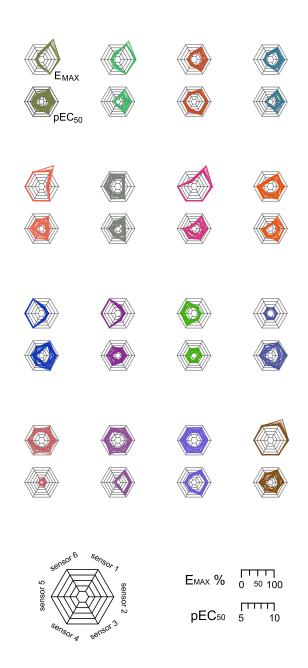
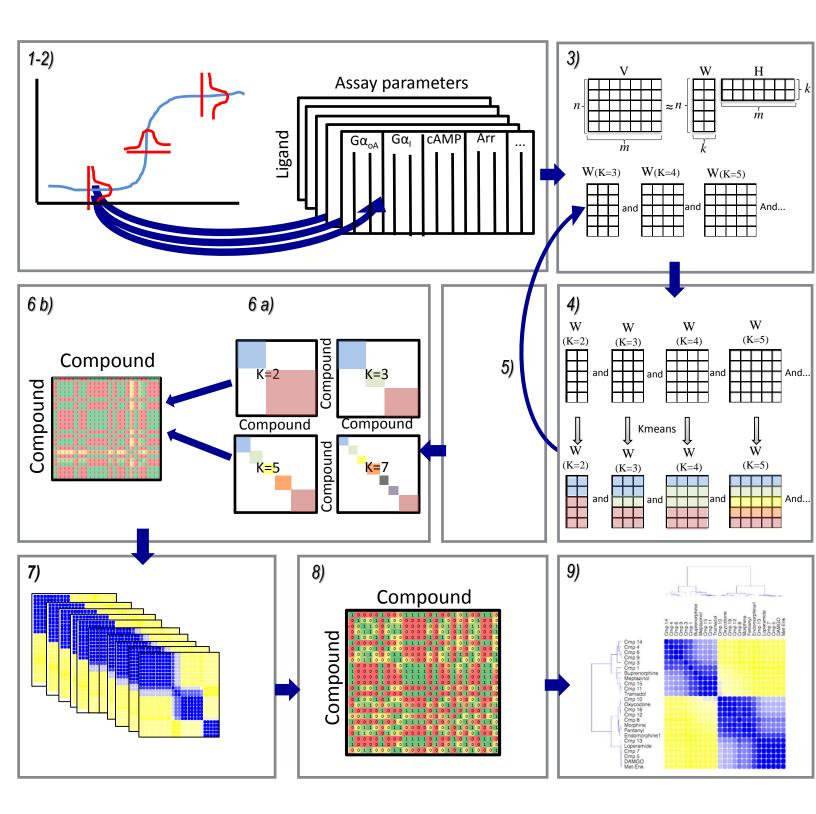
## "EXPLORING USE OF UNSUPERVISED CLUSTERING TO ASSOCIATE SIGNALING PROFILES OF GPCR LIGANDS TO CLINICAL RESPONSE"

Benredjem et al.

