Immunoinformatics design of a novel multiepitope vaccine candidate against non-typhoidal salmonellosis caused by *Salmonella* Kentucky using outer membrane proteins A, C and F

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Abstract

Salmonella Kentucky is a public health threat and responsible for the spread of antimicrobial resistance determinants in human and livestock population across the globe. It is ubiquitous in Africa and an emerging cause of human non-typhoidal gastroenteritis on the continent. In this study, bioinformatics tool was used to design an epitope peptide-based vaccine using outer membrane proteins A, C and F of *Salmonella* Kentucky. We predicted 14 CD8+ and 7 CD4+ T-cell epitopes, putatively restricted by MHC class I and class II alleles. The predicted T-cell epitopes will provide a 94.91 % population coverage when used in a vaccine preparation. Seven highly immunogenic linear B-cell epitopes and 3 conformational B-cell epitopes were predicted. The T-cell and B-cell epitopes were fused using proper linkers to construct a multi-epitope vaccine (MEV). *fliC* protein of *Salmonella* Typhimurium was added at the N-terminal as adjuvant to improve immunogenicity of the peptide construct. The MEV construct had a high quality structure with acceptable physicochemical features. Docking of the MEV against Toll like receptors 1, 2, 4 and 5 and the molecular dynamic simulation of the docked complexes indicated that the formation of these complexes were energetically feasible, stable and strong during immunological activities. Immune stimulation results indicated adequate elicitation of IgG, IgM, CD8+ T-cell, CD4+ T-cell and an array of cytokines (IFN-γ, TGF-b, IL-2, IL-10 and IL-12) with a noticeable decrease in antigen levels. Although the vaccine qualities were commendable, preclinical and clinical trials are required for validation of the protective traits and safety of the designed vaccine.

1. Introduction

Antibiotics are essential tools in modern medicine, indispensable for the treatment of infectious diseases, essential as support therapy in medical interventions (e.g., surgery and cancer

chemotherapy), and in livestock and food animal production [1]. The extensive and inappropriate

use of antibiotics has fuelled the spread of antibiotic resistance mechanisms in pathogenic bacteria,

leading to the very real prospect of a post-antibiotic era. Predictions estimate that by 2050

antibiotic resistant bacteria would have killed more people than cancer will [1]. The World Health

Organization (WHO) has put across that fluoroquinolone-resistant *Salmonella enterica,*

carbapenem-resistant and extended-spectrum *β*-lactamase producing *Enterobacteriaceae* are

amongst the highest priority pathogens posing a severe risk to human health [2]. All of these high

level resistances have been detected in *Salmonella enterica* subsp. *enterica* serovar Kentucky (*S.*

Kentucky). This serovar is considered to be a high risk global Multidrug resistant (MDR) pathogen

with well documented zoonotic potential. It has been isolated across different classes of animals

and in human [3, 4]. The emergence and continual spread of MDR *S.* Kentucky has been

highlighted by different health organizations and nations and its continuous association with high

level fluoroquinolone resistance has gained epidemiological importance globally [5].

Ciprofloxacin and extended-spectrum cephalosporins are the drug of choice for treatment of severe

nontyphoidal *Salmonella enterica* infections in adults. The resistance exhibited by *S.* Kentucky to

these choice drugs has left very limited treatment options [3].

Vaccines have had an unprecedented impact on human and global health, and have been used for

decades, with a much lower probability of resistance emergence when compared with antibiotics

[6, 7], as mechanisms of action of vaccines and antibiotics as regards the tendency to generate

microbial resistance are intrinsically different and this may account for the lower probability of

antimicrobial resistance emergence for vaccines [8]. More so, vaccines are used prophylactically

and thus take effect by acting before the bacteria multiplies following initial infection (resulting in

a low pathogen burden) and before different tissues and organs are affected, which substantially

reduces the likelihood that resistance conferring mutations will emerge and spread [8].

Salmonella outer membrane proteins (OMPs) have been investigated as potential vaccine

candidates over the past several years. The *Salmonella* OMPs viz outer membrane protein A

(OmpA), outer membrane protein C (OmpC) and outer membrane protein F (OmpF), are widely

distributed and conserved among different *Salmonella* serovars which raises the possibility that

they could be used in diagnostics or as part of a subunit or conjugate vaccine [9, 10]. Various

studies have shown that a crude preparation of *Salmonella* OMPs evokes strong immune response

and induces a protective immunity against infection caused by diverse Gram-negative bacteria

[10]. Furthermore, OMPs have surface-exposed epitopes, which are accessible for antibody or T

cell receptor recognition [11, 12]. The WHO has highlighted the importance of developing new

vaccines against infectious bacterial agents in Sub-Saharan Africa [13, 14] and further expressed

that vaccines for nontyphoidal *Salmonella* are urgently required, especially on the continent, as

some risk factors makes Africa a critical region in regard to the emergence of antimicrobial

resistance [3, 15, 16, 17]. The aim of this study is to design a multi-epitope vaccine (MEV) against

Non-typhoidal Salmonellosis (NTS) infection caused by *Salmonella* Kentucky using

immunoinformatics and computational methods, from sequences of OmpA, OmpC and OmpF.

2. Materials and methods

2.1. Retrieval of outer membrane proteins (Omps) of *Salmonella* Kentucky sequences

The National Center for Biotechnology Information (NCBI) database was chosen for the

retrieval of OmpA, OmpC and OmpF sequences of *S*. Kentucky strains. All the accession number

of OMPs of *S*. Kentucky used were noted (https://www.ncbi.nlm.nih.gov/protein/). To maximize

the similarity between proteins of the different strains of *S*. Kentucky OMPs, sequences were

blasted with query set at 99 % to 100 % identity (BLAST: https://blast.ncbi.nlm.nih.gov). A

sequence of flagellin protein (*fliC*) (GenBank accession number KAA0422324.1) of *Salmonella*

enterica subsp. enterica serovar Typhimurium was chosen as an adjuvant to enhance the efficacy

of the vaccine peptide [18, 19].

2.2. Multiple sequence alignment of Omps and generation of consensus sequence

The numerous OMPs FASTA sequences were aligned using Jalview (2.11.2.7). Jalview is

a free cross-platform program for multiple sequence alignment editing, visualization and analysis

(https://www.jalview.org/ [20]. The FASTA sequences of all selected Omp A, C and F from the

NCBI database were manually entered on Jalview software program which automatically aligns

and generates a predicted consensus sequences using Blosum62 parameters [21].

2.3. Epitope mapping

For the prediction of Cytotoxic T lymphocytes (CTL) and helper T lymphocytes (HTL)

activating epitopes, the Immune Epitope Database (IEDB) server (http://tools.iedb.org/main/tcell)

was used to predict peptides that bind to major histocompatibility complex class I (MHC-I) and

major histocompatibility complex class II (MHC-II), respectively. T-cell epitopes are provided by

MHC-I and MHC-II molecules that are recognized by two distinct subsets of T-cells; CD8+ and

CD4+ T-cells, respectively [22, 23].

2.3.1. MHC-I epitopes prediction

The majority of cytotoxic T-cells have T-cell receptors (TCRs) that identify a particular antigen. Therefore, CTL epitope prediction is critical for vaccine designing concepts. CTL epitopes was predicted on the IEDB recommended 2023.09 (NetMHCpan4.1 EL) server (http://tools.iedb.org/mhci/). The HLA allele reference set was predicted and 9-mer length epitope selected. The threshold for epitope identification for a strong binder was set at 0.5% while at 2% for a weak binder. Peptide binding to MHC-I, proteasomal C-terminus cleavage score, and the transport efficiency of Transporter Associated with Antigen Processing (TAP) was used to make these predictions [23, 24]. The peptide binding to MHC-I and Proteasomal C-terminal cleavage scores was generated using an artificial neural network, whereas the TAP score was calculated by the weight matrix [23, 24].

2.3.2. MHC-II epitopes prediction

Helper T lymphocytes are a type of adaptive immune cell that may produce humoral and cellular immune responses in reaction to foreign antigens. Hence, HTL epitopes that may bind to MHC-II alleles are critical in vaccine development. HTL epitopes prediction will be performed on online server IEDB (Immune Epitope Database) (http://www.iedb.org/). The 7-allele human leukocyte antigen (HLA) was used as a reference set to predict the epitopes, and HLA-DR was selected for *Homo sapien*. Afterwards, a 15-mer length epitope with a percentile rank classification was obtained (IEDB recommended 2023.05 (NetMHCIIpan 4.1L). The server assigns IC50 values to the predicted epitopes, which are inversely related to the binding affinity towards the MHC-II. IC50 scores of < 50 nM represent a high binding affinity. The IC50 value < 500 nM corresponds to intermediate binding affinity; however, < 5000 nM is related low binding affinity of epitopes towards MHC-II [18, 22, 24].

