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**Supplemental Information**

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# Quantitative analysis of the correlation between cell size and cellular uptake of particles

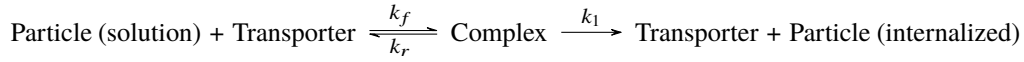
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## DERIVATION OF THE REACTION-DIFFUSION MODEL

In the model, particles are reversibly captured by a cell-surface transporter. The transporter represents a generic molecule accounting for all different endocytic structures in the cell plasma membrane. Each transporter can handle one particle at a time. A particle captured by a transporter may dissociate and return to the solution, or it may be taken inside the cell through endocytosis. These steps are described by the following reaction scheme:



In the above scheme, the three reactions are associated with the following three rate constants:  $k_f$  is associated with the forward reaction that leads to the formation of the particle-transporter complex,  $k_r$  is associated with the reverse reaction that leads to dissociation of the complex, and  $k_1$  is associated with the reaction that leads to particle endocytosis and regeneration of the transporter. The constant  $K_m$  is the Michaelis-Menten constant and is given by Eq. 1:

$$K_m = \frac{k_r + k_1}{k_f} \quad (1)$$

At steady-state condition, the flux of nanoparticles across the cell membrane can be described by the Michaelis-Menten rate law:

$$J = J_m \frac{C_0}{K_m + C_0} \quad (2)$$

Here,  $C_0$  represents nanoparticle concentration at the solution-cell membrane interface, and  $J_m = k_1 n$  represents maximum flux when there are  $n$  transporter molecules per unit area of the cell membrane.

For convenience, we rewrite Eq. 2 in dimensionless form:

$$J^* = \frac{C_0^*}{1 + C_0^*} \quad (3)$$

where  $C_0^* = \frac{C_0}{K_m}$  and  $J^* = \frac{J}{J_m}$ . Further, we consider a spherical cell of radius  $r_0$  and define dimensionless distance  $r^* = \frac{r}{r_0}$  such that  $r^* = 1$  at the cell surface.

The steady state concentration profile around a cell can be given by:

$$\nabla \cdot (D \nabla C^*) = 0 \quad (4)$$

where  $C^* = \frac{C}{K_m}$  is the dimensionless nanoparticle concentration at  $r^* > 1$ . For spherical coordinates Eq. 4 becomes:

$$\frac{d}{dr^*} \left( r^{*2} \frac{dC^*}{dr^*} \right) = 0 \quad (5)$$

where  $r^*$  is the dimensionless radius  $r^* = \frac{r}{r_0}$ . Due to the symmetry of the spherical geometry, we assume no gradient in  $C^*$  in the  $\theta$  and  $\phi$  directions. Applying the two boundary conditions for the system:

$$C^* = C_b^* \text{ at } r^* \rightarrow \infty \quad (6)$$

$$C^* = C_0^* \text{ at } r^* = 1 \quad (7)$$

where  $C_b^* = C_b/K_m$  is the dimensionless bulk nanoparticle concentration, we get the following solution:

$$\frac{C_b^* - C^*}{C_b^* - C_0^*} = \frac{1}{r^*} \quad (8)$$

The particle flux is given Fick's first law:

$$J = -D\nabla C \quad (9)$$

Thus,

$$J = -D \frac{\partial C}{\partial r} \Big|_{r=r_0} = \frac{D}{r_0} (C_b - C_0) \quad (10)$$

which can be brought back to the dimensionless form:

$$J^* = \frac{DK_m}{J_m r_0} (C_b^* - C_0^*) = \Psi (C_b^* - C_0^*) \quad (11)$$

where,

$$\Psi = \frac{DK_m}{J_m r_0} \quad (12)$$

From Eq.11 we get the total particle uptake rate by multiplying flux with cell surface area:

$$\dot{m} = 4\pi r_0^2 J_m \Psi (C_b^* - C_0^*) = 4\pi r_0 DK_m (C_b^* - C_0^*) = k(C_b^* - C_0^*), \quad (13)$$

where  $k = 4\pi r_0 DK_m$ .

Mass conservation requires that the two fluxes in Eq. 3 and Eq. 11 be equal. Thus by equating the two, we obtain the following quadratic equation:

$$C_0^{*2} + \left( \frac{1}{\Psi} + 1 - C_b^* \right) C_0^* - C_b^* = 0 \quad (14)$$

Solving for the nanoparticle concentration at the cell boundary we get:

$$C_0^* = -\frac{1}{2} \left( \frac{1}{\Psi} + 1 - C_b^* \right) + \frac{1}{2} \sqrt{\left( \frac{1}{\Psi} + 1 - C_b^* \right)^2 + 4C_b^*} \quad (15)$$

We then substitute  $C_0^*$  from Eq.15 in Eq.13 to get the total particle uptake rate by the entire cell,

$$\dot{m} = k \left( C_b^* + \frac{1}{2} \left( \frac{1}{\Psi} + 1 - C_b^* \right) - \frac{1}{2} \sqrt{\left( \frac{1}{\Psi} + 1 - C_b^* \right)^2 + 4C_b^*} \right) \quad (16)$$

When considering variation in mean transporter density,  $\tilde{n}$ , with cell size, we substitute the following equation:

$$\frac{\tilde{n}}{\langle n \rangle} = \left( \frac{r_0}{\langle r_0 \rangle} \right)^\alpha \quad (17)$$

into  $\Psi$  to get:

$$\Psi = \frac{DK_m}{J_m r_0} = \frac{DK_m}{k_1 \tilde{n} r_0} = \frac{DK_m}{k_1 \langle n \rangle \left( \frac{r_0}{\langle r_0 \rangle} \right)^\alpha r_0} \quad (18)$$