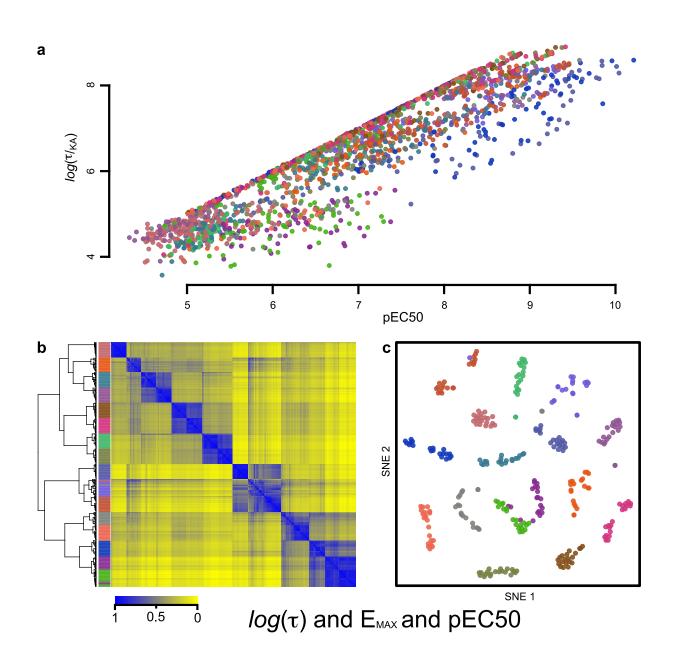


#### Supplementary Figure 1. Profiles of virtual compounds classed by Emax

*average distance*. Each profile is shown as a pair of stacked radar plots giving Emax (top) and pEC50 (bottom) for 6 readouts (sensors 1 to 6). Emax and pEC50 radar plot overlays of the 20 compounds in each profile (see materials and methods) arranged in a 4 x 4 array and loosely grouped as per inter-profile average Euclidian distance of Emax (normalized sensor-wise).

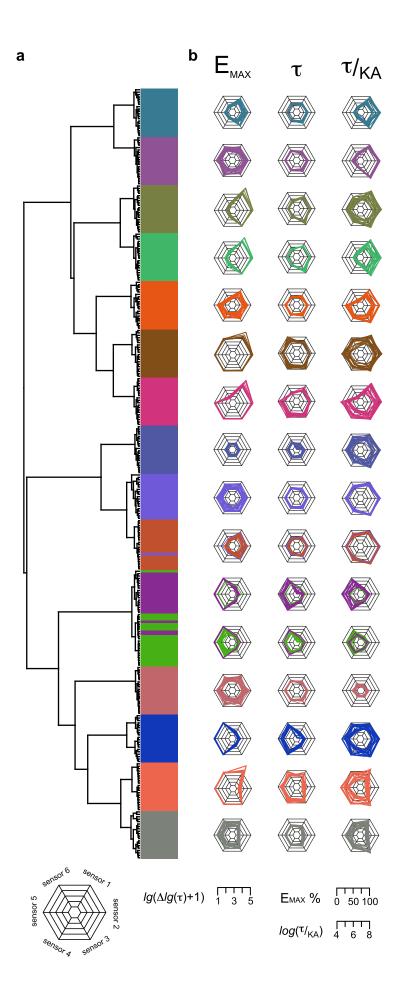


Supplementary Figure 2. Stepwise method used to cluster hMOR ligands according to pharmacodynamic parameters. 1-2) To incorporate the variance associated with the value of each parameter  $(pLog(\tau), Emax, Log(\tau/KA))$  describing the mean concentration response curve for each ligand at distinct biosensors we iteratively sampled from the normal distribution centered at the parameter's mean and dispersed according to its standard deviation, to produce 1000 sampled data matrices. This procedure thereby propagates the variation associated with each mean parameter value. 3) NNMF is independently performed on each sampled matrix to reduce the dimensionality of the data prior to clustering, yielding W (ligand) and H (parameter) basis vectors (upper panel); NNMF is repeated for (k=2 to k=7) (lower panel). 4) Each individual basis vector (K=2-7) is then clustered by K-means. 5) The NNMF and K-means process is repeated 250 times for each value of K and  $\boldsymbol{6}$ ) a) For each K (2-7), a ligand similarity matrix is derived, indicating co-clustering frequency of ligands i and j in the 250 repeats; b) Frequency matrices k=2 through k=7 are averaged into a 'composite similarity matrix' such that each of the 1000 original data samples generates a matrix combining information obtained through 2-7 dimensions, and therefore independent of k. 7) The 'composite similarity matrix' produced from each of the 1000 samples are averaged to create 8) a final ligand similarity matrix quantifying clustering frequency over all 1000 iterations 9) which is then represented as a heat map and a dendrogram.



