Cell membrane glycan contents are biochemical factors that constitute a kinetic barrier to viral particle uptake in a protein-nonspecific manner

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Abstract

Various types of glycoproteins have been suggested to inhibit viral infection of cells via steric repulsion. However, it is difficult to evaluate such physical actions genetically, simply because they are nonspecific and can be caused by any molecule. Therefore, we investigated a method to compare this nonspecific action among cells with diverse membrane protein profiles. We found that a wide range of glycoproteins individually had a strong inhibitory effect on infection, while on the other hand, the total amount of glycans was negatively correlated with the infection level in each cell. Thus, the infection-inhibitory effect of glycoproteins was molecularly nonspecific, but was additively enhanced according to the amount of glycans on the cell surface. In this correlation, glycans function as a fundamental factor. Further investigating the mechanism by which glycans function as a factor in infection control, we conclude that the repulsion between proteins created by branched glycans forms a kinetic energy barrier against packing the virus into the region of protein interstitial space. As a result, the formation of the adhesive interface between the virus and the cell membrane, which is necessary for infection, is inhibited. This study attempted to link the cell's nonspecific physical properties with intracellular biochemicals. A similar approach may be applied to quantify other nonspecific biological phenomena.

Introduction

Numerous types of physical and mechanical factors of cells, both intrinsic mechanical properties such as stiffness, and external mechanical stimuli such as osmotic pressure, have been reported as regulators of important biological events at the cellular level (Delgado and Cabernard, 2020; Du et al., 2023; Enyedi et al., 2016; Jalihal et al., 2020; Saraswathibhatla et al., 2023). Some of these events are regulated by a few important genes, while others are controlled by multiple factors and are considered gene-nonspecific events. As one such physical event, we are studying steric inhibition of viral infection by bulky membrane proteins. Studies in the Covid-19 pandemic have highlighted the fact that, as has long been recognized in other infectious diseases, even infection by the same viral strain can have highly variable consequences for host disease progression To analyze such diverse host-side responses in Covid-19, intensive high-throughput studies have been conducted, accumulating vast amounts of data at the cellular, organ, or individual patient level (Ahern et al., 2022; Biering et al., 2022; Delorey et al., 2021; Ellinghaus et al., 2020; Grant et al., 2021; Hadjadj et al., 2020; Meckiff et al., 2020; Pathak et al., 2022; Ravindra et al., 2021; Yoshida et al., 2022; Ziegler et al., 2021). As a result, various host-side factors have been proposed. Particularly, innate immune molecules such as various cytokines have received significant attention, but several others have also been reported. Mucin-related glycoproteins are among the latter group, as suggested by cellular CRISPR screens as well as by genome-wide association studies (Biering et al., 2022; Pathak et al., 2022). There have also been many studies at the molecular, cellular, or animal level on the function of these highly glycosylated proteins in viral infection, including not only mucin but also other proteins including PSGL1 and CD43 (Chatterjee et al., 2023; Delaveris et al., 2020; Linden et al., 2008; McAuley et al., 2017; Murakami et al., 2020; Wardzala et al., 2022).. In these studies, deletion or increase of such proteins resulted in modulation of viral infectivity in several different infection systems. All of these results suggest that bulky membrane glycoproteins nonspecifically inhibit viral infection.

If the protein size is comparable to the size of the virus and the protein density is high, it is conceivable that the bulky glycoproteins could act as a physical barrier to viral uptake on the cell membrane. However, it is not easy to estimate and compare the steric inhibitory effects of these membrane proteins on different cells with very diverse expression profiles. If glycoproteins affect viral infection in a nonspecific manner, and if this is due to steric inhibition as suggested (Delaveris et al., 2020; Murakami et al., 2020), then polymers without glycans could have the same function. Indeed, synthetic polymers that bind to cell membranes have been shown to modulate viral infection in a manner dependent on molecular size and molecular density (Kaizuka and Machida, 2023; Pyrć et al., 2021). Inferring from this fact, it is possible that viral infection in cells is regulated by the expression profile and density of all membrane proteins.

Here we attempt to biochemically describe this nonspecific steric effect on the cell surface. For this purpose, we combine biochemical dissection for individual molecules with physical analyses. With physical modeling alone, the phenomenon might be described by a small number of parameters, but these parameters cannot be easily associated with genes. On the other hand, it is not straightforward to estimate the steric effects of an entire cell by measuring and summing all the effects of individual genes. To combine these two approaches, we attempted to find biochemical factors that relate steric effects across the cell surface to information of biochemical components in cell. Such factors could link the physical quantity of steric effects with genomic or transcriptomic data of the cell. Previous studies showing steric effects of glycoproteins suggested that glycans may be a fundamental biochemical factor regulating such an overall phenomenon.

To confirm that glycans are a general chemical factor of steric repulsion, an extensive list of glycoproteins on the cell membrane surface would be useful. Therefore, we collect information on glycoproteins on the genome. Elucidation of the mechanism of how glycans regulate steric repulsion will also be useful to quantitatively discuss the relationship between steric repulsion and intracellular molecular composition. For this purpose, we apply the theories of polymer physics and interface chemistry.

Results

List of membrane glycoproteins in human genome and their inhibitory effect on virus infection

Based on the hypothesis that glycans contribute to steric repulsion at the cell surface, we will measure the inhibitory effect of cell membrane proteins on viral infection and compare their glycan content (Figure 1A). The wider the range of proteins to be measured, the better, preferably genome-wide. The method should also be robust to the complexity and diversity of Glycome (Dworkin et al., 2022; Huang et al., 2021; Moremen et al., 2012; Rademacher et al., 1988). Then the conclusions of this study can be applied to a wider range of cases. To simplify this situation, we attempted to collect the glycoproteins in the human genome and compile them into an easy-to-use list for our purposes. Then, by analyzing selected sample molecules from such a list, it may be possible to infer the effect of the entire glycoprotein population on steric inhibition of viral infection. To compile the list of glycoproteins, we first selected all human membrane proteins in the database (UniProt) based on the presence of a transmembrane domain or membrane anchor domain and found that 81.5% (2515 molecules) of these membrane proteins had previously been reported or predicted to be glycosylated

(Bateman et al., 2023). We then used two machine learning-based software packages (NetNGlyc/NetOGlyc and GlycoEP) to determine whether amino acid residues in the ectodomain of all 2515 molecules are glycosylated (Figure 1B, Supplementary Data 1-2)(Chauhan et al., 2013; Gupta and Brunak, 2002; Steentoft et al., 2013). Both software packages predicted one or more O- or N-glycosylation in 2441 and 2290 proteins, respectively, of which 2226 molecules (88.5% of the total) were predicted by both software packages (Figure 1B-C, Supplementary Figure 1A). The number of highly glycosylated molecules for which more than 15% of the amino acids in the extracellular domain were predicted to be glycosylated was 67 and 75, respectively, of which 45 were common to both software packages (Figure 1B-C). The Pearson correlation coefficient between the predicted glycosylation rates of all molecules calculated by each software was 0.656 (Supplementary Figure 1B). Thus, the predictions of the two software programs were in relatively good agreement, with relatively few molecules predicted to be highly glycosylated throughout the human genome. Both software programs also detected three times as many sequences predicted to undergo O-type glycosylation as those predicted to undergo N-type glycosylation (3.08 and 3.00 times more, respectively), and this trend was particularly pronounced for highly glycosylated molecules. Overall, many of the listed highly glycosylated molecules are consistent with molecules already known to be glycosylated, suggesting the consistency of our prediction strategy. It is also likely that some of protein sequences analyzed in this study may be identical to the sequences used in machine learning during software development.

To evaluate the predicted results, the glycosylation of 18 sample molecules selected from the list was measured. These sample molecules include MUC1 and its truncation mutants, other types of highly glycosylated molecules, and receptor and ligand molecules involved in cell-cell interactions. Using HEK293T cell lines exogenously expressing genes of these proteins tagged with fluorescent markers, their glycosylation was measured by binding of a lectin from Arachis hypogaea (PNA), and the number of these proteins in the cells was measured simultaneously. Flow cytometry measurements showed a nearly linear relationship between the signals of bound lectins and membrane protein (Figure 1D, Supplementary Figure 1D). This relationship can be explained by a first-order reaction model of lectin binding to populations of cell with diverse protein expression levels (see Methods). The model also predicted that, when the slope PNA/mol obtained from this linear regression is compared among proteins, it should have a linear relationship with the level of glycosylation of each protein. We assumed that the total glycosylation level per molecule should reflect the number of glycosylation sites that were predicted by the software. Then, we evaluated the correlation between the experimentally determined PNA/mol and the predicted number of glycosylation sites for each protein, and found that the two were indeed in a linear relationship (Figure 1E). Therefore, we can conclude that within these sample molecules, the number of potential glycosylation sites predicted by the

software correlates well with the actual amount of glycans for each molecule.

Although our experiments were performed only in a specific cell type, the measured amount of glycans per molecule correlated well with the number of predicted amino acid sites to be glycosylated. Especially for highly glycosylated proteins, the agreement was good. On the other hand, the measured values for low glycosylation molecules were more strongly influenced by the background glycans of endogenous proteins. This robustness in prediction may result from the sequence diversity of glycosylation sites. When the total amount of glycosylation in each protein is compared as in our case, molecules with a wider spectrum of predicted amino acid sequences should have a greater probability of being glycosylated, even if there is a bias in sequences to be glycosylated in each cellular system. Therefore, we propose that our software-based method generated a list of glycoproteins useful for estimating the total glycan content of each protein in various cell types.

We then examined whether these membrane glycoproteins can inhibit viral infection, and whether their inhibitory effects depend on the degree of protein glycosylation. We measured the infection of SARS-CoV2 pseudoparticle virus based on Lentivirus (SARS-CoV2-PP) consisting with the Spike molecule of SARS-CoV2 (Wuhan-Hu-1) (Figure 1F, Supplementary Figure 1E)(Chan et al., 2020; Ke et al., 2020). Cell surface densities of the viral receptor ACE2 and the membrane glycoprotein to be studied were measured prior to viral infection, and the infection was measured after 48 hours (Supplementary Figure 1E, G). The results showed that all highly glycosylated proteins, with the exception of GYPC, which has the shortest ectodomain, had an inhibitory effect on infection. These proteins include those previously reported (MUC1, CD43) as well as those not yet reported (CD44, SDC1, CD164, etc.)(Delaveris et al., 2020; Murakami et al., 2020). In contrast, other molecules showed little inhibitory effect on infection within the density range we used. Infection of other types of viruses was similarly inhibited by glycoproteins (Supplementary Fig. 1F). Previous results showed that membrane-bound synthetic polyethlenglycols (PEGs) inhibit SARS-CoV-2-PP infection at surface density above 2000 μm^{-2} (Kaizuka and Machida, 2023). In contrast, the range of mean densities at which highly glycosylated molecules could inhibit infection was an order of magnitude lower, ~100 μm^{-2}. This result suggests that glycosylation of membrane proteins has a significant impact on the inhibition of virus infection.

To quantitatively compare the infection inhibitory effects of all glycoproteins in a unified manner, a hierarchical Bayesian model was constructed and data from all molecules were regressed on this unified model at once (Figure 1F, Supplementary Figure 1I). This approach was based on the assumption that each glycoprotein inhibits viral infection by a common mechanism but the degree of inhibition depends on the protein-specific parameter. As a model for regression, a standard sigmoidal

inhibition function was used with the density of glycoproteins as a variable. The parameter IC50 (surface density to achieve 50% inhibition of infection) of the membrane proteins was estimated from the posterior predictive distribution obtained by Markov chain Monte Carlo sampling for this Bayesian model (Supplementary Figure 1J). We found that IC50 was inversely correlated with the amount of glycosylation of each molecule (Pearson correlation coefficient, -0.29) (Figure 1G); IC50 was similarly correlated with the molecular weight including glycans, but was not significantly correlated with amino acid length (correlation coefficient of -0.39 and 0.11, respectively) (Figure 1H, (Supplementary Fig. 1K)). These results indicate that the total amount of glycans has a significant effect on the inhibition of viral infection.

One advantage of using such a hierarchical model is that one can easily obtain the overall trend without making many measurements on all molecules as in ordinary statistics. Thus, it is an effective approach to reduce batch effects in experiments such as ours where many different items need to be compared. Note that due to the nature of Bayesian statistics, the results may differ slightly depending on the prior distribution, and that while the amount of data we had is sufficient for hierarchical inference for all molecules, there may not be enough data for each molecule in analyzing individually in the manner of ordinary statistics.

The molecular weights of the glycans in those proteins were estimated from the data of glycan mass in purified MUC1 ectodomain (Figure 1I). Molecular weight for other proteins were estimated by applying the data for lectin binding assays (Figure 1D-E). From these data, we can estimate that a typical glycoprotein in our system is glycosylated at ~50% of the predicted sites by assuming the average size of O-glycans as decasaccharides with a molecular weight of ~2000. These results indicate that in our experimental system, glycosylation of proteins increases their molecular weight by only a few folds at most. However, even glycoproteins shorter than 200 amino acids had a significant inhibitory effect on virus infection, while some of longer but low-glycosylated proteins didn't.

Cellular glyco-populations and infection control

Since a wide range of glycoproteins inhibit viral infection, it is possible that all types of glycoproteins have an additive effect for this function. To test this hypothesis, we infected a monolayer of epithelial cells with highly heterogeneous populations of glycoproteins with SARS-CoV-2-PP and measured viral infection from cell to cell visually by microscope imaging. We found that highly infected cells were spatially exclusive with highly glycan-expressing cells, indicating that there was a clear inverse correlation between the amount of virus infection and the amount of surface bound lectins in the cells

(Figure 2AB). In this cell line, this inverse correlation was most prominent when quantifying N-Acetylneuraminic acid (Neu5AC) among various types of glycans (Supplementary Figure 2C). It was shown that the number of bound lectins correlated with the amount of glycans, not with number of proteins (Figure 1E). Thus, these results demonstrated that the amount of virus infection in cell anti-correlated with the amount of total glycans on the cell surface.

The correlation between the density of each glycoprotein and viral infection was also measured. CD44, which was shown to account for about 10% of all cell surface glycans (Wyler et al., 2021), showed a weak inverse correlation with viral infection; glycoproteins expressed lower than CD44 or other membrane proteins including ERBB2 did not exhibit any such correlation, although ERBB2 expressed ~4 folds higher amount than CD44 and shared ~7% among all membrane proteins (Figure 2C-D, Supplementary Figure 2A-C). Furthermore, the amount of glycans on the cells did not correlate with the expression of CD44 alone or any other specific protein, suggesting that all the different glycoproteins contributed to the total glycan content in an additive manner (Figure 2E-F, Supplementary Figure 2D). Intracellular glycosylation levels are further regulated by complicated pathways including various types of glycosyltransferases, which are likely confounding factors in the causal relationship between glycoprotein expression and infection inhibition. Proteins that showed very minor correlations might also be present somewhere in the network of confounding factors. Our results demonstrate that total glycan content is a superior indicator than individual glycoprotein expression for assessing infection inhibition effect generated by cell membrane glycocalyx.

We demonstrated that membrane glycoproteins inhibit virus infection in nonspecific manner and this effect is additive, however we also found that the observed inhibitory effect was nonlinear with respect to glycan content (Figure 2B). This is likely because there are many other factors that control viral infection. It should be also noted that the distribution of infection levels per cell is very different from a Gaussian distribution (Russell et al., 2018) (Figure 2B). To further analyze such nonlinear situations, we applied the threshold overlap score (TOS) analysis (Figure 2G-H, Supplementary Figure 2E). This is one statistical method for analyzing nonlinear correlations, and is specialized for colocalization analysis in dual color images (Sheng et al., 2016). TOS analysis involves segmentation of the data based on signal intensity, as in other nonlinear statistics (Reshef et al., 2011). The computed TOS matrix indicates whether the number of objects classified in each region is higher or lower than expected for uniformly distributed data, which reflects co-localization or anti-localization in dual-color imaging data. Calculated TOS matrices show that infection and glycosylation are strongly inversely correlated when both signals are high (Figure 2G-H). This confirms that high infection is very unlikely to occur in cells that express high levels of glycans. The TOS analysis also yielded better anti-correlation scores for some of the individual membrane proteins, especially those that are

heterogeneously distributed across cells (Figure 2H). This suggests that high expression of a single kind of protein can create an infection-protective cell surface, again confirming that the infection inhibition is non protein specific but is determined by the total amount of glycans. On the other hand, for homogeneously distributed proteins such as the viral receptor ACE2, no significant change in TOS from the Pearson correlation was observed (Figure 2D, 2H.).

Influence of membrane glycoproteins on viral binding or uptake

Glycans could be one of the biochemical substances that link the intracellular molecular composition and macroscopic steric forces at the cell surface. To clarify this connection, we further investigated the mechanism by which membrane glycoproteins inhibit viral infection. First, we measured viral binding to cells to determine which step of infection is inhibited. We found that a large number of SARS-CoV2-PP can still bind to cells even when cells expressed sufficient amounts of the glycoprotein that can inhibit viral infection (Figure 3A). This indicates that glycoproteins do not inhibit virus binding to cells, but rather inhibit the steps required for subsequent virus internalization. When cells form the interface with various types of viruses, including SARS-CoV-2, plasma membranes are invaginated for preparing uptake (Ogando et al., 2020). At these interfaces, apposed membranes of viruses and cells are tightly adhered to proceed to fusion. Thus, we hypothesize that membrane glycoproteins do not inhibit the initial binding of viruses to cells via point-to-point molecular binding of receptors and ligands, but rather inhibit the formation of stable interface that is required for membrane fusion and viral uptake.

Both of these two inhibition phenomena are mediated by the steric effect of glycoproteins, but the mechanisms are different. To inhibit all cell-virus receptor-ligand binding, a high density of glycoproteins larger than the size of the receptor-ligand complex is required (Figure 3B). In contrast, much smaller amounts of shorter proteins would be sufficient to inhibit the formation of the cell-virus interface. In our measurements, a protein of ~200 amino acids at a density of ~100 μm^{-2} showed significant inhibition in viral infection. This molecule is shorter than the receptor ACE2, and its density corresponds to only one protein per 100 nm square area, while the diameter of virus is also ~100 nm. And even under these conditions, binding of the virus to the cell was not inhibited (Figure 3A). Therefore, we investigated how such inhibition of interface formation occurs.

We introduced the framework of conventional polymer brush theory to study the structure of virus-cell interfaces containing proteins. This theory provides a general foundation for considering the behavior of polymers at interfaces (Alexander, 1977; de Gennes, 1980; Milner, 1991). In this theory,

the polymers on the surface are considered to be in either a "mushroom" or "brush" regime, depending on its density (Figure 3C). In the mushroom regime, size of polymer is estimated to be mean of radius of gyration in equilibrium, which is defined as Flory radius (R_F). When the surface density becomes very high, the polymer forms a brush, which distorts the polymer and reduces its projected size on the plane. Polymer brush theory also applies to cell membrane proteins that diffuse in lipid membranes (Evans et al., 1996; Hiergeist and Lipowsky, 1996; Shurer et al., 2019). In particular, since glycoproteins have a bottlebrush structure with branched sugar chains on amino acid chains, our system consists of a brush of bottle brushes(Steen et al., 1998).

