

## Combining different design strategies for rational affinity maturation of the MICA-NKG2D interface

Samuel H. Henager, Melissa A. Hale, Nicholas J. Maurice, Erin C. Dunnington, Carter J. Swanson, Megan J. Peterson, Joseph J. Ban, David J. Culpepper, Luke D. Davies, Lisa K. Sanders, and Benjamin J. McFarland\*

Department of Chemistry and Biochemistry, Seattle Pacific University, Seattle, Washington 98119-1997

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**Abstract:** We redesigned residues on the surface of MICA, a protein that binds the homodimeric immunoreceptor NKG2D, to increase binding affinity with a series of rational, incremental changes. A fixed-backbone RosettaDesign protocol scored a set of initial mutations, which we tested by surface plasmon resonance for thermodynamics and kinetics of NKG2D binding, both singly and in combination. We combined the best four mutations at the surface with three affinity-enhancing mutations below the binding interface found with a previous design strategy. After curating design scores with three cross-validated tests, we found a linear relationship between free energy of binding and design score, and to a lesser extent, enthalpy and design score. Multiple mutants bound with substantial subadditivity, but in at least one case full additivity was observed when combining distant mutations. Altogether, combining the best mutations from the two strategies

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Additional Supporting Information may be found in the online version of this article.

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Carter J. Swanson's current address is the Department of Biophysics, University of Michigan, Ann Arbor, MI 48109.

Megan J. Peterson's current address is the Institute of Molecular Biology, University of Oregon, Eugene, OR 97403.

Lisa K. Sanders's current address is the School of Medicine, University of Washington, Seattle, WA 98195.

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\*Correspondence to: Benjamin McFarland, Seattle Pacific University, Suite 205, 3307 Third Avenue West, Seattle, WA 98119-1997. E-mail: [bjm@spu.edu](mailto:bjm@spu.edu)

into a septuple mutant enhanced affinity by 50-fold, to 50 nM, demonstrating a simple, effective protocol for affinity enhancement.

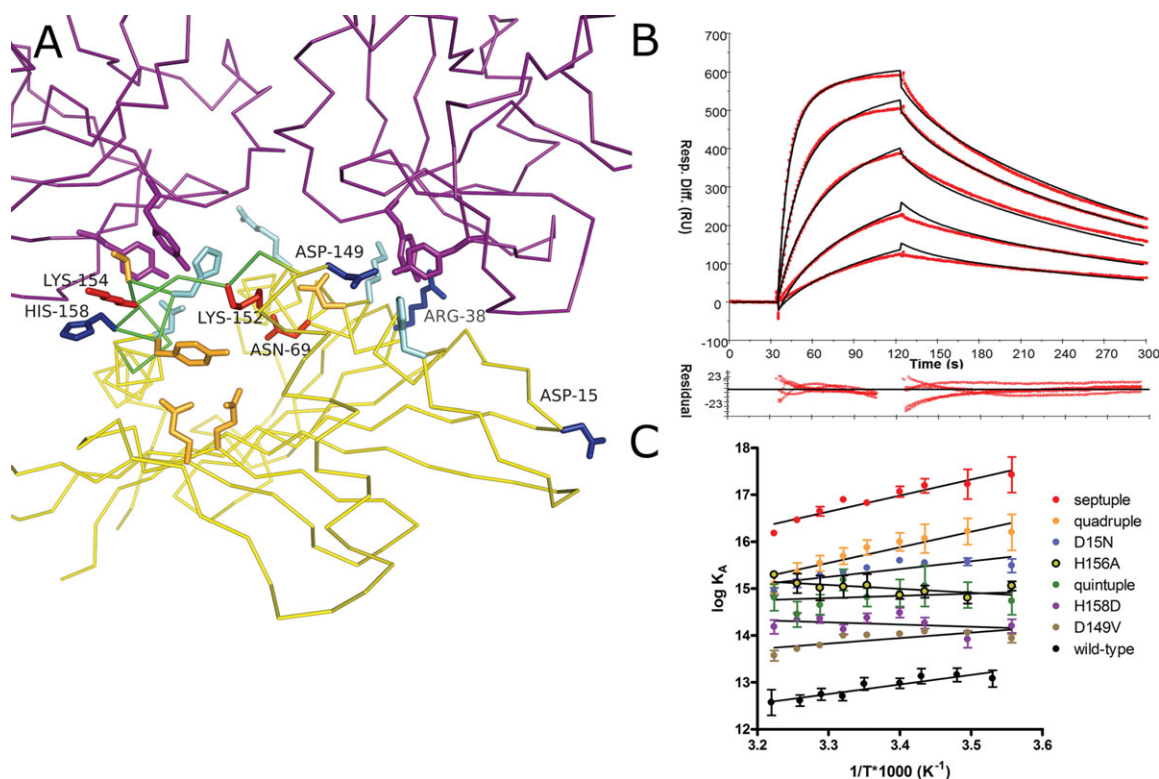
**Keywords:** protein design; protein–protein interaction; immunoreceptors; additivity; free energy of binding; thermodynamics and kinetics of binding; van't Hoff enthalpy

