Original Article

Adaption of human antibody λ and κ light chain architectures to CDR repertoires

Rob van der Kant^{1,2,†}, Joschka Bauer^{3,†}, Anne R. Karow-Zwick³, Sebastian Kube³, Patrick Garidel³, Michaela Blech^{3,*}, Frederic Rousseau^{1,2,*}, and Joost Schymkowitz^{1,2,*}

¹Switch Laboratory, VIB Center for Brain and Disease Research, Herestraat 49, 3000 Leuven, Belgium, ²Department of Cellular and Molecular Medicine, KU Leuven, Herestraat 49 Box 802, B-3000 Leuven, Belgium, and ³Boehringer Ingelheim Pharma GmbH & Co. KG, Biberach/Riss, Germany

^{*}To whom correspondence should be addressed: E-mail: michaela.blech@boehringer-ingelheim.com,

frederic.rousseau@switch.vib-kuleuven.be or joost.schymkowitz@switch.vib-kuleuven.be

[†]Both authors contributed equally to this manuscript.

Edited by: A N Other, Board Member for PEDS

Received 16 May 2019; Revised 0 0; Editorial Decision 20 May 2019; Accepted 11 June 2019

Abstract

Monoclonal antibodies bind with high specificity to a wide range of diverse antigens, primarily mediated by their hypervariable complementarity determining regions (CDRs). The defined antigen binding loops are supported by the structurally conserved β -sandwich framework of the light chain (LC) and heavy chain (HC) variable regions. The LC genes are encoded by two separate *loci*, subdividing the entity of antibodies into kappa (LC_k) and lambda (LC_λ) isotypes that exhibit distinct sequence and conformational preferences. In this work, a diverse set of techniques were employed including machine learning, force field analysis, statistical coupling analysis and mutual information analysis of a non-redundant antibody structure collection. Thereby, it was revealed how subtle changes between the structures of LC_k and LC_λ isotypes increase the diversity of antibodies, extending the predetermined restrictions of the general antibody fold and expanding the diversity of antigen binding. Interestingly, it was found that the characteristic framework scaffolds of κ and λ are stabilized by diverse amino acid clusters that determine the interplay between the respective fold and the embedded CDR loops. In conclusion, this work reveals how antibodies use the remarkable plasticity of the beta-sandwich Ig fold to incorporate a large diversity of CDR loops.

Key words: antibody, architecture, isotype

Introduction

The complexity of the antibody engineering process was dramatically increased by the stepwise development from murine monoclonal antibodies (mAbs), to chimeric mAbs with murine variable (V) and human constant (C) regions (Boulianne *et al.*, 1984; Morrison *et al.*, 1984; Neuberger *et al.*, 1985; Sun *et al.*, 1987), to humanized mAbs with mouse-derived complementarity determining regions (CDRs) fused on the β -sandwiches of the human V framework regions (FR) (Jones *et al.*, 1986; Hale *et al.*, 1988; Riechmann *et al.*, 1988; Verhoeyen *et al.*, 1988), to the state-of-the-art fully human mAbs (Bruggemann *et al.*, 1989, 2015; McCafferty *et al.*, 1990; Bruggemann and Neuberger, 1996; Lonberg, 2008). The genetically engineered mAbs share the characteristic composition of classical mAbs by comprising two identical heavy (HC) and two identical light chains (LC) (Fig. 1A) (Edelman, 1959; Alzari *et al.*, 1988). The variable domain's amino-terminal regions of the HC (V_H) and LC

This is an Open Access article distributed under the terms of the Creative Commons Attribution Non-Commercial License (http://creativecommons.org/licenses/by-nc/4.0/), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited. For commercial re-use, please contact journals.permissions@oup.com

[©] The Author(s) 2019. Published by Oxford University Press.



Fig. 1 Global sequence-structure analysis of antibodies VL domains splitting into kappa and lambda isotypes. (A) Schematic representation of the surface of a full-length antibody that comprises two identical heavy (HC, blue) and light chains (LC, yellow), jointly forming the antigen (Ag, green) binding fragment (Fab, highlighted by red box). **(B)** The Fab fragment consists of HC's constant C_H1 (cyan) and variable V_H domain (red), as well as LC's constant C_L (green) and variable V_L domain (blue). Fab's Ag affinity is cooperatively mediated by six complementarity-determining regions (CDRs) that are equally distributed over V_H and V_L (blue box). **(C)** V_L contributes to the Ag binding via three CDR loops (CDR L1 in magenta, CDR L2 in cyan and CDR L3 in red, Chothia definition) that are structurally orientated by four neighboring framework regions (LFR1 green, LFR2 orange, LFR3 yellow, and LFR4 blue). **(D)** Scheme of the V_L structure that comprises three CDR loops being embedded in four β-strand (arrows) rich LFRs. N, amino-terminal end; C, carboxy-terminal end. **(E)** A set of 333 non-redundant V_L sequences was assigned to the lambda (λ , light gray) and kappa (κ ; dark gray) subtype on the basis of their identity to the λ and κ consensus sequence. **(F-H)** Statistical analysis of the energy contributions to V_L and C_L structures. The boxplots incorporate the dataset's entire value distribution (whiskers), 25th (lower limit of the box) and 75th percentile (upper limit), mean (red dot) as well as median (central line) with a 95% confidence interval (notches). Statistical significances obtained by a Wilcoxon rank-sum test are indicated by ns ($P \le 0.05$), ** ($P \le 0.05$



Fig. 1 Continued

 $V_{L\kappa}$ and $V_{L\lambda}$ isotypes (pdb id 1L7I (Vajdos *et al.*, 2002) and 6axk (Oyen *et al.*, 2017) were used in consistence with Fig. 1**E**. In cytoscape, the network layout was set to perfuse force directed in order to ensure that residues buried in the structure are centered in the 2D representation. The color code corresponds to the regions of the domain as defined in Fig. 1**D**. Large nodes indicate residues that differentially stabilize the complementary isotypes as it was identified in Fig. 5**B**, and square-node representations of the corresponding residues in the contrary isotype simplify the cross-comparison. Residues that interact with the V_H domain are shown in gray.

 (V_L) each comprise three CDRs that mediate the antigen binding (Fig. 1B and C). Therefore, the chimeric and CDR-grafted antibodies retained the affinity of the original mouse antibodies for the antigen targets whilst comprising less sequence motifs that are recognized by the human immune system (Hwang and Foote, 2005).

In particular, the modern-day engineering processes are more technically demanding and require the consideration of structural information on the mAb and the mAb-antigen complex to guide the engineering process and increase the probability of success (Haidar et al., 2012; Hanf et al., 2014). Strikingly, the identification of mutations that improve a given property (e.g. affinity) without comprising other properties (e.g. stability) challenges the engineering process of antibodies. The CDR grafting approach often requires backmutation of key residues of the human FR to the amino acids of the original murine mAb to preserve the functional conformation of the CDRs and thus its high-affinity (Queen et al., 1989; Co and Queen, 1991; Chames et al., 2009). However, the complex interplay between residues of the FR and CDR is not completely understood so far, thereby complicating the rational design of mutations that increase the thermodynamic stability of the mAb structure and mediate the conformation as well as orientation of CDR loops.

In this context, it is interesting that approximately 90-95% of the human IgG1 sequence are conserved, whilst being assigned to the framework region (FR) and constant (C) domains (Harris et al., 2004). The constant FR regions of the LC (LFRs, Fig. 1C and D) have either of the two evolutionarily developed kappa (LCk) or lambda (LCA) sequences, coding for two distinct scaffold isotypes that are employed in grafting the antigen-binding loops (Titani et al., 1967). For reasons thus far unknown, the ratio of LC κ to LC λ varies considerably between species with an average ratio of 95:5 in mouse and 60:40 in human (Popov et al., 1999). The affinity for the antigen is specified by the remaining 5% of the variable sequence part that comprises the six CDRs. The sequence variability is initially obtained by somatic recombination of V(D)J regions, followed by somatic mutations to provide a broad diversity of CDR loops with varying physicochemical complementarities and predictable canonical structures that differ between LCk and LCA (Chothia and Lesk, 1987; North et al., 2011; Raghunathan et al., 2012; Nowak et al., 2016). Although the binding energy is predominantly determined by a limited number of critical interface residues, the antigen residues are stochastically mutated together with the non-binding residues of the CDRs (Clackson and Wells, 1995; Bogan and Thorn, 1998; Sheinerman et al., 2000). Interestingly, by preferring certain amino acids over others, each CDR has its own contact preferences that do not depend on the remaining five CDRs (Zhao and Li, 2010; Raghunathan et al., 2012; Kunik and Ofran, 2013).

For a long time, the antigen affinity was solely attributed to the residues of the CDRs that are oriented by the FR scaffold (Tramontano *et al.*, 1990). However, over the past few years the importance of FR residues for antigen binding was emphasized (Sedrak *et al.*, 2003; Haidar *et al.*, 2012). Several studies confirmed that antigen binding of CDR grafted antibodies was successfully reobtained by back-mutation of FR residues to the original murine residues (Verhoeyen *et al.*, 1988; Queen *et al.*, 1989; Tramontano *et al.*, 1990; Kettleborough *et al.*, 1991; Carter *et al.*, 1992; Foote and Winter, 1992; Xiang *et al.*, 1995; Baca *et al.*, 1997; Chiu *et al.*, 2011; Rodriguez-Rodriguez *et al.*, 2012). Reversely, in some cases the mAb fold was stabilized by mutations in the CDRs (Koenig *et al.*, 2015, 2017). These findings underline the complex interplay between the binding loops and the FR scaffold. Up to now, it is still unclear why distinct structural motifs evolved in the human

antibody repertoires of LC κ and LC λ , and whether the isotypes correlate with the antigen class and/or the antibody's affinity, specificity and LFR structure (Knappik *et al.*, 2000).

In first attempts, structure-based computational design methods were applied to a predetermined antibody scaffold to achieve new affinities and specificities (Liu *et al.*, 2017). Low hit rates (Liu *et al.*, 2017) and simplified binding systems (Chevalier *et al.*, 2017) indicated that mAb engineering shows a growing need for increasing the probability of success by acquiring more knowledge on the relatively unknown interplay between antibody modules and residue interactions.

In this work, statistical evaluations of the abYsis antibody database (Swindells *et al.*, 2017) provide deeper understanding of the complex structure-function relationship of single and clustered residues in LC κ and LC λ scaffolds. Defined networks of interacting residues that mediate the interplay between CDR's distinct canonical structures and the surrounding LFR regions were identified for both isotypes. This work provides further knowledge on how the V_L λ and V_L κ structures evolutionarily adapted to fit to a broad variety of different CDR loop conformations. In summary, stabilizing networks of interacting residues increase the diversity of antibodies, extend the predetermined restrictions of the general antibody fold and expand the diversity of antigen binding.

