

T-Cell Epitopes of the La/SSB Autoantigen: Prediction Based on the Homology Modeling of HLA-DQ2/DQ7 with the Insulin-B Peptide/HLA-DQ8 Complex

AGGELIKI KOSMOPOULOU,¹ METAXIA VLASSI,² ATHANASSIOS STAVRAKOUDIS,^{1,3}
CONSTANTINOS SAKARELLOS,¹ MARIA SAKARELLOS-DAITSIOTIS¹

¹Laboratory of Peptide Chemistry, Department of Chemistry, University of Ioannina,
Ioannina 44110, Greece

²Institute of Biology, National Center for Research "Demokritos," P.O. Box 60228,
Agia Paraskevi 15310, Greece

³Department of Economics, University of Ioannina, Ioannina 44110, Greece

Received 1 June 2005; Accepted 28 January 2006

DOI 10.1002/jcc.20422

Published online in Wiley InterScience (www.interscience.wiley.com).

Abstract: T-cell epitopes are important components of the inappropriate response of the immune system to self-proteins in autoimmune diseases. In this study, the candidate T-cell epitopes of the La/SSB autoantigen, the main target of the autoimmune response in patients with Sjogren's Syndrome (SS), and Systemic Lupus Erythematosus (SLE) were predicted using as a template the HLA-DQ2 and DQ7 molecules, which are genetically linked to patients with SS and SLE. Modeling of DQ2 and DQ7 was based on the crystal structure of HLA-DQ8, an HLA molecule of high risk factor of type I diabetes, which is also an autoimmune disease. The quality and reliability of the modeled DQ2 and DQ7 was confirmed by the Ramachandran plot and the TINKER molecular modeling software. Common and/or similar candidate T-cell epitopes, obtained by comparing three different approaches the Taylor's sequence pattern, the TEPITOPE quantitative matrices, and the MULTIPRED artificial neural network, were subjected to homology modeling with the crystal structure of the insulin-B peptide complexed with HLA-DQ8, and the best superposed candidate epitopes were placed into the modeled HLA-DQ2 and DQ7 binding grooves to perform energy minimization calculations. Six T-cell epitopes were predicted for HLA-DQ7 and nine for HLA-DQ2 covering parts of the amino-terminal and the central regions of the La/SSB autoantigen. Residues corresponding to the P1, P4, and P9 pockets of the HLA-DQ2 and DQ7 binding grooves experience very low SASA because they are less exposed to the microenvironment of the groove. The proposed T-cell epitopes complexed with HLA-DQ2/DQ7 were further evaluated for their binding efficiency according to their potential interaction energy, binding affinity, and IC₅₀ values. Our approach constitutes the ground work for a rapid and reliable experimentation concerning the T-cell epitope mapping of autoantigens, and could lead to the development of T-cell inhibitors as immunotherapeutics in autoimmune diseases.

© 2006 Wiley Periodicals, Inc. J Comput Chem 27: 1033–1044, 2006

Key words: prediction of T-cell epitopes; La/SSB autoantigen; modeling of HLA-DQ2 and HLA-DQ7 molecules; Sjogren's Syndrome (SS); Systemic Lupus Erythematosus (SLE)

Introduction

T cells play a crucial role in specific immune responses against diseases such as infectious diseases, cancer, allergies, and autoimmune diseases. Identification of T-cell epitopes is an important step in the design of vaccines and in developing immunotherapeutic drug-like inhibitors of T-cell epitopes against the inappropriate response of the immune system to self-antigens. However, T cells recognize antigen only after it is processed and presented on the antigen presenting cells (APCs) in association with histocompati-

bility glycoproteins. This process involves major histocompatibility complex (MHC) molecules, which first bind short peptides and then display them to the T cell-specific receptors resulting in the initiation of the immune response.^{1–4}

Correspondence to: A. Stavrakoudis; e-mail: astavrak@cc.uoi.gr

Contract/grant sponsor: Greek General Secretariat for Research and Technology (PENED 2001)

The ability of the immune system to respond to a particular antigen varies between individuals according to their different pattern of MHC genes, which shows a remarkable polymorphism with a great number of variants of HLA class I and II molecules that have been characterized and named to date.⁵ Peptide binding to the peptide-binding groove of MHC is effected by a network of hydrogen bonds between the peptide backbone and the binding groove, and through interactions of peptide side chains, anchors, and pockets of the MHC cavity. By contrast to the class I MHC binding groove, which has closed ends restricting the lengths of bound peptides to 8–11 amino acids, class II MHCs have open ends, and thus present peptides as long as 30 amino acids, although the binding core of the peptide bound within the groove is only nine amino residues. Although peptide binding to MHC is a prerequisite for T-cell recognition, it is not sufficient by itself, as it also depends on the interaction of the displayed peptide with the T-cell receptor^{3,6–8} (TCR).

However, several approaches have traditionally been used for HLA-based epitope prediction.^{9,10} For example, the sequence similarity between a known MHC-binding peptide and known T-cell epitopes or the binding motifs that describe amino acids commonly occurring at particular positions within peptides that bind to a specific MHC molecule.^{11–13} Sequence similarity and binding motifs are simple to implement and easy to understand, but they are of relatively modest accuracy.^{9,10}

Quantitative matrices provide coefficients for each amino acid and each position within the peptide, and the method is based on the assumption that (1) each position within the peptide contributes independently to binding to an MHC, and (2) a residue located at a given peptide position contributes an equal amount to binding, even within different peptides. The quantitative matrix method represents an extension of binding motifs, is an accurate prediction method although the independent contribution-to-binding assumption ignores the contribution of the overall peptide structure to binding.^{14,15}

Artificial neural networks (ANNs) are based on models that can capture complex relationships in the data sets and are not based on assumptions such as quantitative matrices. ANNs are adaptive and can self-improve; they generalize well, and are effective with nonlinear problems. ANNs are accurate predictors, and they require larger amounts of binding data than simpler prediction methods.^{16,17}

Although beneficial in the case of pathogens, MHC molecules are also thought to play a crucial role in the development of autoimmune diseases, as many of them are found more frequently in individuals expressing particular MHC molecules. Well-known examples are rheumatoid arthritis, type I diabetes, celiac disease, and ankylosing spondylitis.^{18–21} In particular, autoimmune rheumatic diseases as Sjogren's Syndrome (SS) and Systemic Lupus Erythematosus (SLE) are genetically linked to DQ2 (HLA-DQA1*0501/DQB1*0201) and DQ7 (HLA-DQA1*0501/DQB1*0301).^{22–24} Several lines of evidence indicate also that DQ8 is a major risk factor for increased susceptibility to type I diabetes,^{25,26} which is also an autoimmune disease.

The $\alpha_1\beta_1$ domain of the DQ molecules exhibit the basic fold of histocompatibility molecules, that is, a “floor” of eight β -pleated sheets bound on two sides by two antiparallel α -helices.^{6,8} There is a 55–60% identity in amino acid positions in the $\alpha_1\beta_1$ domain

of any DQ molecule, and 75% identity in the same domain within the various DQ molecules.²⁷ Despite the polymorphism in both α - and β -chains of DQ alleles, all of the invariant residues deemed crucial for forming hydrogen bonds to the foreign peptide backbone in the case of DR1 are found in the same positions in DQ.^{3,28} Furthermore, the antigen-binding groove of the DQ molecules fulfills the “pocket” motif of this region for the class II MHC molecules. All the depression in the antigen-binding groove may not belong to pockets, so the number of pockets and the residues constituting each pocket may slightly vary depending on the nature of the antigenic peptide bound.^{3,8}