2.4. Prediction of linear B‑cell epitopes

B-lymphocyte epitopes which are essential for the humoral immune system and antibody

production were predicted using the ABCpred server

(https://webs.iiitd.edu.in/raghava/abcpred/ABC_submission.html) and neural network algorithm

with a length of 16 amino acids and cut-of binding score > 0.51 (0.51 threshold) was used to predict

linear B cell epitopes of OmpA, OmpC and OmpF proteins using their consensus sequences. With

these criteria, epitopes with higher scores were chosen for the vaccine construction [18, 19]. Also,

the linear B-cells epitopes were further subjected to antigenicity prediction using antigen sequence

properties tool provided by IEDB website (http://tools.iedb.org/bcell/result/)

2.5. Prediction of antigenicity, allergenicity and toxicity

The VaxiJen v2.0 server (http://www.ddg-pharmfac.net/vaxijen/VaxiJen/VaxiJen.html)

was used to assess the antigenicity of each predicted MHC-I, MHC-II and linear B-Cell epitopes

and the multi-epitope vaccine sequence when constructed. The server threshold was set as 0.4 for

bacteria. This server utilizes the ACC (auto and cross-covariance) to produce an output [25, 26,

27]. To assess whether determined epitopes will cause an allergic reaction or not, the AllerTOP

v2.0 server (http://www.ddg-pharmfac.net/AllerTOP) was utilized [28, 29]. The AllerTOP uses

the ACC transformation of the protein sequence to obtain the closest k value and compare the E

descriptors of amino acids [30]. The ToxinPred server

(https://webs.iiitd.edu.in/raghava/toxinpred/multi_submit.php) was used to check the toxicity of

all selected epitopes [23, 26]. Following the final construction of the study MEV similar analyses

was performed.

2.6. Interferon gamma (IFN-γ) inducing epitope prediction

The presence of IFN-γ inducing epitopes in the proposed multi-epitope vaccine peptide

was predicted by IFNepitope server (http://crdd.osdd.net/raghava/ifnepitope/index.php) using the

scan module. Among algorithms models available, the motif and support vector machine (SVM)

hybrid model was selected. The server generates all possible overlapping peptides from antigen,

based on either IFN-γ inducing and IFN-γ non-inducing datasets [31]. Prediction score >1.0 was

set as a threshold value for epitope selection. Considering that IFNepitope server is trained with

MHC II epitopes, all final MHC II epitopes selected before chimera assembly was submitted [32].

2.7. Epitope conservancy analysis.

165 The prediction of conservation across epitopes was predicted using the IEDB tools

166 (http://tools.iedb.org/conservancy/). Epitope sequences with their corresponding OMP protein

167 class was entered into their respective text area. The minimum conservancy sequence identity

168 threshold was set at >= 100 % [33].

2.8. Population coverage analysis

The IEDB's Population Coverage tool (http://tools.iedb.org/population/) was used to look

at how the affinity of CTL and HTL epitopes for HLA alleles varies by race, location, and country,

affecting the construction of epitope-based vaccines. By keeping the default parameters, the 16

geographical areas was selected for population coverage. The distribution of human MHC binding

alleles was used in this tool to estimate population coverage for the T-cell epitopes, queried by

area, country and ethnicity in different parts across the globe [23].

2.9. Construction of multi‑epitope vaccine sequence

For the final multi-epitope vaccine construction, highly antigenic, non-allergenic and non-

toxic epitopes were chosen. The Selected B cell epitopes (OmpA, OmpC and OmpF) and HTL

epitopes were linked by GPGPG linker and CTL epitopes by an AAY linker. To further enhance

the immunogenicity of the multi-epitope vaccine, an adjuvant flagellin (*fliC*) protein (GenBank

accession number KAA0422324.1) of *Salmonella enterica* subsp. *enterica* serovar Typhimurium

was added through the EAAAK linker at the N terminal of the epitopes [18, 34, 35].

2.10. Prediction of physicochemical characteristics and solubility

The MEV construct was subjected to Expasy Protparam online server

(https://web.expasy.org/protparam/) to predict the physicochemical characteristics of the multi

peptide structure such as the aliphatic index, molecular weight (MW), theoretical isoelectric point

(pI) [36], half-life, instability, and grand average of hydropathicity (GRAVY) [37]. The Protein-

Sol server (http://protein-sol.manchester.ac.uk) was used to determine the solubility value of the

multi-epitope vaccine. A scaled solubility value of more than 0.45 indicates that the protein is more

soluble than that of the average soluble *E. coli* protein in the experimental solubility dataset.

Proteins of lesser scaled solubility value are expected to be insoluble [38].

2.11. Secondary structure prediction

The secondary structure of the MEV construct was generated using PSIPRED and SOPMA

Property online tool, PSIPRED (http://bioinf.cs.ucl.ac.uk/psipred/) is a simple online secondary

structure prediction tool that incorporates two feed-forward neural networks which predict

transmembrane topology, transmembrane helix, folds, and domains efficiently [39], while the

SOPMA   server   (https://npsa.lyon.inserm.fr/cgi-

bin/npsa_automat.pl?page=/NPSA/npsa_sopma.html) is an online tool used to indicate the

properties of the secondary structure. This method correctly predicts 69.5% of secondary structure

property (alpha-helix, beta-sheet, and coil) in proteins database. The combination of SOPMA and

a neural networks method predicts 82.2% of residues for 74% of co-predicted amino acids [40].

2.12. Tertiary structure prediction

Iterative Threading Assembly Refinement (I-TASSER) server (https://zhanglab.ccmb.med.

Umich.Edu/I-TASSER) was used to create a three-dimensional (3D) structure of the vaccine

construct. Based on the sequence-to-structure-to-function paradigm, I-TASSER generates three-

dimensional (3D) atomic models from multiple threading alignments and iterative structural

assembly simulations. The accuracy of the 3D model is provided based on the confidence score

(C-score). The C-score is generally in the range between − 5 and 2, wherein a higher number

indicates better quality [32, 41].

2.13. Refinement and validation of tertiary structure

Validation of the tertiary structure is important in vaccine development because it reveals

possible flaws in the anticipated model [42]. To improve the quality of 3D structure, refinement

of   the   vaccine   model   was   carried   out   with   the   Galaxy   Refine   web   server

(http://galaxy.seoklab.org/cgi-bin/submit.cgi?type=REFINE). GalaxyRefne server is premised on

a sophisticated routine that accomplishes reassembling and uses molecular dynamics modulation

for structural refinement [43]. Furthermore, the ProSA-webserver was used to evaluate the total

quality   score   of   the   precise   input   structure   for   3D   structure   validation.   ERRAT

(http://services.mbi.ucla.edu/ERRAT/) was used to evaluate un-bonded inter-atomic interactions

and high-resolution crystallography structures [44, 45]. To validate the refined tertiary structure of

the vaccine model, the PROCHECK server (https://saves.mbi.ucla.edu) and VADAR version 1.8

(http://vadar.wishartlab.com/index.html?)   was   used   [46].   The   result   of   these   servers   is   the

Ramachandran plot, which shows the percentage of residues in favored, allowed and disallowed

regions based on dihedral angles psi (ψ) and phi (φ) of each amino acid [47].

2.14. Prediction of discontinuous B-cell epitopes

Protein folding can put distant residues together and generate discontinuous B-cell epitopes.

Discontinuous epitopes are predicted using the PI (Protrusion Index) value, and their clustering is

based on the distance R (distance between the Centre of mass of the residue), which is measured.

A higher R value suggests that there are a greater number of expected discontinuous epitopes.

Since more than 90% of B cell epitopes are discontinuous, the presence of these epitopes in the

vaccine structure was predicted by the Ellipro server (http://tools.iedb.org/ellipro/) [23, 48]. The

threshold parameters (Minimum residue score 0.5 and Maximum distance 6 A) was set at default.

Based on the 3D structure of the vaccine, this server provides an ellipsoid score to each residue,

which is defined as a PI value. A score of 0.9 PI implies that 90% of the protein's residues are

included, while the remaining 10% are outside of the ellipsoid. This PI number is determined by

the centre of mass of each residue, which is located outside of the greatest feasible ellipsoid [23,

27].

2.15. Protein–protein docking

The vaccine model is expected to bind to immunological receptors in order to elicit an

immune response. Toll-Like Receptor (TLR); TLR-1, TLR-2, TLR-4 and TLR-5 are involved in

the recognition of *Salmonella* structures and the production of inflammatory cytokines as they are

highly sensitive to bacterial components; TLR-1 (triacylated lipoproteins), TLR-2 (lipoproteins),

TLR-4 (lipopolysaccharide) and TLR-5 (flagellin) [49, 50, 51] and so was selected for docking.