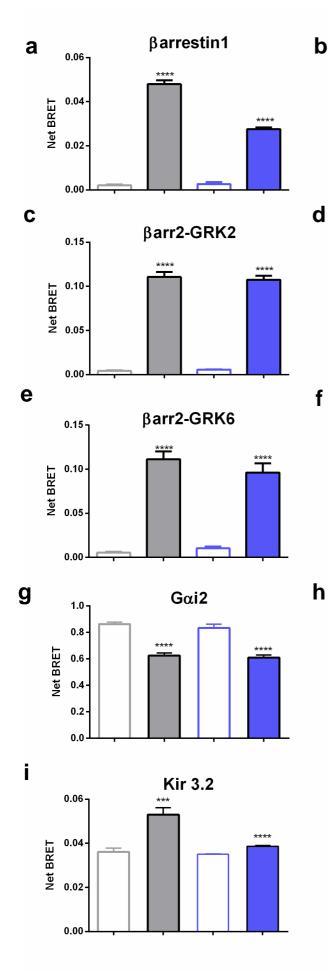
#### Supplementary Figure 3. Log( $\tau$ /KA) and pEC50 values are correlated but not

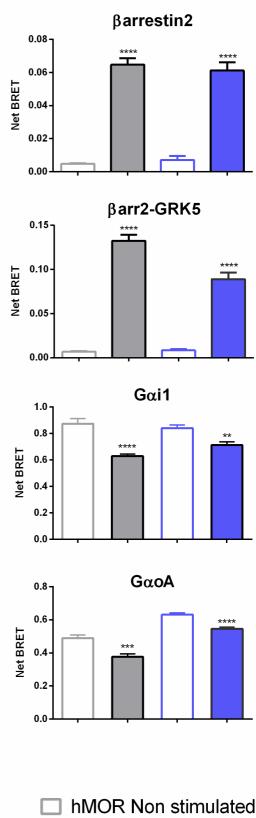
*congruent.* Correlation between  $Log(\tau/KA)$  and pEC50 values generated for the 320 virtual compounds across the 6 readouts (r<sup>2</sup>=0.84) (a). Indicated parameters were subject to NNMF followed by k-means clustering to produce similarity matrices represented as a heat map/dendrogram pair (b) and a t-SNE plot (both computed as described in Fig. 1 (c). Ligands were colour-coded according to their profile.



# Supplementary Figure 4. Graphic representation of parameters defining virtual compounds clustered according to similarities in $Log(\tau)$ , Emax and $Log(\tau/KA)$ .

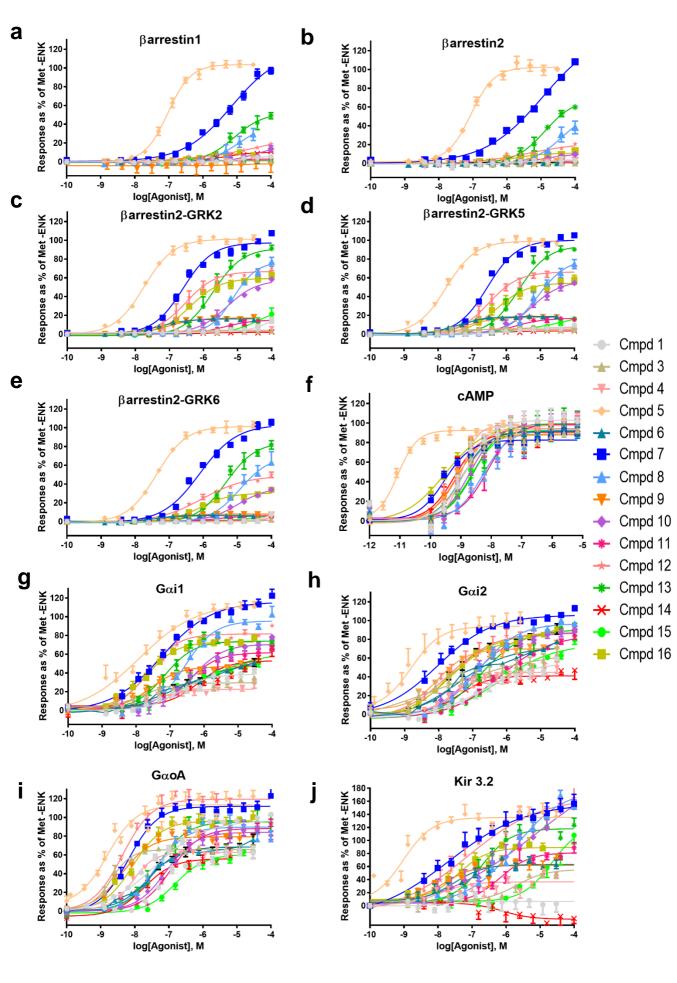
Hierarchical clustering tree (function hclust in R using the ward.D2 metric) with leaf coloured by profile shows the separation of virtual ligands from different profiles (materials and methods). Cuts in the tree essentially coincide with the profiles (a). Radar graphs were computed for each cluster and each parameter considered in the NNMF/k-means clustering showing that group assignment sometimes depends on subtle variations in any of the selected parameters. Radar plot axes are chosen as to best represent the variation in parameter values. Emax has linear axes. We capture the large dynamic range in  $\tau$  while still emphasising variation at the pivot value of 1.0, as log<sub>2</sub> fold changes relative to the minimum observed value. On this scale,  $\tau$  values of 0.1, 1 and 10 are about 2.1, 2.9 and 3.4 respectively (the change between successive grid levels in  $\tau$  value is  $\frac{2^{2^{i}}}{2^{2^{(i-1)}}}$ , or: 2x, 4x, 16x, 256x, 65536x. These are the multipliers of their previous grid level's value; ie: grid level 3 represents a  $\tau$  value that is 16 times as large as that represented at grid level 2.  $\tau/KA$  values are expressed as log<sub>10</sub> (b).