The aim of our study is to predict with accuracy the T-cell epitope candidates of the La/SSB autoantigen, the main target of the autoimmune response in patients with SS and SLE,^{29,30} in regard to the HLA-DQ2 and DQ7 molecules. It deserves to be mentioned that the chemical structures of the $\alpha 1$ and $\beta 1$ chains of DQ2 and DQ7 experience a great similarity with DQ8. HLA-DQ2/DQ7 were modeled on the basis of the crystal structure of HLA-DQ8,³¹ and their compatibility was verified by the Procheck suite of programs,³² the “O” program³³ and the TINKER molecular modeling software.³⁴ A general sequence pattern common to HLA-based T-cell epitopes, determined by examining the residues, which make up epitopes as members of characteristic sets based on their physical properties, was applied (Taylor) to assess epitopes of the La/SSB autoantigen.¹¹ The TEPITOPE^{10,35,36} program that uses structural data from MHC–peptide complexes and incorporates multiple quantitative matrices, was next employed to predict the potential of the La/SSB epitopes to bind DQ7 and DQ2. A new Web-based computational system, MULTIPRED,³⁷ using ANN, was also applied to predict the DQ2 and DQ7 binding peptides of La/SSB. Common and/or similar T-cell epitopes, displayed by comparing Taylor with TEPITOPE and MULTIPRED, were superposed to the insulin-B peptide epitope. The best aligned epitopes were placed into the binding groove of the modeled DQ2 and DQ7 to perform energy minimization studies. Consistent with the obtained candidate T-cell epitopes of the La/SSB autoantigen for the DQ2 and DQ7 molecules are our findings concerning the solvent-accessible surface area (SASA) of the epitopes complexed to the HLA molecules using GETAREA program.³⁸

To further confirm our findings, the potential interaction energy, ΔE_{int} , of the MHC–epitope complexes was estimated, using the TINKER software,³⁴ to acquire a relative energy scale that reflects the degree of the preferred interactions. On the other hand, taking in consideration that only peptides that bind to MHC with affinity above a threshold function as T-cell epitopes, a quantitative prediction of the MHC–epitope binding affinities was also performed, using MHCpred, to obtain the IC_{50} values that are inversely proportional to the binding affinities.^{39–41}

Computational Methods

Sequence similarity of HLA-DQ2 and HLA-DQ7 with HLA-DQ8

The sequence similarity of the HLA-DQ2 and DQ7 molecules with HLA-DQ8 was performed using the Basic Local Alignment Search Tool (BLAST) (www.ncbi.nlm.nih.gov/BLAST/).⁴² The

HLA-DQ8 (PDB code:1JK8) sequence was obtained from the PDB database.⁴³

Homology Modeling of HLA-DQ2 and HLA-DQ7 with the Crystal Structure of the HLA-DQ8

The initial models of DQ2 and DQ7 were obtained using the Swiss-PdbViewer program,⁴⁴ which allows the user to analyze several proteins at the same time and is tightly linked to Swiss-Model,⁴⁵ an automated homology modeling server. Using these two programs, it was possible to thread the DQ2 and DQ7 primary sequences onto the DQ8 3D template and get an immediate feedback of how well the threaded proteins would be accepted by the reference structure before submitting a request to build missing loops and refine side chain packing.

Evaluation of the Homology Model

The Procheck suite of programs³² was used for assessing the stereochemical quality of the modeled HLA-DQ2 and HLA-DQ7 structures at resolution 2 Å. Finally, the compatibility of the modeled molecules was determined using the "O" program.³³ The TINKER molecular modeling software³⁴ was used to superimpose the two molecular structures (DQ8/DQ2 and DQ8/DQ7) in 3D. The superimposition was unit-weighted and the coordinates of the second structure were superimposed on the first structure. Energy minimizations were carried out using the CHARMM27 potential energy function^{46,47} with the GB/SA continuum model for solvation.^{48,49} The dielectric constant was set 1.0. The minimize procedure was performed with a limited memory L-BFGS minimization algorithm. The final RMS gradient was less than 0.01 kcal mol⁻¹ Å⁻¹ for all the minimized structures. VDW- and CHG-cutoffs were set 12 and 15 Å, respectively. The homology modeling procedure was performed on a Silicon Graphics (INDIGO2) workstation. TINKER calculations, superimpositions and energy minimizations, were performed on Linux machine with Dual processor running Mandrake 10.0.

T-Cell Epitope Prediction

The sequence pattern approach (Taylor)³⁵ was applied to detect the potential candidate T-cell epitopes of the La/SSB autoantigen. The La/SSB sequence was provided in FASTA format from Swiss-Prot database (www.expasy.ch), and it was scanned using the PATTIN-PROT program for detecting the characteristic sequence patterns. The similarity level of the detected patterns during the scanning was 100%.

The TEPITOPE program,^{10,35,36} a quantitative matrix method, was used to predict potential candidate T-cell epitopes in the La/SSB sequence. La/SSB sequence (408aa) was loaded into the TEPITOPE sequence editor and the prediction conditions such as HLA-DR alleles (25 HLA-II virtual matrices) and the % threshold value were selected and modified from the default setting. Fourteen HLA-DR alleles were selected (DRB1*0101, DRB1*0102, DRB1*0301, DRB1*0401, DRB1*0402, DRB1*0701, DRB1*0801, DRB1*0802, DRB1*1101, DRB1*1104, DRB1*1305, DRB1*1501, DRB1*1502, DRB5*0101), and the TEPITOPE prediction threshold was set at 4%.

The MULTIPRED computational system³⁷ was also used to predict the candidate T-cell epitopes of the La/SSB autoantigen. The artificial neural networks (ANNs) were selected as the prediction method for class II DR supertype. HLA class II DR hotspots were predicted by ANN method at threshold 20 for average value. MULTIPRED is available at <http://antigen.i2r.a-star.edu.sg/multipred/>.

Prediction of the SASA of the Proposed Epitopes within the HLA -DQ2 and HLA-DQ7 Molecules

GETAREA Web service³⁸ was used for the calculation of the SASA of the proposed epitopes of the La/SSB autoantigen. The Cartesian coordinates of the atoms of the proposed candidate epitopes, complexed with DQ2 and DQ7 models, were stored in PDB format and the radius of the water probe was set 1.4 Å.

Prediction of the Epitope Binding Affinity to HLA-DQ2 and HLA-DQ7

MHCPred was used for the quantitative prediction of the peptide-HLA-DQ2/DQ7 binding affinity. MHCPred is composed of a variety of widely distributed human allele specific Quantitative Structure Activity Relationship (QSAR) models built using partial least squares (PLS). In this study the DRB0101 HLA allele was used, which has the highest sequence similarity with the DQ2 and DQ7 molecules. The binding affinity prediction was based on the contributions of the amino acids and their interactions, within the 9-mer core, of the proposed epitopes that correspond to P1, P4, and P9 binding pockets of DQ2 and DQ7. IC₅₀ values of insulin-B peptide and the predicted epitopes were calculated to measure their binding affinity to the corresponding HLA-DQ molecules. MHCPred is available from the URL: <http://www.jenner.ac.uk/MHCPred>.

Results and Discussion

HLA-DQ2 and HLA-DQ7 Homology Modeling with the Crystal Structure of HLA-DQ8

The homology modeling of the HLA-DQ2 and DQ7 molecules was based on the crystal structure of the HLA-DQ8 molecule. It was found that HLA-DQ2 experiences high-sequence similarity with HLA-DQ8: 91% identity for chain β (DQB1*0201) and 90% identity for chain α (DQA1*0501). Furthermore, HLA-DQ7 is almost identical with HLA-DQ8: 96% identity for chain β (DQB1*0301) and 90% identity for chain α (DQA1*0501). In these conditions, a homology modeling strategy can be applied with very good results, because the alignment between the new sequence and the reference model⁵⁰ can be obtained with few or no gaps (Fig. 1).