The potential of chimeric vaccine construct docking with Toll-Like Receptor (TLR) was evaluated

by ClusPro 2.0 server (https://cluspro.bu.edu/login.php). ClusPro 2.0 is a rigid-body protein–

protein docking service that predicts interactions between two proteins. This software is entirely

automated and employs 3 distinct procedures: the first is a unique fast Fourier transform (FFT)

correlation, the second is clustering the best energy conformations, and the third is evaluating

cluster stability using brief Monte Carlo simulations [52, 53]. The PDB file of the refined vaccine

construct was docked against TLR-1 (PDB Id: 6NIH), TLR-2 (PDB ID: 6NIG), TLR-4 (PDB ID:

3FXI) and TLR-5 (PDB ID: 3JOA) from the PDB database (https://www.rcsb.org/). The best-

docked model was chosen from the models on the ClusPro 2.0 server based on its lowest energy

value.

253 2.16. Molecular dynamic simulation and protein-protein binding

254 affinity analysis

To investigate the stability and physical movements of the MEV-TLR-1, MEV-TLR-2, MEV-

TLR-4 and MEV-TLR-5 docked complexes, molecular dynamics simulation by iMOD server

(iMODS) (http://imods.chaconlab.org) was done. This tool explores normal mode analysis (NMA)

in internal (dihedral) coordinates that naturally reproduce the joint functional motions of biological

macromolecules and generates feasible transition pathways between two homologous structures,

even with large macromolecules [54]. The binding affinity and dissociation constant of the docked

proteins was predicted by Prodigy, a web-server for predicting the binding affinity in protein-

protein complexes (https://wenmr.science.uu.nl/prodigy/), all parameters were set at default [55,

56, 57].

264 2.17. Immune simulation

The vaccine amino acid sequence were submitted to C-ImmSim server

(https://kraken.iac.rm.cnr.it/C-IMMSIM/) in order to determine the immune response profile in

the *in-silico* model. C-ImmSim server evaluates humoral and cellular response to vaccine model

[58] based on Position-specific scoring matrix (PSSM) and machine learning methods. PSSM

stimulates three different anatomical regions of mammals, including Bone marrow (where the

hematopoietic stem cells are stimulated, and myeloid cells produced), the thymus (where naive T

cells are selected to avoid autoimmunity), and tertiary lymphatic organs to define the real-life

immune response. To conduct immune stimulation, the number of antigen to inject was set at 462,

three shots was injected at four weeks interval i.e., at days 0, 28 and 56, so the time steps of

injections was set at 1, 84, and 168 for each injection number; meaning that each time step is 8

hours and time step 1 is the injection administered at time zero. This prime-booster-booster

approach at 4-weeks interval was employed to achieve long-lasting protective immune response,

and was administrated with a total of 336 simulation steps while all other simulation parameters

were set as default [19, 59].

279   2.18. Codon adaptation

Efficacy of the vaccine model in cloning and expression is important for *in-vitro* production.

Codon adaptation and in silico cloning were performed in order to express the final vaccine

construct in a mammalian host since codon usage optimization demonstrated differences between

mammals and *Salmonella enterica* strains. The purpose of this is to guarantee the expression of

the vaccine construct in the selected host. Java Codon Adaptation Tool (JCAT) server

(http://www.prodoric.de/JCat) was used for the reverse translation of the protein sequence of the

vaccine construct into DNA sequence. The rho independent transcription termination, prokaryote

ribosome binding site and cleavage site of restriction enzyme were avoided [60]. In the JCAT,

codon adaptation index (CAI) score is 1.0 but > 0.8 is considered a good score and the favourable

GC content of a sequence should range between 30 % and 70 %.

290   2.19. Restriction enzyme mapping and *in-silico* cloning into plasmid

The NEBcutter Version 3.0.17 server software (https://nc3.neb.com/NEBcutter/) was used to

map out the restriction enzymes on the JCAT codon optimized sequence of the vaccine construct.

NEBcutter v3.0 was designed to assist users with restriction digestions and traditional molecular

cloning workflows. Users can submit a sequence of interest or select from a list of common

plasmids and example sequences. Users can then visualize detected restriction enzyme sites on a

sequence map and perform a custom digest with selected enzymes. The restriction enzymes cutting

sites sequences of HindIII and BamHI was introduced to the DNA sequence obtained by (JCAT)

server at the N-terminal and C-terminal vicinities respectively. A hexa histidine-tag, (6xHis-tag)

was inserted into the DNA sequence before BamHI at the C-terminal. The SnapGene restriction

cloning module was used to insert the DNA sequence into pcDNA3.1_CT-GFP expression vector

(https://www.snapgene.com/plasmids/mammalian_expression_vectors/pcDNA3.1_CT-GFP)

within the multiple cloning sites of the plasmid. The pcDNA3.1_CT-GFP expression plasmid

vector which is mammalian codon optimized for transfection visualization in mammalian cell line

was chosen [44, 60, 61].

3.0. Results

3.1. Retrieval of *S.* Kentucky OMP sequences and generation of consensus sequence

Salmonella Kentucky Omps A, C and F sequences and their accession number were

obtained from the NCBI protein database as FASTA files. A total of 65 outer membrane proteins

(Omps) of *Salmonella* Kentucky were retrieved, comprising of 18 OmpA, 32 OmpC and 15 OmpF.

The FASTA format sequences of all 65 OMPs A, C and F class were aligned separately by Jalview

2.11.2.7. The FASTA sequence of *fliC* protein (GenBank accession number KAA0422324.1) of

Salmonella Typhimurium used as Adjuvant was also retrieved (Table 2).

Table 1. Accession number of the outer membrane proteins A, C and F selected for the

development of MEV retrieved from NCBI protein database.

S/No.	OmpA	OmpC	OmpF
1	ELX43285.1	EDX45415.1	CAH2847802.1
2	EDZ19256.1	EDZ22335.1	CAH2871873.1
3	EDX48073.1	CAH2866635.1	ESG84125.1
4	EJQ7725175.1	CAH2866410.1	ESG88044.1
5	EDF7307973.1	ERN84404.1	ESC06125.1
6	EJW1777139.1	ERN77197.1	ELX43265.1
7	EBL3626682.1	ERN70439.1	ERN84743.1
8	ECV5604453.1	ERN69676.1	ERN79626.1
9	EBM7532700.1	ERN69269.1	ERN78365.1
10	EFL6925197.1	ESG79344.1	ERN73560.1
11	EBW8725894.1	ESG77524.1	ERN62106.1
12	ECI8791934.1	ESC11174.1	EDZ19170.1
13	EGC5146150.1	ELX37395.1	EDX44525.1
14	ESG79962.1	ERN88917.1	EJC3163576.1
15	ESG88025.1	ERN87695.1	EBL4572010.1
16	ESC13401.1	ERN87644.1	
17	CAH2847702.1	ERN82780.1	
18	CAH2871911.1	ERN77612.1	
19		ERN77081.1	
20		ERN76635.1	

21		ERN74999.1	
22		ERN72553.1	
23		ERN70652.1	
24		ERN69005.1	
25		ERN68685.1	
26		ERN67044.1	
27		ERN66706.1	
28		ERN66672.1	
29		ERN66415.1	
30		ERN64040.1	
31		ERN62720.1	
32		ERN62687.1	

316 **Table 2**. **Jalview version 2.11.2.7 generated consensus sequences of the outer membrane**

317 **proteins A, C and F and selected *fliC* protein for the development of MEV.**

Proteins	FASTA sequences/number of amino acids
OmpA	>Consensus sequence comprising 371 amino acid residues

	MKKTAIAIAVALAGFATVAQAAPKDNTWYAGAKLGWSQYHDTGFINND GPTHENQLGAGAFGGYQVNPYVGFEMGYDWLGRMPYKGDNINGAYKA QGVQLTAKLGYPITDDLDVYTRLGGMVWRADTKSNVPGPGGASNKDHD TGVSPVFAGGIEYAITPEIATRLEYQWTNNIGDANTIGTRPDNGLLSVGVS YRFGQQEAAPVVAPAPAPAPEVQTKHFTLKSDVLFNFNKSTLKPEGQQAL DQLYSQLSNLDPKDGSVVVLGFTDRIGSDAYNQGLSEKRAQSVVDYLISK GIPSDKISARGMGESNPVTGNTCDNVKPRAALIDCLAPDRRVEIEVKGVKD VVTQPQARRVEIEVKGVKDVVTQPQA
OmpC	>Consensus sequence comprising 403 amino acid residues
	MKVKVLALLVPALLVAGAANAAEIYNKDGNKLDLYGKVDGLHYFSDDK GSDGDQTYMRIGFKGETQINDQLTGYGQWEYQIQGNQTEGSGDSSTRVA FAGLLFFDAGSFDDGGNYGVTYDVTSWTDVLPEFGGGTYGADNFMQQR GNGYATYRNTDFFGFVDGLDFALQYQGKNGSVSGENTNGRSGLNQNGD GYGGSLTYAIGEGFSVGGAITTSKRTADQNNTANDRLYGNGDRATVYTG GLKYDANNIYLAAQYSQTYNAARFGTSNGSTPSTSYGFANKAQNFEVVA QYQFDFGLRPSVAYLQSKGKDISNGGGASYGDQDIVKYVDVGATYYFNK NMSTYVDYKINLLDKNDFTRDAGINTDDIVALGLVYQFIVALGMVYQFIA TDDIVGVGLVYQF
OmpF	>Consensus sequence comprising 363 amino acid residues