Materials and methods

Database retrieval and analysis

The abYsis database (Swindells *et al.*, 2017) was queried using the human sequences of the PDB as data source. Sequences with warnings and unclassified, unpaired, or unnumbered sequences were excluded, resulting in 1399 antibody structures. Duplicates were removed as well as antibodies that contained errors after downloading. Solely the structures that contained the Fab (300 and 500 amino acids) and provided a resolution lower than 2.8 Å were analyzable by FoldX. Redundancy removal was performed based on light chain sequence at a threshold of 98% sequence identity using the CD-hit algorithm (Li and Godzik, 2006; Fu *et al.*, 2012). The final database contained 333 Fab structures that were renumbered via the Abnum script (Abhinandan and Martin, 2008) following the Chothia numbering scheme.

FoldX

FoldX version 3.0 Beta 6 (c) compilation for Linux was used for all analyses. Initially, the structures were repaired using the 'RepairPDB' command, and information of the residue level was obtained via the 'SequenceDetail' command (Schymkowitz *et al.*, 2005). Interface analysis was performed by the 'AnalyseComplex' command. Intramolecular interface analysis (V_I/C_L) was obtained by splitting the molecule at the hinge region using python scripting and the 'AnalyseComplex' command. Residue level contributions to the interaction energy was obtained by removing the interaction partner (Antigen or HC), using the 'SequenceDetail' command, and subtracting the difference of contributions with and without interaction partner present.

Calculation of significance

Information on the residue level was analyzed using R-studio (RStudio Team, 2016) by running the 'aggregate' function, summing and averaging on the different levels of resolution. Significance levels and comparing means between distributions were determined using

the Wilcoxon signed-rank test and ggpubr package (Alboukadel Kassambara, 2017). Sequence logos were calculated and plotted using the geom_logo command from ggseqlogo package (Wagih, 2017a). Box-plots were generated either by using the standard box-plot command or the geom_boxplot function from the ggplot2 package (Wickham, 2009).

Random Forest

R-studio was used to perform the RandomForest analyses (randomForest R-package version 4.6-14) (Breiman, 2001). The variable n-tree was set at 1000 and importance at TRUE. Only numerical variables were used in the analysis.

Statistical coupling analysis

The python implementation of Statistical Coupling Analysis was used with the default settings to generate the clusters of interacting amino acids (Rivoire *et al.*, 2016).

Mutual information analysis

Mutual information between amino acid identities at Chothia positions and CDR canonical structures was calculated by converting one letter amino acid identities and canonical structures to arbitrarily chosen numbers. Subsequently, the mutual information was calculated using the 'mutinformation' command from the infotheo package (version 1.2.0 (Meyer, 2008)) with default settings. Chord diagrams were generated using the 'chordDiagram' function from the circlize package (version 0.4.4. (Gu *et al.*, 2014)). A mutual information threshold of 0.5 was used for displaying the chords.

Structure viewer

All structural visualization was done using YASARA Structure (version 18.4.24 (Krieger and Vriend, 2014)). Images were generated using Ray-traced screenshots.

Availability of scripts and datasets

Datasets and scripts are available at Protein Engineering, Design and Selection online.

Results and discussion

In silico analysis of the abYsis database

The abYsis database is a web-based antibody repository for antibody sequence and structure-management, analysis, and prediction (Swindells et al., 2017). In this work, abYsis (Version 3.1.0. (Swindells et al., 2017)) was screened for crystal structures of human antibodies and fragments thereof that contained both, heavy (HC) and light chain (LC). The query resulted in 1399 structures of the antigen binding fragment (Fab) with HC and LC of similar size (Fig. 1B). In order to retain only high fidelity structural information and run reliable energy calculations with FoldX (Schymkowitz et al., 2005), the set was limited to crystal structures that exhibit a resolution better than 2.8 Å. To avoid a bias towards thoroughly investigated structures and close relatives thereof (e.g. point mutants), redundancy removal was performed at 98% sequence identity of the LC by performing the CD-Hit algorithm. This clustering approach selected representative entries in case of redundancy (Fu et al., 2012). The entire selection procedure resulted in a set of 333 nonredundant Fab structures that were assigned to 221 LCk and to 112

LC λ structures (relative frequencies of 0.66 and 0.33, respectively, Supplementary Figure 1), reflecting the state-of-the-art diversity of publicly available Fab structures with sufficient resolution. A consensus sequence pursuant to the Chothia numbering system (Chothia and Lesk, 1987) was determined for LCk and LCl subgroups by identification of the amino acid with the highest propensity per position. The percent identity for both consensuses was then calculated for each sequence. Plotting the distances (i.e. identity) of all λ and κ sequences from the respective consensus visualized the clustering of both subgroups (Fig. 1E). In addition, the distribution of sequences to LCk and LCl isotypes also yielded a wide range of sequence diversity towards its consensus sequences. The sequence identity of both LC classes ranged from 70-95%, while the identity to the different groups accounted for 50-70%. As a result, the sequence identity of a small quantity of LCk sequences to the LCk consensus sequence equals that of the LC λ consensus sequence, underlining the difficulty in accurately assigning these ambiguous sequences. In these cases, the sequence was assigned to one of the isotypes via typical λ or κ key residues (Honegger and Pluckthun, 2001) such as position L10 (L, LC residue position derived from the sequence alignment (Chothia and Lesk, 1987)) that is present in κ but absent in the λ alignment, which in turn comprises a λ -typical position L106A that lacks in the k alignment. More specifically, position L71 comprises conserved Phe/Tyr in κ , but Ala/Val/Arg in λ .

The destabilizing effect of incorporating CDRs is distributed differently in κ than in λ

Each Fab structure of the dataset was analyzed using the empirical FoldX force field (Schymkowitz *et al.*, 2005), which was optimized to predict the effect of mutations on the thermodynamic stability of a protein. The resulting information of the *in silico* analysis were subdivided into that of the amino acid level, the region level (FR/CDR), the domain level (C_L/V_L), the chain level, as well as the full HC/LC complex level. These energies are predictions that computationally estimate various factors.

The statistical analysis of the structure dataset demonstrated that both architectural isotypes exhibit a comparable overall thermodynamic stability on the domain level (Fig. 1F). Therefore, the energies of the constituent atoms as calculated by FoldX were added to the residue and polypeptide chain level, thereby creating energy descriptors at the residue and the chain level. FoldX further allowed to characterize the LC-specific energy pattern of the thermodynamic stability of the VL and CL domains by unraveling the energy contributions e.g. electrostatics, solvation or Van der Waals packing of each residue (Table I). On average, the C_L domain of LC λ is more stable than that of LC κ , however this trend is reversed for the V_I domains (Fig. 1G). This suggests that the V_L and C_L regions are structurally independent of each other (i.e. stable by themselves) in the κ architecture, whilst in the λ architecture a highly stable C_I domain seems to be needed to compensate for the rather less stable V_L domain. In this view the C_L of LC λ appears to be a stable platform that compensates through the V_L-C_L interface for the destabilizing effect of the CDRs, which was confirmed by a more detailed analysis below. Assigning the per-residue energy distributions to the specific V_I regions clearly indicated that the scaffold (i.e. LFRs) stabilizes the overall structure, whilst the CDRs exert a destabilizing impact (Fig. 1H). Hence, the structurally destabilizing properties of CDRs are compensated by the stabilizing LFRs in both V_L scaffolds. Despite this general trend, subtle but important differences were identified between both isotypes. Exemplarily, CDR L2 is on

Table I. Descriptions of FoldX variables.

| Variable | Definition | Unit | |
|--|--|----------|--|
| total.energy | The predicted overall stability | kcal/mol | |
| Backbone.Hbond | The contribution of backbone H-bonds | kcal/mol | |
| Sidechain.Hbond | The contribution of sidechain H-bonds | kcal/mol | |
| Van.der.Waals | The contribution of VanderWaals forces | kcal/mol | |
| Electrostatics | The contribution of electrostatic interactions | kcal/mol | |
| Solvation.Polar | The penalty for burying polar residues | kcal/mol | |
| Solvation.Hydrophobic | The contribution of hydrophobic groups | kcal/mol | |
| Van.der.Waals.clashes | The penalty for VanderWaals' clashes (interresidue) | kcal/mol | |
| entropy.sidechain | The entropy cost of fixing the sidechain | | |
| entropy.mainchain | The entropy cost of fixing the mainchain/backbone | kcal/mol | |
| cis_bond | The penalty for having a cis peptide bond | kcal/mol | |
| torsional.clash | The penalty for VanderWaals' torsional clashes (intraresidue) | kcal/mol | |
| backbone.clash | The penalty for VanderWaals' backbone-backbone clashes | kcal/mol | |
| helix.dipole | The contribution of the helix dipole (electrostatic) | kcal/mol | |
| disulfide | The contribution of disulfide bonds | kcal/mol | |
| electrostatic.kon | Th electrostatic interaction between molecules in the precomplex | kcal/mol | |
| energy.Ionisation | The contribution of ionization energy | kcal/mol | |
| sidechain.burial | Burial of the sidechain | fraction | |
| mainchain.burial | Burial of the backbone | fraction | |
| sidechain.Occ | Occupancy of the sidechain | fraction | |
| ainchain.Occ Occupancy of the backbone | | fraction | |

average more destabilizing in V₁ K, which in return is compensated by the remarkably stable LFR3 found in the immediate proximity (Fig. 1H). In contrast, $V_L\lambda$ comprises a more stable LFR4 that forms the hinge region between the variable and constant domain. Again, the interface between the V_L and the C_L domain seems to compensate the incorporation of unstable CDRs in VL. To illustrate the specific integration of distinct structural elements in $V_I \lambda$ and $V_I \kappa$, a two-dimensional representation of the residue-residue interaction networks that stabilize each domain was generated (Fig. 1I and J). To this end, the Van der Waals contacts were determined by FoldX from the representative protein structures of the $V_L \kappa$ and $V_L \lambda$ isotypes (pdb id 1L7I (Vajdos et al., 2002) and 6axk (Oyen et al., 2017)) and displayed as a network using Cytoscape (Shannon et al., 2003). While the networks of $V_L\lambda$ and $VL\kappa$ show much similarity, such as an extensive network of residues interacting with the V_H domain, there are also notable differences in the exact configuration of the network that are discussed below.

Next, differences between the amino acid sequences of $V_L \kappa$ and $V_L\lambda$ were investigated, and the frequency of amino acids at each position was visualized using sequence logos (Wagih, 2017a) (Fig. 2A and B). The size of the letter reflects the amino acid's frequency in the alignment as calculated via Shannon's information-entropy formalism (Shannon, 1948). Kolmogorov-Smirnov and Mann-Whitney tests confirmed that the entropy distributions of the positions did not significantly differ between $V_I \kappa$ and $V_I \lambda$ (Supplementary Figure 2), indicating that the quantity of conserved and variable positions was similar between both isotypes. The analysis further uncovered that the sequence variation is not restricted to the CDRs but extended to the LFRs (11 positions of $V_{I}\kappa$ and 14 of $V_{I}\lambda$ with an entropy of > 1.5 bits). The variability at distinct positions in the LFRs presumably counterbalances for effects arising from CDR's sequence variability. Together with λ - and κ -specific and conserved amino acid positions, these data clearly point towards isotype-specific stabilizing networks of interacting amino acids.

