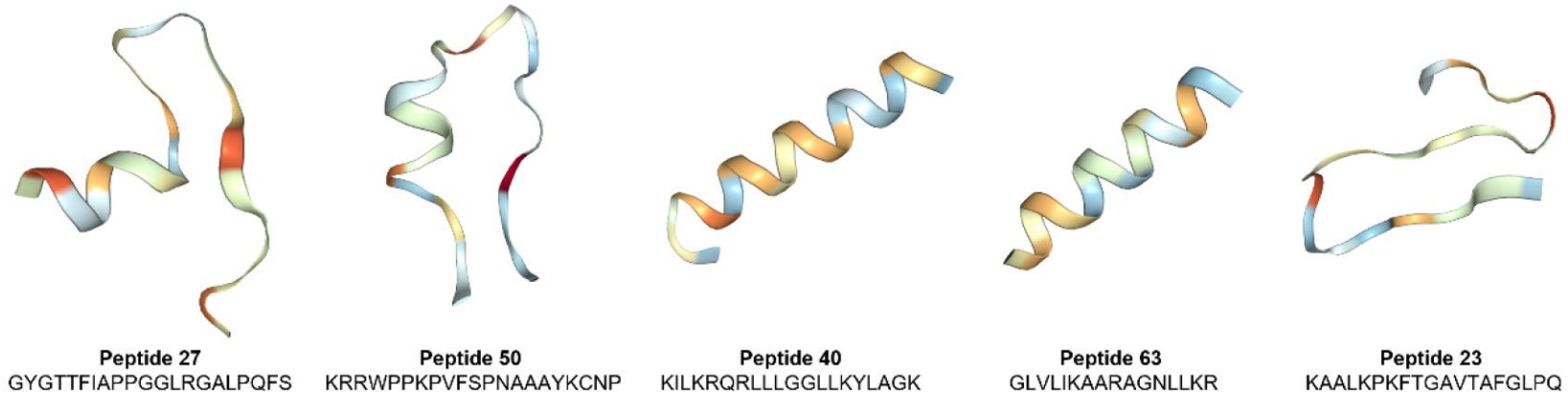
Biophysical/Toxicity Filtering



Clustering and Novelty

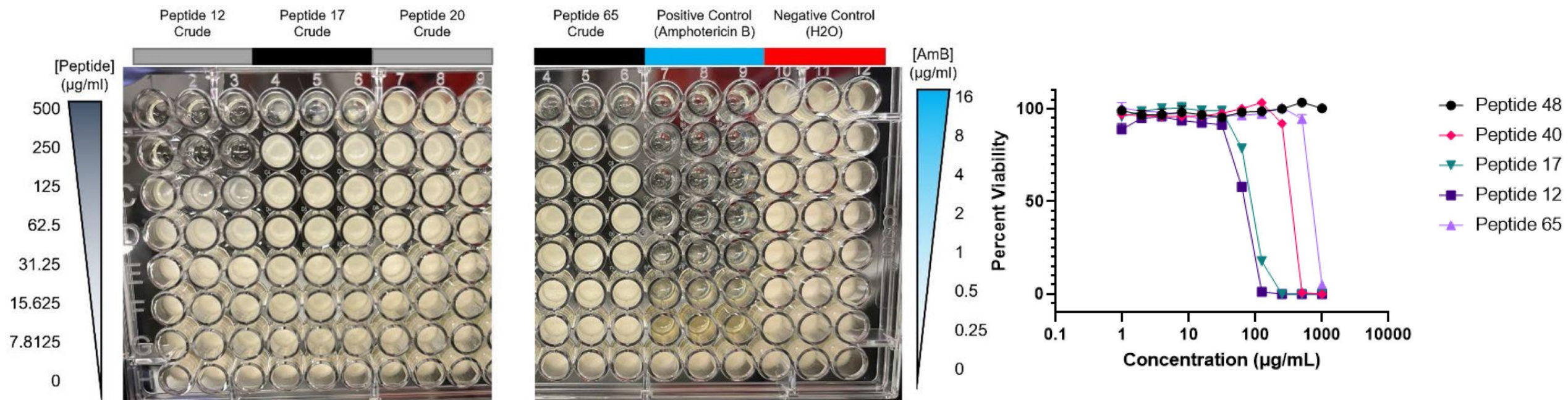


Structural and biophysical characterization of prioritized AFPs.