The initial models of DQ2 and DQ7 were obtained using the Swiss-PdbViewer program. DQ2 and DQ7 were superposed with DQ8 molecule to get the homology modeling requested, deduce the structural alignments, and compare their active sites or any other relevant parts. Amino acid mutations, H-bonds, angles, and distances between atoms were obtained thanks to the intuitive

A

α-chain	DQ7	VADHVASYGVNLYQSYGPSGQY T HEFDGDEQFYVDLGRKETVW C LP FELRQ FRGFDPQFAL	63
α-chain	DQ2	VADHVASYGVNLYQSYGPSGQY T HEFDGDEQFYVDLGRKETVW C LP FELRQ FRGFDPQFAL	63
α-chain	DQ8	VADHVASYGVNLYQSYGPSGQY S HEFDGDEEFYVDL R ERKETVW Q LP LFRFR FRGFDPQFAL	60
α-chain	DQ7	TNIAVLKHNLN S LIKRSNSTAATNEVPEVTVFSKSPVTLGQPNTLCLVDNIFPPVNNIT	123
α-chain	DQ2	TNIAVLKHNLN S LIKRSNSTAATNEVPEVTVFSKSPVTLGQPNTLCLVDNIFPPVNNIT	123
α-chain	DQ8	TNIAVLKHNLN I VIKRSNSTAATNEVPEVTVFSKSPVTLGQPNTLCLVDNIFPPVNNIT	120
α-chain	DQ7	WLTNGHSVTEGVSET T FLSKSDHSFFKI SYLTL L PS A EESYDCKVEHWGLD K PLLKHWEP	183
α-chain	DQ2	WLTNGHSVTEGVSET T FLSKSDHSFFKI SYLTL L PS A EESYDCKVEHWGLD K PLLKHWEP	183
α-chain	DQ8	WLSNGHSVTEGVSET S FLSKSDHSFFKI SYLTL F LPS D DEI I YDCKVEHWGLD E PLLKHWEP	180
α-chain	DQ7	E	184
α-chain	DQ2	E	184
α-chain	DQ8	E	181

B

β-chain	DQ2	SPEDFVYQFKGMCYFTNGTERVRL V SRSIYNREE I VRFDSDV G EFRAVTL L GLPAAEYWN	62
β-chain	DQ8	SPEDFVYQFKGMCYFTNGTERVRL V TRYIYNREE Y ARFDSV G VYRAVTL P LPAAEYWN	60
β-chain	DQ2	SQ K D I L E R K R A A V D R VCRHNYQLELR T LQRRVEPTVTISPSRTEALNHHNLLVCSVTDF	122
β-chain	DQ8	SQ K E V L E R T R A E L D T VCRHNYQLELR T LQRRVEPTVTISPSRTEALNHHNLLVCSVTDF	120
β-chain	DQ2	YPAQIKVRWFRNDQEE T AGVVSTPLIRNGDWT F QILVMLEMTP Q RGDVYTCHVEHPSL Q S	182
β-chain	DQ8	YPAQIKVRWFRNDQEE T AGVVSTPLIRNGDWT F QILVMLEMTP Q RGDVYTCHVEHPSL Q N	180
β-chain	DQ2	P I T V E W R A Q S	192
β-chain	DQ8	P I I V E W R A Q S	190

C

β-chain	DQ7	SPEDFVYQFK A MCYFTNGTERV R YVTRYIYNREEYARFDS D VEVYRAVTL P LP D AAEYWN	62
β-chain	DQ8	SPEDFVYQFK G MCYFTNGTERV L VTRYIYNREEYARFDS D VYRAVTL P LP A AAEYWN	60
β-chain	DQ7	SQ K E V L E R T R A E L D T VCRHNYQLELR T LQRRVEPTVTISPSRTEALNHHNLLVCSVTDF	122
β-chain	DQ8	SQ K E V L E R T R A E L D T VCRHNYQLELR T LQRRVEPTVTISPSRTEALNHHNLLVCSVTDF	120
β-chain	DQ7	YPAQIKVRWFRNDQEE T AGVVSTPLIRNGDWT F QILVMLEMTP Q HGDVYTCHVEHPSL Q N	182
β-chain	DQ8	YPAQIKVRWFRNDQEE T AGVVSTPLIRNGDWT F QILVMLEMTP Q RGDVYTCHVEHPSL Q N	180
β-chain	DQ7	P I T V E W R A Q S	192
β-chain	DQ8	P I I V E W R A Q S	190

Figure 1. Comparison of the α-chain of DQ2 and DQ7 (α-chain of DQ2 and DQ7 share 100% identity) with DQ8 (A), and the β-chain of DQ with DQ8 (B) and the β-chain of DQ7 with DQ8 (C). Different amino acids between α- and β-chains are shown in bold. Amino acids are in one-letter code.

graphic and menu interface. Automatic energy minimization was in place after every superposition of the two molecules (DQ8 with DQ2 and DQ8 with DQ7) to regularize deviations in the protein structure geometry.

The Procheck suite of programs was used for assessing the stereochemical quality of the modeled HLA-DQ2 and HLA-DQ7 structures and the compatibility of the modeled molecules was checked using the “O” program. The quality of the models is similar to the quality expected for structures determined at 2 Å. In the Ramachandran plot most of the residues were found in preferred regions (DQ8: 98.1%, DQ2: 97.8% and DQ7: 98.1% residues), and only a small percentage in disallowed region, which is also observed in the equivalent residues of the template used for the modeling. The RMSD was calculated to 0.034 and 0.033 for DQ8/DQ2 and DQ8/DQ7, respectively, taking in consideration the C^α atoms (Fig. 2).

T-Cell Epitope Prediction using Taylor's (1988) Sequence Pattern

The analysis of known MHC-binding peptides as cytotoxic and helper T-cell epitopes revealed a common pattern in their primary structure: C-H-H-C, G-H-H-C, G-H-H-P, P-H-H-P, C-H-H-P, C-H-H-H-C, P-H-H-C, C-H-P-C, G-P-H-H-P, G-P-H-P, C-H-P-P, C-H-P-H-P, C-P-H-C (C: charged residues, H: hydrophobic residues, P: polar residues and G: glycine). To detect potential candidate T-cell epitopes, the occurrence of these patterns in the primary structure of the La/SSB autoantigen (408 aa) was investigated. Because the minimum size of T-cell epitopes is 9–12 amino acids, no pattern of four or five residues could be sufficient for recognition. Therefore, when a pattern of four amino acids was identified, six residues were added on either side. Similarly, when a five amino acid pattern was found, five residues were added on either side. Thirty-seven epitopes were selected according to the reported motifs (Table 1).

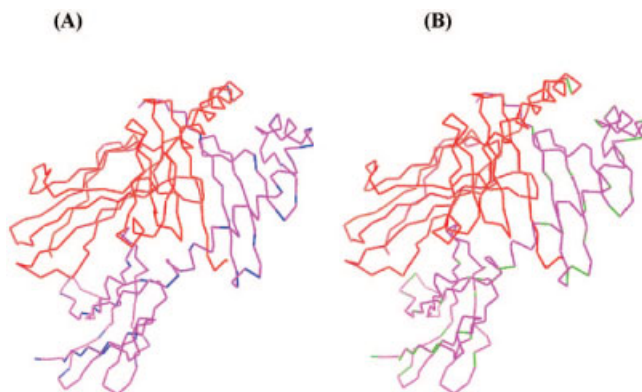


Figure 2. Superimposition of DQ7 onto DQ8 molecule (A) and DQ2 onto DQ8 molecule (B); α - and β -chains of DQ8 are shown in black; α - and β -chains of DQ7 and DQ2 are shown in grey. Structural differences derived from superimposition of DQ8/DQ7 and DQ8/DQ2 are indicated (figure was prepared with the Swiss-PdbViewer program⁴⁴).

T-Cell Epitope Prediction Using TEPITOPE Software

The TEPITOPE program uses HLA/peptide-binding data and structural data derived from the HLA/peptide complexes to predict potential candidate T-cell epitopes *in silico*. It assumes that the topography of a pocket is independent of neighbouring pockets, thus allowing the binding of similar residues to different HLA-II alleles. Extensive experimental work allowed the definition of the pocket profiles for 10 different polymorphic pockets that were combined to build >50 HLA-DR virtual matrices. The TEPITOPE software utilizes virtual matrix data in a linear prediction model, in which peptide conformation is entirely neglected.

The La/SSB sequence (408 aa) was loaded into the TEPITOPE sequence editor to predict promiscuous candidate T-cell epitopes. Fourteen HLA-DR alleles with the greatest sequence similarities to the corresponding HLA-DQ alleles were selected, and the TEPITOPE prediction threshold was set at 4%. This threshold predicts the 4% of the best-scoring peptides in La/SSB.

In a high stringent threshold (1%) less peptides are predicted for the HLA-DR alleles, while in a less stringent threshold as 4% more peptides are predicted.^{10,15,36,50} Usually, it is suggested that the stringency level ranges from 1 to 4% for the first scan. Peptides predicted to bind to the HLA-DR alleles are shown in Table 2.

Quantitative Analysis of the Predicted Epitopes

The quantitative analysis of selected sequences (any length >9 amino acids) indicates at which threshold levels the sequence would be predicted for each of the alleles included in the algorithm and provides the user with a better understanding of the promiscuity of the candidate epitope, which normally is not fully evident when performing the prediction with a single selected threshold. A quantitative analysis for all of the predicted candidate epitopes, given in Table 2, with a stringency “threshold” setting at 4% for all the HLA-II alleles was performed for La/SSB,^{10,15,51} and the predicted epitopes with the best promiscuity are shown in Table 3.