Remarkably, several conserved positions comprise different amino acid identities in $V_L\lambda$ and $V_L\kappa$ (Table II). Exemplarily, $V_L\kappa$

incorporates at position L95 of CDR L3 a conserved proline that was previously identified to adopt the cis-conformation, which restricts the loop's degrees of freedom (Chothia and Lesk, 1987; Al-Lazikani *et al.*, 1997). Further striking variations include positions L7 (P in κ , S in λ), L11 (L in κ , V in λ), L71 (F in κ , A in λ), L105 (E in κ , T in λ), L106 (I in κ , V in λ), L109 (T in κ , P in λ) and L111 (P in κ , S in λ). In particular, the strong differential conservation of the structurally similar residues L and V at position 11 is notable. Interestingly, positions L105-L111 thereof are located in the C-terminal part of LFR4 that is known to affect the λ - and κ -specific elbow angle by forming the V_L-C_L interface (Stanfield *et al.*, 2006). Consequently, these distinct amino acid identities at conserved positions highlight the architectural differences between λ and κ structures.

The isotypes share a common principle behind the antibody-antigen interaction

Interestingly, the C-terminal part of CDR L2 (L54-L56) is highly conserved in V_L λ but variable in V_L κ (*t*-test *P*-value = 0.03, Fig. 2A and B). The contrary sequence variability in this part of the CDR could emerge from differing antigen binding mechanisms between $V_{I}\lambda$ and $V_{I}\kappa$. This binding hypothesis was verified by a more thorough analysis of 88 V_L κ and 38 V_L λ crystal structures being bound to a protein ligand. First, the total energy of the antibody-antigen interaction was unraveled into the contributions of the antibody's heavy chain and λ , respectively, κ light chain (Supplementary Figure 3). As expected, the analysis confirmed the widespread theory (D'Angelo et al., 2018) that the heavy chain contributes on average more to the antigen binding than the light chain of both isotypes. Focusing on the light chain, the thermodynamic stability of V_I with and without antigen bound was investigated for each residue's contribution to the interaction energy with the ligand. Therefore, the frequency of contributing to the binding energy with more than 0.5 kcal/mol (typical FoldX-cutoff for interactions (Schymkowitz et al., 2005; Sanchez et al., 2008)) was calculated per position (Fig. 2C).



Fig. 2 Per-residue analysis of the isotype-specific sequence-structure relationship of V_L . (**A**, **B**) "Sequence logo" (Wagih, 2017a) representation of the amino acid occurrence per Chothia positions in the LFR and CDR (red boxes) of $V_{L\kappa}$ (**A**) and $V_{L\lambda}$ (**B**) sequences. The stack height indicates the conservation of the position, whilst the character height reports the relative conservation of distinct amino acids. The theoretical maximum value for the sequence entropy of a protein alignment is 4.36 bits. 221 $V_{L\kappa}$ and $112 V_{L\lambda}$ sequences were used for the alignment, significantly exceeding the critical quantity of 40 sequences allowing for accurate computation (Crooks *et al.*, 2004). The percentage frequency of contribution to the interaction with antigen (**C**) and V_H domain (**D**) was calculated per position for $V_{L\kappa}$ (red) and $V_{L\lambda}$ (blue). Residues were considered to be relevantly involved in binding if the FoldX force field calculated an interaction energy of at least -0.5 kcal/mol. CDRs are marked by red boxes, and significance levels of the differences > 0.2 kcal/mol between $V_{L\kappa}$ and $V_{L\lambda}$ are indicated (* for $P \le 0.05$, ** for $P \le 0.01$, **** for $P \le 0.001$).

| Definition | Chothia numbers |
|---|--|
| Conserved in both $V_L \kappa$ and $V_L \lambda$, identical amino acids | L5, L6, L16, L23, L35, L36, L37, L38, L40, L41, L44, L46, L48, L49, L57, L61, L62, L63, L64, L67, L68, L73, L75, L82, L86, L87, L88, L98, L99, L101, L102, L103 |
| Conserved in both $V_L \kappa$ and $V_L \lambda$, different amino acids | L7, L11, L71, L105, L106, L109 and L111 |
| Highly variable in both $V_L \kappa$ and $V_L \lambda$ | L3, L13, L17, L19, L22, L27, L28, L29, L30, L30B, L30C, L31, L32, L33, L34, L42, L43, L45, L50, L51, L53, L58, L60, L76, L77, L78, L79, L80, L89, L91, L92, L93, L94, L95A, L95B, L96, L97, L104 |
| Conserved in $V_L \kappa$ while variable in $V_L \lambda$ | L1, L2, L8, L18, L20, L24, L26, L39, L47, L52, L59, L66, L69, L70, L72, L81, L90, L95, L107, L108 |
| Conserved in $V_L \lambda$ while variable in $V_L \kappa$ | L4, L9, L12, L15, L21, L25, L30A, L54, L55, L56, L83, L92, L100 |

Table II. Similarities and differences in the conservation of $V_1 \kappa$ and $V_1 \lambda$ as determined by the alignments.

The antibody interacts almost exclusively with the antigen via its CDRs, confirming the widely accepted theory that sequence variations in the LFRs accommodate sequence selection in the CDRs to mediate binding. Since in more than 50% of the cases only a single residue (L91) is critical for interacting with the antigen, the frequency plots further verified a high diversity in the residues that mediate the binding. By exhibiting interaction frequencies between 20% and 50%, positions L30A-L32 in CDR1 and L91-L94 in CDR3 were identified as the most frequently involved residues for antigen interaction. In contrast, residues of CDR L2, and, in particular, it's highly conserved C-terminal part (L54-L56) are only marginally involved in antigen binding, indicating a rather LFR-like role. Neither of the residue position is involved in antigen binding in more than 50% of the V_L λ or V_L κ structures, which again confirmed that the CDRs of the light chain take a support role in both isotypes, while that of the heavy chain are most frequently involved in antigen recognition.

The V_L–V_H interaction occurs differently between the κ and λ isotypes

The energetic contributions of V_L residues to the interaction with the V_H domain were obtained for all 333 non-redundant Fab structures by removing $V_{\rm H}$ and calculating the free energy differences. Amino acids that contribute with at least -0.5 kcal/mol (corresponding to the accepted uncertainty of FoldX (Schymkowitz et al., 2005)) to the free energy of the V_L-V_H complex were classified as key residues. The threshold allowed to identify conserved key residues that contribute significantly to the interaction with V_H for the set of V_L structures, and to calculate the percentage of key residues per position (Fig. 2D). There is a well-known network of conserved amino acid residues that mediates the interaction between V_H and V_{I} (Chothia *et al.*, 1985), which were confirmed here for both isotypes by exhibiting a frequent contribution to the V_H-V_L interaction (>50% of the structures) and a high conservation (Fig. 2A and B) at positions L36 (Tyr), L38 (Gln), L43 (Ala/Ser), L44 (Pro), L46 (Leu), L49 (Tyr), L87 (Tyr) and L98 (Phe). Interestingly, the sidechain orientation of these conserved residues within the V_L-V_H interface is highly similar for both isotypes (Supplementary Figure 4A-D). The antigen-distant part of the V_L-V_H interface is capped by a hydrogen bonding network, connecting the backbone of a variable residue at position L42 with the conserved Gln at position L38 in LFR2 and the highly conserved Gln at position H39 of V_H (HFR2) (Supplementary Figure 4D). Additionally, conserved residues form a hydrophobic core and interact via π - π stacking of two Tyrosine (H91 - HFR2 and a variable position in CDR H3) and two Tryptophan residues (H47 - HFR2 and H103 - HFR4).

While the majority of interactions between V_L and V_H are common for both subtypes, discrepancies are present. For example, the interaction of λ 's and κ 's V_I regions with V_H most significantly differs in CDR L3 (Fig. 2D). Strikingly, the amino acid composition and conformation of this region is well known to frequently contribute to the interaction with both, antigen and V_H. CDR L3 exhibits on average a shorter and highly consistent length in $V_L \kappa$ if compared to the increased and more variable length of the loop in $V_I\lambda$ (Supplementary Figure 4E, Supplementary Table 1). The substantial sequence differences might be linked to isotype-specific canonical structures of CDR L3 (Chothia and Lesk, 1987; North et al., 2011; Nowak et al., 2016). In $V_L\lambda$, the additionally introduced residues seem to shift the hotspot for the V_H-interaction towards the Cterminus of CDR L3. For instance, CDR L3's N-terminal position L91 interacts significantly more frequent with V_H in $V_L\lambda$ than in $V_{L}\kappa$. Interestingly, this position shows less Shannon entropy in $V_{L}\lambda$ (1.94) if compared to $V_L \kappa$ (3.00), indicating less variation in amino acid identity in $V_L\kappa$, and is often an aromatic amino acid (Trp/Tyr) (Fig. 2A and B). Furthermore, positions L94, L95 and L95 A interact significantly more often with V_H in $V_L \kappa$ than in $V_L \lambda$. Taken together, this suggests that the amino acids at positions L91 and L95 C are more important interactors with both the V_H as well as the antigen in $V_L \lambda$ than in $V_L \kappa$.

$\textbf{V}_L \mathchar`- \textbf{C}_L$ interactions modulate elbow-angle differences between κ and λ

In the next step, the free energy of inter-domain interactions between V_H and V_L (V_L/V_H), C_L and C_H (C_L/C_H) as well as V_L and C_L (V_L/C_L) were analyzed for λ and κ isotypes (Supplementary Figure 5). FoldX calculations yielded a stabilizing total interaction energy between C_L and $V_L \kappa$, however this interaction is significantly weaker in the $V_L \lambda / C_L$ complex (Supplementary Figure 5A). The interaction network that stabilizes the V_L/C_L complex could be assigned to the extraordinary H-bonding of LCk's backbone (Supplementary Figure 5B) and sidechain (Supplementary Figure 5C). This effect is decisively reinforced by LCk's significantly increased quantity of interacting residues with CL (Supplementary Figure 5D). Carefully inspecting representative structures of both isotypes enabled to pinpoint three highly conserved residue positions that formed discrete backbone H-bonding; L105 (Glu in k and Thr in λ), L106 (Val in κ and Ile in λ) and L106A (missing in κ , Leu in λ) (Supplementary Figure 5E). Similarly, two positions responsible for the difference in sidechain H-bonding were identified; L105 (Glu in κ and Thr in λ) and L108 (Arg in κ and Gln in λ) (Supplementary Figure 5F). Moving to the structural level of a representative LC κ , a conserved Glutamine at CLK's position L165 was identified to form a conserved hydrogen bond with the backbone of residues L105-L106A (Supplementary Figure 5G). Furthermore, the highly conserved Arginine L108 forms a hydrogen bond bridge between the backbone of L109 and $C_{L}\kappa$. Another hydrogen bond is formed between the Tyr at residue position 173 in $C_{L}\kappa$ and the negatively charged residue (Glu) at position L105 in $V_{L}\kappa$. The absence of Gly at position L107 (exclusively present in $V_{L}\lambda$) and a consistent hydrogen bonding pattern between V_{L} and C_{L} domains might restrain the flexibility of the hinge region in LC κ but. Moreover, a strong interaction energy between $V_{L}\kappa$ and $C_{L}\kappa$ is reached by the simultaneous formation of two hydrogens bonds via an Arg at position L108, whilst in λ only a singular and weaker hydrogen bond is formed via a conserved Glu at position L108 (Supplementary Figure 5G and H, respectively).