In the framework of polymer brush, cases of approaching particles to the surface containing graft polymers have been studied. These cases can be classified as either "invasion" or "compression" depending on the density of the graft polymer (Figure 3D) (Halperin, 1999) . The case of the virus-cell interface is similar to this previous case, but is distinctive because the protein is mobile and the membrane is flexible. Therefore, we further assume that there are two cases: one is “trap”, which involves molecular trapping and deformation of the cell membrane, and the other is “exclusion”, in which molecular exclusion results in the formation of an adhesive interface. (Figure 3E). Invasion without involving any molecular exclusion occurs only when the molecular density is very dilute. Molecular exclusion is enabled by molecular fluidity of the cell membrane, and such exclusion has been observed on a macroscopic scale at the cell-cell interface in the immune system or in the apoptotic blebs (Le et al., 2024; Sibener et al., 2018; Varma et al., 2006).

Using this framework, we consider the free energy of the virus-cell system. Trapping of membrane proteins at the interface is accompanied by a bending energy penalty or loss of adhesion energy (Figure 3E). These should depend on the size and number of trapped proteins. The free energy of the polymers can also be considered; in the mean-field approximation based on Flory polymer theory, the free energy of brush polymers can be decomposed into two main components: the interaction energy between polymers f_{int} and the elastic energy f_{el} of individual polymers. (Figure 3C) (Alexander, 1977; de Gennes, 1980; Halperin, 1999; Li et al., 2022; Milner, 1991). If the formation of the cell-virus interface involves macroscopic motion of particles, such as molecular exclusion, the process may experience an energy barrier U^* involved in such transition (Figure 3F) (Halperin, 1999). These arguments about free energy involve several assumptions. For example, it was assumed that when these proteins are trapped at the cell-virus interface, the protein volume and Flory radius are conserved. This is probably because lipid bilayers are flexible and their bending takes less energy than protein compression. This should be supported by a series of previous observations on the structure of proteins at the membrane-membrane interface (Carbone et al., 2017; Paszek et al., 2014; Wong and Groves, 2002). Besides, the processes of virus binding to membrane and membrane invagination were not

explicitly included in this discussion because they are common to different types of interfacial structures.

Effect of glycosylation in protein size and conformation

Protein size can be a key parameter in steric interaction. To measure the size of proteins on the plasma membrane *in situ*, fluorescence resonance energy transfer (FRET) between donor fluorescent tags at the ectodomain ends of proteins and acceptor fluorescent molecules incorporated into the plasma membrane was measured in living cells using a fluorescence lifetime imaging microscope (FLIM). (Figure 4A). In this setting, FLIM-FRET measured time average of end-to-end distance of proteins in solution in equilibrium, which is equivalent to the ensemble average of the radii of gyration of the ectodomain in solution, although one end of these proteins was attached to plasma membrane. Since the size of grafted polymers on solid surface measured by FRET was reported to be close to the Flory radius (R_F) of these polymers (Ma et al., 2014), we considered that the protein size measured by FLIM-FRET in our system also corresponds to R_F of each protein.

We found that the FLIM-FRET data were well explained by the FRET model with a planar membrane geometry in which acceptors are distributed on the lipid membrane in two dimensions (Figure 4B) (Gibson and Loew, 1979; Wong and Groves, 2002). We then extended this model to a hierarchical Bayesian model with acceptor density as a variable and applied it to FRET data for all molecules that were measured in the same cell type and with the same fluorescent dye pair. By regressing all measured data on the hierarchical model at once, we obtained R_F for each molecule from the estimated posterior predictive distribution (Supplementary Figure 3A-B). The longest estimated R_F that could be resolved was 7.5 nm. Molecules with barely detectable FRET changes (e.g., MUC1 (14TR, 42TR), CD44) were expected to be larger than this maximum measurable distance and were not included in the analysis. Importantly, R_F of some glycoproteins (e.g., CD43) were found to be smaller than the receptor-ligand binding length of ACE2 and Spike (~27 nm), yet they inhibited viral infection. Thus, this result supports the rationale for our interface hypothesis (Figure 3B).

The measured R_F was compared to the IC50 of infection inhibition (Figure. 4C). The two parameters showed a good correlation for many molecules, but there was a group of molecules that deviated from this correlation. Outliers showing exceptionally weak inhibition (e.g., VCAM1, EPHB1) were found to be poorly glycosylated. This suggests that even proteins with similar equilibrium size in solution may have different inhibitory effects on infection depending on the amount of glycosylation. In the case of glycoproteins, there is a complex confounding relationship between these parameters because

the number of amino acids to be glycosylated increases as the length of amino acids increases. However, it is suggested that glycosylation affects certain molecular properties other than average molecular size to produce the infection inhibitory effect.

Before examining the direct role of glycans in suppressing infection, the effects of glycans on molecular properties were examined from various perspectives. We found that R_F was strongly correlated with the molecular weight including glycans, but weakly correlated with the number of amino acids (correlation coefficient of 0.87 and 0.58, respectively) (Figure 4D-E). This observation is consistent with previous studies showing that Flory radii of branched polymers is determined by the total molecular weight (Hermans et al., 1952; Kreussling and Ullman, 1954). This suggests that R_F reflects the total chain length of amino acids and glycans, for which the total molecular weight is a better measure. It also suggests that for the same amino acid chain length, a protein with more glycans would have a longer R_F. This hypothesis can be tested by estimating the scaling exponent ν in the Flory model for $R_F \sim N^{\nu}$. The chain length N is the number of amino acids in this case. We estimated ν separately for highly glycosylated molecules (MUC1, CD43, CD164, CD24) and for low glycosylated molecules. The resulting ν for the two groups are 0.144 and 0.108, respectively. This shift in ν indicates that glycosylation increases the size of the protein at equilibrium, but the change in R_F is slight, e.g., a 1.3-fold increase for one of the longest ectodomains with N = 4000 when these values of ν are applied. Physically, this change in ν may be caused by the increased intramolecular exclusion induced sterically between glycan chains. This estimated ν are much smaller than that of 0.6 for polymers in good solvents, possibly due to protein folding or anchoring effects on the membrane. In fact, the ν of an intrinsically disordered protein in solution has been reported to be close to 0.6 (Riback et al., 2019; Tesei et al., 2024).

We also analyzed protein conformation. Conformational data for the ectodomain of all 2515 membrane proteins in our list were obtained from the Alpha Fold 2 prediction (Jumper et al., 2021a) and the end-to-end distances of the proteins in these conformations were plotted (Figures 4F, Supplementary Figure 3E-F). Despite the large variation in this index among all proteins, the predicted Flory radii based on the measured scaling exponent ν were intermediate of all data plots, suggesting that protein sizes measured in our FLIM-FRET assays and the predicted conformations were in some agreement. Among the molecules we tested, the measured R_F were consistent with or smaller than those calculated from the Alpha Fold predictions (Figure 4G). However, there were molecules, such as VCAM1 and EPHB1, for which the end-to-end distance in conformation was predicted to be much larger than the Flory radius estimated in our measurements (Figure 4G). There were many other molecules in the 2515 molecules that were plotted much higher than the predicted Flory radius, as shown in Figure 4F. Many of the molecules in this class are low glycosylated and tend to consist of multiple folded domains

connected by flexible linkers, as seen in VCAM1 and EPHB1 (Figures 4H, Supplementary Figure3I). In contrast, the highly glycosylated proteins such as MUC1 (0TR) were predicted to be more globular and have fewer folded domains (Figure 4H, Supplementary Figure 3E-I).

This discussion highlights the difference in size from R_F measurements and predicted conformations: the R_F is derived from an ensemble average, while Alpha Fold2 suggests only one representative conformation. Therefore, protein size estimates from highly anisotropic conformations may deviate significantly from the R_F. This is the case for low glycosylated proteins such as EPHB1 and VCAM1, which should have a very broad conformational landscape around its R_F size (Figure 4H). This may suggest that protein glycosylation reduces the diversity of protein conformational space. This may be caused by the intramolecular interactions between amino acids and domain folding being interfered with by the glycans. If protein glycosylation functions to limit conformational dynamics, proteins may lose macroscopic flexibility with this modification. To test this hypothesis, further experimental validation or prediction with next-generation tools that include information on both conformational dynamics and multiresidue glycans would be needed (Abramson et al., 2024; Jumper et al., 2021b). (Tesei et al., 2024).

In vitro reconstitution of glycoprotein packing on membrane

The analysis in the previous section suggests that branching structures generated by molecular glycosylation may alter protein properties. Such changes may be important for the roles of glycans in infection inhibition (Figure 4C). In the context of polymer brush theory, such changes could modulate molecular packing. Then changes in molecular packing may alter U^* associated with molecular exclusion, if that occurs in the formation of the interface (Figure 3F).

Under this hypothesis, we next investigated whether glycosylation affects protein packing and intermolecular interactions on the plasma membrane. To directly address this question, we biochemically reconstituted membrane protein systems in vitro and quantified protein packing. The ectodomain of the membrane proteins used in the viral infection assay were purified and introduced into fluid lipid bilayers formed on silica beads via affinity tag (Figure 5A). In this geometry, the membrane surface area was fixed and unchanged, allowing the molecular density to be measured without the influence of membrane structure (Lee et al., 2021). A non-glycosylated protein ectodomain produced in E. coli was also used for comparison. Molecular binding density was measured for each lipid-coated bead by flow cytometry.

The non-glycosylated recombinant CD43 and MUC1(14TR) ectodomain produced in E. coli bound at an estimated average saturation density of more than 10,000 molecules μm^{-2}, while the glycosylated CD43 and MUC1 ectodomain produced in HEK 293T cells bound at much lower saturation densities (Figure 5B). Thus, the saturation binding densities of these proteins reduced significantly by glycosylation. The ectodomain of EPHB1, a low-level glycosylated protein, bound in the intermediate density range. The binding density of non-glycosylated molecules was comparable to the saturation binding density shown for green fluorescent protein (GFP) on planar lipid bilayers (~7000 μm^{-2}) (Nye and Groves, 2008). Dissociation constants for membrane-bound glycosylated (g-) proteins (0.61 μM and 0.48 μM for CD43 and MUC1, respectively) were similar to or lower than those for bacterial (b-) proteins (3.84 μM and 12.6 μM for CD43 and MUC1, respectively), indicating that differences in molecular affinity for the lipid bilayer are not responsible for the large differences in saturation binding densities. The binding of all tested molecules was well explained by the standard first order receptor-ligand binding reaction (Figure 5B), and single molecule tracking experiments confirmed that both glycosylated (g-) and non-glycosylated and bacterial (b-) proteins were equally diffusible as individual molecules (Supplementary Figure 4). Therefore, it is unlikely that there are protein-protein or protein-layer interactions that would allosterically affect protein packing.

To compare the packing of proteins with different molecular weights and R_F, we introduce the projected coverage area on the membrane as a normalized parameter, assuming that these molecules could be approximated by a hemisphere of R_F, when they are in the mushroom regime (Halperin, 1999; Milner, 1991) (Figure 5C). Under this assumption, the coverage of highly glycosylated proteins at binding saturation was ~20% for g-MUC1 and ~40% for g-CD43, respectively. These were smaller than the coverage of molecules at hexagonal close packing that is ~90.7%, indicating that these molecules were in the mushroom regime even at binding saturation. In contrast, the coverage of b-CD43 and b-MUC1 at saturated binding was estimated to be greater than 100% under this normalization standard. This suggests that these non-glycosylated molecules were no longer in mushroom regime when they were in binding saturation. Instead, they were likely transited to semi-dilute brush regime, and were distorted to adjust the actual coverage area to be no more than 100% (Hansen et al., 2003; Wu et al., 2002).

These results demonstrated that high glycosylated proteins are more resistant to protein packing than low glycosylated ones. It indicates that there is intermolecular repulsive force between glycosylated proteins, which is most likely generated by steric effect of branched glycans. The system can also be described in the context of the free energy of polymer brush (Figure 5D). The intermolecular interaction f_{int} is derived from the excluded volume effect between two adjacent polymers (Faivre et al., 2018; Kreussling and Ullman, 1954; Paturej et al., 2016). In the case of glycoproteins, f_{int} increases

nonlinearly because branched glycans projected toward adjacent polymers enhance the excluded volume effect. Thus, $f_{int}(d)$ for highly glycosylated proteins at very short inter-polymer distances ($d<R_F$) is expected to be very large in the mushroom regime. In contrast, the $f_{int}(d)$ for low glycosylated proteins is also low in the mushroom region and even lower in the brush region. On the other hand, if the elastic component f_{el} is small and $f_{int}(d)$ for high glycosylated proteins dropped significantly by the brush transition, these molecules are more easily distorted. However, this did not occur in our bead system. This result may suggest that f_{el} is not small for highly glycosylated proteins. This may be related to the differences in flexibility and conformational dynamics between low and high glycosylated proteins, as discussed in Figure 4H. Overall, the net free energy of the polymer, $f_{int} + f_{el}$, is greater for high-glycosylated proteins than for low-glycosylated proteins, thus limiting the packing of glycoproteins.

Despite this strong intermolecular repulsion, a highly glycosylated molecule (e.g. MUC1) could form brush structure in cells when such protein is expressed at very high densities (Shurer et al., 2019). In these cells, plasma membranes were forced to accommodate these large amount of membrane proteins with hydrophobic transmembrane domains. In contrast, in our experiment, proteins were soluble in the aqueous phase, and we can analyze intermolecular repulsion in ectodomain independently from the effect of protein compartmentalization. In addition, cells containing brushed glycoproteins also transformed the cell membrane into a shape with an enormous amount of tubular structure. Such membrane deformation results in the increase of total surface area to reduce the density of glycoproteins, indicating that there is strong intermolecular repulsion between glycoproteins. Note that it has been previously shown that membrane tubules generated upon the insertion of polymers in membranes were neither inhibitory nor activating on viral infection (Kaizuka and Machida, 2023). This is simply because these structures are on the ~μm scale, and much larger than viruses, and we assumed that this logic can also be applied to membrane tubules generated by overcrowded glycocalyx (Shurer et al., 2019).

Super-resolution imaging of virus-cell interface

Glycosylation of proteins induces intermolecular repulsion, which affects the distribution of molecules on the membrane. Here, we measure the distribution of membrane proteins in situ to determine whether protein glycosylation induces molecular exclusion or trap at the virus-cell interface (Figure 3D). To address this question, we used dual-color super-resolution microscopy (STORM) imaging to locate each membrane glycoprotein and viral Spike proteins (Rust et al., 2006). We found that the distribution patterns of these proteins are very diverse (Figure. 6A). To analyze these diverse results

in an unbiased manner, we introduced a cross-correlation function *C(r)* (Figure 6B-C). *C(r)* here is the probability distribution of distances between cellular and viral proteins, calculated as a radial normalization of the histogram of the mutual spacing distances *r* between cellular and viral proteins in the image (Figure 6B)(Schnitzbauer et al., 2018; Stone and Veatch, 2015; Veatch et al., 2012). Although the cross-correlation function has often been used to analyze molecular co-localization in super-resolution images (Schnitzbauer et al., 2018; Stone and Veatch, 2015; Veatch et al., 2012), we intended to apply this function over a longer distance range to analyze protein distributions at the virus-cell interface. Since the localization of Spikes was limited in viruses that were only sparsely distributed throughout the image, *C(r)* in our study can somewhat reflect the average probability distribution of cellular proteins at distance *r* from these viruses in each image. In most of the *C(r)* plots, a peak appears at 0~100 nm, which is near the virus diameter, and the function decays as *r* increases (Figure 6C). This trend may be attributed to the fact that the Spike as well as the cellular proteins were distributed in specific locations (e.g. discrete viruses and plasma membrane), and the rest of the region in images was mostly blank (Figure 6A). In contrast, *C(r)* for molecules uniformly distributed throughout the image tends to converge to 1 as *r* increases (Schnitzbauer et al., 2018; Stone and Veatch, 2015; Veatch et al., 2012).

The next step is to obtain measure of the protein density at the virus-cell interface from *C(r)*. To solve this inverse problem, the information of relationship between *C(r)* and the interface molecular density is needed. To obtain this relationship, we adopted the approach of using simulated images. We prepared a set of *C(r)* plots calculated from simulated images of various types of virus-cell membrane interfaces (Figure 6D). These images were characterized by the parameter *density_(in/out)*, which is the ratio of the mean density of membrane proteins inside and outside the virus-cell interface. Thus, this parameter *density_(in/out)* is the measure to know whether proteins at the virus-cell interface is excluded or not.

Simulated images included those in which the virus is isolated from the cell membrane ("separation") and those in which cell membrane molecules are concentrated on the virus and *density_(in/out)*>1 ("co-localized"). To organize the list of calculated *C(r)* for all simulated images, we introduced the index *C(r)_(out/in)*, which is the ratio of the integral of *C(r)* at *r* = 100~200 nm to the integral of *C(r)* at r = 0~100 nm. This boundary r~100nm was set since the size of virus is approximately 100nm, and we assumed that this index reflects the ratio of the probability distribution of proteins inside and outside the viral–cell interface. Indeed, we found that *C(r)_(out/in)* increased continuously from ~0.2 to ~2.0 at protein exclusion interfaces where *density_(in/out)* ranged from 0 to 1 and the densities were in the range of those in typical STORM images. In addition, the *C(r)_(out/in)* for "separation" and “co-localization" were found to be >2.0 and <0.2, respectively (Figure 6E). Altogether, among these three types of cell–virus interface (co-localization, exclusion, and separation), the parameter

C(r)_(out/in) increases monotonically along with the value of *density_(in/out)*. Therefore, the average *density_(in/out)* for each image can be calibrated from *C(r)* using this relationship.

Next, images of cells with *C(r)_(out/in)<2.0*, which are not in "separation" and represent about 80% of all cells, were analyzed. As indicated above, the majority of viruses in these images would be expected to form an interface with the cells. *C(r)_(out/in)* and calibrated *density_(in/out)* were compared between molecules. *Density_(in/out)* was found to be similarly low for groups of membrane proteins, and molecules with molecular weights greater than 50 kDa (MUC1, CD44, F174B, VCAM1, EPHB1, all tagged with SNAP) were similarly excluded at the virus-cell interface to an average ~80% reduction (Figure 6GH). In contrast, much higher *density_(in/out)* were observed for VAMP2, a SNAP-tagged-only control molecule, and LCK10, a control molecule without any ectodomain, respectively, suggesting that only very low amounts of both of these molecules were excluded. The slight decrease in *density_(in/out)* for these control molecules may be an artifact caused by the oversimplification in the simulation of cell images.

These results showed that membrane proteins above a certain threshold size are excluded from the virus-cell interface, regardless of the degree of glycosylation. Interestingly, the transition from low-exclusion regime to high-exclusion regime occurred nonlinearly and abruptly with protein size (Figure 6H). This may be due to measurement bias in part, since we analyzed only viruses bound to the cell membrane but not ones already internalized in the cell. More viruses may be internalized in cells with smaller proteins, but they are not included in the analysis, and thus the rate of protein exclusion may be overestimated for cells with these smaller proteins. Nevertheless, the overall correlation between Flory radius and *density_(in/out)* can be calculated to be -0.36.