	MMKRKILAAVIPALLAAATANAAEIYNKDGNKLDLYGKAVGRHVWTTT GDSKNADQTYAQIGFKGETQINTDLTGFGQWEYRTKADRAEGEQQNSNL VRLAFAGLKYAEVGSIDYGRNYGIVYDVESYTDMAPYFSGETWGGAYTD NYMTSRAGGLLTYRNSDFFGLVDGLSFGIQYQGKNQDNHSINSQNGDGV GYTMAYEFDGFGVTAAYSNSKRTNDQQDRDGNGDRAESWAVGAKYDA NNVYLAAVYAETRNMSIVENTVTDTVEMANKTQNLEVVAQYQFDFGLR PAISYVQSKGKQLNGADGSADLAKYIQAGATYYFNKNMNVWVDYRFNL LDENDYSSSYVGTDDQAAVGITYQF
fliC	49 amino acid residues
	MAQVINTNSLSLLTQNNLNKSQSALGTAIERLSSGLRINSAKDDAAGQA

3.2. Results for MHC-I and MHC-II epitopes prediction and epitope conservancy analysis

At a threshold value of 0.5 percent for strong binders and following antigenicity, allergenicity and toxicity screening, a final total of 4 CTL epitopes for OmpA, 5 CTL epitopes for OmpC and 5 CTL epitopes for OmpF which were selected for the multi-epitope vaccine construction (Table 3). Their corresponding allele(s) and positions were noted (Table 4). The result from IEDB server using the seven-allele reference set and applicable thresholds generated 4, 2 and 2 HTL epitopes were selected for OmpA, OmpC and OmpF respectively which were selected for the construction of the multi-epitope vaccine (Table 3). Their corresponding allele(s) and positions were noted (Table 4). Also, the results from IEDB server conservancy analysis at $\geq$ 100 % protein sequence identity threshold predicted a minimum and maximum identity of 100 % for all epitopes across the different classes of OMPs A, C and F CTLs and HTLs. Epitope "IEYAITPEI" had a

330   100 % minimum and maximum identity conservancy as an OmpA, but had a minimum identity at

331   33.33 % and a maximum identity at 33.33 % as an OmpC CTL epitope (Table 4).

332   **Table 3. Predicted CTL and HTL epitopes of *S.* Kentucky OmpA, OmpC and OmpF proteins**

333   **from consensus sequences with their immunogenic properties**

Epitopes	Peptide Score	Antigenicity (Score)	Allergenicity	Toxicity
LSVGVSYRF	0.93	Antigenic (1.5084)	Non-Allergen	Non-Toxin
EVQTKHFTL	0.91	Antigenic (1.5694)	Non-Allergen	Non-Toxin
IEYAITPEI	0.81	Antigenic (1.2128)	Non-Allergen	Non-Toxin
VQLTAKLGY	0.84	Antigenic (0.7491)	Non-Allergen	Non-Toxin
FNFNKSTLK	0.74	Antigenic (0.6346)	Non-Allergen	Non-Toxin
YKGDNINGA	0.59	Antigenic (1.2899)	Non-Allergen	Non-Toxin
LAPDRRVEI	0.89	Antigenic (0.5152)	Non-Allergen	Non-Toxin
VALGLVYQF	0.91	Antigenic (0.8219)	Non-Allergen	Non-Toxin

GLRPSVAYL	0.87	Antigenic (0.9049)	Non-Allergen	Non-Toxin
LPEFGGGTY	0.89	Antigenic (0.8301)	Non-Allergen	Non-Toxin
ISNGGGASY	0.82	Antigenic (1.5949)	Non-Allergen	Non-Toxin
RGNGYATYR	0.80	Antigenic (1.0838)	Non-Allergen	Non-Toxin
FNKNMSTYV	0.82	Antigenic (1.1373)	Non-Allergen	Non-Toxin
MSTYVDYKI	0.81	Antigenic (1.0144)	Non-Allergen	Non-Toxin
SQNGDGVGY	0.93	Antigenic (2.5198)	Non-Allergen	Non-Toxin
DENDYSSSY	0.92	Antigenic (0.6581)	Non-Allergen	Non-Toxin
AAVGITYQF	0.84	Antigenic (1.2698)	Non-Allergen	Non-Toxin
IQAGATYYF	0.87	Antigenic (0.6830)	Non-Allergen	Non-Toxin
TAAYSNSKR	0.91	Antigenic (0.4845)	Non-Allergen	Non-Toxin

YYFNKNMNV	0.93	Antigenic (0.8472)	Non-Allergen	Non-Toxin
YAETRNMSI	0.91	Antigenic (0.9418)	Non-Allergen	Non-Toxin

Table 4. The predicted MHC restricted allele(s) of the CTL and HTL epitopes and degree of conservancy for the OMPs A, C and F screened for antigenicity, allergenicity and toxicity

Omps	MHCI Epitopes	MHCII Epitopes	MHC Restricted Allele(s)	Start	End	Percent of protein sequence matches at identity <= 100%	Minimum identity	Maximum identity
OmpA	LSVGVSYRF		HLA-B*58:01, HLA-B*57:01	117	125	100.00% (1/1)	100.00%	100.00%
	EVQTKHFTL		HLA-B*08:01	143	151	100.00% (1/1)	100.00%	100.00%
	IEYAITPEI		HLA-B*40:01	82	90	100.00% (1/1)	100.00%	100.00%
	VQLTAKLGY		HLA-B*15:01, HLA-A*30:02	26	34	100.00% (1/1)	100.00%	100.00%
		FNFNKSTLK	HLA-DRB3*02:02, HLA-DRB5*01:01	152	168	100.00% (1/1)	100.00%	100.00%
		YKGDNINGA	HLA-DRB3*01:01,	9	23	100.00% (1/1)	100.00%	100.00%

			HLA-DRB3*02:02					
		LAPDRRVEI	HLA-DRB1*03:01	254	270	100.00% (1/1)	100.00%	100.00%
		IEYAITPEI	HLA-DRB1*07:01	79	93	100.00% (1/1)	100.00%	100.00%
OmpC	VALGLVYQF		HLA-B*57:01, HLA-B*58:01, HLA-B*53:01, HLA-B*35:01	298	306	100.00% (1/1)	100.00%	100.00%
	IEYAITPEI		HLA-DRB1*07:01	79	93	0.00% (0/1)	33.33%	33.33%
	GLRPSVAYL		HLA-A*02:03, HLA-A*02:01	226	234	100.00% (1/1)	100.00%	100.00%
	LPEFGGGTY		HLA-B*35:01	56	64	100.00% (1/1)	100.00%	100.00%
	ISNGGGASY		HLA-B*15:01, HLA-A*30:02, HLA-A*01:01, HLA-B*35:01	241	249	100.00% (1/1)	100.00%	100.00%
	RGNGYATYR		HLA-A*31:01	73	81	100.00% (1/1)	100.00%	100.00%

		FNKNMSTYV	HLA-DRB3*02:02	263	278	100.00% (1/1)	100.00%	100.00%
		MSTYVDYKI	HLA-DRB1*15:01	265	281	100.00% (1/1)	100.00%	100.00%
OmpF	SQNGDGVGY		HLA-B*15:01, HLA-A*30:02	117	125	100.00% (1/1)	100.00%	100.00%
	DENDYSSSY		HLA-B*44:03, HLA-B*44:02	268	276	100.00% (1/1)	100.00%	100.00%
	AAVGITYQF		HLA-B*58:01, HLA-B*57:01, HLA-B*35:01, HLA-A*32:01	283	291	100.00% (1/1)	100.00%	100.00%
	IQAGATYYF		HLA-A*23:01, HLA-A*24:02, HLA-B*15:01	244	252	100.00% (1/1)	100.00%	100.00%
	TAAYSNSKR		HLA-A*68:01	137	145	100.00% (1/1)	100.00%	100.00%

		YYFNKNMN V	HLA-DRB3*02:02	244	262	100.00% (1/1)	100.00%	100.00%
		YAETRNMSI	HLA-DRB1*07:01	174	190	100.00% (1/1)	100.00%	100.00%

3.3. Linear B-cell epitopes prediction

ABCpred server predicted a total of 35 B-cell epitopes for the consensus sequence of OmpA, 39 B-cell epitopes for the consensus sequence of OmpC and 41 B-cell epitopes for the consensus sequence of OmpF with a cut off binding score at 0.51. B-cell epitopes with a high score of ≥ 0.85 and a minimum peptide rank score of 7 were further subjected to antigenicity, allergenicity and toxicity screening. Finally, 2 B-cell epitopes for OmpA, 2 B-cell epitopes for OmpC and 3 B-cell epitopes for OmpF were selected for multi-epitope vaccine construction (Table 5).