This analysis confirmed that in κ an extensive network of hydrogen bonds firmly staples the hinge region connecting V_L and C_L in place, thereby fixing the elbow angle between the domains. In contrast, λ exhibits significantly less interactions between V_L and C_L, thus creating a higher flexibility of the elbow angle (Stanfield *et al.*, 2006).

Sequence selection in the CDRs is coupled to sequence variation in the entire V_L domain

Besides characterizing individual contributions of single residues of V_L to the binding of antigen and V_H, the V_L fold was further investigated for correlated networks of amino acids using statistical coupling analysis (SCA) (Halabi et al., 2009). The technique measures covariations between pairs of amino acids in a multiple sequence alignment. Thereby, high statistical coupling energies indicate evolutionary dependence between residue pairs. Ideally, clustering of statistical coupling energies yields networks of evolutionary dependent amino acids (Halabi et al., 2009), for which reason it is capable of revealing how sequence selection in one part of the antibody potentially affects the amino acid identity of further parts. While the technique itself is entirely unbiased, it depends critically on the number of sequences comprised within the alignment in order to detect meaningful coupling information (Zafra Ruano et al., 2016). However, given that our analysis is focused on the structuresequence relationship, we limited the analysis to our non-redundant set of sequences for which reliable structural data was available, i.e. the analysis was performed on the entire multiple sequence alignment containing 333 V_L sequences without subgrouping into λ and κ , which is on the low side for this method and hence only the most consistent results should be taken from this. Nevertheless, using typical settings of statistically significant coupling analysis (Lockless and Ranganathan, 1999), three conserved clusters of interacting amino acids were identified (Fig. 3 and Table III) that unequivocally connect sequence variations in the CDRs with different parts of the LFRs. For example, cluster 1 comprises statistically coupled amino acids of the framework regions LFR1 (L7), LFR3 (L62 and L67) and LFR4 (L98, L99, L101, L102 and L104) with a residue of CDR L1 (L25) (Fig. 3A). In other words, the selection outcome of position L25 at the N-terminal end of CDR L1 correlates with adaptive changes in the frame regions LFR1, LFR3, and most prominently in LFR4 that forms CDR L1's opposite side of the domain. Intriguingly, position L25 is not frequently involved in binding (Fig. 2C), but seems to serve as a connection point between the loop to the rest of the structure. Notably, the coupled L7 (LFR1) is a conserved position that differs between the V_L isotypes (Proline in κ , Serine in λ , Fig. 2A and B), suggesting that these different conserved residues help to accommodate a distinct selection of CDR sequences.

The next identified cluster 2 shows statistical coupling between amino acid positions in the framework regions LFR1 (L5, L6 and L22) and LFR3 (L57, L58, L78, L82 and L84) with CDR L1 (L31) and CDR L3 (L94, L95 and L95B), thus connecting the rest of the fold with both CDRs that are strongly involved in interacting with the ligand (Fig. 3B). In particular, residues L31 and L94 are often critically involved in antigen binding (Fig. 2C), and their coupling to LFR residues provides direct evidence of the entire domain adjusting to selections at these critical positions for antigen binding. The role of L95 and L95B seems to be more adaptive as they are not as frequently involved in antigen binding (Fig. 2C). Additionally, cluster 3 comprised statistically coupled amino acid positions of the framework regions LFR1 (L12, L18, L19, L20 and L21), LFR2 (L36, L37, L38, L41 and L45) and LFR3 (L74 and L75) and a central position in CDR L2 (L54) (Fig. 3C). Again, the third cluster connects a sequence selection in one of the CDRs to positions distributed across the entire domain. Taken together, these three amino acid clusters provide clear evidence that CDRs and FRs cannot be studied individually. Since sequence variations in CDR positions impact throughout the entire antibody domain, adaptive changes may be required to accommodate the CDR sequence selection.

Besides that, no specific differences in the network of co-evolving residues were found between $V_L\kappa$ and $V_L\lambda$, in part due to this method's large data requirements to detect subtle connections (Zafra Ruano *et al.*, 2016). Additionally, the conservation analysis most readily identifies the commonalities in the entire family and is less sensitive for identifying differences in subgroups (Lockless and Ranganathan, 1999; Suel *et al.*, 2003). Consequently, additional methods were applied to resolve potential differences between interacting residues in $V_L\kappa$ and $V_L\lambda$.

Mining structural differences between λ and κ

In order to elucidate structural factors that distinguish between VLK and VLA, a machine learning technique called Random Forest (Breiman, 2001) was used in order to identify the most convenient variables differentiating between both classes. According to this method, a large quantity of decision trees is generated that each splits instances of a dataset to their predefined classes ($V_L\kappa$ and $V_L\lambda$), based on a subset of variables that are randomly selected from a predefined pool. Parameters describing the properties of λ and κ Fab structures were extracted from the FoldX analysis, supplemented with other structural descriptors and used as input variables (Supplementary Table 2). The ensemble of decision trees (the forest) was then used to rank the most important variables with respect to their ability to classify between kappa and lambda by determining the mean decrease gini, a factor that weighs the relative importance of each parameter in obtaining a reliable classification (Fig. 4A). The length of the LFR4 region was identified as the variable with the highest importance (Fig. 4B), referring to the fact that LFR4 comprises an additional residue (L106A) in $V_L\lambda$ but not in $V_L\kappa$ (Fig. 4C). The relatively small and flexible glycine is usually present as $V_{I}\lambda$'s additional residue (Fig. 1J) in a stretch forming the $V_{I}\lambda$ - $C_{I}\lambda$ interface, which was previously hypothesized in literature (Stanfield *et al.*, 2006) and confirmed above to allow λ light chains to adopt a more flexible switch region and larger elbow angles between V_L and C_L.

The penalty for peptide bonds in the cis-conformation *i.e.* cisprolines was identified as the second most important variable to classify between κ and λ . Strikingly, $V_L \lambda$ comprises no cis-Prolines



Fig. 3 Statistical Coupling Analysis (SCA) of V_L structures identified three conserved clusters of statistically coupled amino acids. Ranganathan's SCA method determined three statistically coupled networks of amino acids (1, red; 2, blue; 3, magenta) in the V_L domain. The clusters are shown on a representative V_Lκ structure (left, PDB: 117i (Vajdos *et al.*, 2002)) and marked through bars on a topological scheme. The color-coding scheme for CDR and LFR is maintained from Fig. 1C and D.

on average, and $C_L\lambda$ and $C_L\kappa$ both contain one cis-conformation (Fig. 4D). Contrarily, $V_L\kappa$ exhibits two peptide bonds in the cisconformation in LFR1 (L8) and CDR L3 (L95) in the most cases (Fig. 4D) (Spada *et al.*, 1998; Ewert *et al.*, 2003). As a result, the Nterminal β -strand (LFR1) of $V_L\kappa$ is bent by a cis-proline at position L8, while in $V_L\lambda$ this kink in the β -strand results from two consecutive trans-prolines (Fig. 4F).

Correlating with the presence of cis-conformations in LFR1, the length of this region emerged as another important classification parameter between both isotypes. The LFR1 of $V_L\kappa$ exhibits exactly 23 amino acids, whereas the length of the region is restricted to 22 or 21 amino acids in $V_L\lambda$ (Fig. 4E). The cis-proline

at position L8 allows for one extra residue to be placed in LFR1 of $V_{L\kappa}$ (Fig. 4F), where in $V_{L\lambda}$ two prolines at positions L7 and L8 form the bridge connecting the two halves of the beta-sandwich (Fig. 2A, B and F).

Being exclusively found in $V_L\kappa$, the second cis-proline at residue L95 leads to a highly conserved structural feature in the middle of CDR L3 (Fig. 4H, J). Simultaneously, the consistent length of this loop clearly differentiates from the varying length of the corresponding CDR in $V_L\lambda$ lacking the cis-conformation (**Supplementary Figure 4E**). A clear pattern emerges from the structural environment of cis-Pro95 comprising a hydrogen bond between the conserved Thr97 and the frequently found (86%), β -branched Ile2 (Fig. 4H).

Table III. Ranganathan clusters

| Cluster # | Chothia # | Region | |
|-----------|-----------|--------|--|
| 1 | L7 | LFR1 | |
| | L25 | CDRL1 | |
| | L62 | LFR3 | |
| | L67 | LFR3 | |
| | L98 | LFR4 | |
| | L99 | LFR4 | |
| | L101 | LFR4 | |
| | L102 | LFR4 | |
| | L104 | LFR4 | |
| 2 | L5 | LFR1 | |
| | L6 | LFR1 | |
| | L22 | LFR1 | |
| | L31 | CDRL1 | |
| | L57 | LFR3 | |
| | L58 | LFR3 | |
| | L78 | LFR3 | |
| | L82 | LFR3 | |
| | L84 | LFR3 | |
| | L94 | CDRL3 | |
| | L95 | CDRL3 | |
| | L95B | CDRL3 | |
| 3 | L12 | LFR1 | |
| | L18 | LFR1 | |
| | L19 | LFR1 | |
| | L20 | LFR1 | |
| | L21 | LFR1 | |
| | L36 | LFR2 | |
| | L37 | LFR2 | |
| | L38 | LFR2 | |
| | L41 | LFR2 | |
| | L45 | LFR2 | |
| | L54 | CDRL2 | |
| | L74 | LFR3 | |
| | L75 | LFR3 | |

As a consequence, the N-terminal region is fixed to the structure by a network of conserved hydrogen bonds. Interestingly, the $V_L\lambda$ structures relatively often lack the N-terminal positions L1 and L2, which might result from a low electron density in the X-ray diffraction pattern that is obtained during structure elucidation of this typically flexible region. This relates back to the hypothesis that the Nterminal end of LFR1 has a lower thermodynamic stability in $V_L\lambda$, which was previously proposed to explain the susceptibility of human $V_L\lambda$ to amyloid formation and overrepresentation in light chain amyloidosis (Zhao *et al.*, 2018).