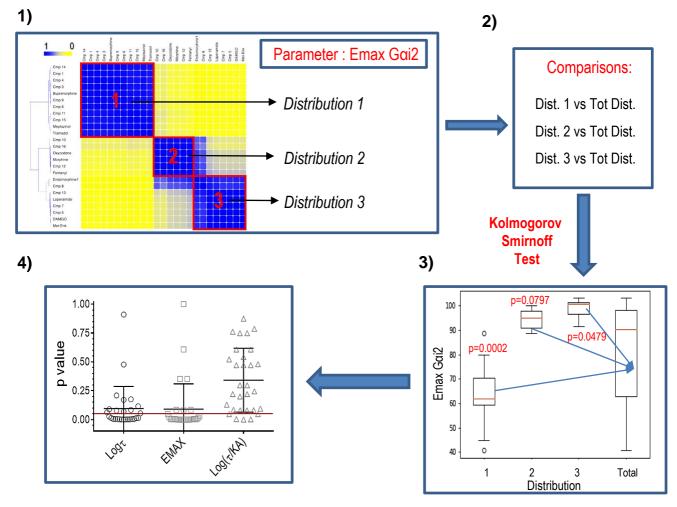


hMOR Non stimulated
hMOR Met-Enk 10uM
hDOR Non stimulated
hDOR Met-Enk 10uM

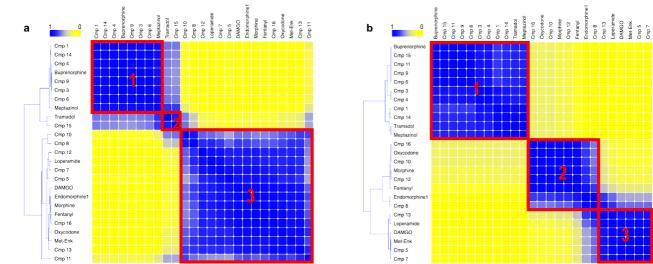
Supplementary Figure 5. net BRET values of hMOR and hDOR responses obtained with different biosensors. Net BRET values obtained in single point BRET assays monitoring hMOR (green) and hDOR (blue) responses across indicated bimolecular biosensors are represented as bar graphs for: (a)  $\beta$ arr1 recruitment, (b)  $\beta$ arr2 recruitment, (c)  $\beta$ arr2 recruitment in presence of GRK2, (d)  $\beta$ arr2 recruitment in presence of GRK5, (e)  $\beta$ arr2 recruitment in presence of GRK6, (f) G $\alpha$ i1 activation, (g) G $\alpha$ i2 activation, (h) G $\alpha$ oA activation and (i) Kir3.1/3.2 activation. Each response was tested in the presence (10µM; *filled bar*) or absence (*empty* bar) of Met-Enkephalin (Met-ENK) and corresponds to mean  $\pm$  SEM of 9-12 independent experiments. Results were analyzed using non-paired t-test. \*\* p ≤ 0.01; \*\*\*\* p ≤ 0.001; \*\*\*\* p ≤ 0.0001.