## Introduction

Improvement of protein–protein binding has utility in applications ranging from *in vitro* assays to *in vivo* therapies.<sup>1</sup> Different strategies for enhancing affinity incorporate combinatorial and/or computational design: combinatorial design tests large populations of randomized mutants in a process similar to antibody affinity maturation, whereas computational or rational design calculates the biochemical stability of protein conformations and amino acid mutations using various scoring functions.<sup>2</sup> Computational optimization of the chemical interactions in proteins has successfully stabilized protein–protein interfaces with final  $K_D$  values ranging from micromolar to picomolar (Supporting Information Table S1), although substantial challenges remain.<sup>3–5</sup>

Computational and combinatorial techniques can work together, as when computational techniques created a *de novo* 200 nM interface between influenza hemagglutinin and a binding scaffold, and then affinity maturation via combinatorial screening produced three mutations that together brought the affinity to 4 nM.<sup>6</sup>

Previously, we used the rational design algorithm RosettaDesign to enhance the affinity of the interface between the immunoproteins NKG2D and MICA.<sup>7</sup> This interaction acts as a dominant activating trigger for NK cells and is involved in several pathologies.<sup>8</sup> Our first design strategy targeted residues that do not directly contact NKG2D to alter the stability of unbound MICA and affect NKG2D binding indirectly [Fig. 1(A)].<sup>7</sup> Extrainterfacial changes



**Figure 1.** Locations redesigned with two strategies and measurement of binding thermodynamics and kinetics. (A) Targets for design highlighted in the structure for the NKG2D-MICA complex (purple: NKG2D homodimer with core tyrosines shown as sticks; yellow: MICA with redesigned residues shown as sticks; green: backbone of “disordered loop” region of MICA that is not observed in the unbound MICA structure; orange/red: subinterfacial residues redesigned in first strategy, with stabilizing residues combined in septuple mutant in red and labeled; light blue/dark blue: interfacial residues redesigned in second strategy, with stabilizing residues combined in septuple mutant in dark blue and labeled). Figure was made using Pymol <http://www.pymol.org/>. (B) SPR sensorgrams and residuals for injection of serial dilutions of NKG2D over a MICA-coupled dextran surface (red: kinetic data collected; black: two-step model fit). (C) van't Hoff plots of four single and three multiple mutants for triplicate SPR data at nine temperatures, with  $K_A$  values calculated from kinetic data and enthalpies of binding calculated from linear slopes as described in Lengyel *et al.*

in MICA that enhanced affinity for NKG2D were predicted to destabilize the region underneath the interface. A triple mutant was found with this strategy that bound with 17-fold enhanced affinity.