Peptide ID	Cluster ID	Sequence	Isoelectric Point	Net Charge	Fraction Hydrophobic AAs
40	17	KILKRQRLLLGGLLKYLAKG	11.22	5.76	0.5
50	13	KRRWPPKPVFSPNAAAYKCNP	10.46	4.75	0.33
27	3	YGTTFIAPPGGLRGALPQFS	8.75	0.76	0.38
63	19	GLVLIKAARAGNLLKR	12	3.76	0.56
23	20	KAALKPKFTGAVTAFGLPQ	10.3	2.76	0.47
12	17	QLLRPLFTKLLGGLSKILKKF	11.33	4.76	0.48
17	17	RLLQALLNNLRKKLKGLLSRLS	12	5.76	0.45
48	17	KKTYTKLKKLNGAIKYLVGHA	10.22	5.84	0.43
65	17	KAKLRQAVLLKLLAGVKSSL	11.39	5.76	0.52
20	17	RLKKLWWKTCLLKGLCTLKA	10.21	5.74	0.45
29	17	GLRHYARVKLKLALLNLNKSC	10.46	4.83	0.48
44	17	KLAKLLALRLKSLVFGFLRYRT	11.74	5.76	0.57
54	17	KAIPLLLRRRSIVLLLRFQGV	12	4.76	0.57

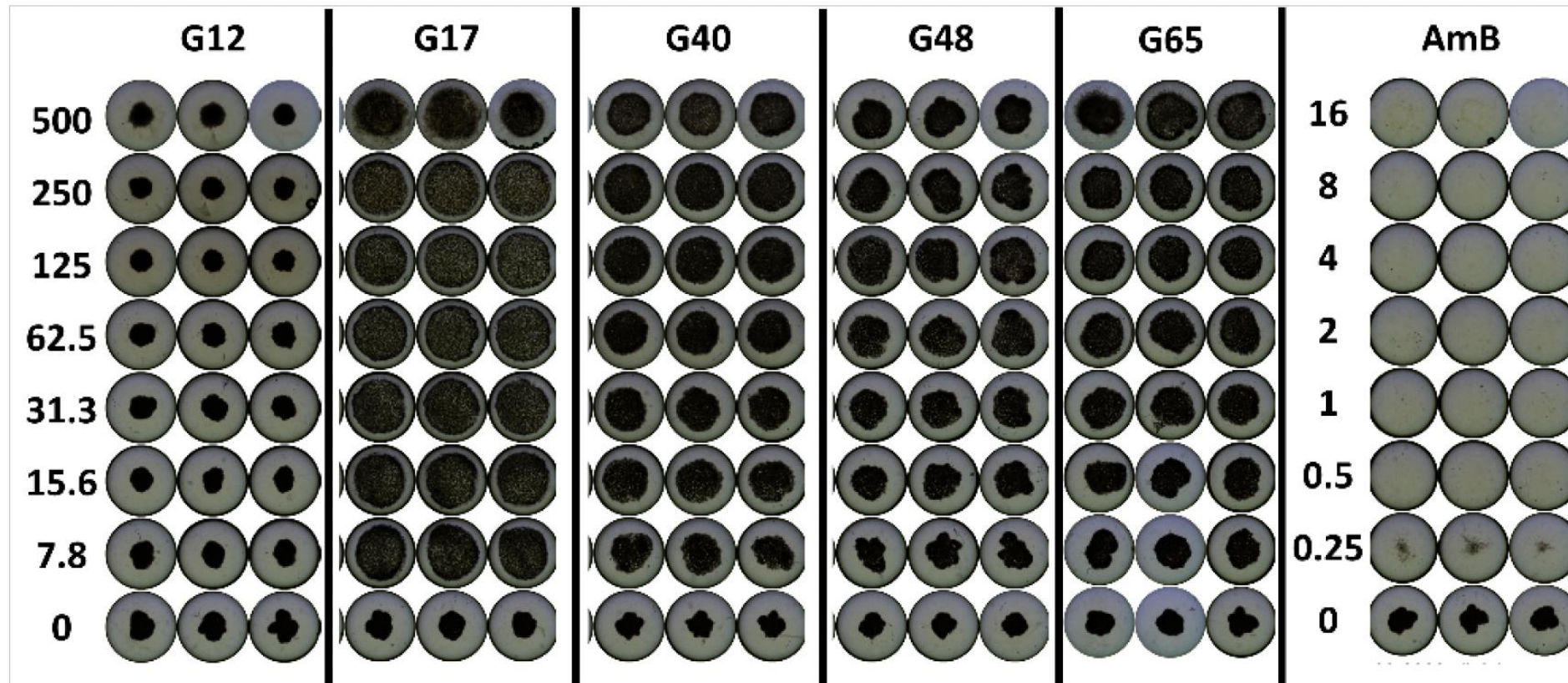
From *in silico* prediction to experimental validation