Supplementary Figure 6.  $\beta$ arr recruitment and G protein responses by novel opioid ligands were monitored using BRET-based biosensors. Novel hMOR ligands were identified in a screening campaign carried out at Pfizer Inc. to identify MOR agonists with poor or no  $\beta$ arr recruitment. A sample of those identified were tested using BRET-based biosensors to monitor response for : (a)  $\beta$ arr1 recruitment, (b)  $\beta$ arr2 recruitment, (c)  $\beta$ arr2 recruitment in presence of GRK2, (d)  $\beta$ arr2 recruitment in presence of GRK5, (e)  $\beta$ arr2 recruitment in presence of GRK6, (f) cAMP, (g) G $\alpha$ i1 activation, (h) G $\alpha$ i2 activation, (i) G $\alpha$ oA activation and (j) Kir3.1/3.2 activation. Results correspond to mean  $\pm$  SEM of 3-12 independent experiments. Curves were normalized to the maximal effect produced by Met-ENK, which was tested in all experimental runs (n = 16-29). Curves were fit with operational model and logistic equations (curves shown were fit with the logistic model; parameters from both fits provided in Supplementary Data 1).



*Supplementary Figure 7. Stepwise method used to determine parameter contribution to ligand segregation into functional clusters. 1)* We measured how well each of the 30 parameters considered individually differentiated the three ligand clusters. This was calculated by identifying which of the parameters (e.g. Gαi2 Emax) showed statistical difference across the compound clusters. Practically, we grouped the Gαi2 Emax values for compounds in each cluster (1, 2, and 3) and 2) measured if they represented biased selections from the total distribution (all values for 25 ligands combined) using a Kolmogorov Smirnoff. *3*) Comparisons for each parameter provides a group of 3 p values. *4*) The procedure is repeated for each of the 30 parameters to generate corresponding p values that are then plotted according to parameter type or according to similarity in relative magnitudes (shown in figure 3c-d).