346 **Table 5. Predicted linear B-cells epitopes of *S*. Kentucky OMP A, C and F from consensus sequences and *flic* protein (adjuvant)**

347 **with their immunogenic properties**

OMPs	B-cell Epitopes (16mers)	Average K and T score	Peptide score	Antigenicity (Score)	Allergenicity	Toxicity
OmpA	DYLISKGIPSDKISAR	1.020	0.89	Antigenic (0.8497)	Non-Allergen	Non-Toxin
	GPGGASNKDHDTGVSP	0.953	0.88	Antigenic (1.7585)	Non-Allergen	Non-Toxin
OmpC	TSNGSTPSTSYGFANK	0.980	0.90	Antigenic (0.8885)	Non-Allergen	Non-Toxin
	AGAANAAEIYNKDGNK	0.971	0.89	Antigenic (1.2510)	Non-Allergen	Non-Toxin
OmpF	VGRHVWTTTGDSKNAD	0.956	0.92	Antigenic (1.4812)	Non-Allergen	Non-Toxin

	GFGVTAAYSNSKRTND	0.994	0.90	Antigenic (1.2497)	Non-Allergen	Non-Toxin
	DGLSFGIQYQGKNQDN	1.001	0.89	Antigenic (1.1403)	Non-Allergen	Non-Toxin
Flic	GenBank accession number KAA0422324.1			Antigenic (0.7058)	Non-Allergen	Non-Toxin

348   Key: **K and T**: Kolaskar and Tongaonkar antigenicity scale

3.4. Interferon gamma (IFN-γ) inducing epitope prediction

Eight MHC class II epitopes were submitted to the IFNepitope server for IFN-γ prediction.

Two HTL epitopes were positive, thus; capable of inducing the production of interferon gamma.

The SVM method predicted epitope "LAPDRRVEI" as a positive inducer and the MERCI method

predicted "IEYAITPEI" epitope as a positive inducer (Table 6).

Table 6. Predicted OMPs A, C and F MHC Class II T-cell epitopes capable of inducing

interferon gamma (IFN-γ)

Epitope 15 length Peptide	Epitope Sequence	Method	Result	Score
DVLFNFNKSTLKPEG	FNFNKSTLK	SVM	NEGATIVE	-0.3144975
RMPYKGDNINGAYKA	YKGDNINGA	SVM	NEGATIVE	-0.073986311
IDCLAPDRRVEIEVK	LAPDRRVEI	SVM	POSITVE	-0.053153702
AGGIEYAITPEIATR	IEYAITPEI	MERCI	POSITVE	1
FNKNMSTYVDYKINL	FNKNMSTYV	SVM	NEGATIVE	-0.96274966
FNKNMSTYVDYKINL	MSTYVDYKI	MERCI	NEGATIVE	1
GATYYFNKNMNVWVD	YYFNKNMNV	SVM	NEGATIVE	-0.62234638
AAVYAETRNMSIVEN	YAETRNMSI	SVM	NEGATIVE	-0.55036682

3.5. Population coverage

The worldwide population percentage coverage of the selected putative HLA class I and HLA

class II restricted epitopes was 94.91 %. This analysis of the MHC I and MHC II alleles confirmed

that the world population will be covered if the intended vaccine architecture was administered.

Based on continental and regional analysis, Europe, North America and North Africa had the

highest population coverage of 97.59 %, 96.92 % and 92.89 % respectively (Fig 1). On the African

continent, the percentage population coverage for West Africa, South Africa, East Africa and

Central Africa were 89.77 %, 83.02 %, 81.86 % and 78.17 % respectively with a class combined

regional average of 85.14 (Table 7). Outside the African continent, East Asia, North-East Asia and

South America were 90.82 %, 79.71 % and 83.0 % respectively (Fig 1). Furthermore the selected

putative HLA class I restricted epitopes exhibited a higher individual percentage coverage (90.02

%) when queried against the HLA class II restricted epitopes (49.02 %) across the world (Fig 1).

Fig 1. Continental and regional coverage of the MHC class I and MHC class II T-Cell

epitopes

Table 7. Percentage population Coverage of MHC class I and MHC class II epitopes in different regions in Africa

Population/ Area	Class I			Class II			Class combined		
	Coverage[a]	Average hit[b]	pc90[c]	Coverage[a]	Average hit[b]	pc90[c]	Coverage[a]	Average hit[b]	pc90[c]
Central Africa	70.01%	1.74	0.33	27.2%	0.42	0.14	78.17%	2.16	0.46
East Africa	76.69%	1.88	0.43	22.21%	0.32	0.13	81.86%	2.2	0.55
North Africa	85.1%	2.09	0.67	52.24%	0.84	0.21	92.89%	2.93	1.14
South Africa	77.2%	1.86	0.44	25.52%	0.26	0.13	83.02%	2.12	0.59
West Africa	86.84%	2.61	0.76	22.25%	0.32	0.13	89.77%	2.93	0.98
Average	79.17	2.04	0.53	29.88	0.43	0.15	85.14	2.47	0.74
Standard deviation	6.13	0.31	0.16	11.34	0.21	0.03	5.39	0.38	0.27

371   **Key**

372   [a] projected population coverage

373   [b] average number of epitope hits / HLA combinations recognized by the population

374   [c] minimum number of epitope hits / HLA combinations recognized by 90% of the population

3.6. Construction of MEV sequence and interferon gamma (IFN-γ) induction capabilities of the MEV

The multi-epitope vaccine construct consists of 462 amino acids residues from a total of 28 selected antigenic T-cells and B-cell epitopes comprising 14 CTLS, 7 HTLs and 7 B-cell epitopes, covalently linked to an immuno-adjuvant (*Salmonella* Typhimurium *fliC* protein; GenBank accession number KAA0422324.1 with 49 amino acid residues). The *fliC* protein was fused to the epitopes of CTLs with an EAAAK linker at the N terminal end of the vaccine construct. The CTL peptides of OmpA, OmpC and OmpF were fused together with an AAY linker and fused to the first HTL OmpA epitope with an AAY linker. The HTL peptides and B-cell epitopes were fused together with a GPGPG linker with the B-cell epitope of OmpF at the C terminal end (Fig 2). Result of antigenicity, allergenicity and toxicity prediction on the MEV construct confirms the vaccine as antigenic (with a score of 1.0458), non-allergenic and non-toxin.

The IFNepitope server support vector machine (SVM) hybrid model result confirmed a positive result capable of inducing IFN-γ and a score of 1.5695871.

Fig 2. The schematic structural arrangement of the final multi-epitope vaccine construct

3.7. Prediction of physicochemical characteristics and solubility of the MEV

The physicochemical parameters and solubility properties of the chimeric vaccine construct using Expasy Protparam and the Protein-Sol servers expressed the following. The molecular weight of the vaccine construct was 47343.98 Da and the bio-computed theoretical isoelectric point (pI) was 9.150. The estimated half-life in mammalian cell is 30 hours, >20 hours and >10 hours yeast and *Escherichia coli* respectively. The solubility of the vaccine was found to

be 0.452 on the protein sol server (value > 0.45 is predicted to have a higher solubility than the

average soluble *E. coli* protein). The instability index of the vaccine was 25.66, signifying that the

vaccine is stable in a solvent environment (> 40 signifies instability). The aliphatic index was

computed to be 57.23 (The aliphatic index of a protein is a measure of the relative volume occupied

by aliphatic side chain of the following amino acids: alanine, valine, leucine and isoleucine. An

increase in the aliphatic index increases the thermo stability of globular proteins). The GRAVY

score was -0.429, which infers that the vaccine proteins have better interactions with water

molecules (To measure the hydrophobic and hydrophilic properties of the protein, general average

hydropathicity (GRAVY) score is a widely used parameter in codon usage bias (CUB) analysis

and its value ranges from −2 to 2. Positive GRAVY score means the protein is hydrophobic, while

negative GRAVY score indicates a hydrophilic protein).

3.8. Prediction of secondary and tertiary structure

Result for secondary structure analysis of the designed multi-epitope vaccine from

PSIPRED and SOPMA server indicated that 77 amino acids (16.67 %) were alpha-helices, 41

amino acids (8.87 %) were extended beta strands, 21 amino acids (4.55 %) were beta turns, and

323 amino acid (69.91 %) were random coils (Fig 3).