Discussion

We hypothesize that the energy barrier U^* required for the virus to form an interface with the cell is increased by glycosylation of membrane proteins in the plasma membrane, thereby suppressing infection. We summarize the mechanism based on our analyses. In the early stages of interface formation, the receptor and ligand form the binding point at the center and there is a region with a longer interfacial distance around this center (Figure 7A). As we have already seen, membrane proteins above a certain size are excluded from this region and an interface is formed (Figure 6H). The driving force for this molecular exclusion may be the adhesion energy of the interfacial membrane. Since membrane adhesion at the interface is a process that stabilizes the energy level of the system, molecular exclusion should be promoted. In reality, however, there are many viruses that bind to cells but are not

taken up due to insufficient molecular exclusion at the interface (Figure 3A, Supplementary Figure 5). This means that there is an energy barrier that resists molecular exclusion from the interface.

A possible factor creating an energy barrier to molecular exclusion is the strong viscosity of the plasma membrane, experimentally confirmed to be on the scale of ~1 $\mu m^2/s$ (Supplementary Figure 4). In such an environment of strong viscosity, when molecular exclusion from the interface bond center to the periphery proceeds, viscous stress is generated to resist the movement (Figure 7A). Viscous stress, however, is created in the lipid bilayer and is common to all transmembrane molecules, regardless of protein glycosylation.

On the other hand, the glycosylation of ectodomain affects the intermolecular repulsion on the plasma membrane when the molecular density increases (Figure 5D). Are there situations in which this repulsion has an effect on molecular exclusion? We assume that the density of excluded molecules increases at the outer edge of the interface and then intermolecular interaction there is strongly affected by glycosylation (Figure 7B). Molecular exclusion occurs only in the region inside the viral interface, while molecules outside the interface only diffuse. And the cell membrane is highly viscous. As a result, we speculate that molecules may become locally and instantaneously crowded in the vicinity of the interface. In such a geometry, the interface between the virus and the cell membrane can only be formed if the virus and membrane proteins are all squeezed into that narrow area (Figure 7C). If the density increase is sufficiently large, the glycosylated molecules may experience strong intermolecular repulsion, preventing them from being packed together with the virus. On the other hand, molecules with low glycosylation may be readily distorted and accept crowding by being brushed. We propose that this difference creates an energy barrier that would kinetically inhibit the processes of interface formation and molecular exclusion.

Based on this model, we can classify the structure of the interface into three types depending on the type of cell membrane protein. The first is the case where the membrane protein is small and thus infection can proceed even if the protein is trapped at the viral cell membrane interface, at least in low-density situations (Figure 7D). For highly glycosylated molecules above a certain size, the glycans interfere with molecular exclusion by generating strong intermolecular repulsion and prevent successful interface formation. As a result, viral infection is inhibited (Figure 7F). For molecules above a certain size but with low glycosylation, intermolecular repulsion is weak and molecular exclusion is easily enabled, resulting in the formation of an interface and progression to infection (Figure 7E).

This nonequilibrium model may be mathematically represented by incorporating terms for viscous stress and molecular diffusion. If the entire process can be mathematically modeled, it may be possible

to relate the energy barrier U^* to the average molecular density and R_F. If such a model can be successfully incorporated into a hierarchical Bayesian model, it may be possible to relate the IC50 value of each molecule to the number of glycans. This model may explain the sharp decline in infection efficiency that could not be reproduced by the simple Sigmoid model (Figure 1F).

This paper has laid the foundation for a strategy to describe molecular nonspecific functions by means of molecules. The next step, for example, would be to obtain quantitative relationships between the cell transcriptome and the amount of glycans on the cell surface, where machine learning may be useful. Future goals of these kinds of studies would be to treat nonspecific phenomena within the same framework as other molecule- and gene-specific functions. In addition, even with the current advances in machine learning and single-cell data technology, it is still difficult in many areas to predict cellular-level phenotypes from genomics and transcriptomes. Therefore, we believe it is useful to mix such auxiliary methods that utilize a combination of statistics and rule-based physical models.

FIGURES

Figure 1.

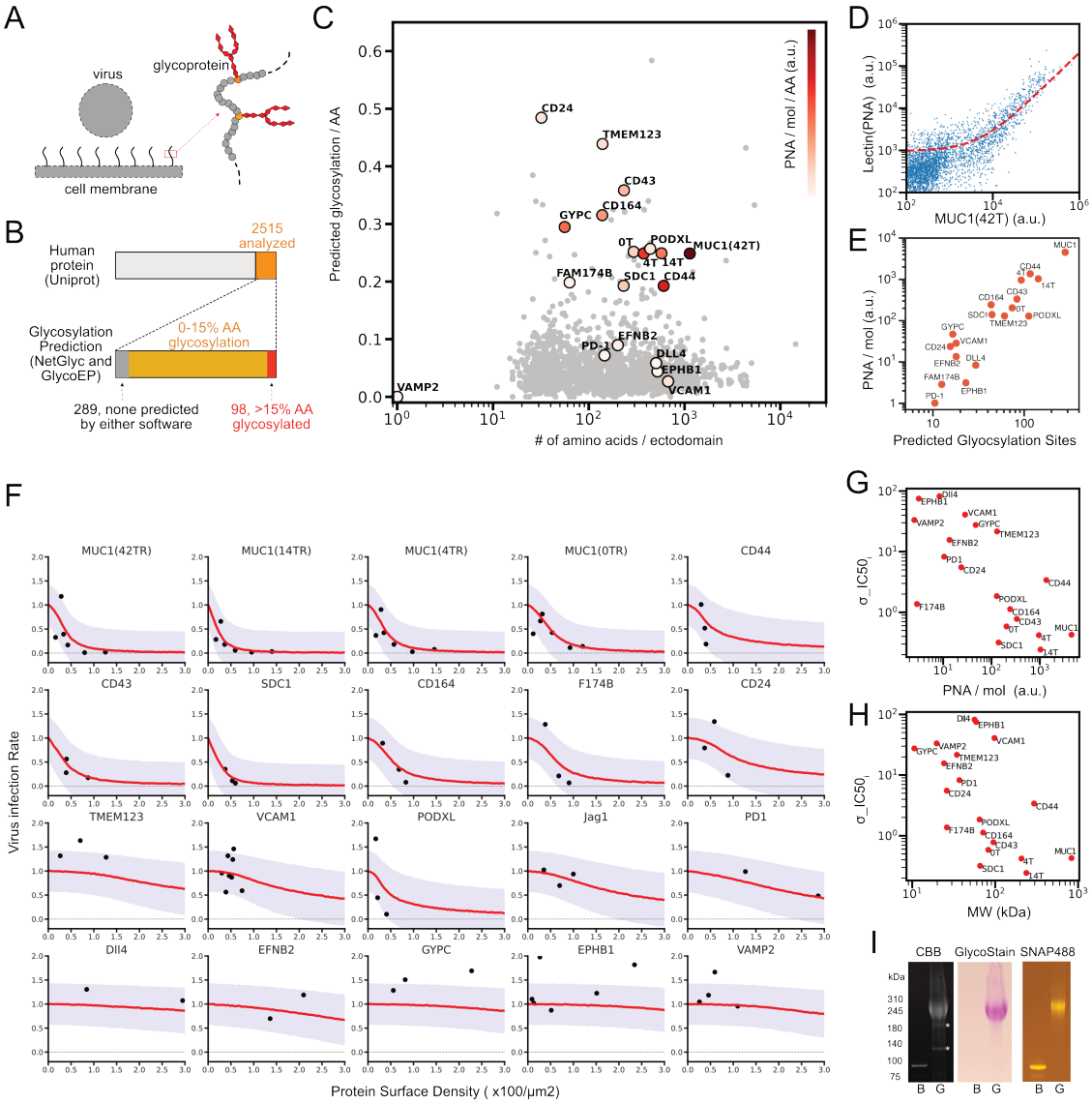

Figure 1. List of glycoproteins in the human genome: predictions and measurement of glycosylation, and virus infection inhibition assays using sample proteins from the list.

A. Schematic of inhibition of virus infection by membrane glycoproteins. B. The number of membrane proteins and predicted glycosylated proteins in human genome from UniProt . C. The number of

predicted glycosylation sites per the number of amino acid sequence of ectodomain for 2515 membrane associated proteins, plotted along with the number of ectodomain amino acid sequence. Color indicates the measured rate for glycosylation per molecule (PNA/mol) per amino acid. 0T, 4T, and 14T indicate truncation mutants of MUC1 that contain 0, 4, and 14 tandem repeat sequences, respectively. D. Flow cytogram for the binding of Alexa Flour 647 labeled PNA to HEK293T cells expressing MUC1(42 tandem repeats) tagged with SNAP surface 488 and the linear regression of the data to the reaction model (red dashed line, see the method section for details). E. Relations of the measured PNA/mol and the number of predicted glycosylation sites for the indicated molecules. F. SARS-CoV2-PP infection assay in HEK293T cells expressing ACE2, TMPRSS2, and each of designated membrane protein. Dots were measured values of the integral of GFP expressions from infected viruses in those samples adjusted by the total ACE2 expressions at the time of infection, and were plotted along with the mean density of membrane protein at the time of infection. Red lines indicate learned predicted infection rates mean from Bayesian hierarchical inference based on sigmoidal function, and purple area represents one sigma below and above the red lines. G. Relations between the measured rate for glycosylation per molecule (PNA/mol) and molecular specific IC50 density in sigmoidal inhibitory function inferred from Bayesian hierarchical modeling in F (σ_IC50). H. Relations between σ_IC50 and estimated molecular weight including glycans in the experimental system. I. Purification and analysis of recombinant proteins, non-glycosylated (bacterial or B) and glycosylated (G) MUC1 (14TR) tagged with SNAP surface 488. Coomassie Brilliant Blue stained (left), glycan stained (middle), and fluorescent (right) for proteins in SDS-PAGE.

Figure 2.

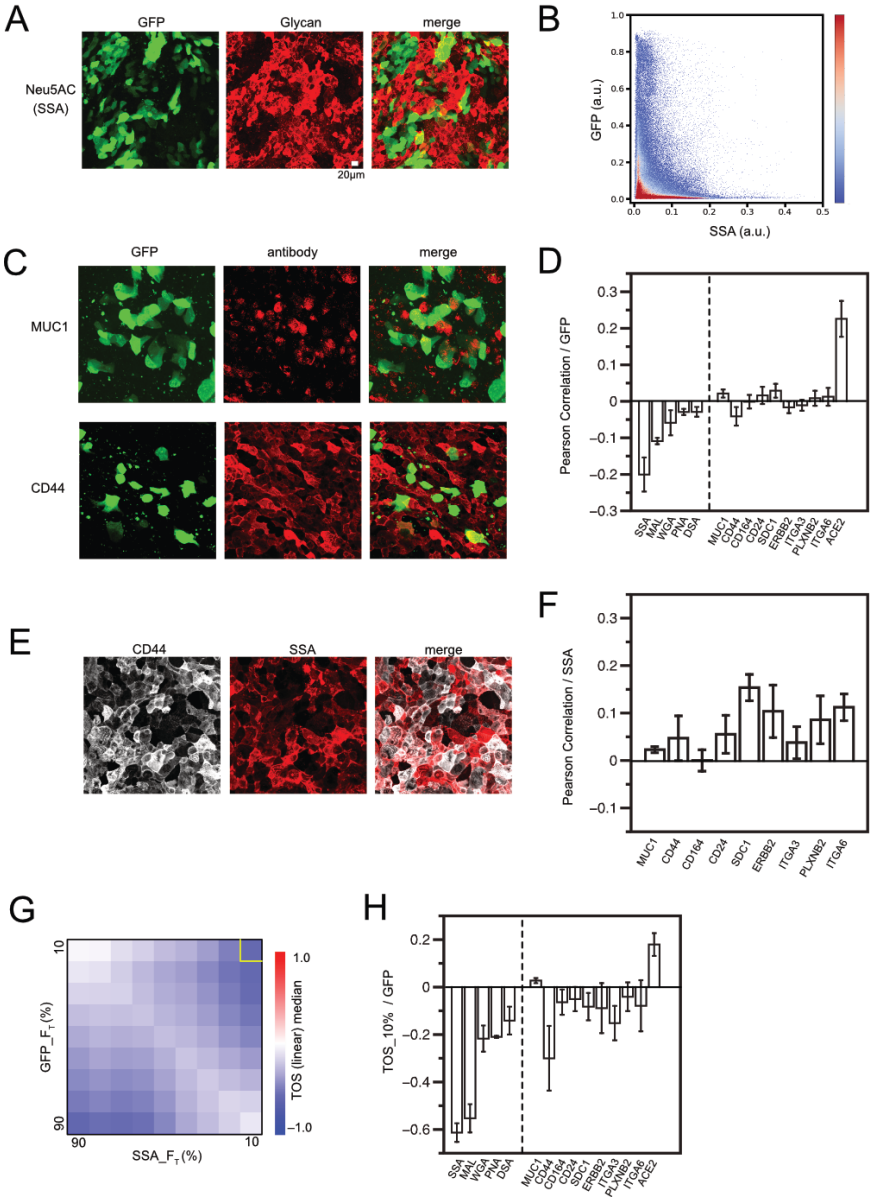

Figure 2. Virus infection in epithelium regulated by glycan contents in each cell.

A. Maximal projection of z-stack of images. SARS-CoV2-pp infected air liquid interface (ALI) cultured Calu-3 cell monolayer, imaged by the binding of Alexa Fluor 647-labeled Neu5AC specific lectin from Sambucus sieboldiana (SSA), and the expression of GFP derived from infected viruses. B.

Plot of fluorescence intensities in all pixels in Figure 2A in both GFP and SSA channels. C. SARS-CoV2-pp infected Calu-3 ALI monolayer, imaged by immunofluorescence for each membrane protein and GFP. Maximal projection of z-stack of images is shown. D. Pearson correlation for fluorescence intensities of lectin/antibody and GFPs in image pixels in maximal projection of z-stack images. Error bars are standard error of mean from images from three or more different samples. Lectins used were SSA, MAL (from Maackia amurensis, Neu5AC specific), WGA (from Triticum vulgaris, GlcNAc specific), PNA, and DSA (from Datura stramonium, GlcNAc specific). E. SARS-CoV2-pp infected Calu-3 ALI monolayer, imaged by immunofluorescence for CD44 and SSA lectin binding. Maximal projection of z-stack of images is shown. F. Pearson correlation of lectin/antibody signal and SSA signal in image pixels in maximal projection of z-stack images. Error bars are standard error of mean from images from three or more different samples. G. TOS analysis for GFP and SSA signal pixels in image of Figure 2A. H. Correlation in top 10% in both axes in the TOS analysis. Error bars are standard error of mean from images from three or more different samples.

Figure 3.

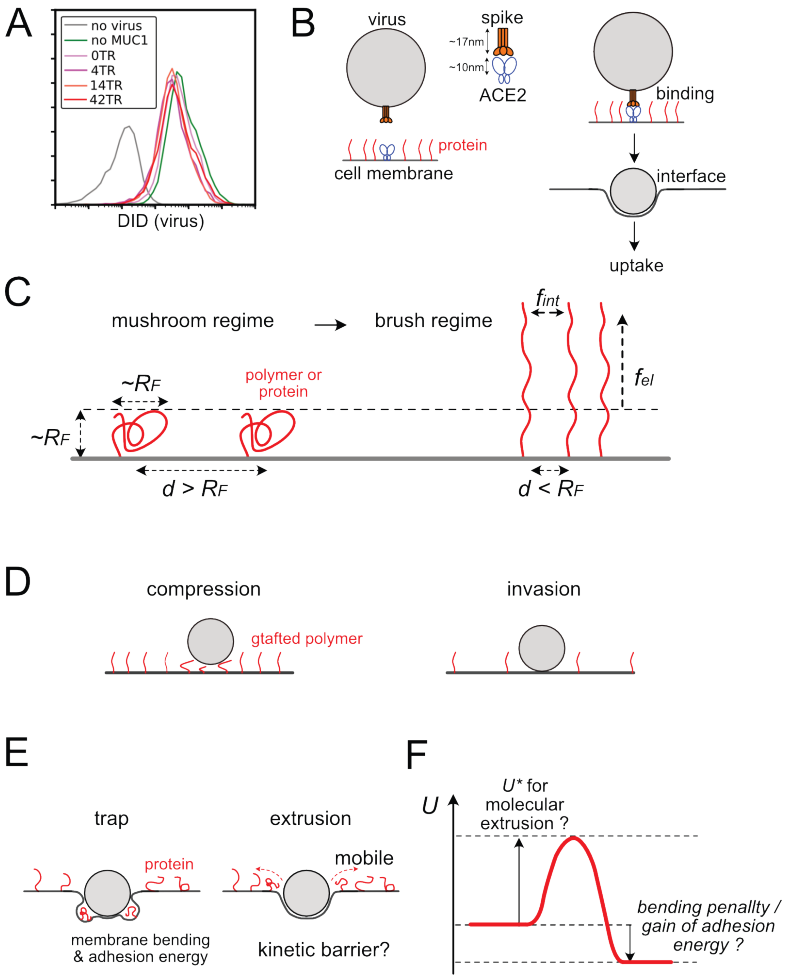

Figure 3. Structure of interface between viruses and cell membranes and polymer brush theory.

A. Flow cytogram of DID labeled SARS-CoV2-PP binding to HEK293T cells expressing ACE2, TMPRSS2, and/or various truncation mutants of MUC1. B. Schematic diagram of the interface structure between the virus and the cell membrane during the process from cell-virus binding to virus uptake via stable interface formation. C. Basics of polymer brush theory and free energy of the polymer in the brush structure. *d*, spacing distance between polymers, R_F, Flory radius of polymers, f_{int}, and f_{el}, intermolecular and elastic free energies per a single polymer. D. Two types of interfacial structures of particle binding to polymer graft surfaces in the conventional polymer brush model. E. Two additional structure types of particle-surface interface, specialized cases for virus-cell interface. F. A chart for free energy of the system *U* during the process of virus-cell interface formation.

Figure 4.