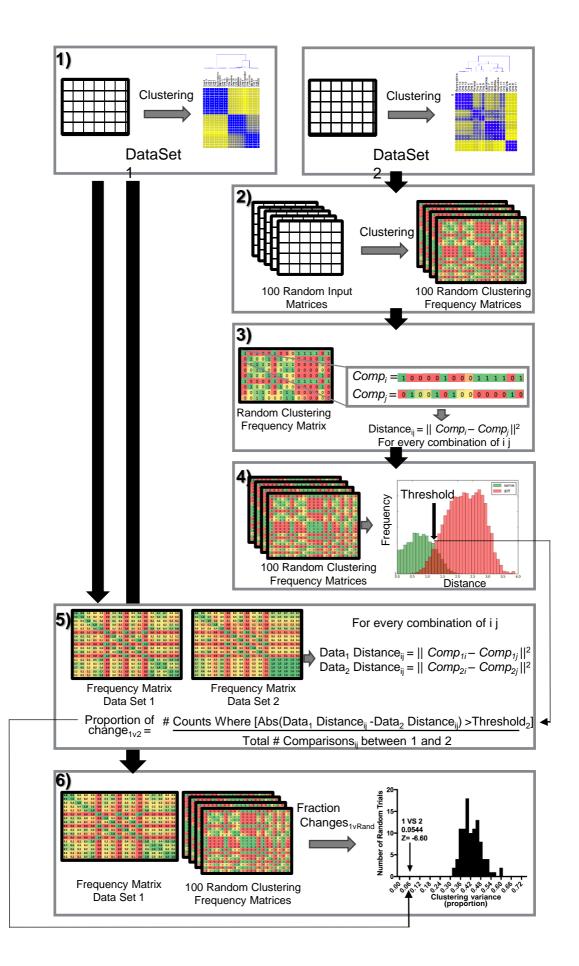


3

G protein hMOR

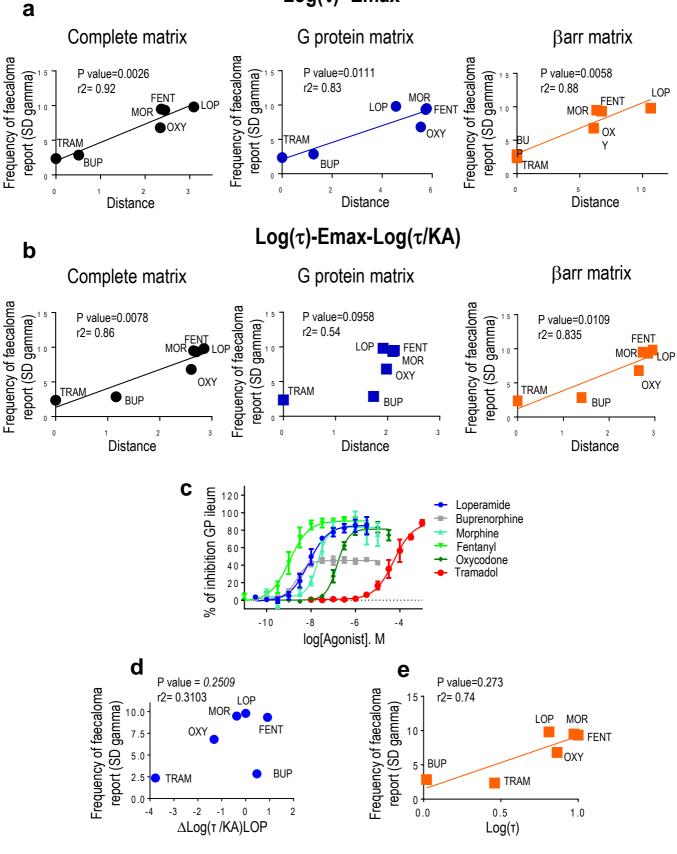
βarrestin hMOR

Supplementary Figure 8. Heat maps and cluster assignements obtained using partial hMOR datasets for βarr or G protein parameters. Shown are heat maps and clusters generated by NNMF and k-means analysis of partial datasets for all G protein mediated-responses (*a*) and all βarr recruitment readouts monitored by BRET (*b*). Blue (1) and yellow (0) respectively indicate consistent assignement of pairs of ligands to the same or different clusters.

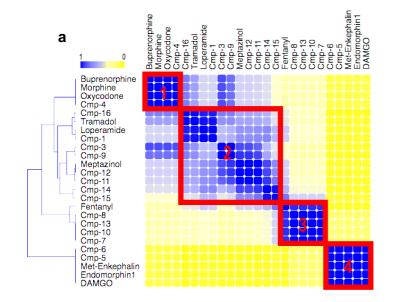


Supplementary Figure 9. Stepwise comparison of clusters produced with *different datasets. 1*) Use clustering methodology to obtain frequency matrix and cluster assignments for both data sets of interest; e.g. set of parameters for all responses tested for hMOR (dataset 1) vs partial dataset for parameters describing  $\beta$  arr responses at the receptor (dataset 2). 2) Create 100 randomized matrices of dataset 2 by permuting the input values to create a matrix of equal size but shuffled values. Then perform NNMF/kmeans analysis on each shuffled matrix resulting in 100 random frequency matrices. 3) For each of the 100 frequency matrices of randomized data, calculate the Euclidian distance between Comp<sub>i</sub> and Comp<sub>j</sub>. Sort distance values based on whether the compounds (i and j) are in the same cluster or different clusters to produce a distribution of distances as shown in next step. 4) Determine a threshold value separating the distribution of distances between compounds in the same cluster and the distances between compounds in different clusters. 5) Calculate and compare the distance<sub>ij</sub> for dataset 1 vs the distance<sub>ij</sub> for dataset 2. The proportion of differences between the two matrices greater than the threshold value represents variance in clustering. 6) Finally, measure the clustering similarity of data set 1 vs the 100 random matrices of dataset 2 to obtain a distribution of proportions greater than the threshold distance; this proportion describes random variance. Use z-score to quantify if the proportion of differences describing variance between dataset 1 and the actual dataset 2 is statistically different from the proportion describing random variance.