The 3D structure was built by I-Tasser server. According to the threading templates, 5 tertiary 3D

structures was predicted. The best C-score model with a -0.69 C-score value was selected for

further refinement and validation. The consistency of the 3D model was improved by galaxy refine

web server. Five improved refined models were produced from the initial MEV model (the -0.69

C-score structure from I-Tasser). Model 2 was the most significant model based on the

computational structural qualities. Model 2 had a GDT-HA score of 0.9221, RMSD of 0.493,

MolProbity of 2.352, a Clash score of 13.7, a zero Poor rotamers (0.0) and Rama favoured value

of 82.0 (Fig 4).

The validation of the refined tertiary structure of the MEV on the PROCHECK and VADAR

version 1.8 servers produced a Ramachandran plot with 264 number of the residues (75.6 %) in

the most favored region, 57 number of residues (16.3%) in additional allowed regions, 19 number

of residues (5.4 %) in generously allowed regions and 9 number of residues (2.6 %) in the

disallowed regions, making a total of 349 number of non-glycine and non-proline residues.

Additionally, there were 77 number of glycine residues, 34 number of proline residues and 2

number of end-residues (excl. Gly and Pro) (Fig 5).

Fig 3. The PSIPRED and SOPMA server graphical demonstration of secondary structure

properties of the final designed MEV

Fig 4. The tertiary structure of the designed MEV predicted by I-TASSER and coloured with

ChimeraX software. *fliC* protein (adjuvant) coloured in Red, CTLs in Purple, HTLs in Blue and

B-cell epitopes in Lime green

Fig 5. Validation: Ramachandran plot analysis of protein residues, showing 75.6 % in favored,

21.7 % in allowed, and 2.6 % in disallowed regions

3.9. Predicted discontinuous B-cell epitopes

436 The prediction of discontinuous epitopes requires the 3D structural information of the

437 protein or polypeptide. Thus, ElliPro server was used to predict three discontinuous B-cell

438 epitopes for the MEV indicating its residues, number of residues and scores (Table 8). The 3D

439 representation of putative B-cell epitopes is shown in Fig 6 with yellow surface.

 Table 8. Predicted discontinuous B-cell epitopes residues of the designed MEV, predicted by

 ElliPro

S/no	Residues	Number of Residues	Score
1	A:M1, A:A2, A:Q3, A:V4, A:I5, A:N6, A:T7, A:N8, A:S9, A:L10, A:S11, A:L12, A:L13, A:T14, A:Q15, A:N16, A:N17, A:L18, A:N19, A:K20, A:S21, A:Q22, A:S23, A:A24, A:L25, A:G26, A:T27, A:A28, A:I29, A:E30, A:R31, A:L32, A:S33, A:S34, A:G35, A:L36, A:R37, A:I38, A:N39, A:S40, A:A41, A:K42, A:D43, A:D44, A:A45, A:A46, A:G47, A:Q48, A:A49, A:E50, A:A51, A:A52, A:A53, A:K54, A:L55, A:S56, A:V57, A:G58, A:V59, A:S60, A:R62	62	0.869

2	A:P235, A:G239, A:N241, A:I242, A:N243, A:G244, A:A245, A:G246, A:P247, A:G248, A:P249, A:P261, A:G262, A:P263, A:G264, A:F265, A:N266, A:K267, A:N268, A:M269, A:S270, A:T271, A:G274, A:P275, A:G276, A:P277, A:G278, A:M279, A:S280, A:Y282, A:V283, A:Y285, A:K286, A:I287, A:G288, A:P289, A:G290, A:P291, A:G292, A:Y294, A:F295, A:N296, A:K297, A:N298, A:M299, A:N300, A:V301, A:G302, A:P303, A:G304, A:P305, A:G306, A:Y307, A:A308, A:E309, A:T310, A:R311, A:N312, A:M313, A:S314, A:I315, A:G316, A:P317, A:G318, A:P319, A:G320, A:D321, A:Y322, A:L323, A:I324, A:S325, A:K326, A:G327, A:I328, A:P329, A:S330, A:D331, A:K332, A:I333, A:S334, A:A335, A:R336, A:G337, A:P338, A:P343, A:G344, A:G345, A:A346, A:S347, A:N348, A:K349, A:D350, A:H351, A:D352, A:T353, A:G354	96	0.681
3	A:A88, A:V91, A:Q92, A:T94, A:A95, A:K96, A:L97, A:G98, A:Y99, A:A100, A:A101, A:Y102, A:V103, A:A104, A:L105, A:G106, A:L107, A:V108, A:Y109, A:Q110, A:F111, A:A112, A:A113, A:Y114, A:G115, A:L116, A:R117, A:P118, A:S119, A:V120, A:Y122, A:L123, A:D175, A:E176, A:N177, A:D178, A:Y179, A:S180, A:S181, A:S182, A:Y183, A:A184, A:A185, A:Y186, A:A187, A:A188, A:V189, A:G190, A:I191, A:T192, A:Y193, A:Q194, A:F195, A:A196, A:A197, A:Y198, A:I199,	100	0.632

A:Q200, A:A201, A:G202, A:A203, A:T204, A:Y205, A:Y206, A:F207, A:A208, A:H408, A:V409, A:W410, A:T411, A:T412, A:T413, A:G414, A:D415, A:S416, A:K417, A:N418, A:A419, A:D420, A:G421, A:P422, A:G423, A:P424, A:G425, A:G426, A:F427, A:G428, A:V429, A:T430, A:A431, A:A432, A:Y433, A:S436, A:R438, A:N440, A:G442, A:P443, A:D447, A:G448, A:Q456		

Fig 6. 3D representation of the discontinuous B cell epitopes of MEV. The yellow surface shows discontinuous B cell epitopes, while grey stick represents the bulk of the polyprotein. (a) With 61 number of residues and a score of 0.869, (b) with 96 number of residues with a score of 0.681 and (c) with 100 number of residues with a score of 0.632

3.10. Protein–protein docking and protein-protein binding affinity simulation

Result from the ClusPro web server provided a protein-protein docking complex with the best model selected based on their lowest energy level score (Table 9). The 3D tertiary structural models of the selected toll-like receptors multi-epitope vaccine docked complexes are on fig 7. ChimeraX software was used for visualization.

Table 9: Result for protein-protein docking on the ClusPro 2.0 server

Protein-Protein Dock complex	Best model (Cluster)	Center Energy	Lowest Energy
MEV-TLR1	8	-1112.4	-1220.2
MEV-TLR2	7	-1396.7	-1396.7
MEV-TLR4	1	-1002.2	-1213.1
MEV-TLR5	2	-1631.5	-1631.5

Fig 7. The ClusPro protein–protein docking of multi-epitope vaccine (MEV) model with Toll-like receptors (TLR). (a) MEV construct with TLR-1 (PDB Id: 6NIH), (b) MEV construct with TLR-2(PDB ID: 6NIG), (c) MEV construct with TLR-4 (PDB ID: 3FXI) and (d) MEV construct with TLR-5 (PDB ID: 3JOA). All models were visualized and coloured using ChimeraX software

3.11. Molecular dynamic simulation and protein-protein binding affinity analysis

Molecular dynamic simulation of the TLR-MEV docked complex was executed by iMODs. Results from the iMOD server tool evaluated the stability and physical movements of all the TLR-MEV docked complexes (Fig. 8 to Fig 11). The main-chain deformability is a measure of the capability of a given molecule to deform at each of its residues. The location of the chain 'hinges' can be derived from high deformability regions. The B-factor values quantifies the uncertainty of each atom in the complex and is calculated by normal mode analysis and are proportional to Root Mean Square. The eigenvalue of the docked complex, shows the energy required to deform the structure. The eigenvalue for the complexes were 8.6598×10^{-6}, 3.6955×10^{-7}, 1.6199×10^{-5} and 6.0634×10^{-6} for TLR1-MEV, TLR2-MEV, TLR4-MEV and TLR-MEV respectively. The covariance matrix plot between the pairs of residues, indicates their correlations (red: correlated, white: uncorrelated, blue: anti-correlated). The elastic network model plot suggests the connection between atoms and springs. The springs are more rigid if their greys are darker.

For the binding affinity analysis, the Prodigy bioinformatics tool shows a Pearson's Correlation r of 0.73 (p-value < 0.0001) between the predicted and the experimental values and a Root Mean Square Error (RMSE) of 1.89 kcal mol^{-1}. Two residues are defined in contact if any of their heavy atom is within a distance of 5.5 Å (Angstrom). The Prodigy server predicted 54 number

of intermolecular contacts for MEV-TLR1 complex, 101 number of intermolecular contacts for

MEV-TLR2, 168 number of intermolecular contacts for MEV-TLR4 and 50 number of

intermolecular contacts for MEV-TLR5. The binding affinity score (ΔG (kcal mol^{-1}) were all

negative for all docked complexes predicted (Table 10).