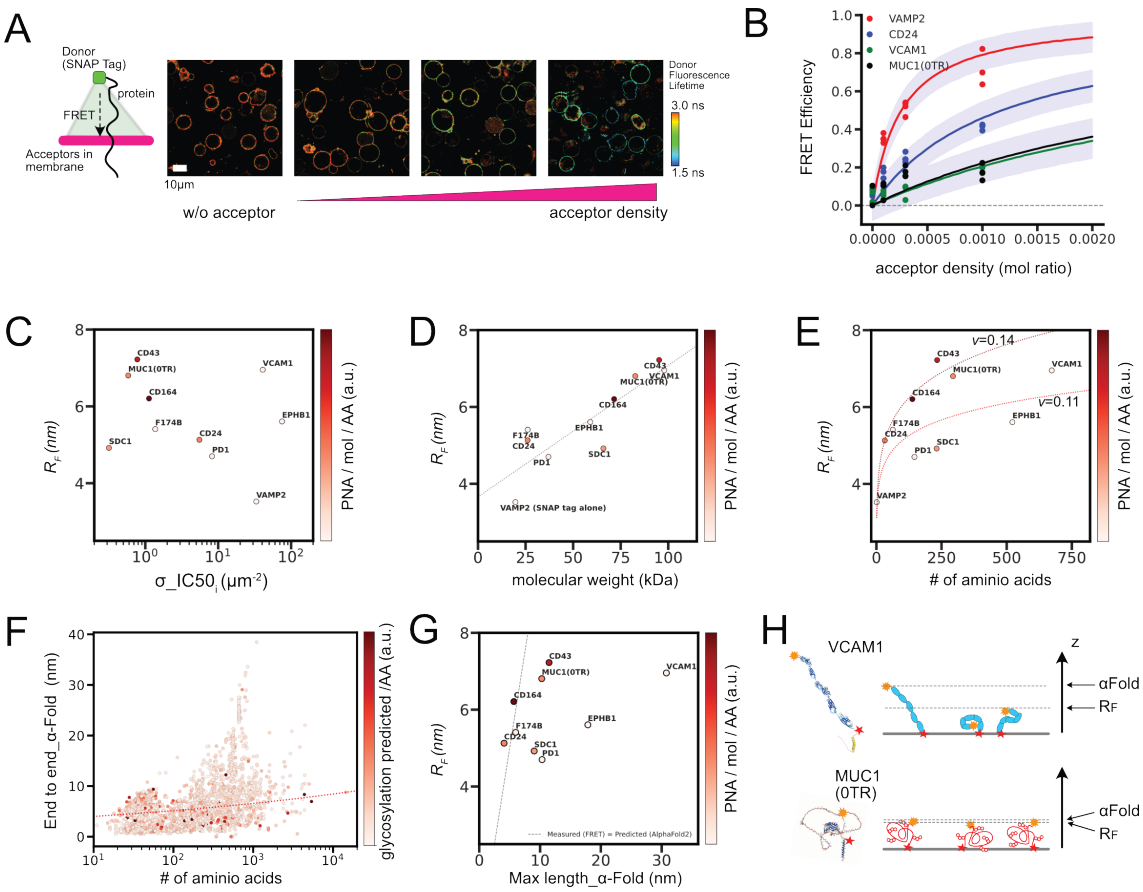

Figure 4. In situ FLIM–FRET measurements for protein sizes, and conformational predictions.

A. Example of FLIM images, for cells expressing SNAP–Surface 488 conjugated CD24 proteins and being incorporated with PlasMem Bright Red dyes in different surface densities. Schematic drawing (left) depicts a geometry of the FRET from a single donor dye conjugated to SNAP tag at the end of protein ectodomain to populations of acceptor dyes incorporated in plasma membrane. B. FRET efficiency estimated from FLIM imaging for cells expressing each protein at different mean acceptor densities. Lines are predicted mean FRET efficiencies from Bayesian hierarchical inference (see method for details), and purple area represents one sigma below and above the lines. C. Relations between inferred Flory radius from FLIM – FRET analyses and inferred $\sigma_{_IC50}$ from infection inhibition assays. Measured glycosylation rage PNA/mol/AA was depicted in color. D. Relations between inferred Flory radius from FLIM – FRET analyses and estimated molecular weight including glycans. Dot line is the result of linear regression. E. Relations between inferred Flory radius from

FLIM – FRET analyses and amino acid length. Dot lines are the fit to Flory model for $R_F \sim N^{\nu}$. F. Relations between the distance between coordinates of two amino acids at both ends of ectodomain in Alpha Fold2 predicted conformations and number of amino acids for all 2515 proteins in the list. The number of predicted glycosylation sates per amino acid was depicted in color. Dot line indicates the Flory model $R_F \sim N^{\nu}$, where $\nu = 0.14$. G. Relations between the distance between coordinates of two amino acids at both ends of ectodomain in Alpha Fold2 predicted conformations for our sample molecules and measured Flory radius from FLIM–FRET assays. Dot line indicates where the measured R_F is equal to the Alpha Fold 2 predicted length. H. Schematic diagram of protein conformational dynamics and two length scales, R_F and Alpha Fold 2 prediction. Yellow and red stars indicate the two ends of the ectodomain.

Figure 5.

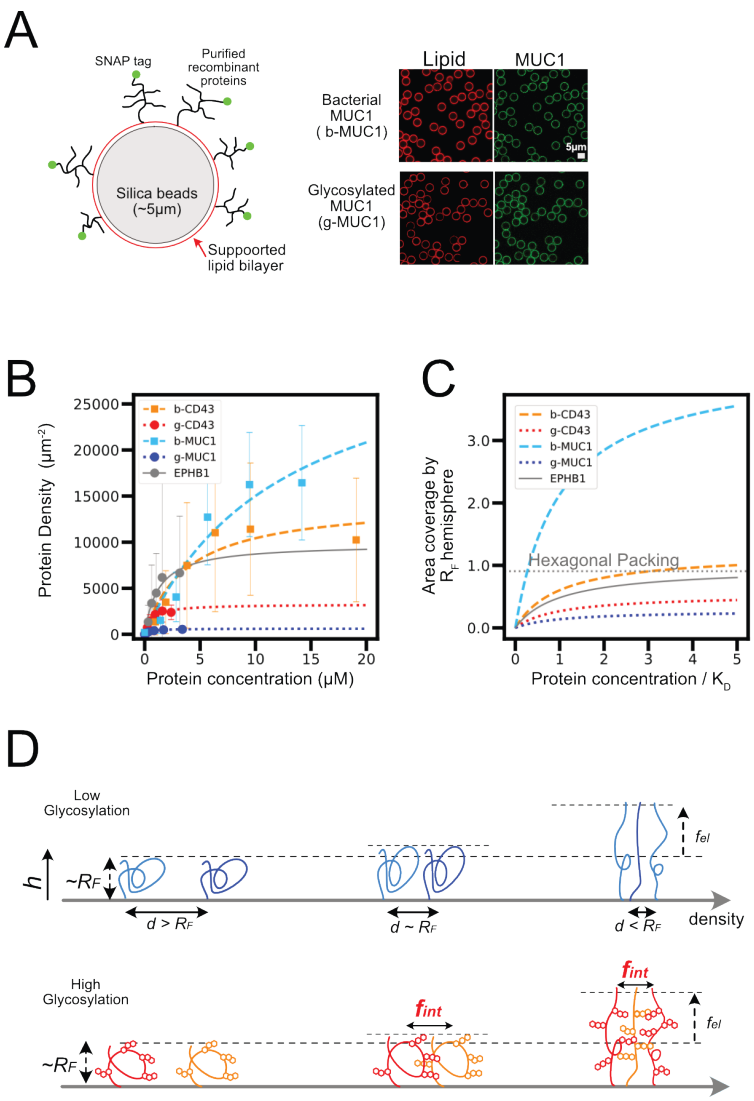

Figure 5. Biochemical reconstitution of protein packing in membrane surface.

A. Lipid bilayers coated on silica beads for incorporating bacterial (b-) and glycosylated (mammalian expressed, g-) proteins, schematic and fluorescent images. B. Representative result for flow cytometry analyses of protein binding to lipid bilayer coated silica beads. Bar is standard deviation in each measurement. Lines are regression curves to receptor binding model $Bx/(K_D + x)$, where x is protein concentration, K_D is the dissociation constant and B is the saturated density. C. Relations of surface area coverage by bound proteins and concentrations of proteins used for membrane binding.

Surface area was normalized by assuming all bound proteins were in hemisphere of radius R_F and the ratio of coverage was calculated. Protein concentrations were normalized by K_D. Dot line in the plot indicates the coverage when hemisphere of radius R_F aligned in a hexagonal close packing. D. Schematic for structures and free energies for glycosylated and non-glycosylated proteins with similar R_F that are in mushroom and brush regimes.

Figure 6.

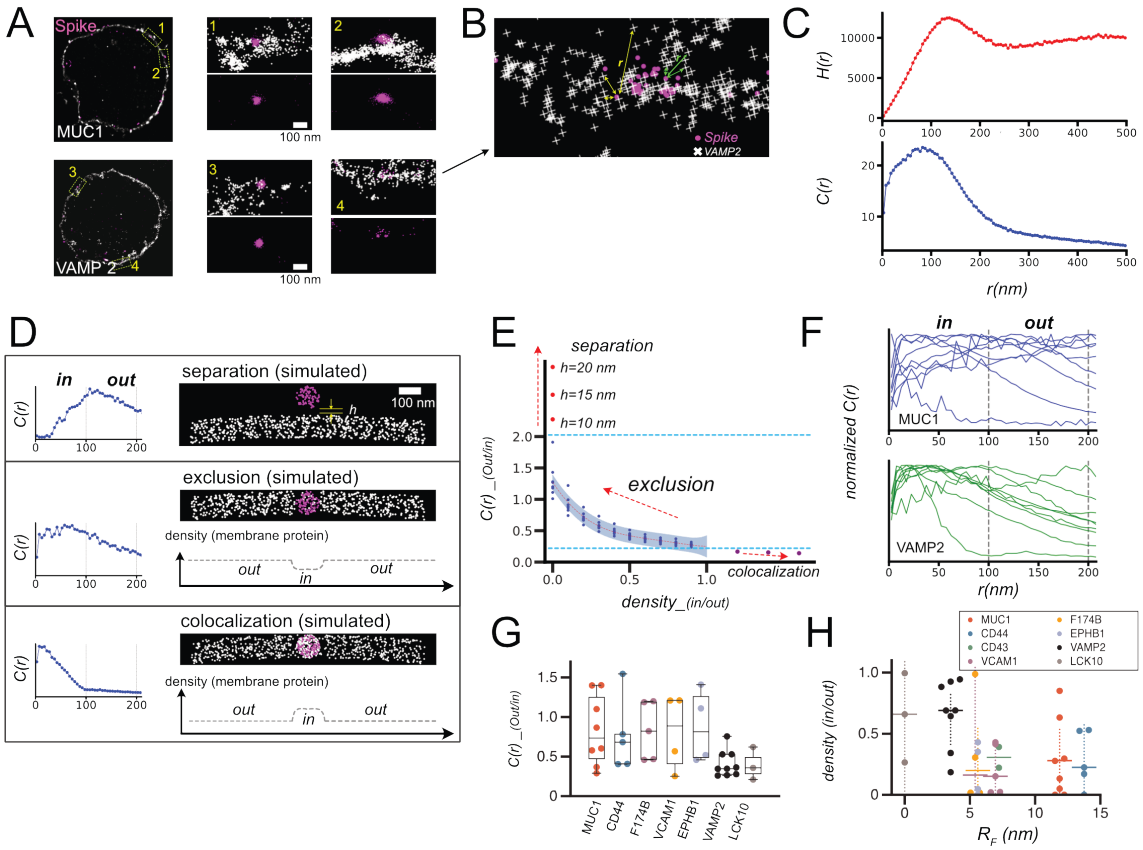

Figure 6. Superresolution imaging of virus and cellular proteins for analyses of virus – cell interface

A. Dual color STORM images of SNAP-MUC1/SNAP-VAMP2 in cells and Spike in SARS-CoV-2-PP bound to the cells. Whole cell images (left) were reconstruction from STORM data, and coordinates determined by STORM were individually plotted in expanded images in right. B. Schematic of calculation of cross correlation. Mutual distance between all combinations of two dyes were calculated from the coordinates determined by STORM imaging. C. Examples of histogram of mutual distances between all combinations of two dyes were calculated from coordinates H(r), and the cross-correlation function C(r) that is the normalized radial average of H(r). Δr, a size of shell and the bin size for histogram, was set to be 5 nm. D. Examples of simulated STORM images, and calculated C(r) from these images. h denotes the distance between virus and cell when they are

separated, and density plot illustrates average protein densities along membranes in these images. E. Plot of C(r)_(out/in) calculated for all simulated images, along with density_(in/out) and h. Blue dashed lines indicate upper and lower bound for C(r)_(out/in) calculated for stable virus – cell interface, and red dot line is the fifth polynomial regression to data point and purple area represents one sigma below and above the line. F. Traces of C(r) for individual cells expressing MUC1 and VAMP2. G. C(r)_(out/in) calculated for all STORM images. H. density_(in/out) for all STORM images converted from C(r)_(out/in) based on the regression in E, were plotted along with R_F for each protein determined by FLIM – FRET (Figure 4).

Figure 7.

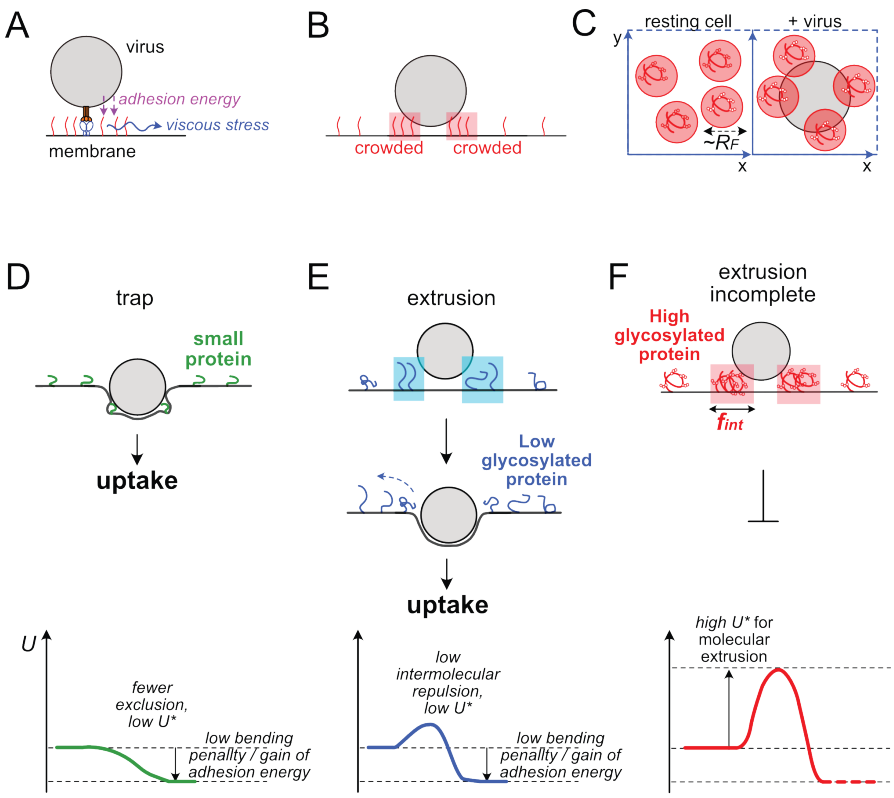

Figure 7. Models for three distinct cases of virus – cell interface.

A. Energy and force involved in molecular exclusion from virus-cell interface. B. Transient distribution of membrane proteins nearby the interface. C. Two-dimensional distribution of viruses and glycoproteins on the surface horizontal direction of the cell membrane. D-F. Schematic of virus-cell interface structure and corresponding free energy chart. D. Virus-cell interface with very small membrane proteins. Due to low energy penalty in constructing virus-cell interface entrapping these small molecules, virus can form interface without excluding proteins, and can infect cells. E-F. Virus-cell interface structure for larger membrane proteins. Interface formation requires protein exclusion. Due to membrane viscosity and inhomogeneous field in adhesive energy, excluded proteins become crowded at proximity of the interface. In the case for highly glycosylated proteins (F), intermolecular repulsion between excluded proteins become very high at high density regions. Such repulsion generates a high kinetic barrier for molecular exclusion, preventing to proceed to subsequent steps for infection. In contrast, in the case for low glycosylated proteins (E), their intermolecular repulsion and energy barrier are lower, and thus these molecules are easier to be excluded from the interface and virus infection is not strongly inhibited.

SUPPLEMENTAL INFORMATION

Supplementary word file including Supplementary figures 1-5 and Supplementary data files 1-3 are provided separately.

Materials availability

All unique/stable reagents generated in this study are available from the corresponding author with a completed materials transfer agreement.

Data and code availability

Original code as well as raw and processed data analyzed through the code are available in an online repository (https://github.com/ykaizuka/virus). Any additional information required to reanalyze the data reported in this paper is available from the corresponding author upon request.

Acknowledgement

We thank Kazuaki Tokunaga (Nikon) for his help in STORM sample preparation and imaging, and Hidenobu Nakao (NIMS) for helpful discussion. This work has been supported by intramural funding from NIMS.

Competing interests

The authors declare no competing interests.