Peptide ID	Sequence	<i>F. graminearum</i>	<i>S. cerevisiae</i>	<i>C. albicans</i>	<i>C. auris</i>	HepG2 (LC ₅₀)	Fit (R ²)
12	QLLRPLFTKLLGGLSKILKKIF	250	500	500	>500	66.06	0.985
17	RLLOALLNHLRKKLKGILLSRLS	500	>500	>500	>500	85.88	0.998
40	KILKRORLLLGGLLKYLAKG	250*	500	500*	>500*	315.5	0.994
48	KKTYTKLKKLNGAIKYLVGHA	500	500	500	>500	NT	N/A
65	KAKLRQAVLLKLLAGVKSLSL	500	>500	500	>500	704.2	0.987
AmB	N/A	1	0.5	0.5	0.5	N/A	N/A

*MIC value determined on both crude purity and >95% purity peptide.

Potency of AFPs against *Candida auris*



Predicted secondary structures of high-potency low-cytotoxicity AFPs

A.

Peptide 48

KKTYTKLKKLNGAIKYLVGHA



B.

Peptide 65

KAKLRQAVLLKLLAGVKSSL



- | | |
|---|---|
| ■ | Very high (pI _{DDT} > 90) |
| ■ | Confident (70 < pI _{DDT} < 90) |
| ■ | Low (50 < pI _{DDT} < 70) |
| ■ | Very low (pI _{DDT} < 50) |

Summary

- Authors created a semi-automated pipeline that uses GAN to design novel antifungal peptide sequences.
- Experimental validation showed that five peptides inhibited a wheat pathogen, and four of them were also effective against a human pathogen.
- Peptides 48 and 65 were the most promising candidates identified due to combined antifungal efficiency and low cytotoxicity to human liver cells.

Strengths and weaknesses

- Generation of an AI/ML pipeline with very limited data for training.
- Successfully were able to synthesize and experimentally test selected peptides
- Very limited biophysical characterization of the synthesized peptides.
- No mechanism of action characterization of the peptides.
- Lack of clarity for rationale behind the parameters used to select peptides.

Future directions

- Characterize the mechanisms of action of the peptides they identified.
- Test peptides from other clusters on human pathogens of interest, not just cluster 17.
- Develop specialized classifiers for identification of peptide candidates that are effective against multi-drug resistant pathogens.
- Optimization of found peptides to increase efficiency.