Figure 8. iMODs simulation of TLR1-MEV docked complex. (a) Main-chain deformability

simulation. (b) B-factor values quantifying the uncertainty of each atom. (c) The eigenvalue

showing the energy required to deform the structure. (d)The variance associated to each normal

mode is inversely related to the eigenvalue. Colored bars show the individual (Purple) and

cumulative (green) variances. (e) Covariance matrix indicates coupling between pairs of residues

(f) The elastic network model, suggesting the connection between atoms and springs.

Figure 9. iMODs simulation of TLR2-MEV docked complex. (a) Main-chain deformability

simulation. (b) B-factor values quantifying the uncertainty of each atom. (c) The eigenvalue

showing the energy required to deform the structure. (d)The variance associated to each normal

mode is inversely related to the eigenvalue. Colored bars show the individual (Purple) and

cumulative (green) variances. (e) Covariance matrix indicates coupling between pairs of residues

(f) The elastic network model, suggesting the connection between atoms and springs.

Figure 10. iMODs simulation of TLR4-MEV docked complex. (a) Main-chain deformability

simulation. (b) B-factor values quantifying the uncertainty of each atom. (c) The eigenvalue

showing the energy required to deform the structure. (d)The variance associated to each normal

mode is inversely related to the eigenvalue. Colored bars show the individual (Purple) and

cumulative (green) variances. (e) Covariance matrix indicates coupling between pairs of residues

(f) The elastic network model, suggesting the connection between atoms and springs.

Figure 11. iMODs simulation of TLR5-MEV docked complex. (a) Main-chain deformability

simulation. (b) B-factor values quantifying the uncertainty of each atom. (c) The eigenvalue

showing the energy required to deform the structure. (d)The variance associated to each normal

mode is inversely related to the eigenvalue. Colored bars show the individual (Purple) and

cumulative (green) variances. (e) Covariance matrix indicates coupling between pairs of residues

(f) The elastic network model, suggesting the connection between atoms and springs.

Table 10. Prediction of binding Affinity and Dissociation constant

Protein-protein complex	ΔG (kcal mol^{-1})	K_d (M) at 25℃	ICs charged-charged	ICs charged-polar	ICs charged-apolar	ICs polar-polar	ICs polar-apolar	ICs apolar-apolar	NIS charged	NIS apolar
MEV-TLR1	-10.4	2.3e-08	13	20	9	3	7	2	27.61	26.01
MEV-TLR2	-9.4	1.4e-07	12	12	13	15	14	35	28.08	28.83
MEV-TLR4	-18.1	5e-14	23	33	38	13	36	25	24.81	32.01
MEV-TLR5	-8.8	3.6e-07	3	6	11	0	9	21	19.56	42.13

507 **Key:**

508 **ICs** – Intermolecular Contacts

509 **ΔG** – Binding Affinity (Gibbs free energy)

510 **K$_d$** – Dissociation constant

511 **NIS** – Non interacting surface

3.12. Immune simulation

The administration and repetitive exposure to the MEV vaccine elicited a significant increase in the antibody response with a simultaneous decrease in the antigen level over time. There was a significant IgM and IgG humoral response indicating some levels of seroconversion. Humoral responses for both IgM and IgG peaked higher to the booster doses than the prime dose, and IgM was predominantly higher than IgG (and its isotype) (Fig. 12a).

Following the administration of the prime dose, CD8+ T-cell and CD4+ responses were actively elicited. The CD4+ T-helper lymphocytes peaked after the second booster, with the active entity state and Th-memory phenotype significantly increased following the first booster and sustained with minimal decay after 100 days (Fig. 13a and Fig. 13b). Similarly, Following the prime dose, there was a highly significant spike in IFN-g response (associated with both CD8+ T-cell and CD4+ Th 1 response), and fairly significant spike in IL-2, IL-10, IL-12 and TGF-b (Transforming growth factor-beta) cytokines response associated with T-reg phenotype (TGF-b and IL-10). These responses were sustained after the two booster doses for IFN-g response and increased significantly for IL-2, IL-10, IL-12 and TGF-b (Fig 15b). These immune readouts are generally associated with a wider base in the spike peak of antigenic quantification.

Analysis of B-cell population per cell showed overall B-cell population and B-cell memory responses were higher and stable showing minimal decay. B-cell memory was sufficiently elicited and peaked following the second booster dose and was sustained over 100 days. The same results go for B-cell population per state where active B-cell population was higher and stable for the same number of periods (Fig 12b and Fig 12c). There was also a concomitant increase in dendritic cells and natural killer cells and macrophages activities throughout the duration of the simulation (Fig. 14b, Fig. 14c and Fig. 14d). This points to another good performance indicator of the vaccine

construct showing its ability to stimulate the right immunological compartment for effective response. Overall, these results revealed that with each vaccination schedule there was a steady and concomitant increase in immune responses over time.

Fig 12. Distribution of B lymphocytes and their isotypes. (a) Antigen and immunoglobulins. Antibodies are sub-divided per isotype. (b) B lymphocytes: total count, memory cells, and sub-divided in isotypes IgM, IgG1 and IgG. (c) B lymphocytes population per entity-state (i.e., showing counts for active, presenting on class-II, internalized the Ag, duplicating and anergic. (d) Plasma B lymphocytes (PLB) count sub-divided per isotype (IgM, IgG1 and IgG2).

Fig 13. (a) CD4+ T-helper lymphocytes count. The plot shows total and memory counts. (b) CD4+ T-helper lymphocytes count sub-divided per entity-state (i.e., active, resting, anergic and duplicating). (c) CD4+ T-regulatory lymphocytes count. Both total, memory and per entity-state counts are plotted here. (d) CD8+ T-cytotoxic lymphocytes count. Total and memory shown

Fig 14. (a). CD8+ T-cytotoxic lymphocytes count per entity-state. (b) Natural Killer cells (total count). (c) Dendritic cells. DC can present antigenic peptides on both MHC class-I and class-II molecules. The curves show the total number broken down to active, resting, internalized and presenting the ag. (d) Macrophages. Total count, internalized, presenting on MHC class-II, active and resting macrophages.

Fig 15. (a) Epithelial cells. Total count broken down to active, antigen-infected and presenting on class-I MHC molecule. (b) Cytokines. Concentration of cytokines and interleukins. D in the inset plot is danger signal together with leukocyte growth factor IL-2.

3.13. Codon adaptation and *in-silico* plasmid cloning

The length of the optimized vaccine codon sequence was 1,386 nucleotides. The original GC-

Content submitted protein was 40.892862223204. The GC content of the improved sequence on

the Java codon optimization tool (JCAT) became 70.77922077922078 % which is highly effective

for translational efficiency. The calculated codon adaptive index was 0.955790963248539. The

NEBcutter Verstion 3.0.17 server software (https://nc3.neb.com/NEBcutter/) was used to map out

the restriction enzymes on the JCAT codon optimized sequence of the MEV construct. The DNA

sequence coding proteins for the MEV was inserted between HindIII and BamHI in the multiple

cloning site (MCS). In-silico cloning was done using the SnapGene software. The estimated length

of the Plasmid-MEV clone was 6844 bp (Fig. 16).

Fig 16. In-silico cloning of the final MEV in pcDNA3.1_CT-GFP expression vector. The red

part indicate the coding gene for the multi-epitope vaccine. The black part indicates the plasmid

vector backbone. The pDNA size is 6844 bp.

4. Discussion

OMPs roles in antibiotic resistance, as control centers of the cell for access of exogenous

information, and potential applications as biosensors makes them advantageous as vaccine

candidates. The design of computational chimeric membrane proteins seeks to harness the power

of these gateways and signaling networks expressed by OMPs [62]. This study combined the

immunogenicity of OMPs and *fliC* in the design of a novel MEV.

A total of 29 epitopes were predicted to be capable of eliciting both cellular and humoral immune

responses via the activation of T-cell and B-cell responses. 15 CTL epitopes were predicted across

the three classes of OMPs using stipulated thresholds in this study. Epitope "IEYAITPEI" was

found to be replicated in OmpA MHC class I and MHC class II epitopes and also in OmpC MHC

I epitopes. All epitopes were highly conserved at with a minimum and maximum conservancy

identity at 100 % (Table 4), ensuring the vaccine is efficacious against the diverse bacterial

variants. All the CTL peptide epitopes also showed highly exposed residue, therefore capable of

triggering an adequate cytotoxic response. Generally CD8+ T-cell recognizes the antigen of a

pathogen after its attachment with the MHC I molecules, therefore triggering a cytotoxic response

against the pathogen [63]. All selected epitopes were non-toxic and non-allergic therefore

decreasing the tendency for our vaccine candidates eliciting a type II hypersensitivity reaction and

cellular apoptosis via toxigenic reactions. Eight (8) HTL epitopes were also predicted across the

three classes of OMPs using stipulated thresholds and immunogenicity scores. They were further

subjected to IFN-γ induction capacity, as the release of IFN-γ by the CD4+ helper T-cell population

contributes to necessary effector cell activation and the generation of antibody mediated responses

to infections [64]. IFN-γ has a critical role in recognizing and eliminating pathogens. It is a central

effector of cell mediated immunity and also coordinates a plethora of anti-microbial functions and

critical in mediating intestinal immunity to *Salmonella* spp. [64, 65]. The findings of this study

predicted that two HTL epitopes, "LAPDRRVEI" and "IEYAITPEI" could induce IFN-γ

production (Table 6). This finding is satisfactory as IFN-γ is basically expected to initiate a

signaling cascades of receptor-ligand interactions (i.e. other cytokines and pattern recognition

receptors (PRRs) such as interleukin-4 (IL-4), TNF-α, and lipopolysaccharides [64, 66]. More so,

over-activity of IFN-γ has been reported to cause excessive tissue damage, necrosis and

inflammation and may contribute to disease pathology [64].