Additionally distinguishing $V_{L}\kappa$ from $V_{L}\lambda$, CDR L3 is fixed via hydrogen bonding between the backbone of position L93 and a conserved Gln90 (85%) that further hydrogen bridges with Thr97 (Fig. 4H). This considerably conserved network of hydrogen bonds consistently stabilizes the structural environment of the antigenbinding loop between $V_{L}\kappa$ chains. In contrast, $V_{L}\lambda$ exhibits a broad range of amino acids at position L90 (Ser: 46%, Ala: 21%, Thr: 17%, Val: 16%) as well as more unspecific interaction partners (Val at L97:76%), providing CDR L3 a greater level of variability to adopt versatile loop conformations and broad affinities to ligands. The isotype-specific structural features seem to be linked to the particular function of the respective CDR L3. While this region is on average only moderately involved in target binding in $V_L\kappa$, the loop is critically important in $V_L\lambda$ with L91 significantly contributing to the antigen interaction (Fig. 2C).

λ and κ structures are stabilized by differential interaction networks

After determining differences between the sequence (Figs 1–3) and structural appearance (Figs 1, 2 and 4) of $V_L\lambda$ and $V_L\kappa$, next the underlying scaffolds were investigated for stability differences. To this end, the contribution of each residue to the thermodynamic stability ($\Delta G_{contrib}$) of the respective fold was calculated using FoldX (example data in Fig. 5A). To identify energetic differences between the scaffolds of both isotypes, the per-residue contribution to the thermodynamic stability of $V_L\lambda$ was subtracted by that of $V_L\kappa$.

$$\Delta\Delta G_{\text{contrib}} = \Delta G_{\text{contrib}} \lambda - \Delta G_{\text{contrib}} \kappa$$

The statistical significance of energetic differences was calculated using the Wilcoxon signed rank test (Fig. 5A), and $\Delta\Delta G_{contrib}$ was plotted against the -log10 p-value resulting in a so-called volcano plot (Fig. 5B). Difference of at least $\Delta\Delta G_{contrib} = \pm 0.5 \text{ kcal/mol}$ combined with a p-value <0.05 were assigned as significant. The method identified 28 positions that are evenly distributed throughout the domain, half of which contribute to the stability of the λ fold, while the remaining positions favor the κ scaffold. The identified residues were highlighted on a representative structure (Fig. 5C) and on a two-dimensional interaction network representation (Fig. 1I, J), both illustrating that the isotypes are stabilized by different networks of interacting residues. Positions that predominantly stabilize the $V_L\lambda$ structure (L7, L8, L15, L27, L28, L30, L30C, L39, L55, L67, L70, L91, L97 and L108) are widespread and differ in the conservation degree; L7, L8, L15 and L55 (all highly conserved Prolines, the last located in CDRL2), L27, L28, L30, L30C and L91 (variable positions in CDR L1 and CDR L3), L39 (variable position in LFR2), L67, L70, L97 and L108 (relatively conserved positions in LFR3 and LFR4). Similarly, the remaining positions that contribute to the stability of V₁κ (L2, L17, L22, L25, L29, L33, L47, L54, L71, L80, L83, L85, L94, L95) are distributed throughout the domain while offering a broad range of conservation scores. L2, L17 and L22 (relatively highly conserved positions in LFR1), L25, L29 and L33 (relatively highly conserved positions in CDR L1), L47 (completely conserved position in LFR2), L54 (relatively highly conserved position in CDR L2), L71 (completely conserved position in LFR3), L80, L83 and L85 (variable positions in LFR3), L94 (highly variable position in CDR L3) and L95 (highly conserved proline in CDR L3).

In the following, the domain's antigen binding site is exemplarily studied in more detail to illustrate isotype-specific interaction networks. In V_L κ (Fig. 5D), the cluster of interacting residues connects CDR L1 (Ala/Ser at L25, an aliphatic residue at L29 and Leu33) with LFR1 (Ile2) and LFR3 (Phe71) (Fig. 5B). V_L λ is stabilized by a different network in which several variable positions of CDR L1 (L27, L28, L30) interact with LFR3 (Thr/Ser at L70, Ser67) (Fig. 5E). Furthermore, the cluster comprises a frequently found Tyr/Trp at position L91 that was shown to mediate antigen and V_H interaction. Other parts of the domain reveal further differences in stabilizing clusters, thus showing that despite the high similarity in overall structure, V_L λ and V_L κ are stabilized in a fundamentally different manner.

λ and κ frameworks adapt to the conformation of the CDRs

To elucidate how the selection of certain CDR loop conformations requires adaptations in the framework region, a variation of the



Fig. 4 Structural differences between V_{LK} and $V_{L\lambda}$ were determined by RandomForest. (A) The most reliable classifiers for assigning the dataset of full light chain structures to the κ and λ isotypes are identified by the mean decrease gini (variables defined in **Supplementary Table 1**). (B) Unknown sequences can be reliably assigned to the κ and λ isotype according to the length of LFR4. (C) An overlay of representative C α -traces displays how the exclusion (V_{LK} , green, 5ifa (Huang *et al.*, 2004)) or incorporation ($V_{L\lambda}$, red, 3ujj (Guan *et al.*, 2013)) of L106A in LFR4 affects the structure. (D) $V_{L\lambda}$ structures exhibited a significantly lower energy penalty for peptide bonds in the cis-conformation if compared to V_{LK} structures. (E) The number of residues in LFR1 enables to distinguish between V_{LK} and $V_{L\lambda}$ sequences. (F) Representative structures of $V_{L\lambda}$ (3ujj (Gorny *et al.*, 2011), red) and V_{LK} (5ifa (Jardine *et al.*, 2016), green) illustrate structural differences in LFR1. V_{LK} structures frequently contain a cis-proline at position L8, stabilizing a fold that dramatically differs from $V_{L\lambda}$ structures that favor trans-prolines at positions L7 and L8. (G) 'Sequence logo' representation of the amino acids identities in LFR1 of V_{LK} (Jottom). (H, I) Representative structures of V_{LK} (H, green, PDBs: 3drq (Julien *et al.*, 2008), 4gv (Schiele *et al.*, 2015), 4gm4 (Kong *et al.*, 2015) and $V_{L\lambda}$ (Giffer in the conserved environment of residue L95. Yellow cylinders, hydrogen bonds; yellow and orange structure, heavy chair, cyan residue, Gln L90; magenta, Pro L95; orange, Thr L97; blue, Phe L98; green, Val L97. (J) 'Sequence logo' representation of the amino acids occurrence spatially neighboring residues of L95 in V_{LK} (top) and $V_{L\lambda}$ (bottom).



Fig. 5 Key residues contribute significantly different to the folding stability of V_{LK} and $V_{L\lambda}$ structures. (**A**) Key residues that differed most clearly in their energy contribution to the folding stability of either V_{LK} or $V_{L\lambda}$ were identified. The Wilcoxon rank-sum test yielded a statistical significance of $P \le 0.0001$ (****) for key residues. The amino acid conservation in the 'sequence logo' format was extracted from Fig. 2**A** and **B**. In accordance to the schema in Fig. 1**C**, the color coding of the lower bar indicates the CDR L2 and LFR3. (**B**) The volcano plot visualizes the per-residue preference for stabilizing either the $V_{L\lambda}$ (negative energy values) or the V_{LK} fold (positive energy values) by plotting the difference of mean energy contribution to both structure types against the -log10 P-value (negative 10 base log of the P-value). Highly significant data points correspond to low P-values that appear at the top of the plot. The mean energy difference threshold was set at > 0.5 kcal/mol (corresponding to the accepted uncertainty of FoldX (Schymkowitz *et al.*, 2005)) and the P-value threshold at P < 0.05 (corresponding to a -log10 P-value of < 1.30). The dots are color coded according to Fig. 1**C** and **D**. (**C**) The isotype-specific folds are stabilized by particular residue positions (Fig. 5**B**) that are highlighted on representative V_{LK} (red clusters, PDBid: 5ifa (Huang *et al.*, 2004) and $V_{L\lambda}$ structures (blue clusters, PDBid: 3ujj (Guan *et al.*, 2013). (**D**-**E**) Distinct clusters of stabilizing amino acids near the antigen binding site are shown for (**D**) V_{LK} (PDBid: 5ifa (Huang *et al.*, 2004) and (**E**) $V_{L\lambda}$ (PDBid: 3ujj (Guan *et al.*, 2013).

Shannon information analysis was performed (Lenaerts *et al.*, 2008, 2009a,b; Zafra Ruano *et al.*, 2016). State-of-the-art CDR databases were used that classify canonical structures according to their length (Dunbrack (North *et al.*, 2011; Adolf-Bryfogle *et al.*, 2015)) and

overall structural similarity (Deane (Nowak *et al.*, 2016)) (Table IV). For the entirety of V_L structures, the mutual information network between framework's residue identities and both CDR loop libraries (Fig. **6A**, **Supplementary Figure 6A**) were visualized as