### $Log(\tau)$ - Emax



### Supplementary Figure 10. Correlating specific signals to reported opioid side effects. Partial matrices in which drugs were classified according to G protein or $\beta$ arr responses were generated using either Log( $\tau$ )-Emax (*a*) or Log( $\tau$ )-Emax-Log( $\tau$ /KA) (*b*) as classification criteria. Distances separating ligands in partial and complete matrices were consigned, and correlated to frequency of faecaloma report as indicated in the figure. Inhibitory effect of standard opioid ligands on contractility of guinea pig ileum were assessed (*c*) Normalized transduction coefficients ( $\Delta$ Log( $\tau$ /KA)<sub>LOP</sub>) (*d*) and operational efficacy (Log( $\tau$ )) values (*e*) were correlated to corresponding SD gamma scores for faecaloma report.



Signaling clusters Cmpd 14 Cmpd 1 Cmpd 3 Buprenorphine Cmp 9 Cmpd 6 Cmpd 11 Cmpd 15 Meptazinol Tramadol Cmpd 10 Cmpd 6 Oxycodone Morphine Cmpd 12 Fentanyl Endomorphin 1 Cmpd 8 Cmpd 13 Loperamide Cmpd 7 Cmpd 5 DAMGO

Met-Enkephalin

b

Structural	
clusters	

clusters				
Buprenorphine				
Morphine				
Oxycodone				
Cmpd 4				
Cmpd 16				
Tramadol				
Loperamide				
Cmpd 1				
Cmpd 3				
Cmpd 9				
Meptazinol				
Cmpd 12				
Cmpd 11				
Cmpd 14				
Cmpd 15				
Fentanyl				
Cmpd 8				
Cmpd 13				
Cmpd 10				
Cmpd 7				
Cmpd 6				
Cmpd 5				
Met-Enkephalin				
Endormorphin 1				
DAMGO				

#### Supplementary Figure 11. Structural and signaling clusters display non-

*random similarity*. Shown is the similarity heat map and clusters generated by NNMF and k-means analysis of 75 Tanimoto similarity values describing opioid ligand resemblance according to three different structural footprints (ECFP-6; FCFP-6; MDL MACCS). Yellow and blue respectively indicate ligands that never or always cluster together (*a*). Graphical comparison of cluster composition in functional and structural matrices. Colours show how ligands in the three signaling clusters redistribute when classified using structural criteria (*b*).

#### **CLUSTER #1**

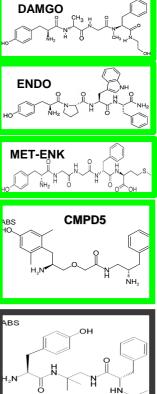
НÓ

#### **CLUSTER #2**

#### ÇH₃ BUP LOP ٦N MEPT но / OH .OH • HCI N Ън ċн₃ 0 ОСН₃ 0 HO ℃H<sub>3</sub> ABS QН MOR N--N $_{\rm H}$ TRAM Ň HO Ó Ĥ ∠CH<sub>3</sub> H• N-CH3 N CMPD11 -Ñ. HO ċн₃ \_0 ΟΧΥ ABS HO CMPD14 Ó QН ́О-H۰ HC O<sup>2</sup> CMPD4 CMPD15 Ð ABS CMPD9 CH2 l<sub>a</sub>N **CLUSTER #3** CMPD6