Seven linear B-cells epitopes were predicted. Their corresponding position, length,

sequence and antigenicity can be seen in Table 5. These Seven antigenic B-cell epitopes in this

study were selected based on artificial neural network (ANN), and the Kolaskar and Tongaonkar

antigenicity scale method of the IEDB server. The Kolaskar and Tongaonkar antigenicity scale

method predicts with a 75 % accuracy the antigenic determinants of a protein than other known

methods. The linear B-cell epitopes predicted had a non-toxic attribute and were non-allergenic

making them an ideal vaccine candidate. The B-cell epitope prediction results signifies that the

hydrophobic residues, such as cysteine, leucine, and valine, on the surface of proteins tend to have

antigenic characteristics [67].

When designing a vaccine, consideration is given to the population coverage capacities of

the MHC class I and MHC class II T cell epitopes predicted. The presence of over a thousand

human MHC allele across the world is a significant factor that must be considered, as only those

who possess a particular MHC allele recognizing the epitope in our vaccine construct will launch

an immunological response upon vaccination [68, 69]. The global population coverage of our

vaccine was 94.91 % which signifies that over 94 % of the world population will be conferred

protection if immunized with a vaccine preparation containing the listed CD8+ and CD4+ T cell

epitope of our protein chimera. Europe had the highest population cover at 97.52 % (Fig 1) and

will have a significantly higher protection from our vaccine chimera than any other region in the

World. *Salmonella* Kentucky *ST198* was first identified in Egypt and now widespread in Africa

[3, 70, 71, 72], we were particularly interested in seeing how our vaccine coverage performed with

respect to the different regions in Africa. The coverage of the vaccine on the African content was

significantly plausible at 85.14 % across all regions, the CD8+ T cell epitope had a significantly

higher coverage than its CD4+ T cell counterpart (Table 7). The vaccine coverage in North Africa

was astronomically higher than all other region standing at 92.89 % class combined average. At

52.24 % the CD4+ T cell coverage in North Africa was almost twice the population cover for the

other region by the same class of T-cell (Table 7). The variations exhibited in these regions may

be attributed to the ethnicity and race as seen from the dataset. There is a mixed race of Arabs,

Caucasoid, Black, and the Tunisia Berber having a combined similarity in alleles to Europe and

Africa combined than to the rest of the Black African regions when compared. In a recent study,

variations seen in population coverage was attributed to the IEDB server population coverage tool

having less deposition of alleles from continents like Africa and Asia as compared to the Europe

and America [59], and this may also be responsible for the variation seen in our study.

630   The MEV was constructed using the predicted T-cell epitopes, B-cell epitopes and *fliC*

protein and linked using AAY, GPGPG and EAAK protein linkers (Fig 2 and Fig 4). Linkers play

an important role in maintaining immunogenicity and properties of proteins in a MEV chimera. A

MEV without linkers may result in a new protein with unknown properties or may result in the

formation of neo-epitopes and or junctional epitopes [73, 74]. Also, from an immunological

standpoint, protein fusions are attractive since each antigen of the fusion takes advantage of the

additional T-cell help provided by the T-cell epitopes of the partner thus; resulting in an enhanced

antigen-specific immunogenicity and antibody titers [75]. The physicochemical properties of the

MEV construct revealed a highly antigenic, non-allergenic and non-toxic chimera. The molecular

weight was 47.343 kD with a theoretical PI of 9.150. Theoretically the molecular weight of a

peptide used in MEV should be less than 110 kD [76, 77], and the theoretical PI score indicates

that our MEV chimera is basic in nature. The MEV was predicted to be thermo stable, soluble

(Hydrophilic) and composed of more random coils (69.91 %) from the protein secondary structure

(Fig 3). The high proportion of random coils in the MEV only affirms that the protein is likely to

have an efficient antigenic potential [77, 78]. It could also represent the natural antigenicity of

native unfolded alpha- helices secondary structure [18]. The Ramachandran plot result showed

that the overall 3D model of the MEV is adequate as more than 95 % of residues were located in

the allowed region (Fig 5). ERRAT verification also corroborated the stereo-chemical accuracy of

the MEV 3D structure.

Evaluation of protein-protein interactions showed that the least energy values of all our

docked complex shows a stable TLR-MEV interactions (Table 9). Molecular simulation analysis

also indicated a less chance of deformation of the complexes during immune response activity

based on their maximum eigenvalues (Fig 8 to Fig 11) [54]. In order to predict the likelihood of

these complexes been formed, the Gibbs free energy (ΔG) was quantified. In thermodynamics

terms, Gibbs free energy (ΔG), or binding affinity of a complex is a quantitative analysis for the

determination of actual interaction in a cell at specific conditions [79]. The results of this study

revealed that all of the TLR-MEV docked complexes were energetically feasible, as indicated by

the negative values of Gibbs free energy (ΔG) and the multiple intermolecular contacts (Table 10).

This confirms that our MEV possess the capacity to induce, bind and sustain adequate

immunological interactions.

The C-ImmSim server was employed to predict the stimulated immune response against

our MEV. These simulations predictions provide results that match those observed in real-life

immunological response [18]. The administration and repetitive exposure of the MEV elicited

adequate B-cell isotypes and B-cell Memory cells. These cells were produced and sustained over

extensive number of days (Fig 12a). B-cell lymphocytes and its isotype functions in antibody

production and generation of protective immunity [80]. Adequate CD4+ Th cells and CD8+ T-

cells were also elicited following the administration of MEV. These T-cells classes elicited by our

MEV are a critical component of adaptive immunity in *Salmonella* infection, and a robust T-cell

response is required for both clearance of primary infection and resistance to subsequent challenge

(Cummings *et al*., 2009). Because *Salmonella* is known to reside within intra-macrophage

phagosomes, recent studies have highlighted a collaboration of CD4+ helper cells, and B-cell

responses in mediating resistance to *Salmonella* infection [81], as exhibited by our MEV

stimulations. Similarly there was a concomitant production of NK cells, dendritic cells and

macrophages following the first dose of the MEV. Cytokines, IFN-γ, TGF-b, IL-2, IL-10 and IL-

12 were significantly elicited and sustained (Fig. 15b). The overall activity of our MEV following

immune simulation can imply that our choice of epitopes significantly stimulated the required

immunological responses necessary for the protection and the clearance of *Salmonella* following

infection. In mammalian expression systems, the codon optimization strategy consists of

increasing the proportion of preferred mammalian codons in target genes. The noticeable high GC

content of 70.78 % of the improved MEV protein sequence and the CAI score of over 0.95 signifies

a likely effective expression of our target genes in humans as codon usage in human are larger than

most other non-mammalian species reaching more than 95 % GC3 content. Interestingly, GC-rich

genes are also well expressed several-fold to over a 100-fold more efficiently than GC-poor

counterparts [82].

5. Conclusion

Based on the results from this study, the following conclusions were drawn; the selected MHC

class I and MHC class II epitopes were antigenic, non-allergenic, and non-toxigenic and will

provide 94.91 % population coverage when used in a MEV construction. Epitopes "LAPDRRVEI"

and "IEYAITPEI" are IFN-γ inducing epitopes, and all epitopes selected for the MEV were 100

% conserved. The MEV protein construct was made up of 16.67 %, alpha-helices, 8.87 % extended

beta strands, 4.55 % beta turns, and 69.91 % random coils. The MEV was also Soluble,

thermostable, basic in nature, with a molecular weight of 47.343kd. Molecular dynamic simulation

of docked complexes of the MEV and TLRs indicated that the formation of these complexes were

energetically feasible, they possessed a high binding affinity with eigenvalues indicating a lesser

chance of deformation during immunological activity, and finally, the MEV induced adequate IgM

and IgG responses and their isotypes, CD4+ and CD8+ T-cells, NK cells, dendritic cells,

macrophages and cytokines including; IFN-γ, TGF-b, IL-2, IL-10 and IL-12. The result from this

in silico studies although commendable should be subjected to an *in-vitro*, pre-clinical and clinical

validation.

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