In Figure 3 are shown, as an example, the threshold levels in the form of bar histograms for the epitope IFVVFDSEISA (154–164) and PLEIMIKFNRLNRLTTD (48–64) presented in Table 3.

T-Cell Epitope Prediction Using MULTIPRED Computational System

MULTIPRED is a Web-based computational system for the prediction of peptides that bind multiple HLA alleles.³⁷ It uses hidden Markov models (HMMs) and artificial neural networks (ANNs) as predictive engines. A novel data representation method enables MULTIPRED to predict candidate T-cell epitopes that promiscuously bind multiple HLA class I and class II HLA-DR alleles.

Table 1. T-Cell Epitope Prediction of the La/SSB Autoantigen (Taylor, 1988).

Pattern	Potential candidate T-cell epitopes of La/SSB	Region of La/SSB
	FNLPRD KFL KEQIKLD	(28–43)
	LSKSKAEL ME ISEDKT	(72–87)
	MRRTLH KAFK GSIFVV	(142–157)
C—H—H—C	SIESAK KFV ETPGQKY	(160–175)
	GEIKWID FVR GAKEGI	(257–272)
	NKEVTWEL VE GEVEKE	(298–313)
	EGEVE KEAL KKIIEDQ	(307–322)
	EKEAL KKI IEDQQESL	(311–326)
G—H—H—C	DENGAT GPV KRAREET	(377–389)
G—H—H—P	RSVYIK GFP TATLDD	(111–126)
P—H—H—P	WLEDK GQV LNQMRR	(130–145)
	DFNVIVE ALS SKSAEL	(64–79)
C—H—H—P	GKGKGN KAA QPGSGKG	(338–353)
	FQGK TKF ASDDEHDE	(357–372)
	EETDK EEP ASKQQKTE	(387–402)
C—H—H—H—C	GWVPLE IMIK FNRLN	(45–59)
	RRSP SKPL EVTEDEY	(89–104)
	YF FGDF NLPRDKFLKE	(23–38)
P—H—H—C	ILFKD DYF AKKNEERK	(182–197)
	LEEKIG CLL KKFGDLD	(226–241)
	PLEIMIK FNRL NRLTT	(48–63)
C—H—P—C	IMIK FNRL NRLTTDFN	(51–66)
	SKAEL MEIS EDKTKIR	(75–90)
	PSK PLPE VTDEYKNDV	(93–108)
G—P—H—H—P	WLEDK GQV LNQMRR	(130–144)
G—P—H—P	AKDANN GNL QLRNKEV	(286–301)
	MAALE AKICH QIEYYF	(10–25)
C—H—P—P	KFNRL NRL TTDFNVIV	(54–69)
	ALGKAK DAN GNLQLR	(282–297)
	LQLRN KEV TWELVEGE	(294–309)
C—H—P—H—P	GSGK GKVQ FQGGKTK	(349–363)
	RD KFL KEQIKLDEGWV	(32–47)
	TLDDI KEW LEDKGVVL	(123–138)
C—P—H—C	SIFVV FDSE ISAKK FV	(153–168)
	VV FDSE ISAKK FV ETP	(156–171)
	EEDAEM KS LEEKIGCL	(218–233)
	SNHGEI KWID FVRGAK	(254–269)

Residues in bold correspond to the indicated pattern.

C: charged residues, **H:** hydrophobic residues, **P:** polar residues and **G:** glycine.

HLA-DR (class II) proteins bind peptides through the binding groove, which is nine amino acids long. The training data comprise 2396 9-mer peptides (448 binders and 1948 nonbinders) related to eight HLA-DR alleles (DRB1*0101, DRB1*0301, DRB1*0401, DRB1*0701, DRB1*0801, DRB1*1101, DRB1*1301, DRB1*1501), which are included in the selected HLA-DR alleles for the TEPITOPE prediction, with the greatest sequence similarities to

Table 2. T-Cell Epitope Prediction of the La/SSB Autoantigen (TEPITOPE) for the Selected Matrices in a Stringency Level at 4% Threshold.

HLA-II allele	Predicted T-cell epitopes of La/SSB
DRB1*0101	f nrlnrnt, I RRSPSKPL,- Y IKGFPTDA, I niqmrrtl FVVFDSES, L HILFSNHG, f vgakegi
DRB1*0102	M AAL E AKIC, i kfnrlnrnt, I RRSPSKPL lniqmrrtl, FVVFDSES,- L HILFSNHG
DRB1*0301	I KLDEGW V PLEIMIKFNR, Y KNDVKNRS LHKAFKGS I fvdiesia, L LILFKDDY IGCLLK F SG, I LFSNHGEI, F VRG A KEGI
DRB1*0401	Y FGDFNLPR, W VPLEIMIK, Inrlttdfnvivealsks irrspskpl, y kndvknrs, f ptdatldd, i qmrrtlhk FVVFDSES A , l hilfsnhg, f qgkktkfa
DRB1*0402	i mikfnrln, i vealsksk, i rrspskpl, V KNR S VYIK I QMRRTLHK, F VVFDSES, i lfkddyfa, l hilfsnhg
DRB1*0701	I rnkevtwe, l nkwskgr, F Q G K K T K F A ikfnrlnrl, I RRSPSKPL,- M RRTLHK A FKGS I FVVFDSES
DRB1*0801	f vetpgqkyketdllil, I LFSNHGEI,- F VRG A KEGI wvpleimik F NRLNRLTT, V KNR S vyikgfptd iqmrrtlhk, F VVFDSES,- V EAK L R A K Q ,- I LFKE K A K E LQLRNKEVTWE, W KSKGRR F KGKGKGNK, F Q G K K T K F A
DRB1*0802	wvpleimikfnrlnrltt, f nviveals y kndvknrsvyik, I QMRRTLHK,- F VVFDSES V EAK L R A K Q E Q E A , i lfkekake, l qlnkevtwe W KSKGRR F KGKGKGNK, F Q G K K T K F A
DRB1*1101	wvpleimikfnrlnrltt, f nviveals I QMRRTLHK, F VVFDSES, F Q G K K T K F A
DRB1*1104	W V P leimikfnrlnrltt, I QMRRTLHK FVVFDSES, V Q F Q G K K T K
DRB1*1305	W V P LEIMIM K FNRLNRLTT, f nviveals iqmrrtlhkaf, F VVFDSES
DRB1*1501	m ikfnrlnr L T T , I RRSPSKPL, i qmrrtlhk FVVFDSES, L ILFKDDY F , L HILFSNHG
DRB1*1502	m ikfnrlnr L T T , I RRSPSKPL, i qmrrtlhk FVVFDSES, L ILFKDDY F , L HILFSNHG
DRB5*0101	wvpleimikfnr, i vealsksk, I RRSPSKPL iqmrrtlhkaf, F VV f dsies a kk f vetpgqky L HILFSNHG, h lfkekak, w kskgrfkk, v qfqqkktk

The bold letter indicates the starting point of each PF (Peptide Frames) at position P1. Promiscuous candidate epitopes with a nonameric peptide frame and multiple overlapping frames are predicted. The sequences in lowercase indicate the presence of a residue in a PF with more than 10× inhibitory effect.

Table 3. Predicted T-Cell Epitopes of the La/SSB Autoantigen with the Best Promiscuity (TEPITOPE) after a Quantitative Analysis with a Stringency Threshold at 4%.