| | Dunbrack | | | Deane | | |
|-----|------------------|---------|---------|---------------|---------|---------|
| CDR | Canonical | K count | L count | Canonical | K count | L count |
| L1 | L1-8-* | 0 | 2 | L1-10,11,12-A | 52 | 0 |
| | L1-9-* | 4 | 0 | L1-11-A | 0 | 10 |
| | L1-10-1 | 4 | 0 | L1-11-B | 0 | 4 |
| | L1-11-1 | 103 | 0 | L1-12-A | 2 | 0 |
| | L1-11-2 | 11 | 1 | L1-12-B | 3 | 0 |
| | L1-11-3 | 2 | 36 | L1-12-D | 1 | 0 |
| | L1-12-1 | 13 | 0 | L1-13-A | 0 | 1 |
| | L1-12-2 | 10 | 0 | L1-13,14-A | 0 | 26 |
| | L1-12-3 | 0 | 1 | L1-17-A | 1 | 0 |
| | L1-13-1 | 0 | 28 | Unclustered | 4 | 5 |
| | L1-13-2 | 1 | 3 | | | |
| | L1-14-2 | 0 | 24 | | | |
| | L 1-14-cis9-* | 0 | 1 | | | |
| | L1-15-1 | 9 | 0 | | | |
| | L1-15-2 | 1 | 0 | | | |
| | L1-16-1 | 24 | 0 | | | |
| | L1-16-cis9-* | 1 | 0 | | | |
| | L1 17 1 | 9 | 0 | | | |
| | | 29 | 16 | | 150 | 66 |
| 1.2 | | 29 | 10 | | 63 | 44 |
| L2 | 12.0- | 192 | 77 | | 0.5 | -++ |
| | L2-8-1 L2-8-2 | 182 | 10 | L2-/-D | 2 | 0 |
| | L2-8-2 | 3 | 10 | | | |
| | L2-8-3 | 2 | 0 | | | |
| | L2-8-4 | 1 | 5 | | | |
| | L2-8-5 | 1 | 1 | | | |
| | L2-8-cis3-* | 2 | 1 | | | |
| | L2-12-2 | 0 | 1 | | | |
| | <na></na> | 28 | 16 | <na></na> | 156 | 68 |
| L3 | L3-5-* | 10 | 1 | L3-5-A | 4 | 1 |
| | L3-6-cis4-* | 0 | 1 | L3-7-A | 1 | 0 |
| | L3-7-1 | 1 | 0 | L3-8-A | 2 | 0 |
| | L3-8-1 | 9 | 0 | L3-9-A | 0 | 3 |
| | L3-8-2 | 4 | 0 | L3-9-B | 0 | 1 |
| | L3-8-cis6-1 | 1 | 0 | L3-9,10-A | 51 | 0 |
| | L3-9-1 | 4 | 12 | L3-10-A | 0 | 3 |
| | L3-9-2 | 12 | 2 | L3-10-C | 1 | 2 |
| | L3-9-cis5,7-* | 1 | 0 | L3-10-D | 0 | 1 |
| | L3-9-cis7-1 | 116 | 0 | L3-10,11-A | 0 | 15 |
| | L3-9-cis7-2 | 1 | 0 | L3-12-A | 0 | 1 |
| | L3-9-cis7-3 | 4 | 0 | L3-13-A | 0 | 2 |
| | L3-10-1 | 5 | 27 | Unclustered | 10 | 15 |
| | L3-10-cis5,8-* | 1 | 0 | | | |
| | L3-10-cis6-* | 0 | 2 | | | |
| | L3-10-cis7-* | 3 | 0 | | | |
| | L3-10-cis7,8-1 | 6 | 0 | | | |
| | L3-10-cis8-1 | 1 | 0 | | | |
| | L3-11-1 | 8 | 37 | | | |
| | L3-11-cis7-1 | 5 | 0 | | | |
| | L3-11-cis8-* | 1 | 1 | | | |
| | L3-12-1 | 1 | 11 | | | |
| | L3-12-cis8-* | 0 | 1 | | | |
| | L3-13-1 | 0 | 2 | | | |
| | <na></na> | 27 | 15 | <na></na> | 152 | 68 |

Table IV. Counts of canonical structures for Dunbrack and Deane definitions.

Chord diagrams, expressing the quantity of mutual information between residue positions (nodes) via the thickness of edges. Thereby, the connection between CDR conformations and sequence patterns of $V_L\lambda$ and $V_L\kappa$, and thus adaptations in the LFR accommodating for CDR canonical classes was unraveled. An extensive list of couplings between residue positions of the scaffold and loop

conformations of CDR L1 and L3 was identified. CDR L2 did not show any mutual information with framework reisdues, which is likely due to its limited number of canonical structures (Table IV, (North *et al.*, 2011; Nowak *et al.*, 2016)). Given that loop conformations of λ and κ are assigned to different canonical categories, the coupling is directly related to isotype-specific residue positions that



Fig. 6 Chord diagrams of mutual information between canonical structures and framework residues. **(A, B, C)** Mutual information of Dunbrack's canonical structures (North *et al.*, 2011) and framework residues of **(A)** V_L, **(B)** V_L λ and **(C)** V_L κ was calculated, and values > 0.5 are shown. The color of the

were already determined by sequence alignments (Fig. 2A, B). Interestingly, the mutual information between framework positions and canonical structures of CDR L1 seems to exceed that of CDR L3 (Fig. 6A, quantity of edges), suggesting a particular dependence of CDR L1's canonical structures on framework identities.

To study $V_L\lambda$ - and $V_L\kappa$ -specific sequence adaptions to its distinct CDR loop classes, equivalent chord diagrams were constructed isotype-specifically applying Dunbrack's (Fig. 6B and C) and Deane's (Supplementary Figure 6B and C) CDR loop classes. $V_L\lambda$ comprises an intricate network of connected amino acid residues, for which reason many positions throughout the domain accommodate the canonical structures of CDR L1 and CDR L3 (Fig. 6B). The conformational cluster of CDR L1 is connected to positions of the surrounding $V_L\lambda$ scaffold except region LFR4. This connection is used as an example to validate the mutual information method below.

The canonical structures of VLA's CDR L1 favor three representative Dunbrack classes, i.e. L1-11-3, L1-13-1 and L1-14-2 (Table IV). Residues of CDR L2 (L51) and LFR3 (L66) clearly correlate with that of the surrounding CDR L1 (L29) and its Cterminal end (L33) by forming an interaction network (Fig. 7). Canonical structure L1-11-3 (Fig. 7A) is uniquely stabilized by a cross-linked network of hydrogen bonds involving the class-specific side chains of AspL51 and AsnL66 as well as the backbone at position L33 and L29(L29...AsnL66...AspL51...L33). Two of these positions (AsnL51, LysL66) are consistently modified in sequence of the second canonical structure L1-13-1, which dramatically affects the conformation of CDR L1 (Fig. 7B). The C-terminal end of the loop is fixed via hydrogen bonding of the altered AsnL51 side chain and the backbone of L33, while the middle of the loop is stabilized by a hydrogen bond between the varied LysL66 side chain and the L29 backbone. Similarly, the third canonical structure L1-14-2 is oriented by the unchanged LysL66 side chain and backbone of L29, but hydrogen binding between CDR L1 and L2 is prevented by a class-specific ValL51 (Fig. 7C). The rather nonspecific, hydrophobic interactions of ValL51 presumably permit a more flexible loop orientation of CDR L1. An overlay of these three canonical classes (Fig. 7D) indicates that the lacking hydrogen bond of L51 relaxes the backbone of CDR L1-14-2 into an extended beta-strand. In contrast, the loop conformation of L1-11-3 is precisely positioned by a well-defined hydrogen bond network between L33, L51, L66 and L28. The sequence variability of CDR L2 in $V_L\lambda$ seems to contribute less to antigen binding (Fig. 2C) rather than to support the remaining hypervariable regions to form distinct canonical structures. The herein identified unique interaction networks between framework residues and canonical CDR structures strongly supports the hypothesis stating that the conformation of CDRs of $V_{I}\lambda$ depend stronger on framework positions than in the case of $V_L \kappa$. For grafting CDRs on $V_L\lambda$ scaffolds, this finding underlines an increased importance of considering key residues of the scaffold and verifying the loop orientation of its CDR L1, L2 and L3. VIK exhibits less couplings between loop conformations and LRF scaffold, suggesting that loop grafting could potentially be less complicated (Fig. 6C).

chords corresponds with CDR's canonical group (salmon: CDR L3, purple: CDR L1), and chord width correlates with the extent of mutual information (in bits). The coloring scheme of Chothia positions reflects their topological region similar to that used in Figs 1–3.



Fig. 7 Networks of interacting amino acids stabilize distinct canonical structures of CDR L1 in $V_{L\lambda}$. (**A**) Dunbrack's CDR cluster L1-11-3 is favored by a hydrogen bond network between Asp L51 of CDR L2 and Asn L66 of LFR3, cooperatively coordinating the C-terminal end of CDR L1 (L33) and the center of CDR L1 (L29). PDB 4m5y was representatively used to visualize the structure (Hong *et al.*, 2013). (**B**) Canonical class L1-13-1 is stabilized by hydrogen bonding between Asn L51 of CDR L2 and Val L33 of CDR L1, and between Lys L66 of LFR3 and Ile L29 of CDR L1. The structure of PDB 3n9g was exemplary used for visualization (Kaufmann *et al.*, 2010). (**C**) The canonical structure L1-14-2 is favored by a hydrogen bond between Val L29 of CDR L1 and Lys L66 of LFR3, whilst L33 and L51 do not interact as it was shown for PDB 3kdm (Niemi *et al.*, 2011). (**D**) An overlay of (**A**-**C**) highlights the structural differences between the canonical classes L1-13-1 and L1-14-2. The consistent hydrogen bonds between the sidechain of L66 and the central part CDR L1, and between the sidechain of L51 of CDR L2 and L33 of the C-terminus of CDR L1 define the Dunbrack canonical classes of CDR L1 in $V_L\lambda$.

Conclusion

The role of loops, particularly longer ones, in protein structures is often underappreciated as the focus goes to the regular hydrogen bonded elements of (secondary and tertiary) structure and the hydrophobic core, with the loops required to connect more interesting structure parts (Pei *et al.*, 1997; Fiser *et al.*, 2000). This is particularly pronounced in the concept of CDR loop grafting in the field of antibody engineering. However, 20–30% of protein structures are composed of elements that can be classified as loop structures while playing an integral and essential role in the folding and stability of the protein structure (Vanhee *et al.*, 2011). Moreover, loop structures can act as tensioned springs that propagates strain throughout the surrounding structure, a mechanistic concept that

seems to occur typically around active sites (Rousseau *et al.*, 2001; Gutteridge and Thornton, 2004).

The field of antibody engineering has gradually incorporated a more integrative view, in which the CDRs are fitted into the framework regions rather than being grafted on top of it. In the current study, advanced statistical analysis of protein structures was employed to comprehensively map the network of interactions that connect the CDRs to the rest of the V_L domain. A special focus was further set on the structural difference between V_L λ and V_L κ isotypes to highlight the specific structural adaptations through the domains. The view that emerges is that there are residues distributed over the V_L domain whose amino acid identity are adapted to the structure of the CDRs. The analysis forms the starting point to

design a back-mutation algorithm that identifies and modifies problematic positions to optimize the placement of defined loop configurations on scaffold regions. The applied methods are in principle amenable to analyze any protein domain, but the availability of structural information with sufficient resolution and diversity are a prerequisite. Taking the latter into consideration, the analysis of novel developments such as more complex antibody formats are currently out of scope.

The structural differences between $V_L\lambda$ and $V_L\kappa$ reveal how the V_L domain adapts to entirely different loop classes. Most notably, solely $V_L\lambda$'s CDR L1 contains a helical segment sittings tightly in the beta-sandwich of the Ig fold, partly distorting the inter-sheet interaction of the sandwich. Another important difference to $V_L\kappa$ is found in the linker region between V_L and V_C , which forms less interactions and a more flexible elbow angle conformation in $V_L\lambda$. The structural differences are apparent in both, the conservation pattern of each isotype, and the network of interactions stabilizing each structure. It is hence consistent that grafting of loops on a V_L domain will require isotype-specific adaptations of its key residues which identities associate with its CDR loop classes.