Because none of these mutations directly contacts NKG2D, we began a second round of rational design in which MICA residues that directly contact NKG2D were optimized with RosettaDesign to enhance interfacial affinity, with the goal of combining the mutations from the two strategies. Single mutations predicted to enhance affinity were expressed, purified, and tested experimentally. Then mutations were combined iteratively with other surface mutations, and with the most affinity-enhancing mutations from our first subinterfacial design strategy, to investigate the cumulative effect of designed mutations at a protein–protein interface.

## Results and Discussion

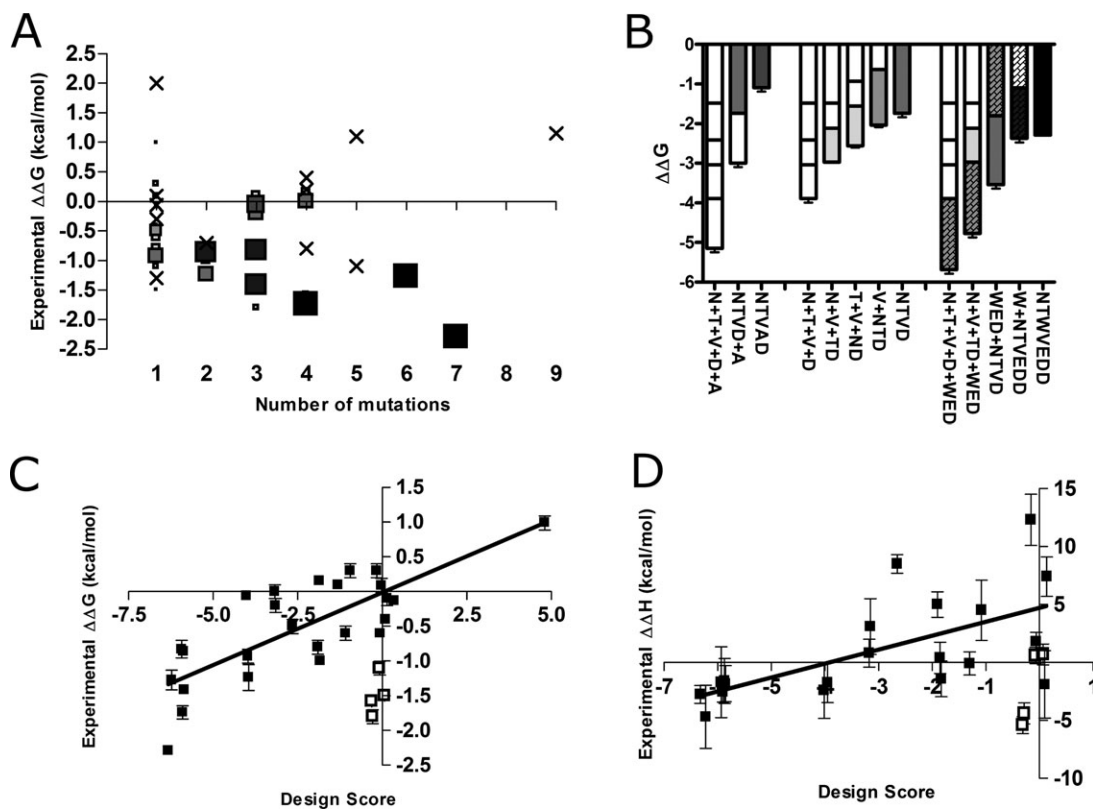
RosettaDesign<sup>9</sup> calculated an optimal amino acid (selecting any amino acid except cysteine) 100 times for each of the 22 MICA residues that contact NKG2D in the MICA-NKG2D complex structure (PDB ID: 1HYR).<sup>10</sup> Each location was varied individually and all other residues were wild-type. For 11 locations, Rosetta either returned the wild-type residue or a similar residue with insignificant predicted stabilization (score  $> -0.05$ ), and the other 11 mutations were investigated through experiment (bold type in Supporting Information Table S2). Also, calculations were done in which all MICA contact residues were allowed to vary at once. In the set of 100 such calculations, alternative stabilizing residues were chosen by the algorithm more than 10% of the time at six locations, which were added to the experimental set as single mutants (normal type in Supporting Information Table S2). These 17 single mutants were produced by site-directed mutagenesis, expressed in *Escherichia coli* as inclusion bodies, then refolded and purified by affinity and size-exclusion chromatography. Each MICA mutant was amine-coupled to a dextran surface on a gold chip and its affinity for NKG2D measured by surface plasmon resonance (SPR) [Fig. 1(B) and Supporting Information Table S2]. For 11 mutants binding with affinities similar to or stronger than wild-type, affinities were determined at nine temperatures and van't Hoff plots constructed to calculate enthalpies of binding [Fig. 1(C)]. Overall, this simple design technique produced seven mutants that stabilized the interaction with NKG2D by 0.5 kcal/mol or more, with two stabilized by more than 1.0 kcal/mol [Fig. 2(A)].