HLA-DR alleles	Predicted epitopes
DRB1*0101, DRB1*0102 DRB1*0301, DRB1*0401 DRB1*0402, DRB1*0701 DRB1*1501, DRB1*1502 DRB5*0101	DLHILFSNHGE (248–258)
DRB1*0101, DRB1*0102 DRB1*0301, DRB1*0401 DRB1*0402, DRB1*0701 DRB1*0801, DRB1*0802 DRB1*1101, DRB1*1104 DRB1*1305, DRB1*1501 DRB1*1502, DRB5*0101	MIKFNRLNRLTTD (52–64)
DRB1*0101, DRB1*0102 DRB1*0301, DRB1*0401 DRB1*0402, DRB1*0701 DRB1*0801, DRB1*0802 DRB1*1101, DRB1*1104 DRB1*1305, DRB1*1501 DRB1*1502, DRB5*0101	KFNRLNRLTTD (54–64)
DRB1*0301, DRB1*0401 DRB1*0801, DRB1*0802 DRB1*1101, DRB1*1104 DRB1*1305, DRB5*0101	PLEIMIKFNRLNRLTTD (48–64)
DRB1*0401, DRB1*0402 DRB1*0802, DRB1*1101 DRB1*1305, DRB5*0101	RLNRLTTDFNVIVEALS K S K (57–76)
DRB1*0301, DRB1*0801 DRB1*0802, DRB1*1101 DRB1*1104, DRB1*1305 DRB5*0101	EIMIKFNRLNR (50–60)
DRB1*0101, DRB1*0102 DRB1*0301, DRB1*0401 DRB1*0402, DRB1*0701 DRB1*0801, DRB1*0802 DRB1*1101, DRB1*1104 DRB1*1305, DRB1*1501 DRB1*1502, DRB5*0101	IFVVFDSES A (154–164)
DRB1*0101, DRB1*0102 DRB1*0401, DRB1*0402 DRB1*0701, DRB1*0801 DRB1*0802, DRB1*1101 DRB1*1104, DRB1*1305 DRB1*1501, DRB1*1502 DRB5*0101	NIQMRRTLHKA (139–149)
DRB1*0301, DRB1*0401 DRB1*0801, DRB1*0802 DRB1*1101, DRB1*1104 DRB1*1305, DRB5*0101 DRB1*0301, DRB1*0701	QIKLDEGW V PLEIMIK F NRL (39–58)
DRB1*0301, DRB1*0701	TLHKAFKGS I FVVFDSES A (145–164)

the corresponding HLA-DQ alleles except DRB1*1301. These data are mainly from the MHCPEP database,⁵² published articles, and a set of HLA nonbinding peptides.

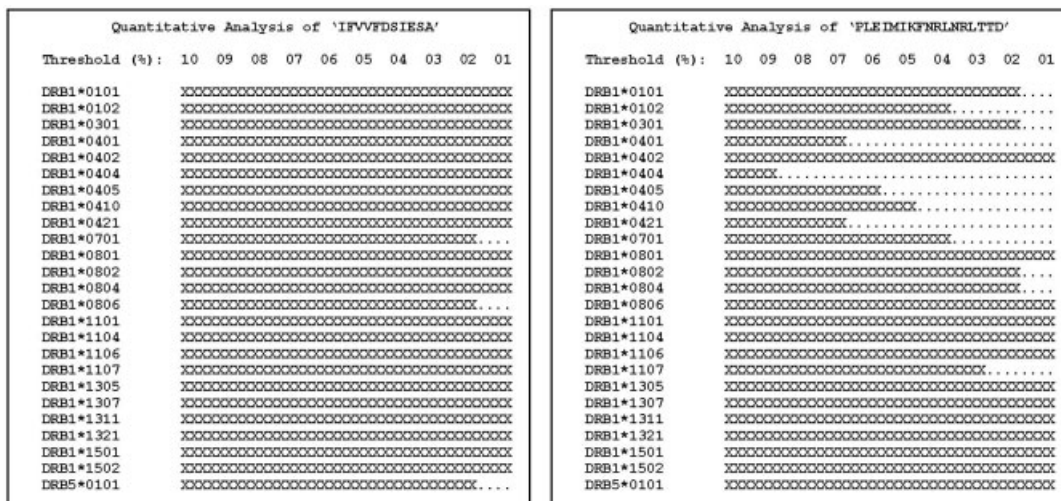


Figure 3. TEPITOPE'S quantitative analysis window. The "X" bars indicate the threshold levels at which the selected peptides were predicted for the HLA-II alleles.

To predict the candidate T-cell epitopes of La/SSB autoantigen (408 aa) the class II DR supertype and the ANN method were selected. The 9-mer binding scores range from 1 to 9, with scores 4–9 referring to predicted binders (8–9 high binders, 7–6 moderate binders, 5–4 low binders). Scores 1–3 refer to predicted non-binders. The first 20 predicted 9-mer peptides of La/SSB autoantigen, with the highest sum, indicating the total sum of the individual binding scores, in descending order of the binding scores to multiple HLA class II alleles were selected. Subsequently, the hotspots at threshold 20 for average value were obtained and the predicted hotspot regions of La/SSB autoantigen sorted by average are given in Table 4.

Comparison of the Candidate Epitopes Predicted by Taylor's Sequence Pattern Approach with the TEPITOPE Software and the MULTIPRED Computational System

T-cell epitopes, predicted by TEPITOPE and MULTIPRED, comprising common and/or similar patterns with Taylor's approach are indicated in Table 5. In this study, the sequence pattern method of Taylor, which is a binding motif approach, was used as starting point because it is simple to implement and easy to understand. Subsequently, TEPITOPE, a quantitative matrix method, which is an extension of binding motifs, was applied, and 20 candidate

T-cell epitopes incorporating Taylor's motifs were identified. Finally, by applying MULTIPRED, based on HMMs and ANNs, which are adaptive, can self-improve, generalize well, and are effective with nonlinear problems, nine candidate T-cell epitopes comprising, common, and/or similar motifs with Taylor and TEPITOPE approaches, were found. One may assume that common candidate T-cell epitopes deriving from the combined application of more than one prediction methods may proved more accurate and reliable.

Homology Modeling of the Potential Candidate Epitopes with the Insulin-B Peptide and Energy Minimization Calculations of the DQ2/DQ7 Epitope Complexes

The insulin-B peptide bound to DQ8 revealed three major contact points with DQ8, glutamic acid, tyrosine, and glutamic acid side chains (E, Y, E), within the polymorphic pockets designated **P1**, **P4**, and **P9**. The same pockets were observed in the modeled DQ2 and DQ7.³¹ T-cell epitopes predicted by Taylor's approach with common and/or similar patterns with TEPITOPE and MULTIPRED were superposed with the insulin-B peptide. A variety of combinations were performed to find the best superposed epitopes to the insulin-B peptide: *LVEALYLVCGERGG*. As an example, the SIFVVFDSIESAKKFV (153–168) candidate epitope of La/SSB,

Table 4. HLA Class II DR Predicted Hotspot Regions of the La/SSB Autoantigen (MULTIPRED) Sorted by Average.

Position	Sequences	Average	Length
45–67	GWVPLEIMIKFNRLNRLTTDFNV	26.75	23
134–169	KGQVLNIQMRRTLHKAFKGSIFVVFDSIESAKKFVE	23.86	36
18–37	CHQIEYYFGDFNLPRDKFLK	21.39	20
178–194	TDLLILFKDDYFAKKNE	20.73	17
102–127	DEYKNDVKNRSVYIKGFPTDATLDDI	20.43	26

Table 5. Comparison of the Candidate T-Cell Epitopes Identified by the Taylor's Sequence Pattern Approach, the TEPITOPE Program, and the MULTIPRED Computational System.