**PYTHON CODE IMPLEMENTING THE REACTION-DIFFUSION MODEL**

Use the following Python code to create a Python file, such as model.py. Execute the Python file, which will generate Fig. 5B of the paper.

```
#!/usr/bin/python
import matplotlib
matplotlib.use("TkAgg")
import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
import matplotlib.ticker as mtick
import numpy as np
import random
import math

from pylab import genfromtxt;
font = {'family' : 'serif',
        'weight' : 'normal',
        'size'   : 20}

matplotlib.rc('font', **font)
plt.rc('axes', labelsiz=22)

#mat0 = genfromtxt("L_molecule_avg_dist7.dat");
#mat1 = genfromtxt("L_molecule_avg_dist8.dat");
#mat2 = genfromtxt("L_molecule_avg_dist9.dat");

Fs = 10000
```

```

f = 1
sample = Fs

a = 0.05 # particle radius in micron
w = 10.0 # ug/mL solution; nanoparticle solution on weight-basis
spg = 1.06 # Polystyrene (nanoparticle material) specific gravity.
m_particle = (4.0/3)*(np.pi)*((a/10000)**3)*1.00*(10**6) # Mass of a
nanoparticle in microgram
Cb = (w/(10**(12)))/m_particle # Bulk particle concentration; number
of particles per um^3 of the bulk solution

r0 = 10.0 # Mean cell size (radius)
mur = np.log(r0) # Mean cell size (radius) in log scale
sigmar = 0.5 # Standard deviation for cell size distribution

KB = 1.38064852e-23 # Boltzmann constant
T = 298.15 # Temperature
nu = 1e-3 # Water viscosity, Pa.s

D = (KB * T / (6 * np.pi * nu * a * 1e-6))*1e12 # particle
diffusivity micron^2/s

kf = 0.1 # Goldstein, intrinsic on rate
nmu0 = 0.119 # Number of coated pits per unit surface area (150 in a
cell of 10 micron radius)
nstd = 0.4 # standard deviation - cell -to cell variability in surface
density of pit
kr = 0.1 # Mean residence time of a particle in a pit is 10 second

```

```
k1 = 0.02 # Mean lifetime of a pit is 50 seconds; this is inverse of
the pit lifetime
```

```
#npit = np.exp(np.random.normal(np.log(nmu), nstd, sample))
```

```
#y = 4 * np.pi * r * D * r * km / (D + r * km)
```

```
#y = 4 * np.pi * r * r * km
```

```
def evaluate_f2(*vartuple):
```

```
    kf = vartuple[0]
```

```
    kr = vartuple[1]
```

```
    k1 = vartuple[2]
```

```
    n = vartuple[3]
```

```
    r = vartuple[4]
```

```
    Cb = vartuple[5]
```

```
    D = vartuple[6]
```

```
    Jm = k1 * n
```

```
    Km = (kr + k1)/kf
```

```
    Cb = Cb/Km # dimensionless bulk concentration
```

```
    Psi = D*Km / (Jm * r)
```

```
    Zet = ((1 / Psi) + 1 - Cb)
```

```
    C0 = -Zet/2 + (math.sqrt(Zet*Zet + 4*Cb))/2
```

```
    k = 4 * np.pi * r * D * Km
```

```
    m = k * (Cb - C0)
```

```

return(m);

n_elem = 6;
#z1 = [[0 for x in range(sample)] for y in range(n_elem)]

#z = [[0 for xx in range (sample)] for yy in range(5)]

y = np.empty([n_elem, sample])

factor = np.array([1, 0.1, 0.03, 0.01, 0.003, 0.001])
colors = np.array(['k', 'orange', 'g', 'r', 'c', 'b'])
plots = np.empty([n_elem])
alpha = np.array([1, 0.5, 0, -0.5, -1, -2])

marker_size = 0.5

for j in range(n_elem):
    csize = np.random.normal(mur, sigmar, sample)
    x = np.exp(csize)
    for i in range(sample):
        r = x[i]
        nm_u = nm_u0*((r/r0)**(alpha[2]))
        ntot = np.exp(np.random.normal(np.log(nm_u), nstd))
        vall = evaluate_f2(kf, kr, k1, ntot, r, Cb, factor[j]*D)

        Dmean = D
        rmean = r0

        kmeanCb = 4*(np.pi)*rmean*Dmean*Cb # k*(Cb*) =
4*(pi)*r_0D*Km*(Cb/Km) = 4*(pi)*r_0*D*Cb

```

```

        y[j,i] = val1/kmeanCb # Normalized by k*Cb*

        plt.scatter(x, y[j,:], color= colors[j], marker= ".", s =
marker_size)

        #plt.plot(x, y[j,:], color= colors[j])

# x-axis label
plt.xlabel("Cell radius ( $\mu\text{m}$ )")
# frequency label
#plt.ylabel("Uptake ( $\text{m}/\sim\{k\}C_b$ )")
plt.ylabel("Uptake")
# plot title
#plt.title('My scatter plot!')
# showing legend
leg = plt.legend()
leg.get_frame().set_alpha(0.0)
#plt.xscale("log");
plt.xlim(1,20);
plt.ylim(0,0.012);

plt.tick_params(direction='in', length=6, width=2, colors='k',
                grid_color='r', grid_alpha=0.5, pad=10)

plt.gca().yaxis.set_major_formatter(mtick.FormatStrFormatter('%0.1g'))
plt.tight_layout()
plt.savefig('Fig5B.png', format='png', dpi=1500)
# function to show the plot
plt.show()

```