The best single mutations at the interface were combined in 18 multiple-mutant MICA molecules, which were analyzed for NKG2D binding by SPR (Supporting Information Table S2). Most of the

single mutants stabilized the interaction with NKG2D significantly, but combining mutations at the interface resulted in eight MICA molecules stabilized by 0.5 kcal/mol or more, four of which were stabilized by more than 1.0 kcal/mol [Fig. 2(A)]. The best multiple mutant from this step of the strategy combined four of the best five single mutations, increasing affinity by  $-1.74$  kcal/mol about half of a kcal/mol better than the best single mutant. The H156A mutation was excluded from this combination after we observed that, despite its highly stabilizing character in the context of wild-type MICA, this mutation produced negative additivity when combined with other mutations suggested by RosettaDesign in several multiple mutants [Fig. 2(B)]. H156A fails the first of our three design tests below because Rosetta predicts an unrealistically large upper-quintile stabilization to both bound and unbound proteins. Inspection of the predicted structural model for H156A reveals that His156 forms few specific interactions with NKG2D, and when it is mutated to an alanine, a cavity is created in the center of the disordered loop region of MICA that may allow other mutations to shift in a manner not captured by our fixed-backbone assumptions and/or may increase stability and reduce flexibility of this region in which flexibility is important to binding.<sup>7</sup> Removing this mutation from the quintuple mutant resulted in a 0.65 kcal/mol stabilization of interaction with NKG2D.

In the final step of design, we combined the best three subinterfacial mutations found previously<sup>7</sup> with the four best interfacial mutations. The resulting mutant bound NKG2D with a 50-fold enhanced affinity, which is a  $-2.29$  kcal/mol stabilization relative to wild-type at 25°C [Fig. 2(A)]. This is similar to many computational results (Supporting Information Table S1), but it is also partially subadditive by about a kcal/mol relative to the added affinities of the triple and quadruple mutants from the two design strategies [Fig. 2(B)]. The affinity enhancement of the septuple mutant was confirmed with a previously developed size-exclusion chromatography assay<sup>11</sup> in which the mutant was mixed with NKG2D and injected at a slow flow rate. Under these conditions, the septuple mutant eluted as a large peak ( $\sim 60$  kDa), indicating that the complex had persisted through the column, but wild-type MICA eluted as a small peak ( $\sim 30$  kDa) corresponding to unbound MICA monomer and NKG2D dimer.