REFERENCES

Abramson J, Adler J, Dunger J, Evans R, Green T, Pritzel A, Ronneberger O, Willmore L, Ballard AJ, Bambrick J, Bodenstein SW, Evans DA, Hung C-C, O'Neill M, Reiman D, Tunyasuvunakool K, Wu Z, Žemgulytė A, Arvaniti E, Beattie C, Bertolli O, Bridgland A, Cherepanov A, Congreve M, Cowen-Rivers AI, Cowie A, Figurnov M, Fuchs FB, Gladman H, Jain R, Khan YA, Low CMR, Perlin K, Potapenko A, Savy P, Singh S, Stecula A, Thillaisundaram A, Tong C, Yakneen S, Zhong ED, Zielinski M, Žídek A, Bapst V, Kohli P, Jaderberg M, Hassabis D, Jumper JM. 2024. Accurate structure prediction of biomolecular interactions with AlphaFold 3. *Nature*. doi:10.1038/s41586-024-07487-w

Ahern DJ, Ai Z, Ainsworth M, Allan C, Allcock A, Angus B, Ansari MA, Arancibia-Cárcamo C V., Aschenbrenner D, Attar M, Baillie JK, Barnes E, Bashford-Rogers R, Bashyal A, Beer S, Berridge G, Beveridge A, Bibi S, Bicanic T, Blackwell L, Bowness P, Brent A, Brown A, Broxholme J, Buck D, Burnham KL, Byrne H, Camara S, Candido Ferreira I, Charles P, Chen W, Chen Y-L, Chong A, Clutterbuck EA, Coles M, Conlon CP, Cornall R, Cribbs AP, Curion F, Davenport EE, Davidson N, Davis S, Dendrou CA, Dequaire J, Dib L, Docker J, Dold C, Dong T, Downes D, Drakesmith H, Dunachie SJ, Duncan DA, Eijsbouts C, Esnouf R, Espinosa A, Etherington R, Fairfax B, Fairhead R, Fang H, Fassih S, Felle S, Fernandez Mendoza M, Ferreira R, Fischer R, Foord T, Forrow A, Frater J, Fries A, Gallardo Sanchez V, Garner LC, Geeves C, Georgiou D, Godfrey L, Golubchik T, Gomez Vazquez M, Green A, Harper H, Harrington HA, Heilig R, Hester S, Hill J, Hinds C, Hird C, Ho L-P, Hoekzema R, Hollis B, Hughes J, Hutton P, Jackson-Wood MA, Jainarayanan A, James-Bott A, Jansen K, Jeffery K, Jones E, Jostins L, Kerr G, Kim D, Klenerman P, Knight JC, Kumar V, Kumar Sharma P, Kurupati P, Kwok A, Lee A, Linder A, Lockett T, Lonie L, Lopopolo M, Lukoseviciute M, Luo J, Marinou S, Marsden B, Martinez J, Matthews PC, Mazurczyk M, McGowan S, McKechnie S, Mead A, Mentzer AJ, Mi Y, Monaco C, Montadon R, Napolitani G, Nassiri I, Novak A, O'Brien DP, O'Connor D, O'Donnell D, Ogg G, Overend L, Park I, Pavord I, Peng Y, Penkava F, Pereira Pinho M, Perez E, Pollard AJ, Powrie F, Psaila B, Quan TP, Repapi E, Revale S, Silva-Reyes L, Richard J-B, Rich-Griffin C, Ritter T, Rollier CS, Rowland M, Ruehle F, Salio M, Sansom SN, Sanches Peres R, Santos Delgado A, Sauka-Spengler T, Schwessinger R, Scozzafava G, Screaton G, Seigal A, Semple MG, Sergeant M, Simoglou Karali C, Sims D, Skelly D, Slawinski H, Sobrinodiaz A, Sousos N, Stafford L, Stockdale L, Strickland M, Sumray O, Sun B, Taylor C, Taylor S, Taylor A, Thongjuea S, Thraves H, Todd JA, Tomic A, Tong O, Trebes A, Trzupek D, Tucci FA, Turtle L, Udalova I, Uhlig

H, van Grinsven E, Vendrell I, Verheul M, Voda A, Wang G, Wang L, Wang D, Watkinson P, Watson R, Weinberger M, Whalley J, Witty L, Wray K, Xue L, Yeung HY, Yin Z, Young RK, Youngs J, Zhang P, Zurke Y-X. 2022. A blood atlas of COVID-19 defines hallmarks of disease severity and specificity. *Cell* **185**:916-938.e58. doi:10.1016/j.cell.2022.01.012

Alexander S. 1977. Polymer adsorption on small spheres. A scaling approach. *Journal de Physique* **38**:977–981. doi:10.1051/jphys:01977003808097700

Bateman A, Martin M-J, Orchard S, Magrane M, Ahmad S, Alpi E, Bowler-Barnett EH, Britto R, Bye-A-Jee H, Cukura A, Denny P, Dogan T, Ebenezer T, Fan J, Garmiri P, da Costa Gonzales LJ, Hatton-Ellis E, Hussein A, Ignatchenko A, Insana G, Ishtiaq R, Joshi V, Jyothi D, Kandasaamy S, Lock A, Luciani A, Lugaric M, Luo J, Lussi Y, MacDougall A, Madeira F, Mahmoudy M, Mishra A, Moulang K, Nightingale A, Pundir S, Qi G, Raj S, Raposo P, Rice DL, Saidi R, Santos R, Speretta E, Stephenson J, Totoo P, Turner E, Tyagi N, Vasudev P, Warner K, Watkins X, Zaru R, Zellner H, Bridge AJ, Aimo L, Argoud-Puy G, Auchincloss AH, Axelsen KB, Bansal P, Baratin D, Batista Neto TM, Blatter M-C, Bolleman JT, Boutet E, Breuza L, Gil BC, Casals-Casas C, Echioukh KC, Coudert E, Cuche B, de Castro E, Estreicher A, Famiglietti ML, Feuermann M, Gasteiger E, Gaudet P, Gehant S, Gerritsen V, Gos A, Gruaz N, Hulo C, Hyka-Nouspikel N, Jungo F, Kerhornou A, Le Mercier P, Lieberherr D, Masson P, Morgat A, Muthukrishnan V, Paesano S, Pedruzzi I, Pilbout S, Pourcel L, Poux S, Pozzato M, Pruess M, Redaschi N, Rivoire C, Sigrist CJA, Sonesson K, Sundaram S, Wu CH, Arighi CN, Arminski L, Chen C, Chen Y, Huang H, Laiho K, McGarvey P, Natale DA, Ross K, Vinayaka CR, Wang Q, Wang Y, Zhang J. 2023. UniProt: the Universal Protein Knowledgebase in 2023. *Nucleic Acids Res* **51**:D523–D531. doi:10.1093/nar/gkac1052

Biering SB, Sarnik SA, Wang E, Zengel JR, Leist SR, Schäfer A, Sathyan V, Hawkins P, Okuda K, Tau C, Jangid AR, Duffy C V., Wei J, Gilmore RC, Alfajaro MM, Strine MS, Nguyenla X, Van Dis E, Catamura C, Yamashiro LH, Belk JA, Begeman A, Stark JC, Shon DJ, Fox DM, Ezzatpour S, Huang E, Olegario N, Rustagi A, Volmer AS, Livraghi-Butrico A, Wehri E, Behringer RR, Cheon D-J, Schaletzky J, Aguilar HC, Puschnik AS, Button B, Pinsky BA, Blish CA, Baric RS, O'Neal WK, Bertozzi CR, Wilen CB, Boucher RC, Carette JE, Stanley SA, Harris E, Konermann S, Hsu PD. 2022. Genome-wide bidirectional CRISPR screens identify mucins as host factors modulating SARS-CoV-2 infection. *Nat Genet* **54**:1078–1089. doi:10.1038/s41588-022-01131-x

Carbone CB, Kern N, Fernandes RA, Hui E, Su X, Garcia KC, Vale RD. 2017. In vitro reconstitution of T cell receptor-mediated segregation of the CD45 phosphatase. *Proceedings of the National Academy of Sciences* **114**. doi:10.1073/pnas.1710358114

Chan JF-W, Yuan S, Kok K-H, To KK-W, Chu H, Yang J, Xing F, Liu J, Yip CC-Y, Poon RW-S,

Tsoi H-W, Lo SK-F, Chan K-H, Poon VK-M, Chan W-M, Ip JD, Cai J-P, Cheng VC-C, Chen H, Hui CK-M, Yuen K-Y. 2020. A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster. *The Lancet* **395**:514–523. doi:10.1016/S0140-6736(20)30154-9

Chatterjee M, Huang LZX, Mykytyn AZ, Wang C, Lamers MM, Westendorp B, Wubbolts RW, van Putten JPM, Bosch B-J, Haagmans BL, Strijbis K. 2023. Glycosylated extracellular mucin domains protect against SARS-CoV-2 infection at the respiratory surface. *PLoS Pathog* **19**:e1011571. doi:10.1371/journal.ppat.1011571

Chauhan JS, Rao A, Raghava GPS. 2013. In silico Platform for Prediction of N-, O- and C-Glycosites in Eukaryotic Protein Sequences. *PLoS One* **8**:e67008. doi:10.1371/journal.pone.0067008

de Gennes PG. 1980. Conformations of Polymers Attached to an Interface. *Macromolecules* **13**:1069–1075. doi:10.1021/ma60077a009

Delaveris CS, Webster ER, Banik SM, Boxer SG, Bertozzi CR. 2020. Membrane-tethered mucin-like polypeptides sterically inhibit binding and slow fusion kinetics of influenza A virus. *Proceedings of the National Academy of Sciences* **117**:12643–12650. doi:10.1073/pnas.1921962117

Delgado MK, Cabernard C. 2020. Mechanical regulation of cell size, fate, and behavior during asymmetric cell division. *Curr Opin Cell Biol* **67**:9–16. doi:10.1016/j.ceb.2020.07.002

Delorey TM, Ziegler CGK, Heimberg G, Normand R, Yang Y, Segerstolpe Å, Abbondanza D, Fleming SJ, Subramanian A, Montoro DT, Jagadeesh KA, Dey KK, Sen P, Slyper M, Pita-Juárez YH, Phillips D, Biermann J, Bloom-Ackermann Z, Barkas N, Ganna A, Gomez J, Melms JC, Katsyv I, Normandin E, Naderi P, Popov Y V., Raju SS, Niezen S, Tsai LT-Y, Siddle KJ, Sud M, Tran VM, Vellarikkal SK, Wang Y, Amir-Zilberstein L, Atri DS, Beechem J, Brook OR, Chen J, Divakar P, Dorceus P, Engreitz JM, Essene A, Fitzgerald DM, Fropf R, Gazal S, Gould J, Grzyb J, Harvey T, Hecht J, Hether T, Jané-Valbuena J, Leney-Greene M, Ma H, McCabe C, McLoughlin DE, Miller EM, Muus C, Niemi M, Padera R, Pan L, Pant D, Pe'er C, Pfiffner-Borges J, Pinto CJ, Plaisted J, Reeves J, Ross M, Rudy M, Rueckert EH, Siciliano M, Sturm A, Todres E, Waghray A, Warren S, Zhang S, Zollinger DR, Cosimi L, Gupta RM, Hacohen N, Hibshoosh H, Hide W, Price AL, Rajagopal J, Tata PR, Riedel S, Szabo G, Tickle TL, Ellinor PT, Hung D, Sabeti PC, Novak R, Rogers R, Ingber DE, Jiang ZG, Juric D, Babadi M, Farhi SL, Izar B, Stone JR, Vlachos IS, Solomon IH, Ashenberg O, Porter CBM, Li B, Shalek AK, Villani A-C, Rozenblatt-Rosen O, Regev A. 2021. COVID-19 tissue atlases reveal SARS-CoV-2 pathology and cellular targets. *Nature* **595**:107–113. doi:10.1038/s41586-021-03570-8

Du H, Bartleson JM, Butenko S, Alonso V, Liu WF, Winer DA, Butte MJ. 2023. Tuning

immunity through tissue mechanotransduction. *Nat Rev Immunol* **23**:174–188. doi:10.1038/s41577-022-00761-w

Dworkin LA, Clausen H, Joshi HJ. 2022. Applying transcriptomics to study glycosylation at the cell type level. *iScience* **25**:104419. doi:10.1016/j.isci.2022.104419

Ellinghaus D, Degenhardt F, Bujanda L, Buti M, Albillos A, Invernizzi P, Fernández J, Prati D, Baselli G, Asselta R, Grimsrud MM, Milani C, Aziz F, Kässens J, May S, Wendorff M, Wienbrandt L, Uellendahl-Werth F, Zheng T, Yi X, de Pablo R, Chercoles AG, Palom A, Garcia-Fernandez A-E, Rodriguez-Frias F, Zanella A, Bandera A, Protti A, Aghemo A, Lleo A, Biondi A, Caballero-Garralda A, Gori A, Tanck A, Carreras Nolla A, Latiano A, Fracanzani AL, Peschuck A, Julià A, Pesenti A, Voza A, Jiménez D, Mateos B, Nafria Jimenez B, Quereda C, Paccapelo C, Gassner C, Angelini C, Cea C, Solier A, Pestaña D, Muñiz-Diaz E, Sandoval E, Paraboschi EM, Navas E, García Sánchez F, Ceriotti F, Martinelli-Boneschi F, Peyvandi F, Blasi F, Téllez L, Blanco-Grau A, Hemmrich-Stanisak G, Grasselli G, Costantino G, Cardamone G, Foti G, Aneli S, Kurihara H, ElAbd H, My I, Galván-Femenia I, Martín J, Erdmann J, Ferrusquía-Acosta J, Garcia-Etxebarria K, Izquierdo-Sanchez L, Bettini LR, Sumoy L, Terranova L, Moreira L, Santoro L, Scudeller L, Mesonero F, Roade L, Rühlemann MC, Schaefer M, Carrabba M, Riveiro-Barciela M, Figuera Basso ME, Valsecchi MG, Hernandez-Tejero M, Acosta-Herrera M, D'Angiò M, Baldini M, Cazzaniga M, Schulzky M, Cecconi M, Wittig M, Ciccarelli M, Rodríguez-Gandía M, Bocciolone M, Miozzo M, Montano N, Braun N, Sacchi N, Martínez N, Özer O, Palmieri O, Faverio P, Preatoni P, Bonfanti P, Omodei P, Tentorio P, Castro P, Rodrigues PM, Blandino Ortiz A, de Cid R, Ferrer R, Gualtierotti R, Nieto R, Goerg S, Badalamenti S, Marsal S, Matullo G, Pelusi S, Juzenas S, Aliberti S, Monzani V, Moreno V, Wesse T, Lenz TL, Pumarola T, Rimoldi V, Bosari S, Albrecht W, Peter W, Romero-Gómez M, D'Amato M, Duga S, Banales JM, Hov JR, Folseraas T, Valenti L, Franke A, Karlsen TH. 2020. Genomewide Association Study of Severe Covid-19 with Respiratory Failure. *New England Journal of Medicine* **383**:1522–1534. doi:10.1056/NEJMoa2020283

Enyedi B, Jelcic M, Niethammer P. 2016. The Cell Nucleus Serves as a Mechanotransducer of Tissue Damage-Induced Inflammation. *Cell* **165**:1160–1170. doi:10.1016/j.cell.2016.04.016

Evans E, Klingenberg DJ, Rawicz W, Szoka F. 1996. Interactions between Polymer-Grafted Membranes in Concentrated Solutions of Free Polymer. *Langmuir* **12**:3031–3037. doi:10.1021/la9509559

Faivre J, Shrestha BR, Xie G, Olszewski M, Adibnia V, Moldovan F, Montembault A, Sudre G, Delair T, David L, Matyjaszewski K, Banquy X. 2018. Intermolecular Interactions

between Bottlebrush Polymers Boost the Protection of Surfaces against Frictional Wear. *Chemistry of Materials* **30**:4140–4149. doi:10.1021/acs.chemmater.8b01676

Galush WJ, Nye JA, Groves JT. 2008. Quantitative Fluorescence Microscopy Using Supported Lipid Bilayer Standards. *Biophys J* **95**:2512–2519. doi:10.1529/biophysj.108.131540

Gibson GA, Loew LM. 1979. Application of Forster resonance energy transfer to interactions between cell or lipid vesicle surfaces. *Biochem Biophys Res Commun* **88**:141–146. doi:10.1016/0006-291X(79)91708-X

Grant RA, Morales-Nebreda L, Markov NS, Swaminathan S, Querrey M, Guzman ER, Abbott DA, Donnelly HK, Donayre A, Goldberg IA, Klug ZM, Borkowski N, Lu Z, Kihshen H, Politanska Y, Sichizya L, Kang M, Shilatifard A, Qi C, Lomasney JW, Argento AC, Kruser JM, Malsin ES, Pickens CO, Smith SB, Walter JM, Pawlowski AE, Schneider D, Nannapaneni P, Abdala-Valencia H, Bharat A, Gottardi CJ, Budinger GRS, Misharin A V., Singer BD, Wunderink RG, Grant RA, Morales-Nebreda L, Markov NS, Swaminathan S, Querrey M, Guzman ER, Abbott DA, Donnelly HK, Donayre A, Goldberg IA, Klug ZM, Borkowski N, Lu Z, Kihshen H, Politanska Y, Sichizya L, Kang M, Shilatifard A, Qi C, Lomasney JW, Argento AC, Kruser JM, Malsin ES, Pickens CO, Smith SB, Walter JM, Pawlowski AE, Schneider D, Nannapaneni P, Abdala-Valencia H, Bharat A, Gottardi CJ, Budinger GRS, Misharin A V., Singer BD, Wunderink RG, Wagh AA, Hauser AR, Wolfe AR, Thakrar A, Yeldandi A V., Wang AA, Levenson AR, Joudi AM, Tran B, Gao CA, Kurihara C, Schroedl CJ, Horvath CM, Meza D, Odell DD, Kamp DW, Winter DR, Ozer EA, Shanes ED, Bartom ET, Rendleman EJ, Leibenguth EM, Wehbe F, Liu GY, Gadhvi GT, Navarro HT, Sznajder JI, Dematte JE, Le J, Arnold JM, Du JC, Coleman J, Bailey JI, Deters JS, Fiala JA, Starren J, Ridge KM, Secunda K, Aren K, Gates KL, Todd K, Gradone LD, Textor LN, Wolfe LF, Pesce LL, Nunes Amaral LA, Rosenbaum ML, Kandpal M, Jain M, Sala MA, Saine M, Carns M, Alexander MJ, Cuttica MJ, Prickett MH, Khan NH, Chandel NS, Soulakis ND, Rivas OR, Seed PC, Reyfman PA, Go PD, Sporn PHS, Cooper PR, Tomic R, Patel R, Garza-Castillon R, Kalhan R, Morimoto RI, Mylvaganam RJ, Kim SS, Gatesy SWM, Thakkar S, Ben Maamar S, Han S, Rosenberg SR, Nozick S, Green SJ, Russell SR, Poor TA, Zak TJ, Lombardo TA, Stoeger T, Shamaly T, Ren Z. 2021. Circuits between infected macrophages and T cells in SARS-CoV-2 pneumonia. *Nature* **590**:635–641. doi:10.1038/s41586-020-03148-w

Gupta R, Brunak S. 2002. Prediction of glycosylation across the human proteome and the correlation to protein function. *Pac Symp Biocomput* 310–22.