FENTANYL

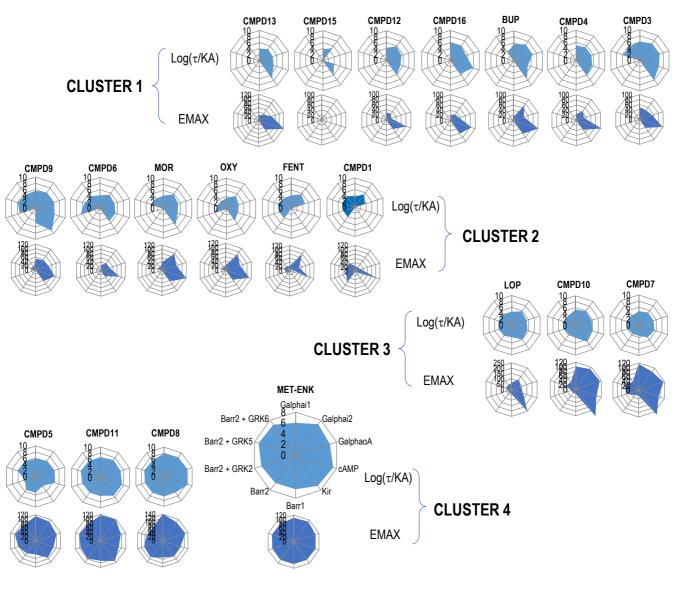
#### **CLUSTER #4**



0

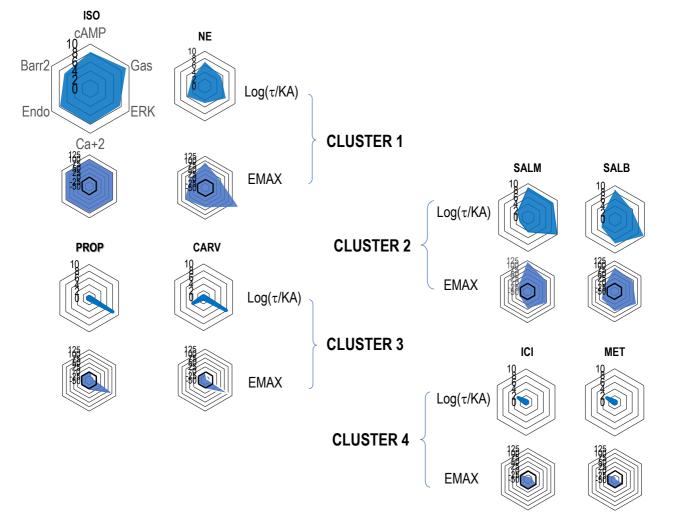
#### Supplementary Figure 12. Chemical structures for standard and novel opioid

*ligands.* Ligand structures are ordered according to the categories established by clustering Tanimoto similarity values. Either novel compounds, standard ligands or both are provided as representatives of each category. Frames for the different structures are color coded to represent their standing in functional clusters as follows: cluster #1 gray; cluster #2 peach; cluster #3 light green.



#### Supplementary Figure 13. Graphic representation of pharmacodynamic

*parameters of hDOR ligands in different clusters.* Radial graphs were used to represent operational transduction coefficients ( $Log(\tau/KA)$ ) and logistic Emax values. Each radius corresponds to the magnitude of  $Log(\tau/KA)$  or Emax values. Transduction coefficients are in logarithmic scale, Emax values were normalized to maximal Met-ENK response, and are presented on linear scale. The key specified only for Met-ENK applies to all radial graphs and shows the order in which information for each biosensor is provided.



Supplementary Figure 14. Graphic representation of pharmacodynamic

*parameters of*  $\beta 2_{ADR}$  *ligands included in different clusters.* Radial graphs were used to represent operational transduction coefficients (Log( $\tau$ /KA)) and logistic Emax values. Each radius corresponds to the magnitude of Log( $\tau$ /KA) or Emax values. Transduction coefficients are in logarithmic scale, Emax values were normalized to maximal ISO response, and are presented on linear scale. The key specified only for ISO applies to all radial graphs and shows the order in which information for each biosensor is provided.

Pathway	Cluster A	Cluster B	Cluster C
GαoA		Log(т) Emax	
Gai1		Log(т) Emax	
Gai2		Log(τ) Emax	
cAMP			Emax
Kir		Emax	Log(т)
βarr 1	Logτ Emax Log(τ/KA)		
βarr 2	Logτ Emax Log(τ/KA)		
βarr 2-GRK2	Emax	Log(t)	
βarr 2-GRK5	Log(τ) Emax		
βarr 2-GRK6	Log(τ) Emax		Log(т/KA)

Supplementary Table 1. Operational and logistic parameters driving ligand segregation into clusters for hMOR responses