Design scores were calculated with RosettaDesign for all expressed mutants to compare fixed-backbone design calculations with experimental results (Supporting Information Table S3). We calibrated and cross-validated our NKG2D-MICA calculations with 44 designed models recapitulating published binding data for mutations at two



**Figure 2.** Comparison of design scores (=bound complex score–unbound MICA score relative to wild-type scores) to binding thermodynamics of single and multiple mutants relative to wild-type MICA. (A) Experimentally determined free energies of binding for all mutants tested arranged by number of mutations made ( $\square$ : passed all three tests and sized and shaded by relative design score, with best design score largest and colored black; X: failed one of the three design score tests). (B) Additivity of mutants arranged with three sets of examples: negative additivity of H156A, subadditivity of D15N, and both subadditivity and full additivity of N69W. Bars shaded by number of mutations, from white:one mutation to black:seven mutations; patterned bars:subinterfacial mutations from the first strategy. N = D15N; T = R38T; V = D149V; D = H158D; A = H156A. Third section only: W = N69W; E = K152E; second D = K154D. (C) Relationship between experimentally determined free energy of binding and design score and (D) between enthalpy of binding and design score for mutants shown as black boxes that pass the three tests ( $\square$ : first-strategy N69W and second-strategy D15N mutants discussed in the text and closely related combined mutants WED and NWED).  $R^2$  values for linear regression fits = 0.61 and 0.40, respectively.

antibody-antigen interfaces<sup>12</sup> and a TCR-MHC interface<sup>13</sup>, with affinities ranging from picomolar to micromolar (Supporting Information Table S4). Some design scores were apparent outliers by about an order of magnitude, either from steric clashes producing high repulsive energies or from unrealistic stabilization calculations for particular interactions. Three tests separated out the most extreme upper-quintile calculated results:

1 *Is the change the total design score undergoes upon mutation within the 80th percentile of all total scores?* This was calculated as the absolute value of any of the following relative to wild-type: unbound ligand alone, bound protein–protein complex, or the subtracted value of unbound-bound [Eq. (1)]. For our set of NKG2D-MICA scores, this corresponded to a value less than about  $\pm 20$  (Supporting Information Fig. S1). In terms of Table S2, a passing score means the following equation was true for the columns titled unbound,

bound, and bound-unbound (which is the unbound value subtracted from the bound value to calculate the change in energy upon binding):

$$|\text{Total design score}| < 20 \quad (1)$$

2 *Is the change the total design score undergoes on mutation within the 80th percentile of all of Rosetta's repulsive term ( $fa_{rep}$ ) scores?* For our set of NKG2D-MICA scores, this also corresponded to a value less than about  $\pm 20$ . In terms of the columns in Table S3, a passing score means the following equation was true for the columns  $\Delta_{rep\_MICA}$  (unbound),  $\Delta_{rep\_complex}$  (bound), and the two columns subtracted (as  $\Delta_{rep\_complex} - \Delta_{rep\_MICA}$ ):

$$|fa_{rep} \text{ for mutant} - fa_{rep} \text{ for wild-type}| < 20 \quad (2)$$

These two tests are similar to the criterion that the design should not be predicted to significantly



destabilize the unbound molecules,<sup>14</sup> also excluding unusually large predicted stabilization. Eight designs of the 41 NKG2D-MICA mutants failed one or both of the first two tests.

3 For the subtracted value of bound-unbound only: does Rosetta's side chain hydrogen bonding term (*hb\_sc*) stay the same or decrease? This threshold was suggested by Sammond *et al.* to counteract Rosetta's reported tendency to replace a good hydrogen bond with a less specific — for example, hydrophobic — interaction in the bound complex,<sup>14</sup> and corresponds to the 80th percentile of our set of *hb\_sc* scores. We follow Sammond *et al.* in using the subtracted value only (=bound-unbound), to the first decimal place, so that a score of less than 0.05 is considered to stay the same within error. In terms of the columns in Table S3, the  $\Delta hb\_sc\_MICA$  value was subtracted from the  $\Delta hb\_sc\_complex$  value so that a passing score means the following equation was true:

$$[(hb\_sc\ for\ mutant\ complex - hb\_sc\ wild\text{-}type\ complex) - (hb\_sc\ for\ mutant\ MICA - hb\_sc\ for\ wild\text{-}type\ MICA)] < 0.05 \quad (3)$$

Four more NKG2D-MICA designs failed this test.