Taylor's approach	Tepitope	Multipred
MRRTLH KAFKGS SIFVV (142–157)	TLHK AFKGS IFVV FD SIESA (145–164)	KGQVLNIQMRRTLH KAFKGS IFVV FD SIES AKKFVE (134–169)
DFNVIVE ALSKS KAE L (64–79)	RLNRLTTDFNVIVE ALSKS K (57–76)	—
GWV PLEIMIKFN RLN (45–59)	PLEIMIKFN RLNRLTTD (48–64)	GWV PLEIMIKFN RLNRLTTDFNV (45–67)
PLE IMIKFN RLNRLTT (48–63)	QIKLDEGWV PLEIMIKFN RL (39–58)	GWV PLEIMIKFN RLNRLTTDFNV (45–67)
RRSPSK PLPE VTDEY (89–104)	KIRRS PKPLPE (87–97)	—
	KFN RLNRLTTD (54–64)	
PLE IMIKFN RLNRLTT (48–63)	MIKFN RLNRLTTD (52–64)	GWV PLEIMIKFN RLNRLTTDFNV (45–67)
	PLE IMIKFN RLNRLTTD (48–64)	
	QIKLDEGWV PLEIMIKFN RL (39–58)	
	KFN RLNRLTTD (54–64)	
	MIKFN RLNRLTTD (52–64)	GWV PLEIMIKFN RLNRLTTDFNV (45–67)
IMIKFNRLNRLTTDFN (51–66)	PLE IMIKFN RLNRLTTD (48–64)	
	QIKLDEGWV PLEIMIKFN RL (39–58)	
	KFN RLNRLTTD (54–64)	
KFNRLNRLTTDFNVIV (54–69)	MIKFN RLNRLTTD (52–64)	GWV PLEIMIKFN RLNRLTTDFNV (45–67)
	PLE IMIKFN RLNRLTTD (48–64)	
SIFVV FD SIES AKKFV (153–168)	IFVV FD SIESA (154–164)	KGQVLNIQMRRTLH KAFKGS IFVV FD SIES AKKFVE (134–169)
VV FD SIES AKKFVETP (156–171)	TLHK AFKGS IFVV FD SIESA (145–164)	KGQVLNIQMRRTLH KAFKGS IFVV FD SIES AKKFVE (134–169)
SNHGE IKWID FVRGAK (254–269)	DLHILFSNHGE IKWID F (248–265)	—

Common and/or similar sequence patterns are shown in bold.

obtained by the three prediction approaches, was superposed with the insulin-B peptide. The Swiss-Pdb Viewer program was used for the alignment of the two sequences and the eight possible candidate epitopes (Fig. 4), derived from the superimposition of the SIFVVFDIESAKKFV onto the insulin-B peptide LVEALYLVCGERGG, were subjected to energy minimization calculations with the modeled DQ7. It was found that the modeled HLA-DQ7/epitope (154–167) complex did not experience any significant structural differences. Subsequently, the Procheck suite of programs was utilized for assessing the stereochemical quality of the DQ7/epitope (154–167) complex, and finally, the compatibility of the complex was confirmed using the “O” program (Fig. 5). The described approach of the step by step alignment and the energy minimization calculations were performed with all the common candidate epitopes, and the final proposed epitopes of the La/SSB autoantigen for the HLA-DQ2/DQ7 are given in Table 6.

By applying homology modeling and energy minimization experiments of the selected epitopes, after comparing three different computational methods, the best superposed epitopes to the insulin-B peptide with the lowest structural differences to the reference peptide were identified (Table 6). It is concluded that these peptides possess the highest probability to be binders of the HLA-DQ2/DQ7 molecules.

SASA of the Proposed Epitopes within the HLA -DQ2 and HLA-DQ7 Molecules

GETAREA, a Web service, is one of the most efficient programs for calculating the SASA, which allowed us to submit the Cartesian coordinates of atoms of the proposed candidate epitopes, complexed with DQ2 and DQ7, stored in the PDB format, to obtain the SASA of the epitopes²⁴ within the grooves.

The residues of the proposed epitopes (Table 6) corresponding to the P1, P4, and P9 pockets of the antigen-binding groove of the modeled DQ2 and DQ7 should have very low solvent accessibility compared to the neighboring and in particular to the terminal residues, which are extended out of the ends of the peptide-binding groove. In Figure 6 is depicted the total surface area for the La/SSB epitope 311–324 in its complexed form with HLA-DQ2 and for epitope 149–161 complexed with HLA-DQ7.

The SASA experiments confirm that the residues corresponding to the P1, P4, and P9 pockets (Table 6) of the binding grooves exhibit low solvent accessibility because they are less exposed to the microenvironment.

Potential Interaction Energy, Binding Affinity, and IC₅₀ Values of the Proposed Epitopes

TINKER software³⁴ was used for the calculation of the potential interaction energy. The potential interaction energy, ΔE_{int} , of the DQ2/DQ7–epitope complexes, was calculated from the equation:

$$\Delta E_{\text{int}} = E_{\text{pMHC}} - E_{\text{MHC}} - E_{\text{p}}$$

where ΔE_{pMHC} is the total potential energy of the MHC–epitope complex in the bound state, E_{MHC} and E_{p} are the potential energies of the MHC molecule and the predicted epitope in the unbound state, respectively. In Table 7 are listed the proposed MHC–epitope complexes starting from the most preferred to the less favorable.

Furthermore, MHCpred was applied for the quantitative prediction of the peptide–HLA-DQ2/DQ7 binding affinity. There is increasing evidence suggesting that as the MHC binding affinity of



Figure 4. Superimposition of the candidate epitope SIFVVFD S I E S A K K F V (153–168) to the insulin-B peptide LVEALYL V C G E R G G. The same residues are indicated with the symbol (*), while residues with similar characteristics with the symbols (..) and (.). Amino acid residues corresponding to the P1, P4, and P9 pockets are shown in light gray. Note that the length of the candidate epitopes ranges from 12 to 14 amino acid residues.

a peptide rises, the greater the probability to be recognized by a TCR of the T-cell repertoire so that the immune response is better initiated. One of the ways to measure binding affinity is to calculate the IC_{50} value, which indicates the concentration required for 50% inhibition in a competitive binding assay. A peptide binding to an MHC may be recognized, by a TCR, if it binds with a $pIC_{50} > 6.3$ ($pIC_{50} = -\log IC_{50}$) or IC_{50} values between 0.01 to 5000 nM.

In Table 8 are quoted the proposed epitopes according to their IC_{50} values, which are inversely proportional to their binding affinity. Epitopes for HLA-DQ7 are all good binders except the epitope 78–90, while in the case of HLA-DQ2, epitopes spanning the sequences 131–144 and 161–174 are less effective.

Conclusions

In this study, the candidate T-cell epitopes of the La/SSB autoantigen, main target of the autoimmune response in patients with SS

and SLE, were predicted using as templates the HLA-DQ2 and DQ7 molecules, which are genetically linked to patients with autoimmune rheumatic diseases, and in particular, with Sjogren's Syndrome (SS) and Systemic Lupus Erythematosus (SLE). Modeling of DQ2 and DQ7 was based on the crystal structure of DQ8, an HLA molecule of high-risk factor of type I diabetes, which is also an autoimmune disease. The quality of the modeled HLA-DQ2/DQ7 is similar to the quality expected for structures determined at 2 Å. Almost all residues of the modeled DQ2 and DQ7 were found in the preferred regions of the Ramachandran plot. Superimposition of modeled DQ2 and DQ7 with DQ8 using TINKER molecular modeling software gave satisfactory RMSD values (0.034 for DQ8/DQ2 and 0.033 for DQ8/DQ7), confirming the compatibility and reliability of the modeled HLA molecules.

Three different approaches were applied and compared in our study to identify T-cell epitope candidates of the La/SSB autoantigen: Taylor's sequence pattern method, TEPITOPE quantitative matrices, and MULTIPRED artificial neural networks. The obtained common and/or similar candidate T-cell epitopes were subjected to homology modeling with the insulin-B peptide, and the best superposed epitopes were placed into the modeled HLA-DQ2 and DQ7 binding grooves to perform energy minimization

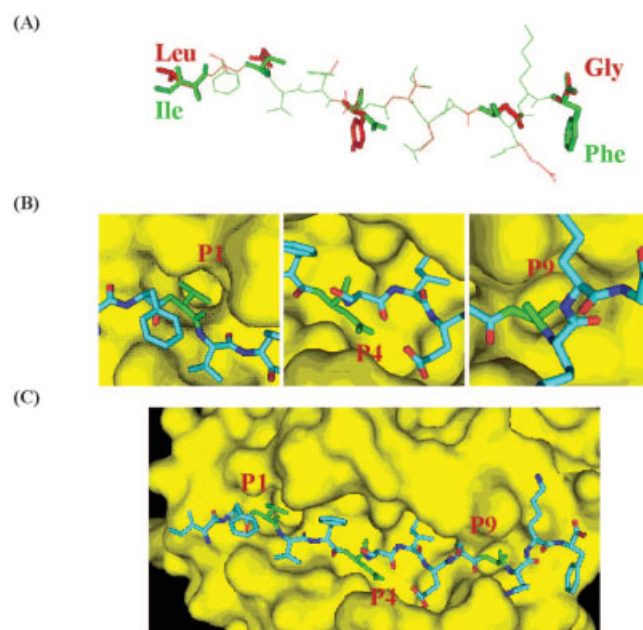


Figure 5. The best aligned epitope IFVVFD S I E S A K K F V (154–167) (shown in green) obtained after superimposition with the insulin-B peptide LVEALYL V C G E R G G (shown in red). The first and the last amino acid residues of the candidate epitope (Ile and Phe) and the insulin-B peptide (Leu and Gly) are indicated as sticks (A). The contact residues, V156, D159, and A164, of the candidate epitope (154–167) (shown in green) placed into the binding pockets P1, P4, and P9 of the modelled HLA-DQ7 (B). Molecular surface representation of the modeled HLA-DQ7/epitope (154–167) complex. The surface of the binding site of the modeled HLA-DQ7 molecule is shown in yellow, and the contact residues in pockets P1, P4, and P9 are shown in green (C). (Figure prepared with PyMol.⁵³)

Table 6. The Proposed T-Cell Epitopes of the La/SSB Autoantigen for the HLA-DQ7 and HLA-DQ2 Molecules.