The analytical framework of this work provided new insight into the V_L architecture, but have not yet been turned into a protocol for antibody framework engineering in response to loop grafting. A method still to be developed could predict the most appropriate amino acid choices at crucial framework positions under consideration of its CDR loop classes. Although machine learning algorithms appear to be ideally suited for this task at first sight, the available set of diverse and high-quality structural data is currently too limited to allow the training of a sufficiently accurate method. Besides that, in the most cases accurate loop class assignments are precluded by solely knowing the CDR loop sequences rather than their exact structures. The absence of accurate structural models further limits the potential application of force field calculations to identify optimal amino acid identities at critical positions. As a consequence of the mentioned restrictions, the best current approach may be based on selectively varying amino acids on critical positions in the V_L domain followed by experimentally selecting the best variants with regard to its biophysical properties and antigen affinity. The fact that several of the aspects that stood out form our analysis have been incorporated in existing antibody design workflows (Lapidoth et al., 2015; Adolf-Bryfogle et al., 2018) further underlines the validity of our findings.

Supplementary Data

Supplementary data are available at *Protein Engineering*, *Design and Selection* online.

Funding

The VIB Switch Laboratory was supported by grants from VIB, University of Leuven, the Funds for Scientific Research Flanders (FWO), the Flanders Institute for Science and Technology (IWT) and the Federal Office for Scientific Affairs of Belgium (Belspo), IUAP P7/16 and by the European Research Council under the European Union's Horizon 2020 Framework Programme, ERC Grant agreement 647458 (MANGO) to JS. RVDK was supported by Boehringer Ingelheim Pharma GmbH & Co and VIB.

Author contributions

JS, FR, JB, MB and PG designed the project. RVDK, JS and FR carried out the bioinformatics analysis. All authors contributed to data interpretation. RVDK, JB, JS and FR wrote the paper with input from all other authors.

Competing financial interests

MB, SK, AK, JB, PG were employees of Boehringer Ingelheim Pharma GmbH & Co. KG during the course of the project.

References

- Abhinandan,K.R. and Martin,A.C.R. (2008) Mol. Immunol., 45, 3832-3839. Acharya,P., Tolbert,W.D., Gohain,N. et al. (2014) J. Virol., 88,
- 12895–12906. Adolf-Bryfogle,J., Kalyuzhniy,O., Kubitz,M., Weitzner,B.D., Hu,X., Adachi,
- Y., Schief, W.R. and Dunbrack, R.L., Jr. (2018) *PLoS Comput. Biol.*, 14, e1006112. doi:10.1371/journal.pcbi.1006112. First published on 2018/04/28.
- Adolf-Bryfogle, J., Xu, Q., North, B., Lehmann, A. and Dunbrack, R.L., Jr. (2015) Nucleic Acids Res., 43, D432–D438. doi:10.1093/nar/gku1106. First published on 2014/11/14.
- Al-Lazikani, B., Lesk, A.M. and Chothia, C. (1997) J. Mol. Biol., 273, 927–948. doi:10.1006/jmbi.1997.1354. First published on 1998/02/12.
- Alzari,P.M., Lascombe,M.B. and Poljak,R.J. (1988) Annu. Rev. Immunol., 6, 555–580. doi:10.1146/annurev.iy.06.040188.003011. First published on 1988/01/01.
- Baca, M., Presta, L.G., O'Connor, S.J. and Wells, J.A. (1997) J. Biol. Chem., 272, 10678–10684. First published on 1997/04/18.
- Bogan, A.A. and Thorn, K.S. (1998) J. Mol. Biol., 280, 1-9.
- Boulianne,G.L., Hozumi,N. and Shulman,M.J. (1984) *Nature*, **312**, 643–646. First published on 1984/12/13.
- Breiman, L. (2001), Machine Learning. unknown.
- Bruggemann, M., Caskey, H.M., Teale, C., Waldmann, H., Williams, G.T., Surani, M.A. and Neuberger, M.S. (1989) Proc. Natl Acad. Sci. USA., 86, 6709–6713. First published on 1989/09/01.
- Bruggemann, M. and Neuberger, M.S. (1996) Immunol. Today, 17, 391–397. First published on 1996/08/01.
- Bruggemann, M., Osborn, M.J., Ma, B., Hayre, J., Avis, S., Lundstrom, B. and Buelow, R. (2015) Arch. Immunol. Ther. Exp. (Warsz), 63, 101–108. doi: 10.1007/s00005-014-0322-x. First published on 2014/12/04.
- Carter, P., Presta, L., Gorman, C.M. et al. (1992) Proc. Natl Acad. Sci. USA., 89, 4285–4289. First published on 1992/05/15.
- Chames, P., Van Regenmortel, M., Weiss, E. and Baty, D. (2009) Br. J. Pharmacol., 157, 220–233. doi:10.1111/j.1476-5381.2009.00190.x. First published on 2009/05/23.
- Chevalier, A., Silva, D.A., Rocklin, G.J. *et al.* (2017) *Nature*, 550, 74–79. doi: 10.1038/nature23912. First published on 2017/09/28.
- Chiu, W.C., Lai, Y.P. and Chou, M.Y. (2011) *PLoS One*, 6, e16373. doi:10. 1371/journal.pone.0016373. First published on 2011/02/10.
- Chothia, C. and Lesk, A.M. (1987) J. Mol. Biol., 196, 901-917.
- Chothia, C., Novotny, J., Bruccoleri, R. and Karplus, M. (1985) J. Mol. Biol., 186, 651–663. First published on 1985/12/05.
- Clackson, T. and Wells, J.A. (1995) Science, 267, 383-386.
- Co,M.S. and Queen,C. (1991) Nature, 351, 501–502. doi:10.1038/ 351501a0. First published on 1991/06/06.
- Crooks,G.E., Hon,G., Chandonia,J.M. and Brenner,S.E. (2004) Genome Res., 14, 1188–1190. doi:10.1101/gr.849004.
- D'Angelo,S., Ferrara,F., Naranjo,L., Erasmus,M.F., Hraber,P. and Bradbury, A.R.M. (2018) Front. Immunol., 9, 395. doi:10.3389/fimmu.2018. 00395. First published on 2018/03/24.
- Edelman, G.M. (1959) J. Am. Chem. Soc., 81, 3155-3156. doi:10.1021/ja01521a071.
- Ewert, S., Huber, T., Honegger, A. and Plückthun, A. (2003) J. Mol. Biol., 325, 531–553.
- Eylenstein, R., Weinfurtner, D., Härtle, S., Strohner, R., Böttcher, J., Augustin, M., Ostendorp, R. and Steidl, S. (2016) MAbs, 8, 176–186.
- Faber, C., Shan, L., Fan, Z., Guddat, L.W., Furebring, C., Ohlin, M., Borrebaeck, C.A. and Edmundson, A.B. (1998) *Immunotechnology*, 18, 253–270.
- Fiser, A., Do, R.K. and Sali, A. (2000) Protein Sci., 9, 1753–1773. doi:10.1110/ ps.9.9.1753. First published on 2000/10/25.

- Foote, J. and Winter, G. (1992) J. Mol. Biol., 224, 487–499. First published on 1992/03/20.
- Fu,L., Niu,B., Zhu,Z., Wu,S. and Li,W. (2012) Bioinformatics, 28, 3150–3152. doi:10.1093/bioinformatics/bts565.
- Gilman, M.S.A., Moin, S.M., Mas, V. et al. (2015) PLoS Pathog., 17, e1005035.
- Gorny, M.K., Sampson, J., Li, H. et al. (2011) PLoS One, 6, e27780.
- Gu,Z., Gu,L., Eils,R., Schlesner,M. and Brors,B. (2014) *Bioinformatics*, 30, 2811–2812. doi:10.1093/bioinformatics/btu393. First published on 2014/ 06/16.
- Guan, Y., Pazgier, M., Sajadi, M.M. et al. (2013) Proc. Natl Acad. Sci. USA, 110, E69–E78.
- Gutteridge, A. and Thornton, J. (2004) FEBS Lett., 567, 67–73. doi:10.1016/j. febslet.2004.03.067. First published on 2004/05/29.
- Haidar, J.N., Yuan, Q.A., Zeng, L., Snavely, M., Luna, X., Zhang, H., Zhu, W., Ludwig, D.L. and Zhu, Z. (2012) Proteins, 80, 896–912. doi:10.1002/ prot.23246. First published on 2011/12/20.
- Halabi,N., Rivoire,O., Leibler,S. and Ranganathan,R. (2009) Cell, 138, 774–786. doi:10.1016/j.cell.2009.07.038. First published on 2009/08/26.
- Hale,G., Dyer,M.J., Clark,M.R., Phillips,J.M., Marcus,R., Riechmann,L., Winter,G. and Waldmann,H. (1988) *Lancet*, 2, 1394–1399. First published on 1988/12/17.
- Hanf,K.J., Arndt,J.W., Chen,L.L. et al. (2014) Methods, 65, 68–76. doi:10. 1016/j.ymeth.2013.06.024. First published on 2013/07/03.
- Harris, R.J., Shire, S.J. and Winter, C. (2004) Drug Develop. Res., 61, 137-154. doi:10.1002/ddr.10344.
- Honegger, A. and Pluckthun, A. (2001) J. Mol. Biol., 309, 657-670. doi:10. 1006/jmbi.2001.4662.
- Hong,M., Lee,P.S., Hoffman,R.M.B. et al. (2013) J. Virol., 87, 12471–12480.
- Huang, C.-c., Venturi, M., Majeed, S. et al. (2004) Proc. Natl Acad. Sci. USA, 101, 2706–2711.
- Hwang,W.Y. and Foote,J. (2005) *Methods*, **36**, 3–10. doi:10.1016/j.ymeth. 2005.01.001. First published on 2005/04/26.
- Jardine, J.G., Kulp, D.W., Havenar-Daughton, C. et al. (2016) Science, 351, 1458-1463.
- Jones, P.T., Dear, P.H., Foote, J., Neuberger, M.S. and Winter, G. (1986) Nature, 321, 522–525. doi:10.1038/321522a0. First published on 1986/ 05/04.
- Julien, J.-P., Bryson, S., Nieva, J.L. and Pai, E.F. (2008) J. Mol. Biol., 384, 377–392.