Application of these thresholds to other interfaces could use either the percentile or the raw score depending on the number of scores in the design set. Cross-validation with the experimental binding data published for 44 mutations at the three other interfaces showed that the three tests marked out 20 of Rosetta's scores for these mutations as suspect, 17 of which were successful applications of the tests (either incorrect predictions by Rosetta or correct predictions of destabilization; Supporting Information Fig. S2). Interestingly, all three cases in which the tests did not succeed—experimentally stabilizing mutants correctly predicted by Rosetta yet incorrectly excluded by the tests—replaced glycine residues: two of these predicted the effects of mutating glycines in the low-affinity MHC-TCR complex and the third altered a glycine in an antibody CDR loop. The MHC-TCR complex produced the most incorrect predictions by Rosetta. For example, several TCR mutants that replace a smaller residue with a larger one fail tests 1 and 2 because of steric repulsion in the complex (D26W and G28L) or in the unbound TCR (G28I). *In silico*, the fixed-backbone model cannot avoid these repulsions, but *in vitro*, these mutants improve binding; in these cases, small backbone movements would minimize repulsion. Rosetta scores for two other TCR mutations (G28M and S100T) passed all three tests, yet incorrectly predicted destabilization of the complex; in these cases, loop adjustments may allow stabilizing interactions to form in the complex by the new side chain atoms

that cannot be reached in our fixed-backbone models. In general, Rosetta was able to more accurately estimate quantitative effects of mutation for the higher-affinity antibody-antigen complexes, but in all three cases, the tests would have pre-filtered the predictions so that a more experimentally amenable set of stabilizing mutations remained.

After these tests were applied to curate the Rosetta data for NKG2D-MICA, correlations were observed for the remaining data, using the subtracted design score suggested by Sammond *et al.*<sup>14</sup> The best design score corresponds to the best experimental result, which is the septuple mutant [Fig. 2(A)]. A linear relationship is observed between the change in free energy of binding as determined by SPR and the design score [Fig. 2(C)], and a similar but more dispersed relationship is observed between van't Hoff enthalpy of binding and design score (note that enthalpy measurements have a larger standard error as well) [Fig. 2(D)]. Linear relationships within some error have been observed between free energy of binding and design score for various design methods.<sup>12,15,16</sup> The linear relationship shown here between enthalpy of binding and Rosetta's design score suggests that fixed-backbone Rosetta calculations better recapitulate characteristics associated with enthalpy (e.g., charge-charge interactions, close atom packing) than with entropy (e.g., flexibility).

Each design strategy produced one significantly stabilizing ( $\Delta\Delta G < -0.5$  kcal/mol), peripherally located mutation that Rosetta does not predict as stabilizing: N69W for the subinterfacial strategy and D15N for the interfacial strategy. These may promote NKG2D-MICA interface formation through mechanisms more complex than optimizing direct atomic contacts. For example, N69W is predicted to destabilize the unbound MICA molecule, which biophysical tests have confirmed,<sup>7</sup> and which is reflected in the positive total design score for unbound MICA relative to wild-type. In MHC molecules, which are structurally homologous to MICA, flexibility of the helices in the center of the binding surface influences T-cell receptor binding.<sup>17,18</sup> Such movements in MICA would not be captured by fixed-backbone calculations. D15N alters charge distribution on the outer edge of the interface, and is predicted to stabilize the MICA-NKG2D complex, but also to stabilize the unbound MICA by the same amount so that the subtracted design score prediction is close to zero. Empirically, we found that this mutation, alone and in combination with other mutants, successfully stabilizes the interface.