Hadjadj J, Yatim N, Barnabei L, Corneau A, Boussier J, Smith N, Péré H, Charbit B, Bondet V, Chenevier-Gobeaux C, Breillat P, Carlier N, Gauzit R, Morbieu C, Pène F, Marin N, Roche N, Szwebel T-A, Merkling SH, Treluyer J-M, Veyer D, Mouthon L, Blanc C,

Tharaux P-L, Rozenberg F, Fischer A, Duffy D, Rieux-Laucat F, Kernéis S, Terrier B. 2020. Impaired type I interferon activity and inflammatory responses in severe COVID-19 patients. *Science (1979)* **369**:718–724. doi:10.1126/science.abc6027

Halperin A. 1999. Polymer Brushes that Resist Adsorption of Model Proteins: Design Parameters. *Langmuir* **15**:2525–2533. doi:10.1021/la981356f

Hansen PL, Cohen JA, Podgornik R, Parsegian VA. 2003. Osmotic Properties of Poly(Ethylene Glycols): Quantitative Features of Brush and Bulk Scaling Laws. *Biophys J* **84**:350–355. doi:10.1016/S0006-3495(03)74855-3

Hermans JJ, Klamkin MS, Ullman R. 1952. The Excluded Volume of Polymer Chains. *J Chem Phys* **20**:1360–1368. doi:10.1063/1.1700763

Hiergeist C, Lipowsky R. 1996. Elastic Properties of Polymer-Decorated Membranes. *Journal de Physique II* **6**:1465–1481. doi:10.1051/jp2:1996142

Huang Y-F, Aoki K, Akase S, Ishihara M, Liu Y-S, Yang G, Kizuka Y, Mizumoto S, Tiemeyer M, Gao X-D, Aoki-Kinoshita KF, Fujita M. 2021. Global mapping of glycosylation pathways in human-derived cells. *Dev Cell* **56**:1195-1209.e7. doi:10.1016/j.devcel.2021.02.023

Jalihal AP, Pitchiaya S, Xiao L, Bawa P, Jiang X, Bedi K, Parolia A, Cieslik M, Ljungman M, Chinnaiyan AM, Walter NG. 2020. Multivalent Proteins Rapidly and Reversibly Phase-Separate upon Osmotic Cell Volume Change. *Mol Cell* **79**:978-990.e5. doi:10.1016/j.molcel.2020.08.004

Jumper J, Evans R, Pritzel A, Green T, Figurnov M, Ronneberger O, Tunyasuvunakool K, Bates R, Žídek A, Potapenko A, Bridgland A, Meyer C, Kohl SAA, Ballard AJ, Cowie A, Romera-Paredes B, Nikolov S, Jain R, Adler J, Back T, Petersen S, Reiman D, Clancy E, Zielinski M, Steinegger M, Pacholska M, Berghammer T, Bodenstein S, Silver D, Vinyals O, Senior AW, Kavukcuoglu K, Kohli P, Hassabis D. 2021a. Highly accurate protein structure prediction with AlphaFold. *Nature* **596**:583–589. doi:10.1038/s41586-021-03819-2

Jumper J, Evans R, Pritzel A, Green T, Figurnov M, Ronneberger O, Tunyasuvunakool K, Bates R, Žídek A, Potapenko A, Bridgland A, Meyer C, Kohl SAA, Ballard AJ, Cowie A, Romera-Paredes B, Nikolov S, Jain R, Adler J, Back T, Petersen S, Reiman D, Clancy E, Zielinski M, Steinegger M, Pacholska M, Berghammer T, Bodenstein S, Silver D, Vinyals O, Senior AW, Kavukcuoglu K, Kohli P, Hassabis D. 2021b. Highly accurate protein structure prediction with AlphaFold. *Nature* **596**:583–589. doi:10.1038/s41586-021-03819-2

Kaizuka Y, Machida R. 2023. Antiviral Activity of Cell Membrane-Bound Amphiphilic Polymers. *Langmuir* **39**:5408–5417. doi:10.1021/acs.langmuir.3c00054

Kaizuka Y, Machida R, Ota Y. 2021. Mechanochemical Regulation of Cell Adhesion by Incorporation of Synthetic Polymers to Plasma Membranes. *Langmuir* **37**:366–375. doi:10.1021/acs.langmuir.0c02955

Ke Z, Oton J, Qu K, Cortese M, Zila V, McKeane L, Nakane T, Zivanov J, Neufeldt CJ, Cerikan B, Lu JM, Peukes J, Xiong X, Kräusslich H-G, Scheres SHW, Bartenschlager R, Briggs JAG. 2020. Structures and distributions of SARS-CoV-2 spike proteins on intact virions. *Nature* **588**:498–502. doi:10.1038/s41586-020-2665-2

Kreussling F, Ullman R. 1954. The excluded volume of branched chains. *Journal of Polymer Science* **12**:123–132. doi:10.1002/pol.1954.120120110

Le T, Ferling I, Qiu L, Nabaile C, Assunção L, Roskelley CD, Grinstein S, Freeman SA. 2024. Redistribution of the glycocalyx exposes phagocytic determinants on apoptotic cells. *Dev Cell* **59**:853-868.e7. doi:10.1016/j.devcel.2024.01.020

Lee AA, Huang WYC, Hansen SD, Kim NH, Alvarez S, Groves JT. 2021. Stochasticity and positive feedback enable enzyme kinetics at the membrane to sense reaction size. *Proceedings of the National Academy of Sciences* **118**. doi:10.1073/pnas.2103626118

Li C-W, Romeis D, Koch M, Merlitz H, Sommer J-U. 2022. Theoretical analysis of the elastic free energy contributions to polymer brushes in poor solvent: A refined mean-field theory. *J Chem Phys* **157**. doi:10.1063/5.0103351

Linden SK, Sutton P, Karlsson NG, Korolik V, McGuckin MA. 2008. Mucins in the mucosal barrier to infection. *Mucosal Immunol* **1**:183–197. doi:10.1038/mi.2008.5

Ma Z, LeBard DN, Loverde SM, Sharp KA, Klein ML, Discher DE, Finkel TH. 2014. TCR Triggering by pMHC Ligands Tethered on Surfaces via Poly(Ethylene Glycol) Depends on Polymer Length. *PLoS One* **9**:e112292. doi:10.1371/journal.pone.0112292

Mariani V, Biasini M, Barbato A, Schwede T. 2013. lDDT: a local superposition-free score for comparing protein structures and models using distance difference tests. *Bioinformatics* **29**:2722–2728. doi:10.1093/bioinformatics/btt473

McAuley JL, Corcilius L, Tan H-X, Payne RJ, McGuckin MA, Brown LE. 2017. The cell surface mucin MUC1 limits the severity of influenza A virus infection. *Mucosal Immunol* **10**:1581–1593. doi:10.1038/mi.2017.16

Meckiff BJ, Ramírez-Suástegui C, Fajardo V, Chee SJ, Kusnadi A, Simon H, Eschweiler S, Grifoni A, Pelosi E, Weiskopf D, Sette A, Ay F, Seumois G, Ottensmeier CH, Vijayanand P. 2020. Imbalance of Regulatory and Cytotoxic SARS-CoV-2-Reactive CD4+ T Cells in COVID-19. *Cell* **183**:1340-1353.e16. doi:10.1016/j.cell.2020.10.001

Milner ST. 1991. Polymer Brushes. *Science (1979)* **251**:905–914. doi:10.1126/science.251.4996.905

Moremen KW, Tiemeyer M, Nairn A V. 2012. Vertebrate protein glycosylation: diversity,

synthesis and function. *Nat Rev Mol Cell Biol* **13**:448–462. doi:10.1038/nrm3383

Murakami T, Carmona N, Ono A. 2020. Virion-incorporated PSGL-1 and CD43 inhibit both cell-free infection and transinfection of HIV-1 by preventing virus–cell binding. *Proceedings of the National Academy of Sciences* **117**:8055–8063. doi:10.1073/pnas.1916055117

Nye JA, Groves JT. 2008. Kinetic Control of Histidine-Tagged Protein Surface Density on Supported Lipid Bilayers. *Langmuir* **24**:4145–4149. doi:10.1021/la703788h

Ogando NS, Dalebout TJ, Zevenhoven-Dobbe JC, Limpens RWAL, van der Meer Y, Caly L, Druce J, de Vries JJC, Kikkert M, Bárcena M, Sidorov I, Snijder EJ. 2020. SARS-coronavirus-2 replication in Vero E6 cells: replication kinetics, rapid adaptation and cytopathology. *Journal of General Virology* **101**:925–940. doi:10.1099/jgv.0.001453

Paszek MJ, DuFort CC, Rossier O, Bainer R, Mouw JK, Godula K, Hudak JE, Lakins JN, Wijekoon AC, Cassereau L, Rubashkin MG, Magbanua MJ, Thorn KS, Davidson MW, Rugo HS, Park JW, Hammer DA, Giannone G, Bertozzi CR, Weaver VM. 2014. The cancer glycocalyx mechanically primes integrin-mediated growth and survival. *Nature* **511**:319–325. doi:10.1038/nature13535

Pathak GA, Karjalainen J, Stevens C, Neale BM, Daly M, Ganna A, Andrews SJ, Kanai M, Cordioli M, Polimanti R, Harerimana N, Pirinen M, Liao RG, Chwialkowska K, Trankiem A, Balaconis MK, Nguyen H, Solomonson M, Veerapen K, Wolford B, Roberts G, Park D, Ball CA, Coignet M, McCurdy S, Knight S, Partha R, Rhead B, Zhang M, Berkowitz N, Gaddis M, Noto K, Ruiz L, Pavlovic M, Hong EL, Rand K, Girshick A, Guturu H, Baltzell AH, Niemi MEK, Rahmouni S, Guntz J, Beguin Y, Cordioli M, Pigazzini S, Nkambule L, Georges M, Moutschen M, Misset B, Darcis G, Guiot J, Azarzar S, Gofflot S, Claassen S, Malaise O, Huynen P, Meuris C, Thys M, Jacques J, Léonard P, Frippiat F, Giot J-B, Sauvage A-S, Frenckell C Von, Belhaj Y, Lambermont B, Nakanishi T, Morrison DR, Mooser V, Richards JB, Butler-Laporte G, Forgetta V, Li R, Ghosh B, Laurent L, Belisle A, Henry D, Abdullah T, Adeleye O, Mamlouk N, Kimchi N, Afrasiabi Z, Rezk N, Vulesevic B, Bouab M, Guzman C, Petitjean L, Tselios C, Xue X, Afilalo J, Afilalo M, Oliveira M, Brenner B, Brassard N, Durand M, Schurr E, Lepage P, Ragoussis J, Auld D, Chassé M, Kaufmann DE, Lathrop GM, Adra D, Hayward C, Glessner JT, Shaw DM, Campbell A, Morris M, Hakonarson H, Porteous DJ, Below J, Richmond A, Chang X, Polikowski H, Lauren PE, Chen H-H, Wanying Z, Fawns-Ritchie C, North K, McCormick JB, Chang X, Glessner JR, Hakonarson H, Gignoux CR, Wicks SJ, Crooks K, Barnes KC, Daya M, Shortt J, Rafaels N, Chavan S, Timmers PRHJ, Wilson JF, Tenesa A, Kerr SM, D'Mellow K, Shahin D, El-Sherbiny YM, von Hohenstaufen KA, Sobh A, Eltoukhy MM, Nkambul Lindokuhle, Elhadidy TA, Abd Elghafar MS, El-Jawhari

JJ, Mohamed AAS, Elnagdy MH, Samir A, Abdel-Aziz M, Khafaga WT, El-Lawaty WM, Torky MS, El-shanshory MR, Yassen AM, Hegazy MAF, Okasha K, Eid MA, Moahmed HS, Medina-Gomez C, Ikram MA, Uitterlinden AG, Mägi R, Milani L, Metspalu A, Laisk T, Läll K, Lepamets M, Esko T, Reimann E, Naaber P, Laane E, Pesukova J, Peterson P, Kisand K, Tabri J, Allos R, Hensen K, Starkopf J, Ringmets I, Tamm A, Kallaste A, Alavere H, Metsalu K, Puusepp M, Batini C, Tobin MD, Venn LD, Lee PH, Shrine N, Williams AT, Guyatt AL, John C, Packer RJ, Ali A, Free RC, Wang X, Wain L V., Hollox EJ, Bee CE, Adams EL, Palotie A, Ripatti S, Ruotsalainen S, Kristiansson K, Koskelainen S, Perola M, Donner K, Kivinen K, Palotie A, Kaunisto M, Rivolta C, Bochud P-Y, Bibert S, Boillat N, Nussle SG, Albrich W, Quinodoz M, Kamdar D, Suh Noémie, Neofytos D, Erard V, Voide C, Bochud P-Y, Rivolta C, Bibert S, Quinodoz M, Kamdar D, Neofytos D, Erard V, Voide C, Friolet R, Vollenweider P, Pagani JL, Oddo M, zu Bentrup FM, Conen A, Clerc O, Marchetti O, Guillet A, Guyat-Jacques C, Foucras S, Rime M, Chassot J, Jaquet M, Viollet RM, Lannepoudenx Y, Portopena L, Bochud PY, Vollenweider P, Pagani JL, Desgranges F, Filippidis P, Guéry B, Haefliger D, Kampouri EE, Manuel O, Munting A, Papadimitriou-Olivgeris M, Regina J, Rochat-Stettler L, Suttels V, Tadini E, Tschopp J, Van Singer M, Viala B, Boillat-Blanco N, Brahier T, Hügli O, Meuwly JY, Pantet O, Gonseth Nussle S, Bochud M, D'Acremont V, Estoppey Younes S, Albrich WC, Suh N., Cerny A, O'Mahony L, von Mering C, Bochud PY, Frischknecht M, Kleger G-R, Filipovic M, Kahlert CR, Wozniak H, Negro TR, Pugin J, Bouras K, Knapp C, Egger T, Perret A, Montillier P, di Bartolomeo C, Barda B, de Cid R, Carreras A, Moreno V, Kogevinas M, Galván-Femenía I, Blay N, Farré X, Sumoy L, Cortés B, Mercader JM, Guindo-Martinez M, Torrents D, Garcia-Aymerich J, Castaño-Vinyals G, Dobaño C, Gori M, Renieri A, Mari F, Mondelli MU, Castelli F, Vaghi M, Rusconi S, Montagnani F, Bargagli E, Franchi F, Mazzei MA, Cantarini L, Tacconi D, Feri M, Scala R, Spargi G, Nencioni C, Bandini M, Caldarelli GP, Canaccini A, Ognibene A, D'Arminio Monforte A, Girardis M, Antinori A, Francisci D, Schiaroli E, Scotton PG, Panese S, Scaggiante R, Monica M Della, Capasso M, Fiorentino G, Castori M, Aucella F, Biagio A Di, Masucci L, Valente S, Mandalà M, Zucchi P, Giannattasio F, Coviello DA, Mussini C, Tavecchia L, Crotti L, Rizzi M, Rovere MT La, Sarzi-Braga S, Bussotti M, Ravaglia S, Artuso R, Perrella A, Romani D, Bergomi P, Catena E, Vincenti A, Ferri C, Grassi D, Pessina G, Tumbarello M, Pietro M Di, Sabrina R, Luchi S, Furini S, Dei S, Benetti E, Picchiotti N, Sanarico M, Ceri S, Pinoli P, Raimondi F, Biscarini F, Stella A, Zguro K, Capitani K, Nkambule L, Tanfoni M, Fallerini C, Daga S, Baldassarri M, Fava F, Frullanti E, Valentino F, Doddato G, Giliberti A, Tita R, Amitrano S, Bruttini M, Croci S, Meloni I, Mencarelli MA, Rizzo C Lo, Pinto AM, Beligni G, Tommasi A, Sarno L Di,

Palmieri M, Carriero ML, Alaverdian D, Busani S, Bruno R, Vecchia M, Belli MA, Mantovani S, Ludovisi S, Quiros-Roldan E, Antoni MD, Zanella I, Siano M, Emiliozzi A, Fabbiani M, Rossetti B, Bergantini L, D'Alessandro M, Cameli P, Bennett D, Anedda F, Marcantonio S, Scolletta S, Guerrini S, Conticini E, Frediani B, Spertilli C, Donati A, Guidelli L, Corridi M, Croci L, Piacentini P, Desanctis E, Cappelli S, Verzuri A, Anemoli V, Pancrazzi A, Lorubbio M, Miraglia FG, Venturelli S, Cossarizza A, Vergori A, Gabrieli A, Riva A, Paciosi F, Andretta F, Gatti F, Parisi SG, Baratti S, Piscopo C, Russo R, Andolfo I, Iolascon A, Carella M, Merla G, Squeo GM, Raggi P, Marciano C, Perna R, Bassetti M, Sanguinetti M, Giorli A, Salerni L, Parravicini P, Menatti E, Trotta T, Coiro G, Lena F, Martinelli E, Mancarella S, Gabbi C, Maggiolo F, Ripamonti D, Bachetti T, Suardi C, Parati G, Bottà G, Domenico P Di, Rancan I, Bianchi F, Colombo R, Barbieri C, Acquilini D, Andreucci E, Segala FV, Tiseo G, Falcone M, Lista M, Poscente M, Vivo O De, Petrocelli P, Guarnaccia A, Baroni S, Hayward C, Porteous DJ, Fawns-Ritchie C, Richmond A, Campbell A, van Heel DA, Hunt KA, Trembath RC, Huang QQ, Martin HC, Mason D, Trivedi B, Wright J, Finer S, Akhtar S, Anwar M, Arciero E, Ashraf S, Breen G, Chung R, Curtis CJ, Chowdhury M, Colligan G, Deloukas P, Durham C, Finer S, Griffiths C, Huang QQ, Hurles M, Hunt KA, Hussain S, Islam K, Khan Ahsan, Khan Amara, Lavery C, Lee SH, Lerner R, MacArthur D, MacLaughlin B, Martin H, Mason D, Miah S, Newman B, Safa N, Tahmasebi F, Trembath RC, Trivedi B, van Heel DA, Wright J, Griffiths CJ, Smith A V., Boughton AP, Li KW, LeFaive J, Annis A, Niavarani A, Aliannejad R, Sharififard B, Amirsavadkouhi A, Naderpour Z, Tadi HA, Aleagha AE, Ahmadi S, Moghaddam SBM, Adamsara A, Saeedi M, Abdollahi H, Hosseini A, Chariyavilaskul P, Jantarabenjakul W, Hirankarn N, Chamnanphon M, Suttichet TB, Shotelersuk V, Pongpanich M, Phokaew C, Chetruengchai W, Putchareon O, Torvorapanit P, Puthanakit T, Suchartlikitwong P, Nilaratanakul V, Sodsai P, Brumpton BM, Hveem K, Willer C, Wolford B, Zhou W, Rogne T, Solligard E, Åsvold BO, Franke L, Boezen M, Deelen P, Claringbould A, Lopera E, Warmerdam R, Vonk JudithM, van Blokland I, Lanting P, Ori APS, Feng Y-CA, Mercader J, Weiss ST, Karlson EW, Smoller JW, Murphy SN, Meigs JB, Woolley AE, Green RC, Perez EF, Wolford B, Zöllner S, Wang J, Beck A, Sloofman LG, Ascolillo S, Sebra RP, Collins BL, Levy T, Buxbaum JD, Sealfon SC, Jordan DM, Thompson RC, Gettler K, Chaudhary K, Belbin GM, Preuss M, Hoggart C, Choi S, Underwood SJ, Salib I, Britvan B, Keller K, Tang L, Peruggia M, Hiester LL, Niblo K, Aksentijevich A, Labkowsky A, Karp A, Zlatopolsky M, Zyndorf M, Charney AW, Beckmann ND, Schadt EE, Abul-Husn NS, Cho JH, Itan Y, Kenny EE, Loos RJF, Nadkarni GN, Do R, O'Reilly P, Huckins LM, Ferreira MAR, Abecasis GR, Leader JB, Cantor MN, Justice AE, Carey DJ, Chittoor G, Josyula NS, Kosmicki JA, Horowitz JE,