Sequence	Region of La/SSB
DQ7 molecule	
IVEALS SK KAEL	68–79
ELMEISED KT KIR	78–90
AFKGSIFV FD SI	149–161
GSIFV FD SIESAK	152–165
IFV FD SIESAKKF	154–167
AKDAN NG NLQLRNK	286–299
DQ2 molecule	
LKEQIKLDE GW V	36–47
IVEALS SK KAEL	68–79
SKAELMEISED KT	75–87
LEDKG Q VLNI Q MRR	131–144
AFKGSIFV FD SIE	149–162
IESAK KK FVETPG Q K	161–174
AKDAN NG NLQLR	286–297
AKDAN NG NLQLRNK	286–299
EKEAL KK IIED Q ES	311–324

The amino acid residues (in bold) correspond to the P1, P4, and P9 pockets of the antigen binding groove.

Table 7. Potential Interaction Energy (ΔE_{int}) of the MHC–Epitope Complexes (DQ8-p, DQ7-p, and DQ2-p), in kcal/mol.

Complex	ΔE_{int}
DQ8	
DQ8-p	–74.778
DQ7	
DQ7-p _(149–161)	–122.63
DQ7-p _(78–90)	–72.785
DQ7-p _(286–299)	–69.358
DQ7-p _(154–167)	–65.879
DQ7-p _(68–79)	–51.545
DQ7-p _(152–165)	–28.388
DQ2	
DQ2-p _(286–297)	–88.272
DQ2-p _(149–162)	–86.230
DQ2-p _(131–144)	–76.134
DQ2-p _(286–299)	–74.111
DQ2-p _(161–174)	–71.061
DQ2-p _(311–324)	–65.917
DQ2-p _(68–79)	–49.201
DQ2-p _(36–47)	–47.912
DQ2-p _(75–87)	–47.781

calculations and epitopes with the lowest structural differences were obtained. Six epitopes were attributed to the HLA-DQ7 and nine to HLA-DQ2. It was also found that residues corresponding to the P1, P4, and P9 pockets of the HLA-DQ2 and DQ7 binding grooves experience very low solvent accessibility in contrast with

the neighboring and the terminal residues because they are less exposed to the microenvironment of the groove.

The proposed T-cell epitopes were classified according to their binding efficiency. It is concluded that five epitopes, out of six, for HLA-DQ7 and seven epitopes, out of nine, for HLA-DQ2 are good

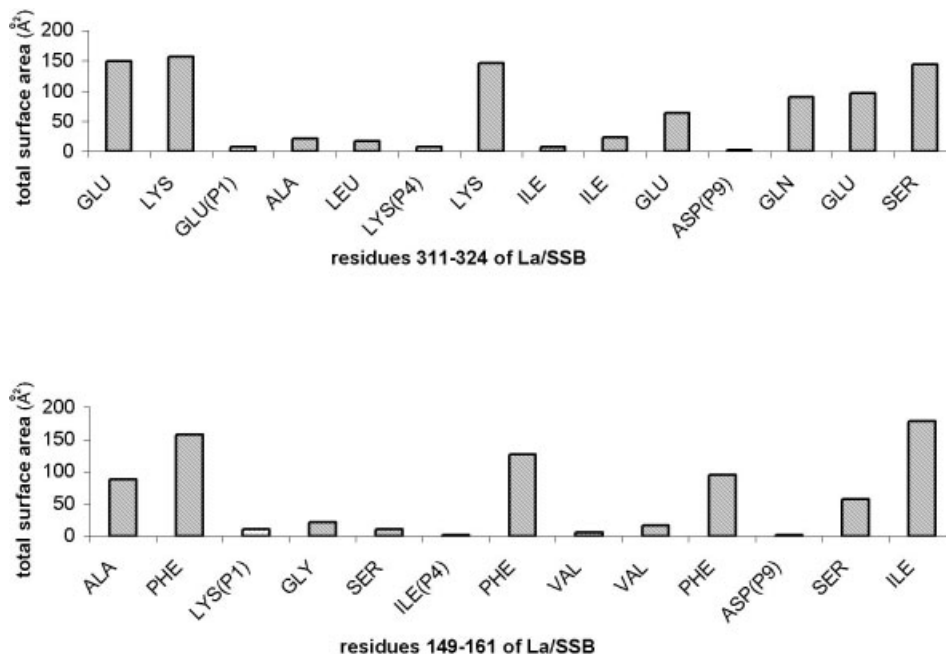
**Figure 6.** The total surface areas for the La/SSB epitopes 311–324 and 149–161 complexed with HLA-DQ2 and HLA-DQ7, respectively.

Table 8. Binding Affinity Prediction of the Proposed Epitopes for HLA-DQ2 and HLA-DQ7 (MHCpred).

Epitope sequence	9-mer peptides	Predicted $-\log_{10}IC_{50}$ (M)	Predicted IC_{50} Value (nM)
DQ8	DQ8		
35–47	E ₃₇ A L Y L V C G E ₄₅	6.988	102.80(0.29)
DQ7	DQ7		
152–165	I ₁₅₄ F V V F D S I E ₁₆₂	7.714	19.32(0.33)
68–79	E ₇₀ A L S K S K A E ₇₈	7.348	44.87(0.29)
286–299	D ₂₈₈ A N N G N L Q L ₂₉₆	6.816	152.76(0.33)
149–161	K ₁₅₁ G S I F V V F D ₁₅₉	6.685	206.54(0.38)
154–167	V ₁₅₆ V F D S I E S A A ₁₆₄	6.455	350.75(0.38)
78–90	M ₈₀ E I S E D K T K ₈₈	6.004	990.83(0.29)
DQ2	DQ2		
68–79	E ₇₀ A L S K S K A E ₇₈	7.348	44.87(0.29)
311–324	E ₃₁₃ A L K K I I E D ₃₂₁	7.17	67.61(0.25)
75–87	A ₇₇ E L M E I S E D ₈₅	7.151	70.63(0.25)
288–297	D ₂₈₈ A N N G N L Q L ₂₉₆	6.816	152.76(0.33)
288–299	D ₂₈₈ A N N G N L Q L ₂₉₆	6.816	152.76(0.33)
149–162	K ₁₅₁ G S I F V V F D ₁₅₉	6.685	206.54(0.38)
36–47	E ₃₈ Q I K L D E G W ₄₆	6.348	448.75(0.21)
131–144	D ₁₃₃ K G Q V L N I Q ₁₄₁	6.196	636.80(0.38)
161–174	E ₁₆₂ S A K K F V E T ₁₇₀	6.137	729.46(0.29)

The first column shows the epitope sequence, the second column shows the 9-mer core of the-epitope sequence, the third column shows the predicted- $\log_{10}IC_{50}$ (M) (pIC_{50}), and the fourth column shows the IC_{50} values (nM). The confidence of the prediction (max = 1) is shown in parentheses. P1, P4, and P9 residues are in bold. For comparison, values of the insulin-B peptide for DQ8 are also indicated.

binders of MHC, and they may be sufficiently recognized by the immune system.

Our study constitutes the ground work for a rapid and reliable experimentation concerning the T-cell epitope mapping of the La/SSB autoantigen, and could lead to the development of immunotherapeutic drug-like molecules as inhibitors of the T-cell inappropriate immune response in autoimmune diseases.