Combining mutations at an interface can result in different degrees of additivity,<sup>19,20,15</sup> with subadditivity observed for a T-cell receptor-MHC interface<sup>21</sup> and a single-chain Fv-PSA interface.<sup>22</sup> Similarly, we repeatedly observed subadditivity and negative additivity at this interface [Fig. 2(B)]. In a

study of antibody affinity maturation, interface affinity was found to be inherently limited,<sup>23</sup> so the NKG2D-MICA interface architecture may impose a structural limit here, particularly the requirement that a homodimer engage a monomer with two symmetric half-sites on a flat surface. Also, mutations located in independent modules distant from each other combine additively,<sup>19,20</sup> and the arrangement of each NKG2D half-site as residues clustered around a pair of tyrosines may cause each half-site to cooperate as a single non-additive module. When the NKG2D-MICA crystal structure was analyzed for modules according to the technique of Reichmann *et al.*, each NKG2D half site consisted of a single cooperative module (unpublished data). Distance from the half-site cores may explain why the peripheral mutation N69W provides a fully additive gain observed in this study when combined with the sextuple mutant to make the septuple mutant [Fig. 2(B)]. However, factors other than distance must affect cooperativity, because two alterations in charge distribution at the interface at opposite ends of the NKG2D footprint, D15N and H158D, combine with negative additivity in the ND mutant [Fig. 2(B)].

## Conclusion

Here, we demonstrate a rational, iterative enhancement of MICA that qualitatively changed NKG2D affinity from weak ( $K_D = 2.5 \mu\text{M}$ ) to moderately tight ( $K_D = 51 \text{ nM}$ ) with seven mutations, engineering affinity past thresholds appropriate for applications such as immunoprecipitation and vaccination.<sup>24,25</sup> Different strategies of mutating residues that were at and below the binding interface enhanced affinity, although when combined, mutants often bound with partial or negative additivity. Three tests identified 32 out of 85 design scores as incorrect or destabilizing, with no wrongly identified scores for NKG2D-MICA, and with three wrongly identified scores combined for three other protein-protein interfaces. RosettaDesign scores could be compared with experimentally determined free energies, showing that simple design calculations with fixed backbone design can systematically enhance an existing protein interface.

## Methods

### Computational

RosettaDesign<sup>26</sup> v2.1 was used to model side chain mutations and calculate energies with the `-fixbb -repack_neighbors -soft_rep` options selected.<sup>27,14</sup> Structural coordinates from the PDB file (1HYR for NKG2D-MICA) were relaxed, repacked, and remodeled with Rosetta to provide wild-type models, which were then mutated, repacked, and evaluated. For each mutant, Rosetta calculated a score 100 times and an example with the lowest score from that set

was used. Most scores converged two to nine times within the set of 100.

## Experimental

Recombinant MICA and NKG2D proteins were produced and purified with affinity chromatography to  $>95\%$  purity and sized with size-exclusion chromatography using methods identical to those previously published in report of the first design strategy<sup>7</sup> to allow for comparison of results, including production of proteins by undergraduates in a biochemistry teaching laboratory.<sup>28</sup> Plasmids for expression of several mutant MICA molecules were constructed by Genscript (Piscataway, NJ).

SPR assays were also consistent with earlier work to allow for direct comparison of results, performed on a BIAcore 3000 and fit with a two-step model, which was supported by controls and biophysical tests.<sup>7</sup> We confirmed in Lengyel *et al.* that relative affinities on mutation for the MICA-NKG2D system are similar for a two-step kinetic model and a simple equilibrium model. (Recently, two-step modeling of SPR kinetic data has been validated biophysically for another protein-protein interface.<sup>29</sup>) The accuracy of our independent measurements can be assessed by comparing pairs of proteins with highly conservative mutations that were made and evaluated by different groups of students at different points in the project, giving identical results within error: e.g., wild-type vs. R64K ( $\Delta\Delta G = -0.06 \pm 0.1 \text{ kcal/mol}$ ); and R38T\_H158D vs. R38T\_H158D+Y157F ( $\Delta\Delta G = -0.03 \pm 0.1 \text{ kcal/mol}$ ). Kinetic data were gathered at five to nine temperatures and then combined into van't Hoff plots, with enthalpy calculated as reported in Lengyel *et al.*

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