Baras A, Gass MC, Yadav A, Mirshahi T, Hottenga JJ, Bartels M, de geus EEJC, Nivard MMG, Verma A, Ritchie MD, Rader D, Li B, Verma SS, Lucas A, Bradford Y, Abedalthagafi M, Alaamery M, Alshareef A, Sawaji M, Massadeh S, AlMalik A, Alqahtani S, Baraka D, Harthi F Al, Alsolm E, Safieh LA, Alowayn AM, Alqubaishi F, Mutairi A Al, Mangul S, Almutairi M, Aljawini N, Albesher N, Arabi YM, Mahmoud ES, Khattab AK, Halawani RT, Alahmadey ZZ, Albakri JK, Felemban WA, Suliman BA, Hasanato R, Al-Awdah L, Alghamdi J, AlZahrani D, AlJohani S, Al-Afghani H, AlDhawi N, AlBardis H, Alkwai S, Alswailm M, Almalki F, Albeladi M, Almohammed I, Barhoush E, Albader A, Alotaibi S, Alghamdi B, Jung J, fawzy MS, Alrashed M, Zeberg H, Nkambul Lindo, Frithiof R, Hultström M, Lipcsey M, Tardif N, Rooyackers O, Grip J, Maricic T, Helgeland Ø, Magnus P, Trogstad L-IS, Lee Y, Harris JR, Mangino M, Spector TD, Emma D, Moutsianas L, Caulfield MJ, Scott RH, Kousathanas A, Pasko D, Walker S, Stuckey A, Odhams CA, Rhodes D, Fowler T, Rendon A, Chan G, Arumugam P, Karczewski KJ, Martin AR, Wilson DJ, Spencer CCA, Crook DW, Wyllie DH, O'Connell AM, Atkinson EG, Kanai M, Tsuo K, Baya N, Turley P, Gupta R, Walters RK, Palmer DS, Sarma G, Solomonson M, Cheng N, Lu W, Churchhouse C, Goldstein JI, King D, Zhou W, Seed C, Daly MJ, Neale BM, Finucane H, Bryant S, Satterstrom FK, Band G, Earle SG, Lin S-K, Arning N, Koelling N, Armstrong J, Rudkin JK, Callier S, Bryant S, Cusick C, Soranzo N, Zhao JH, Danesh J, Angelantonio E Di, Butterworth AS, Sun Y V., Huffman JE, Cho K, O'Donnell CJ, Tsao P, Gaziano JM, Peloso G, Ho Y-L, Smieszek SP, Polymeropoulos C, Polymeropoulos V, Polymeropoulos MH, Przychodzen BP, Fernandez-Cadenas I, Planas AM, Perez-Tur J, Llucià-Carol L, Cullell N, Muiño E, Cárcel-Márquez J, DeDiego ML, Iglesias LL, Soriano A, Rico V, Agüero D, Bedini JL, Lozano F, Domingo C, Robles V, Ruiz-Jaén F, Márquez L, Gomez J, Coto E, Albaiceta GM, García-Clemente M, Dalmau D, Arranz MJ, Dietl B, Serra-Llovich A, Soler P, Colobrán R, Martín-Nalda A, Martínez AP, Bernardo D, Rojo S, Fiz-López A, Arribas E, de la Cal-Sabater P, Segura T, González-Villa E, Serrano-Heras G, Martí-Fàbregas J, Jiménez-Xarrié E, de Felipe Mimbrera A, Masjuan J, García-Madrona S, Domínguez-Mayoral A, Villalonga JM, Menéndez-Valladares P, Chasman DI, Sesso HD, Manson JE, Buring JE, Ridker PM, Franco G, Davis L, Lee S, Priest J, Sankaran VG, van Heel D, Biesecker L, Kerchberger VE, Baillie JK. 2022. A first update on mapping the human genetic architecture of COVID-19. *Nature* **608**:E1–E10. doi:10.1038/s41586-022-04826-7

Paturej J, Sheiko SS, Panyukov S, Rubinstein M. 2016. Molecular structure of bottlebrush polymers in melts. *Sci Adv* **2**. doi:10.1126/sciadv.1601478

Pyrć K, Milewska A, Duran EB, Botwina P, Dabrowska A, Jedrysik M, Benedyk M, Lopes R,

Arenas-Pinto A, Badr M, Mellor R, Kalber TL, Fernandez-Reyes D, Schätzlein AG, Uchegbu IF. 2021. SARS-CoV-2 inhibition using a mucoadhesive, amphiphilic chitosan that may serve as an anti-viral nasal spray. *Sci Rep* **11**:20012. doi:10.1038/s41598-021-99404-8

Rademacher TW, Parekh RB, Dwek RA. 1988. GLYCOBIOLOGY. *Annu Rev Biochem* **57**:785–838. doi:10.1146/annurev.bi.57.070188.004033

Ravindra NG, Alfajaro MM, Gasque V, Huston NC, Wan H, Szigeti-Buck K, Yasumoto Y, Greaney AM, Habet V, Chow RD, Chen JS, Wei J, Filler RB, Wang B, Wang G, Niklason LE, Montgomery RR, Eisenbarth SC, Chen S, Williams A, Iwasaki A, Horvath TL, Foxman EF, Pierce RW, Pyle AM, van Dijk D, Wilen CB. 2021. Single-cell longitudinal analysis of SARS-CoV-2 infection in human airway epithelium identifies target cells, alterations in gene expression, and cell state changes. *PLoS Biol* **19**:e3001143. doi:10.1371/journal.pbio.3001143

Reshef DN, Reshef YA, Finucane HK, Grossman SR, McVean G, Turnbaugh PJ, Lander ES, Mitzenmacher M, Sabeti PC. 2011. Detecting Novel Associations in Large Data Sets. *Science (1979)* **334**:1518–1524. doi:10.1126/science.1205438

Riback JA, Bowman MA, Zmyslowski AM, Plaxco KW, Clark PL, Sosnick TR. 2019. Commonly used FRET fluorophores promote collapse of an otherwise disordered protein. *Proceedings of the National Academy of Sciences* **116**:8889–8894. doi:10.1073/pnas.1813038116

Russell AB, Trapnell C, Bloom JD. 2018. Extreme heterogeneity of influenza virus infection in single cells. *Elife* **7**. doi:10.7554/eLife.32303

Rust MJ, Bates M, Zhuang X. 2006. Sub-diffraction-limit imaging by stochastic optical reconstruction microscopy (STORM). *Nat Methods* **3**:793–796. doi:10.1038/nmeth929

Saraswathibhatla A, Indana D, Chaudhuri O. 2023. Cell–extracellular matrix mechanotransduction in 3D. *Nat Rev Mol Cell Biol* **24**:495–516. doi:10.1038/s41580-023-00583-1

Schnitzbauer J, Wang Y, Zhao S, Bakalar M, Nuwal T, Chen B, Huang B. 2018. Correlation analysis framework for localization-based superresolution microscopy. *Proceedings of the National Academy of Sciences* **115**:3219–3224. doi:10.1073/pnas.1711314115

Sheng H, Stauffer W, Lim HN. 2016. Systematic and general method for quantifying localization in microscopy images. *Biol Open* **5**:1882–1893. doi:10.1242/bio.019893

Shurer CR, Kuo JC-H, Roberts LM, Gandhi JG, Colville MJ, Enoki TA, Pan H, Su J, Noble JM, Hollander MJ, O'Donnell JP, Yin R, Pedram K, Möckl L, Kourkoutis LF, Moerner WE, Bertozzi CR, Feigenson GW, Reesink HL, Paszek MJ. 2019. Physical Principles of Membrane Shape Regulation by the Glycocalyx. *Cell* **177**:1757-1770.e21.

doi:10.1016/j.cell.2019.04.017

Sibener L V., Fernandes RA, Kolawole EM, Carbone CB, Liu F, McAffee D, Birnbaum ME, Yang X, Su LF, Yu W, Dong S, Gee MH, Jude KM, Davis MM, Groves JT, Goddard WA, Heath JR, Evavold BD, Vale RD, Garcia KC. 2018. Isolation of a Structural Mechanism for Uncoupling T Cell Receptor Signaling from Peptide-MHC Binding. *Cell* **174**:672-687.e27. doi:10.1016/j.cell.2018.06.017

Stauffer W, Sheng H, Lim HN. 2018. EzColocalization: An ImageJ plugin for visualizing and measuring colocalization in cells and organisms. *Sci Rep* **8**:15764. doi:10.1038/s41598-018-33592-8

Steen P Van den, Rudd PM, Dwek RA, Opdenakker G. 1998. Concepts and Principles of O-Linked Glycosylation. *Crit Rev Biochem Mol Biol* **33**:151–208. doi:10.1080/10409239891204198

Steentoft C, Vakhrushev SY, Joshi HJ, Kong Y, Vester-Christensen MB, Schjoldager KT-BG, Lavrsen K, Dabelsteen S, Pedersen NB, Marcos-Silva L, Gupta R, Paul Bennett E, Mandel U, Brunak S, Wandall HH, Levery SB, Clausen H. 2013. Precision mapping of the human O-GalNAc glycoproteome through SimpleCell technology. *EMBO J* **32**:1478–1488. doi:10.1038/emboj.2013.79

Stone MB, Veatch SL. 2015. Steady-state cross-correlations for live two-colour super-resolution localization data sets. *Nat Commun* **6**:7347. doi:10.1038/ncomms8347

Tesei G, Trolle AI, Jonsson N, Betz J, Knudsen FE, Pesce F, Johansson KE, Lindorff-Larsen K. 2024. Conformational ensembles of the human intrinsically disordered proteome. *Nature* **626**:897–904. doi:10.1038/s41586-023-07004-5

Varma R, Campi G, Yokosuka T, Saito T, Dustin ML. 2006. T Cell Receptor-Proximal Signals Are Sustained in Peripheral Microclusters and Terminated in the Central Supramolecular Activation Cluster. *Immunity* **25**:117–127. doi:10.1016/j.immuni.2006.04.010

Veatch SL, Machta BB, Shelby SA, Chiang EN, Holowka DA, Baird BA. 2012. Correlation Functions Quantify Super-Resolution Images and Estimate Apparent Clustering Due to Over-Counting. *PLoS One* **7**:e31457. doi:10.1371/journal.pone.0031457

Wardzala CL, Wood AM, Belnap DM, Kramer JR. 2022. Mucins Inhibit Coronavirus Infection in a Glycan-Dependent Manner. *ACS Cent Sci* **8**:351–360. doi:10.1021/acscentsci.1c01369

Wong AP, Groves JT. 2002. Molecular topography imaging by intermembrane fluorescence resonance energy transfer. *Proceedings of the National Academy of Sciences* **99**:14147–14152. doi:10.1073/pnas.212392599

Wu PG, Brand L. 1994. Resonance Energy Transfer: Methods and Applications. *Anal*

Biochem **218**:1–13. doi:10.1006/abio.1994.1134

Wu T, Efimenko K, Genzer J. 2002. Combinatorial Study of the Mushroom-to-Brush Crossover in Surface Anchored Polyacrylamide. *J Am Chem Soc* **124**:9394–9395. doi:10.1021/ja027412n

Wyler E, Mösbauer K, Franke V, Diag A, Gottula LT, Arsiè R, Klironomos F, Koppstein D, Hönzke K, Ayoub S, Buccitelli C, Hoffmann K, Richter A, Legnini I, Ivanov A, Mari T, Del Giudice S, Papies J, Praktiknjo S, Meyer TF, Müller MA, Niemeyer D, Hocke A, Selbach M, Akalin A, Rajewsky N, Drosten C, Landthaler M. 2021. Transcriptomic profiling of SARS-CoV-2 infected human cell lines identifies HSP90 as target for COVID-19 therapy. *iScience* **24**:102151. doi:10.1016/j.isci.2021.102151

Yoshida M, Worlock KB, Huang N, Lindeboom RGH, Butler CR, Kumasaka N, Dominguez Conde C, Mamanova L, Bolt L, Richardson L, Polanski K, Madissoon E, Barnes JL, Allen-Hyttinen J, Kilich E, Jones BC, de Wilton A, Wilbrey-Clark A, Sungnak W, Pett JP, Weller J, Prigmore E, Yung H, Mehta P, Saleh A, Saigal A, Chu V, Cohen JM, Cane C, Iordanidou A, Shibuya S, Reuschl A-K, Herczeg IT, Argento AC, Wunderink RG, Smith SB, Poor TA, Gao CA, Dematte JE, Budinger GRS, Donnelly HK, Markov NS, Lu Z, Reynolds G, Haniffa M, Bowyer GS, Coates M, Clatworthy MR, Calero-Nieto FJ, Göttgens B, O'Callaghan C, Sebire NJ, Jolly C, De Coppi P, Smith CM, Misharin A V., Janes SM, Teichmann SA, Nikolić MZ, Meyer KB. 2022. Local and systemic responses to SARS-CoV-2 infection in children and adults. *Nature* **602**:321–327. doi:10.1038/s41586-021-04345-x

Ziegler CGK, Miao VN, Owings AH, Navia AW, Tang Y, Bromley JD, Lotfy P, Sloan M, Laird H, Williams HB, George M, Drake RS, Christian T, Parker A, Sindel CB, Burger MW, Pride Y, Hasan M, Abraham GE, Senitko M, Robinson TO, Shalek AK, Glover SC, Horwitz BH, Ordovas-Montanes J. 2021. Impaired local intrinsic immunity to SARS-CoV-2 infection in severe COVID-19. *Cell* **184**:4713-4733.e22. doi:10.1016/j.cell.2021.07.023

METHOD DETAILS

Materials

All reagents are listed in the supplementary data file 1, with information of software used in this study.

List of Membrane Glycoproteins in Human Genome

From UniProt database (Homo sapiens UniprotKB, 2021 September release), amino acid sequences of all membrane associated proteins, either topologically containing domains associated with "extracellular" or GPI-anchored, with positive in glycosylation either experimentally or by prediction were collected. These sequences were then used as input to two software packages, NetNGlyc ver 1.0 / NetOGlyc ver 4.0 (https://services.healthtech.dtu.dk/service.php?NetNGlyc-1.0, https://services.healthtech.dtu.dk/service.php?NetOGlyc-4.0), and GlycoEP (https://webs.iiitd.edu.in/raghava/glycoep/submit.html). Glycosylation sites were predicted for all these sequences. Default settings in the both software packages were used and the setting of Binary profile of patterns was selected for GlycoEP. Then, the candidate sites were selected by thresholding in scores, based on the software recommendations. To meet the 4000 amino acid sequence maximum cutoff in NetNGlyc, part of cytoplasmic sequences in three long proteins (UniProt Entry: Q14517, Q07954, Q9NYQ8) were eliminated in the calculations. Next, we identified the ectodomain regions of these proteins, by collecting topological information from UniProt. For multiple transmembrane protein, only the largest extracellular domain was selected. Then, candidate glycosylation sites only between these ectodomain regions were selected, and complied and counted for making the final list (Supplementary data). For convenience of availability, mouse genes for Dll4 and Jag1 were used in the infection inhibition assay, and the predicted glycosylation of these genes was calculated separately (glycosylation rate/AA was 0.0837 and 0.0584 for the human DLL4 gene and mouse Dll4 gene, respectively, and 0.0513 and 0.0334 for the human JAG1 gene and mouse Jag1 genes were 0.0513 and 0.0334, respectively). Results are complied in the supplementary data file 2 and 3.

PNA binding assay and reaction model

HEK293T cells were transiently transfected with various membrane proteins 24 hours prior to the measurement. These cells that were pre-stained with 5 μM SNAP-Surface 647 (New England Biolabs) for one hour at room temperature if necessary were stained with 5μg/mL of Alexa488 labeled lectins

(PNA, WGA (Wako Fujifilm) or SSA (J-Chemical)) for one hour at room temperature. These labeled lectins were obtained by labeling in house with Alexa488 NHS ester (Thermo). Ligands with differential degree of labeling were prepared in order to have signals in wide range without signal saturations in flow cytometry assay. After washout with PBS, cells were subject to flow cytometry assay, using SH800 (Sony).

The binding of PNA lectins to cells was modeled by making various modifications to the standard ligand-receptor binding. Each sample consists of a test tube of cells expressing one kind of membrane protein. Reaction for each sample is batch-based, with excess PNA ligand of concentration [L] in a tube. The reaction was approximated to be a first-order binding with the receptor, which is an individual sugar chain on a membrane protein. Due to steric hindrance, it was assumed that at most only one lectin binds to one sugar chain. It was also assumed that PNA binding reaction is governed by the same kinetics for glycans branched from all the different membrane proteins. In other words, all glycans of all tubes are equivalent in the reaction kinetic. Glycans in all tubes are assumed to be in equilibrium in the binding to lectin, as [L] is very excess, despite the variance of total number of glycans between tubes. Thus, the only difference between the samples is the number of glycans per one protein molecule. In this setting, PNA binding to the sugar chains at equilibrium is described as follows

$$K_D = \frac{[L][R]}{[LR]},$$

where K_D is the dissociation constant, and [R] and [LR] are the unbound and ligand-bound receptor sugar chains of each cell, respectively. Assuming that the diameter and surface area of all cells are equal, [R] and [LR] in this equation can be replaced by the total number of ligand-unbound receptor sugar chains in the cell. On the other hand, when G_i, the number of glycosylation sites that are specific to protein type i, is introduced, the total number of glycans in the cell $[R_{_total}]$ should be described as follows:

$$[R_{_total}] = [P] * G_i,$$

where [P] is the number of proteins in the cell. $[R_{_total}]$ is expressed as

$$[R_{_total}] = [R] + [LR],$$

where $[R_{_total}]$ is different in all cells. For first order reactions, a linear relationship is expected between [LR] and $[R_{_total}]$, which can also be translated into a relationship with [P]:

$$\frac{[LR]}{[R_{_total}]} = \frac{[LR]}{[P] * Gi}$$

where [P] and [LR] are measured as signals from the fluorescent SNAP substrate and PNA, respectively, in the flow cytometry assay. If the flow cytometry data for cells expressing protein type i can be regressed to a linear relationship, the slope $[PNA/mol]_{_i}$ should be

$$\left[\frac{PNA}{mol}\right]_i = [LR] / [P] = [LR] / [R_total] * Gi = \frac{[LR]}{([R] + [LR])} * Gi = \frac{1}{(KD/[L] + 1)} * Gi.$$

Since KD and [L] were constant for all proteins, the $[PNA/mol]_{_i}$ obtained from the linear regression for each protein i should have a linear relationship with G_i across all different proteins.

Virus production

All viruses were produced in HEK 293T cells as previously described(Kaizuka and Machida, 2023). SARS-CoV-2 pseudoparticles were produced using pLV-eGFP (obtained from Pantelis Tsoulfas), pCAG-HIVgp (obtained from Hiroyuki Miyoshi, Riken BRC, Japan), and a vector where VSV-G gene in the pCMV-VSV-G-RSV-Rev (obtained from Hiroyuki Miyoshi, Riken BRC, Japan) was replaced with Spike gene (SARS-CoV-2, Wuhan-Hu-1, obtained from SinoBio, China). Lentiviruses were produced using pLV-eGFP, pCAG-HIVgp, and pCMV-VSV-G-RSV-Rev. Adenoassociated viruses were produced using Plasmids of AAV GFP, pAdDeltaF6, and pAAV2/2 (Obtained from Fred Gage, James M. Wilson, and Melina Fan, respectively). Adenoviruses were produced by replicating AxCAEGFP, generated from backbone vector pAxcw that contains genes of AdV511,12 (obtained from Dr. Murata, Riken BRC). Viruses were collected from supernatant medium, and if necessary, concentrated using Lenti-X concentrator kit (Takara bio, Japan). Lenti-X™ p24 Rapid Titer Kit (Takara Bio) was used to measure the titer of collected SARS-Cov2-PP by ELISA (Enzyme-Linked Immunosorbent Assay). For virus binding assay, SARS-CoV2-PP were prepared by labelling with 0.4μM DiIC18(5) solid (1,1'-Dioctadecyl-3,3,3',3'-Tetramethylindodicarbocyanine, 4-Chlorobenzenesulfonate Salt, or DID) (Thermo) with Biospin6 (Biorad) to remove residual dyes. Binding of viruses was measured by flow cytometry after washing cells.