References

- Jensen, P. E. *Biopolymers* 1997, 43, 303.
- Madden, D. R., et al. *Cell* 1993, 75, 693.
- Stern, L. J.; Brown, J. H.; Jardetzky, T. S.; Gorga, J. C.; Urban, R. G.; Strominger, J. L.; Wiley, D. C. *Nature* 1994, 368, 215.
- De Groot, A. S.; Sbai, H.; Aubin, C. S.; McMurray, J.; Martin, W. *Immunol Cell Biol* 2002, 80, 255.
- Robinson, J.; Malik, A.; Parham, P.; Bodmer, J. G.; Marsh, S. G. *Tissue Antigens* 2000, 55, 280.
- Bjorkman, P. J.; Saper, M. A.; Samroui, B.; Bennett, W. S.; Strominger, J. L.; Wiley, D. C. *Nature* 1987, 329, 506.
- Fremont, D. H.; Matsumura, M.; Strura, E. A.; Peterson, P. A.; Wilson, I. A. *Science* 1992, 257, 919.
- Brown, J. H.; Jardetzky, T. S.; Gorga, J. C., et al. *Nature* 1993, 364, 33.
- Brusic, V.; Bajic, V. B.; Petrovsky, N. *Methods* 2004, 34, 436.
- Bian, H.; Reidhaar-Olson, J. F.; Hammer, J. *Methods* 2003, 29, 299.
- Rothbard, J. B.; Taylor, W. R. *EMBO J* 1988, 7, 93.
- Taylor, W. R. *J Mol Biol* 1986, 188, 233.
- Celis, E.; Larson, J.; Otvos, L., Jr.; Wunner, W. H. *J Immunol* 1990, 145, 305.
- Brusic, V.; Rudy, G.; Honeyman, M.; Hammer, J.; Harrison, L. *Bioinformatics* 1998, 14, 121.
- Sturniolo, T.; Bono, E.; Ding, J.; Radrizzani, L.; Tuereci, O.; Sahin, M.; Braxenthaler, M.; Gallazzi, F.; Protti, M. P.; Sinigaglia, F.; Hammer, J. *Nat Biotechnol* 1999, 17, 555.
- Brusic, V.; Flower, D. R. *Biosilico* 2004, 2, 18.
- Honeyman, M. C.; Brusic, V.; Stone, N. L.; Harrison, L. C. *Nat Biotechnol* 1998, 16, 966.
- Altman, D. M.; Sansom, D.; Marsh, S. G. E. *Immunol Today* 1991, 12, 267.
- Ollerup, J.; Hillert, J.; Frederickson, J., et al. *Proc Natl Acad Sci USA* 1989, 86, 7113.
- Bergseng, E.; Xia, J.; Kim, C.-Y.; Khosla, C.; Sollid, L. M. *J Biol Chem* 2005, 280, 21791.
- Sollid, L. M.; Marcussen, G. E. K., et al. *J Exp Med* 1989, 169, 345.
- Harley, J. B.; Reichlin, M.; Arnett, F. C.; Alexander, E. L.; Bias, W. B.; Provost, T. T. *Science* 1986, 232, 1145.
- Scofield, R. H.; Frank, M. B.; Neas, B. R.; Horowitz, R. M.; Handgrave, K. L.; Fugisake, A.; McArthur, R.; Harley, J. B. *Clin Immunol Immunopathol* 1994, 72, 335.
- Todd, J. A.; Acha-Orbea, H.; Bell, J. I. *Science* 1988, 240, 1003.
- Wong, F. S.; Moustakas, A. K.; Wen, L.; Papadopoulos, G. K.; Janeway, C. A., Jr. *Proc Natl Acad Sci USA* 2002, 99, 5551.
- Martinez, N. R.; Augstein, P.; Moustakas, A. K.; Papadopoulos, G. K.; Gregori, S.; Adorini, L.; Jackson, D. C.; Harrison, L. C. *J Clin Invest* 2003, 111, 1365.
- Brown, J. H.; Jardetzky, T.; Saper, M. A.; Samroui, B.; Bjorkman, P. J.; Wiley, D. C. *Nature* 1988, 332, 845.
- Paliakakis, K.; Routsias, J.; Petratos, K.; Ouzounis, C.; Kokkinidis, M.; Papadopoulos, G. K. *J Struct Biol* 1996, 117, 145.
- Routsias, J. G.; Kosmopoulou, A.; Makri, A.; Panou-Pomonis, E.;

- Sakarellos, C.; Sakarellos–Daitsiotis, M.; Moutsopoulos, H. M.; Tzioufas, A. G. *J Med Chem* 2004, 47, 4327.
30. Terzoglou, A. G.; Routsias, J. C.; Sakarellos, C.; Sakarellos–Daitsiotis, M.; Moutsopoulos, H. M.; Tzioufas, A. G. *J Autoimmun* 2003, 21, 47.
31. Lee, K. H.; Wucherpfennig, K. W.; Wiley, D. C. *Nat Immunol* 2001, 2, 501.
32. Laskowski, R. A.; MacArthur, M. W.; Moss, D. S.; Thornton, J. M. *J Appl Crystallogr* 1993, 26, 283.
33. Jones, T. A.; Bergdoll, M.; Kjeldgaard, M. *Crystallography and Modelling Methods in Molecular Design*; Springer Verlag: Berlin, 1990.
34. Ponder, J. W. *TINKER: Software Tools for Molecular Design*, 4.1; Washington University School of Medicine: St. Louis, MO, 2003.
35. Kwok, W. W.; Gebe, J. A.; Liu, A.; Agar, S.; Ptacek, N.; Hammer, J.; Koelle, D. M.; Nepom, G. T. *Trends Immunol* 2001, 22, 583.
36. Bian, H.; Hammer, J. *Methods* 2004, 34, 468.
37. Zhang, G. L.; Kham, A. M.; Srinivasan, K. N.; August, T.; Brusic, V. *Nucleic Acids Res* 2005, 33, W173.
38. Fraczkiwicz, R.; Braun, W. *J Comp Chem* 1988, 19, 319.
39. Guan, P.; Doytchinova, I. A.; Zygouri, C.; Flower, D. R. *Appl Bioinformatics* 2003, 2, 63.
40. Guan, P.; Doytchinova, I. A.; Zygouri, C.; Flower, D. R. *Nucleic Acids Res* 2003, 31, 3621.
41. Hattotuwa, C. K.; Guan, P.; Doytchinova, I. A.; Zygouri, C.; Flower, D. R. *J Mol Graph Model* 2004, 22, 195.
42. Altschul, S. F.; Madden, T. L.; Scaffar, A. A.; Zhang, Z.; Miller, W.; Lipman, D. J. *Nucleic Acids Res* 1997, 25, 3389.
43. Westbrook, J.; Feng, Z.; Chen, L.; Yang, H.; Berman, H. M. *Nucleic Acids Res* 2003, 31, 489.
44. Guex, N.; Peitch, M. C. *Electrophoresis* 1997, 18, 2714.
45. Schwede, T.; Kopp, J.; Guex, N.; Peitch, M. C. *Nucleic Acids Res* 2003, 31, 3381.
46. Brooks, B. R.; Bruccoleri, R. E.; Olafson, B. D.; States, D. J.; Swaminathan, S.; Karplus, M. *J Comp Chem* 1983, 4, 187.
47. MacKerell, A. D.; Brooks, B., Jr.; Brooks, C. L.; Nilsson, L.; Roux, B.; Won, Y.; Karplus, M. *Encyclopedia Comp Chem* 1998, 1, 271.
48. Still, W. C.; Tempczyk, A.; Hendrickson, T. *J Am Chem Soc* 1990, 112, 6127.
49. Qiu, D.; Shenkin, P. S.; Hollinger, F. P.; Still, W. C. *J Phys Chem A* 1997, 101, 3005.
50. Westhead, D. R.; Thornton, J. M. *Curr Opin Biotechnol* 1998, 9, 383.
51. Hammer, J.; Bono, E.; Gallazzi, F.; Belunis, C.; Nagy, Z.; Sinigaglia, F. *J Exp Med* 1994, 180, 2353.
52. Brusic, V.; Rudy, G.; Harrison, L. C. *Nucleic Acids Res* 1998, 26, 368.
53. DeLano, W. L. *The PyMol Molecular Graphics System*, 2002 (on World Wide Web <http://www.pymol.org>).