- Kaufmann,B., Vogt,M.R., Goudsmit,J., Holdaway,H.A., Aksyuk,A.A., Chipman,P.R., Kuhn,R.J., Diamond,M.S. and Rossmann,M.G. (2010) *Proc. Natl Acad. Sc.i USA.*, 107, 18950–18955. doi:10.1073/pnas. 1011036107. First published on 2010/10/20.
- Kettleborough, C.A., Saldanha, J., Heath, V.J., Morrison, C.J. and Bendig, M.M. (1991) Protein Eng., 4, 773–783. First published on 1991/10/01.
- Knappik,A., Ge,L., Honegger,A. et al. (2000) J. Mol. Biol., 296, 57–86. doi: 10.1006/jmbi.1999.3444. First published on 2000/02/05.
- Koenig,P., Lee,C.V., Sanowar,S., Wu,P., Stinson,J., Harris,S.F. and Fuh,G. (2015) J. Biol. Chem., 290, 21773–21786. doi:10.1074/jbc.M115. 662783. First published on 2015/06/20.
- Koenig, P., Lee, C.V., Walters, B.T., Janakiraman, V., Stinson, J., Patapoff, T.W. and Fuh, G. (2017) *Proc. Natl Acad. Sci. USA*, **114**, E486–E495. doi:10. 1073/pnas.1613231114. First published on 2017/01/07.
- Kong,L., Lee,J.H., Doores,K.J. et al. (2013) Nat. Struct. Mol. Biol., 20, 796–803.
- Krieger, E. and Vriend, G. (2014) Bioinformatics, 30, 2981–2982. doi:10. 1093/bioinformatics/btu426. First published on 2014/07/06.
- Kunik,V. and Ofran,Y. (2013) Protein Eng. Des. Sel., 26, 599–609. doi:10. 1093/protein/gzt027. First published on 2013/06/12.
- Lapidoth,G.D., Baran,D., Pszolla,G.M., Norn,C., Alon,A., Tyka,M.D. and Fleishman,S.J. (2015) *Proteins*, 83, 1385–1406. doi:10.1002/prot.24779. First published on 2015/02/12.
- Lee, J.H., Leaman, D.P., Kim, A.S. et al. (2015) Nat. Commun., 6, 8167.

- Lenaerts, T., Ferkinghoff-Borg, J., Schymkowitz, J. and Rousseau, F. (2009a) BMC Syst. Biol., 3, 9. doi:10.1186/1752-0509-3-9. First published on 2009/01/20.
- Lenaerts, T., Ferkinghoff-Borg, J., Stricher, F., Serrano, L., Schymkowitz, J.W. and Rousseau, F. (2008) BMC Struct. Biol., 8, 43. doi:10.1186/1472-6807-8-43. First published on 2008/10/10.
- Lenaerts, T., Schymkowitz, J. and Rousseau, F. (2009b) Curr. Protein Pept. Sci., 10, 133-145. First published on 2009/04/10.
- Li,W. and Godzik,A. (2006) *Bioinformatics*, 22, 1658–1659. doi:10.1093/ bioinformatics/btl158.
- Liu,X., Taylor,R.D., Griffin,L., Coker,S.F., Adams,R., Ceska,T., Shi,J., Lawson,A.D. and Baker,T. (2017) *Sci. Rep.*, 7, 41306. doi:10.1038/ srep41306. First published on 2017/01/28.

Lockless, S.W. and Ranganathan, R. (1999) Science, 286, 295-299.

- Lonberg, N. (2008) Handb. Exp. Pharmacol., 181, 69–97. doi:10.1007/978-3-540-73259-4_4. First published on 2007/12/12.
- McCafferty, J., Griffiths, A.D., Winter, G. and Chiswell, D.J. (1990) Nature, 348, 552–554. doi:10.1038/348552a0. First published on 1990/12/06.
- Meyer, P.E. (2008), PhD thesis of the Universite Libre de Bruxelles.
- Morrison, S.L., Johnson, M.J., Herzenberg, L.A. and Oi, V.T. (1984) Proc. Natl. Acad. Sci. USA., 81, 6851–6855. First published on 1984/11/01.
- Neuberger, M.S., Williams, G.T., Mitchell, E.B., Jouhal, S.S., Flanagan, J.G. and Rabbitts, T.H. (1985) Nature, 314, 268–270. First published on 1985/03/21.
- Niemi,M.H., Takkinen,K., Amundsen,L.K., Soderlund,H., Rouvinen,J. and Hoyhtya,M. (2011) J. Mol. Recognit., 24, 209–219. doi:10.1002/jmr. 1039. First published on 2011/03/02.
- North, B., Lehmann, A. and Dunbrack, R.L., Jr. (2011) J. Mol. Biol., 406, 228–256. doi:10.1016/j.jmb.2010.10.030. First published on 2010/ 11/03.
- Nowak, J., Baker, T., Georges, G., Kelm, S., Klostermann, S., Shi, J., Sridharan, S. and Deane, C.M. (2016) *MAbs*, 8, 751–760. doi:10.1080/19420862. 2016.1158370. First published on 2016/03/11.
- Oyen, D., Torres, J.L., Wille-Reece, U. et al. (2017) Proc. Natl. Acad. Sci. USA., 114, E10438–E10445. doi:10.1073/pnas.1715812114. First published on 2017/11/16.
- Pei,X.Y., Holliger,P., Murzin,A.G. and Williams,R.L. (1997) Proc. Natl. Acad. Sci. USA., 94, 9637–9642. First published on 1997/09/02.
- Popov,A.V., Zou,X., Xian,J., Nicholson,I.C. and Brüggemann,M. (1999) J. Exp. Med., 189, 1611–1620.
- Queen, C., Schneider, W.P., Selick, H.E. et al. (1989) Proc. Natl. Acad. Sci. USA., 86, 10029–10033. First published on 1989/12/01.
- Raghunathan,G., Smart,J., Williams,J. and Almagro,J.C. (2012) J. Mol. Recognit., 25, 103–113. doi:10.1002/jmr.2158. First published on 2012/ 03/13.
- Riechmann, L., Clark, M., Waldmann, H. and Winter, G. (1988) *Nature*, 332, 323–327. doi:10.1038/332323a0. First published on 1988/03/24.
- Rivoire,O., Reynolds,K.A. and Ranganathan,R. (2016) PLoS Comput. Biol., 12, e1004817. doi:10.1371/journal.pcbi.1004817. First published on 2016/06/03.
- Rodriguez-Rodriguez,E.R., Ledezma-Candanoza,L.M., Contreras-Ferrat,L. G., Olamendi-Portugal,T., Possani,L.D., Becerril,B. and Riano-Umbarila, L. (2012) J. Mol. Biol., 423, 337–350. doi:10.1016/j.jmb.2012.07.007. First published on 2012/07/28.
- Rousseau, F., Schymkowitz, J.W.H., Wilkinson, H.R. and Itzhaki, L.S. (2001) Proc. Natl. Acad. Sci. U. S. A., 98, 5596–5601. doi:10.1073/pnas.101542098.
- RStudio Team (2016), RStudio: Integrated Development for R. RStudio, Inc., Boston, MA. http://www.rstudio.com/.
- Sanchez,I.E., Beltrao,P., Stricher,F., Schymkowitz,J., Ferkinghoff-Borg,J., Rousseau,F. and Serrano,L. (2008) *PLoS Comput. Biol.*, 4, e1000052. doi:10.1371/journal.pcbi.1000052. First published on 2008/04/05.
- Schiele,F., van Ryn,J., Litzenburger,T., Ritter,M., Seeliger,D. and Nar,H. (2015) MAbs, 7, 871–880.
- Schymkowitz, J., Borg, J., Stricher, F., Nys, R., Rousseau, F. and Serrano, L. (2005) Nucleic Acids Res., 33, W382–W388.
- Sedrak, P., Hsu, K. and Mohan, C. (2003) Mol. Immunol., 40, 491–499. First published on 2003/10/18.

Kassambara, A. (2017).

Shannon, C.E. (1948) Bell Syst. Tech. J., 27, 379-423.

- Shannon, P., Markiel, A., Ozier, O., Baliga, N.S., Wang, J.T., Ramage, D., Amin, N., Schwikowski, B. and Ideker, T. (2003) *Genome Res.*, 13, 2498–2504. doi:10.1101/gr.1239303.
- Sheinerman,F.B., Norel,R. and Honig,B. (2000) Curr. Opin. Struct. Biol., 10, 153–159. First published on 2000/04/08.
- Spada,S., Honegger,A. and Pluckthun,A. (1998) J. Mol. Biol., 283, 395–407. doi:10.1006/jmbi.1998.2068. First published on 1998/10/14.
- Stanfield,R.L., Zemla,A., Wilson,I.A. and Rupp,B. (2006) J. Mol. Biol., 357, 1566–1574.
- Suel,G.M., Lockless,S.W., Wall,M.A. and Ranganathan,R. (2003) Nat. Struct. Biol., 10, 59–69.
- Sun,L.K., Curtis,P., Rakowicz-Szulczynska,E., Ghrayeb,J., Chang,N., Morrison,S.L. and Koprowski,H. (1987) Proc. Natl. Acad. Sci. USA., 84, 214–218. First published on 1987/01/01.
- Swindells,M.B., Porter,C.T., Couch,M., Hurst,J., Abhinandan,K.R., Nielsen, J.H., Macindoe,G., Hetherington,J. and Martin,A.C.R. (2017) J. Mol. Biol., 429, 356–364.
- Titani,K., Wikler,M. and Putnam,F.W. (1967) Science, 155, 828–835. First published on 1967/02/17.
- Tramontano,A., Chothia,C. and Lesk,A.M. (1990) J. Mol. Biol., 215, 175–182. doi:10.1016/S0022-2836(05)80102-0. First published on 1990/ 09/05.

- Vajdos,F.F., Adams,C.W., Breece,T.N., Presta,L.G., de Vos,A.M. and Sidhu, S.S. (2002) J. Mol. Biol., 320, 415–428. doi:10.1016/S0022-2836(02) 00264-4. First published on 2002/06/25.
- Vanhee,P., Verschueren,E., Baeten,L., Stricher,F., Serrano,L., Rousseau,F. and Schymkowitz,J. (2011) Nucleic Acids Res, 39, D435–D442. doi:10. 1093/nar/gkq972. First published on 2010/10/26.
- Verhoeyen, M., Milstein, C. and Winter, G. (1988) Science, 239, 1534–1536. First published on 1988/03/25.
- Wagih,O. (2017a) Bioinformatics, 33, 3645–3647. doi:10.1093/ bioinformatics/btx469.
- Wickham, H. (2009) Elegant Graphics for Data Analysis. Springer-Verlag, Springer, New York, 260.
- Xiang,J., Sha,Y., Jia,Z., Prasad,L. and Delbaere,L.T. (1995) J. Mol. Biol., 253, 385–390. doi:10.1006/jmbi.1995.0560. First published on 1995/10/ 27.
- Zafra Ruano, A., Cilia, E., Couceiro, J.R., Ruiz Sanz, J., Schymkowitz, J., Rousseau, F., Luque, I. and Lenaerts, T. (2016) *PLoS Comput. Biol.*, 12, e1004938. doi:10.1371/journal.pcbi.1004938.
- Zhao,L. and Li,J. (2010) BMC Struct. Biol., 10, S6. doi:10.1186/1472-6807-10-S1-S6. First published on 2010/05/28.
- Zhao, J., Zhang, B., Zhu, J., Nussinov, R. and Ma, B. (2018) *Biochim. Biophys. Acta*, 1864, 2294–2303. doi:10.1016/j.bbadis.2017.12.009. First published on 2017/12/16.