Virus binding and infection assay and measurement of cell protein density

Cells were cultured in standard conditions using medium (DMEM for HEK 293T cell, and EMEM for Calu-3 cell: cells were obtained from ATCC) supplemented with 10% FBS. Air liquid interface culture of Calu-3 cells were conducted using Transwell (Corning, USA), according to the protocol provided by the manufacturer.

HEK293T cells transiently transfected with ACE2-iRFP, TMPRSS2-TagRFP657 and target membrane protein tagged with either mTagBFP2 or SNAP at 24 hours prior to the virus infection. These cells

were pre-stained with 5 μM SNAP-Surface 488 for one hour at room temperature if necessary and were analyzed by flow cytometry to quantify the surface densities of ACE2 and the target membrane protein. These cells from the same batch were then infected with SARS-CoV2-PP or other viruses for 3 hours at 37C in suspension. Viruses were administrated at ~0.015 pg/cell according to the p24 ELISA for virus stock solutions, and typically about 20% of cells were infected in the absence of any inhibitory protein expression. After removal of viruses, infected cells were cultured for 2 days. Then, cells were collected for flow cytometry assay to analyze infection by measuring the expression of GFP gene introduced by infected viruses. In virus binding assay, cells were measured by flow cytometry after 3 hours of incubation of cells with viruses that were stained with DID.

Membrane proteins and functional tags used in this study were SNAP-CD24, SNAP-CD43, SNAP-CD44, SNAP-164, SNAP-SDC1, SNAP-F174B, SNAP-VCAM1, SNAP-VAMP2, SNAP-PD-1, SNAP-MUC1 (42TR), SNAP-MUC1 (0TR, deletion in aa 32-961), SNAP-MUC1 (4TR, deletion in aa 32-879), SNAP-MUC1 (14TR, deletion in aa 32-703), PODXL-mTagBFP2, TMEM123-mTagBFP2, EFNB2-mTagBFP2, EPHB1-mTagBFP2, Jag1-mTagBFP2, Dll4-mTagBFP2, and GYPC-mTagBFP2. They were all constructed in the pAcGFP-n1 vector (Invitrogen) where AcGFP was either removed for SNAP tagged construct or replaced with mTagBFP2.

Protein surface densities as well as GFP expression were calibrated from flow cytometry data, in similar manner as previously described(Kaizuka et al., 2021; Kaizuka and Machida, 2023). This calibration method is based on the calibration strategy between intensities of two different dyes using fluorimeter, developed for microscopy imaging (Galush et al., 2008). Liposome standards containing fluorescent molecules (0.01– 0.75 mol% perylene (Sigma), 0.1–1.25 mol% Bodipy FL (Thermo), and 0.005– 0.1% DiD) as well as DOPC (Avanti polar lipids) were measured in flow cytometry. Meanwhile, by fluorimeter, fluorescence signals of these liposomes and known concentrations of recombinant mTagBFP2, AcGFP and TagRFP-657 proteins and SNAP-Surface 488 and Alexa 647 dyes (New England Biolabs) were measured in the same excitation and emission ranges as in flow cytometry assays. Ratios between the integral of fluorescent intensities in this range between two dyes of interest are used for converting the signals measured in flow cytometry. For example, AcGFP signals measured in flow cytometry are converted to Bodipy-FL by the ratio, and then calibrate to molecular densities measured by liposome standards containing BodipyFL. All fluorescent proteins were assumed to be matured and fluorescent. For SNAP-tagged proteins, we confirmed that the binding of fluorescent substrate to cells expressing SNAP-tagged membrane proteins were saturated when incubated with 5μM substrate, and background fluorescent signal of nonspecific binding was minimal (Supplementary Figure 1G). Thus, we also assumed that most of SNAP-tagged proteins in cells were fluorescent and all the fluorescent signals from these proteins were detected in our assays. ACE2-

TagBFP expressions varied between samples, which affects the infection rate (Supplementary Figure 1H). We checked the ACE density of cells at the time of virus infection, and only cells with ACE2 expressed in the range where infection linearly increases with ACE2 density were chosen for infection assays, and the final results of GFP intensities were adjusted with the mean ACE2 densities measured at the time of infection and the calibration line (Supplementary Figure 1H). Inhibition of infection was evaluated by the average density of target membrane proteins measured at the time of infection, and the infection rate of samples was normalized by the infection rate of control infection samples that did not express inhibitory proteins in the cells.

For the imaging of virus infections in air liquid interface culture, after the 10 days of air-liquid interface culturing of Calu-3 cell monolayer in Transwell, SARS-CoV2-PP were administrated at ~0.015 pg/cell for 3 hours at 37C, then cells were cultured for 2 days after the washout of residual viruses. Prior to imaging, cells were stained with Hoechst 33342, Alexa647 labeled lectins, primary and secondary antibodies, sequentially. Stacked images in z axis were maximum projected by Fiji/ImageJ to compare signals in different channels. Pearson correlation and TOS correlation were calculated for maximum projection images and were performed by EzColocalization plugins in Fiji/ImageJ for all pixels without selecting any ROIs for cells (Stauffer et al., 2018). Thus, all pixels were classified depending on intensity of two signals, in unbiased manners. Then, expectation for two signals were calculated separately in all these classes, resulting in a computed TOS matrix in which those numbers indicate whether the number of objects classified in each region is higher or lower than expected for uniformly distributed data.

Virus infection inhibition, hierarchical Bayesian modeling

Virus infection was assumed to be inhibited dependent on the density of inhibitor glycoprotein on cell membrane, and a standard sigmoidal dose-response curve for inhibitory reaction was introduced:

$$Y = \frac{1}{(1 + (X/\sigma_{IC50})^n)}$$

Where Y is the infection rate, X is the density of glycoprotein, and n is the Hill coefficient describing a variable from the ideal sigmoidal. Infection rate Y reaches 0.5 at the density = $\sigma_{_IC50}$.

In hierarchical Bayesian modeling, for the Hill coefficient, a common prior distribution (normal distribution) was set for all molecules, and for the IC50 values for each kind of protein_i, a Half Cauchy prior distribution was set for each molecule separately because it is non-negative and can take a wide range of values (Supplementary Figure 1I). In this setting with Gaussian noise, Markov chain

Monte Carlo sampling was executed in the scheme of probabilistic programming language NumPyro, repeated for four times (https://num.pyro.ai). Once convergence was confirmed over four rounds of sampling, the common Hill coefficient and protein specific IC50 were determined from the posterior distributions (Supplementary Figure 1I).

FLIM-FRET

FRET between a donor molecule of fluorescently labeled SNAP tag fused to the end of the ectodomain of membrane protein and an acceptor molecule of small and nonspecific plasma membrane dye was measured. Live HEK293T cells expressing various SNAP-tagged membrane proteins were stained with 5μM or less of SNAP-Surface 488 substrate, a modified ATTO 488 molecule, and with either membrane dyes, PlasMem Bright Red (Dojindo) or MemGlow 590 (Cytoskelton). Doubly stained cells were imaged by Leica SP8 equipped with FLIM module, and the lifetime of fluorescence of donor ATTO 488 was measured and imaged in the FLIM mode. The life time was estimated as the time constant in the exponential decay in the histogram of time interval between the excitation laser pulse and emitted photons. A histogram was generated from ROI images cropped from cell membranes for each image, thus the measured life time reflected photon emissions from all dyes located in the image ROIs.

We introduced a simple model to analyze the height of protein ectodomain from the membrane, from FLIM-FRET data. In this case, the donor ATTO 488 dyes conjugated to the terminus SNAP tags were assumed to locate along the concentric circle at the fixed distance z from the plasma membrane. Then, we also approximated that FRET occurred between a single donor and multiple acceptor molecules located in a nearby plane at the distance of z. This planar geometry approximation was made since the scale of Forster distance (~nm) is much shorter than cell diameter (~10μm). FRET for a single donor to populations of acceptors in a plane can be obtained by radially integrating energy transfer between a single pair of donor and acceptor, $k_i = (1/\tau_D)(Ro/R)^6$, toward all acceptors in a nearby plane as(Gibson and Loew, 1979; Wong and Groves, 2002):

$$k_T = \frac{\sigma\, \pi\, R_0^6}{2\tau_D\, z^4}$$

Where Ro is Forster distance for the donor-acceptor pair, R is actual distance between the two, τ_D is the lifetime of donor without FRET to acceptor, and σ is the density of acceptor. Then, the FRET efficiency E can be described as(Gibson and Loew, 1979; Wong and Groves, 2002):

$$E_{_model} = \frac{k_T}{k_T + {}^{1}/_{\tau_D}} = \frac{\sigma}{\sigma + \frac{2z^4}{\pi}\frac{1}{R_0^6}}$$

In FLIM measurement, FRET efficiency was measured by donor lifetime as follows:

$$E_{_FLIM} = 1 - \frac{F_{DA}}{F_D} = 1 - \frac{\tau_{DA}}{\tau_D}$$

Where τ_{DA} is the lifetime of donor with FRET to acceptor.

In our measurements, we imaged lifetime of donors τ_{DA} in cell populations in several different mean acceptor densities. Therefore, we plotted $E_{_FLIM}$ for different σ, regressed the plot to $E_{_model}$, and obtained z as the distance from membrane to SNAP for each protein.

Forster distance Ro is specific for each donor – acceptor dye pair. In our experiments, we found that SNAP – surface 488 (Atto 488 dye) and PlasMem Bright Red were good FRET pairs, in the context of both FRET efficiency and dye stability in membrane localization. Unfortunately, details of molecular and optical information regarding PlasMem Bright Red are not disclosed, and Ro for this pair of dyes cannot be directly calculated. Therefore, we estimated the Ro for PlasMem Bright Red by comparing two experiments in the same setting with this dye and the other dye with known Ro value, Glow 590. Ro for ATTO488 and MemGlow 590 was determined as 5.68 nm, calculated from optical and spectral information of the two dyes(Wu and Brand, 1994). Then, we went through the above procedure, and estimated the effective Ro for ATTO 488 and PlasMem Bright Red to be 6.45nm. Note that this value is only valid in our experimental setting, since the molecular information for PlasMem Bright Red was unclear and its surface density on cells was not measurable. Due to this uncertainty, upon the estimation and the use of effective Ro value, we needed to set "effective surface density" for PlasmMem Bright Red for FLIM-FRET measurement, which is equal to the actual density of MemGlow 590 in cells stained with designated dye concentrations. Under this assumption, the effective Ro was estimated from the regressions in the plot in Supplementary Figure 3A, and this effective value was applied to all other FLIM-FRET analyses. We confirmed by flow cytometry that fluorescence signals of bound PlasMem Bright Red to cells linearly increased as MemGlow 590, when the both days were added to cell suspension in staining procedure at the equal molar ratios. Therefore, the actual surface density for PlasMem Bright Red should be linearly varied from these effective values.

FLIM-FRET data for different molecules were analyzed in a single Bayesian statistical model:

$$Y_i = \frac{\sigma}{(\sigma + \alpha_i)},$$

$$\alpha_i = \frac{2}{\pi}\frac{1}{Ro^6}z_i^4,$$

by setting the acceptor density σ as variable, and inferring α_i for each molecule to calculate z_i, which is the Forster distance for each molecule, while (2/π)/(1/Ro^6) is constant through all molecules. α_i were bound in the half normal distribution whose variance μ were bound in Gaussian prior distribution, and the Gaussian noise *sc* was added to Y (supplementary Figure 3C). Markov chain Monte Carlo sampling was repeated four times in the scheme of probabilistic programming language NumPyro. Once convergence was confirmed, the protein specific z_i was determined from the posterior distributions of α_i (supplementary Figure 3D).

Protein expression and biochemical analysis

cDNA for N-terminus daul-Strep-TagII / SNAP tagged and C-terminus His10 tagged ectodomains of human MUC1 (14TR) and CD43 genes were cloned into pAcGFP-n1 vector (Takara), and cDNA for N-terminus SNAP tagged and C-terminus His10 tagged ectodomains of human MUC1 (14TR) and CD43 genes were cloned into pGEX-6p1 vector (Cytiva). Mammalian expression vectors were transfected into HEK293T cells and after 48 hours of transfections, cell culture medium supernatant was collected. After filtering, the supernatant containing secreted glycoproteins were concentrated more than 10 times by using Amicon Ultra (Merck Millipore), and then subjected to Strep-tactin column (iba). Trapped glycoproteins were collected by elution from the column. Bacterial expression vectors were introduced into E.Coli BL21, IPTG-inducted at 4C for overnight, and then affinity purified using GST tag and GST-bind resin (Novagen) followed by cleavage with PreScission protease (GE Healthcare). These proteins were then stained with 5μM SNAP – Surface 488 or SNAP –Cell TMR Star, and cleaned by Micro Biospin 6. C-terminus His-tagged human EPHB1 ectodomain was obtained from Sino biological, and labeled with ATTO 488 NHS-ester. Protein concentration were measured by Bradford assay, and the concentration of fluorescent dyes in protein solution was measured by using standard ATTO 488 dyes with known concentrations, by a standard plate reader. In SDS-PAGE analysis, fluorescent and bright field images of gels were obtained using LumiCube Plus imager (Liponics, Tokyo, Japan) and glycan staining was performed by using Pierce Glycoprotein Staining Kit (Thermo Fisher).

Analysis using Alpha Fold 2

Alpha Fold 2 structural prediction data for all 2515 proteins used for glycosylation analyses were

obtained from UniProt. From coordinates of atoms except for hydrogen, centroid of amino acid at two ends of ectodomain were calculated, and the distance between these two amino acids were calculated as the length of ectodomain in the predicted conformation for all the proteins. In parallel, the longest distance among all amino acids in ectodomain from the first amino acid in the ectodomain next to the transmembrane domain was calculated. In addition, predicted local Distance Difference test (plDDT)(Mariani et al., 2013) which was used as the score to access Alpha Fold 2 predictions was also obtained from the database. MUC1 (0TR) was not a natural protein and its predicted conformation was not in the database. Therefore, we input its sequence into Alpha Fold 2 (ver 2.2 in Google colaboratory) and obtained the predicted conformation.

In vitro reconstitution on lipid bilayers

Silica beads (4.63µm diameter, Bangs Laboratory) were coated with lipid bilayers, in similar manner as described previously (Lee et al., 2021). Beads were treated for 30 minutes by ten-fold volume of Piranha solution (3:1 mix of sulfuric acid and hydrogen peroxide) and rinsed extensively by water, and then ~0.2g/cm^3 of cleaned beads were incubated in PBS with small unilamellar vesicles (SUVs), by adjusting lipid concentration ~1mM in this mixture. SUV contained 10 mol% of 1,2-dioleoyl-sn-glycero-3- [(N-(5-amino-1-carboxypentyl)iminodiacetic acid)succinyl] (DGS-NTA(Ni), Avanti Polar lipids), 20mol% of 1,2-dioleoyl-sn-glycero-3-phosphatidylserine (DOPS, Avanti Polar lipids), and 70 mol% of 1,2-Dioleoyl-sn-glycero-3-phosphatidylcholine (DOPC, Avanti Polar lipids). If necessary, 0.02% of tetramethylrhodamine thiocarbamoyl-1,2-dihexadecanoyl-sn-glycero-3-phosphoeth-anolamine, triethylammonium salt (TRITC-DHPE, Thermo) was also included. SUVs were prepared by sonication of 1mL lipid suspension in PBS (final 1.8mM total lipids). After washout of excess SUVs, bilayer coated beads were incubated with proteins of designated concentrations, and subjected to flow cytometry measurement for protein binding to single beads. Surface densities for proteins on beads were measured by flow cytometry and calibrated as described above for measuring densities in cells. Plots for mean surface densities of proteins d vs protein concentration x a in solution were regressed to the standard receptor saturation binding model, $d = Bx/(K_D + x)$, where K_D is the dissociation constant and B is the saturated density.

For single molecule tracking experiments, planar supported lipid bilayers were created on cover glass preetched by Piranha solution. SNAP –Cell TMR star (New England Biolabs) labeled proteins were incubated with bilayers at 10 pM concentrations, and the dynamics of sparsely distributed proteins on bilayers were imaged by total internal reflection microscopy imaging at 10 fps (Leica AF6000LX equipped with a Cascade II EMCCD camera (Roper)). Images were analyzed by Track Mate plugin

of Fiji/ImageJ.

STORM

Nikon N-STORM system with ECLIPSE Ti2-E equipped with Andor iXon3 EMCCD camera was used for STORM imaging. Cells expressing various SNAP-tagged membrane proteins were fixed and stained with SNAP – surface Alexa 647 and anti-SARS-CoV/SARS-CoV-2 (COVID-19) Spike monoclonal antibody (clone 1A9) and CF568 labeled anti-Mouse IgG secondary antibody. Pairs of mCherry protein tagged for Lck10 and Alexa 647 labeled anti-Mouse IgG secondary antibody were also used. Stained cells were loaded on glass bottom chamber (Lab-Tek II, Nunc) precoated with 1% PEI, and then cells were immersed in STORM imaging buffer, 50mM Tris (pH8.0) – 10mM NaCl buffer containing 10% Glycerol, 0.56mg/mL Glucose oxidase, 34μg/mL Catalase, 0.1M Cysteamine. Both Alexa 647 and CF568 dyes were reactivated continuously by 405nm laser and imaged by using 561nm and 647nm excitation lasers.

Coordinates for centroids of all detected fluorescent STORM spots were collected. Window for image analysis was determined as with 10% margin for longest distance between detected spots to both x- and y- directions. Viral protein spots not close to cell membranes were eliminated by thresholding with nearby spot density for cell protein. Also, viral protein spots only sparsely located were eliminated by thresholding with nearby spot density for viral protein.
For coordinates of spots remained after these thresholding processes, cross correlation function in a defined size of image window can be described in a discrete form as follows, which is equivalent to the average localization density in the whole field of view(Schnitzbauer et al., 2018):

$$C(r, \Delta r) = \frac{XY}{A(r, \Delta r)\, N_a\, N_b} * H_{AB}(r, \Delta r),$$

Where X and Y are the size of image window in both axes, Na, Nb are the number of spots for each kind of protein in the whole window, $A(r, \Delta r) = \pi \Delta r\, (2r + \Delta r)$ is the area of a shell with inner radius r and outer radius $r + \Delta r$, and $H_{AB}(r, \Delta r)$ is a histogram of mutual distance between two kinds of dyes (A, B) in a whole image. Δr, a size of shell and the bin size for histogram, was set to be 5 nm in our analyses.

In the simulated images, the cell membrane is generated as a shell 10 μm in diameter and 100 nm wide, consisting of 10000 spots of randomly generated membrane proteins within the shell. one virus image consists of 200 random spots within a circle 100 nm in diameter, with one image contains one virus. The coordinates of the center of the virus were varied among the simulated images. $C(r)$ for these

simulated images was computed as above; a plot of *C(r)* versus density_(out/in) showed that a polynomial was a reasonable fit, so Bayesian inference was performed with a fifth order polynomial.