Genome-wide analysis of DNA uptake across the outer membrane of naturally competent

Haemophilus influenzae

Marcelo Mora[1], Joshua Chang Mell[2], Garth D. Ehrlich[2,3], Rachel L. Ehrlich[2] and Rosemary J.

Redfield[1][¶]*

[¶]* Lead Contact and Corresponding Author: redfield@zoology.ubc.ca.

AUTHOR AFFILIATIONS:

1. Department of Zoology, University of British Columbia, Vancouver, BC, Canada V6T 1Z3.

2. Department of Microbiology & Immunology; Center for Genomic Sciences, Institute of

Molecular Medicine and Infectious Disease; Drexel University College of Medicine, 12

Philadelphia PA, USA 19102.

3. Department of Otolaryngology – Head and Neck Surgery, Drexel University College of

Medicine, 12 Philadelphia PA, USA 19102.

SUMMARY

The genomes of naturally competent Pasteurellaceae and Neisseriaceae have many short

uptake sequences (USS), which allow them to distinguish self-DNA from foreign DNA. To fully

characterize this preference we developed genome-wide maps of DNA uptake using both a

sequence-based computational model and genomic DNA that had been sequenced after uptake

by and recovery from competent *Haemophilus influenzae* cells. When DNA fragments were

shorter than the average USS spacing of ~1000 bp, sharp peaks of uptake were centered at USS

and separated by valleys with 1000-fold lower uptake. Long DNA fragments (1.5-17 kb) gave

much less variation, with 90% of positions having uptake within two-fold of the mean. All

detectable uptake biases arose from sequences that fit the USS uptake motif. Simulated

competition predicted that, in its respiratory tract environment, *H. influenzae* will efficiently

take up its own DNA even when human DNA is present in 100-fold excess.

INTRODUCTION

Many bacteria are naturally competent, able to actively bind DNA fragments at the cell surface

and pull them into the cytoplasm, where the incoming fragments may contribute nucleotides to

cellular pools or recombine with homologous genomic sequences (Lorenz and Wackernagel,

1994). The genetic exchange associated with this latter process contributes to adaptation and is

known to have promoted resistance to antibiotics (Bae et al., 2014) and increased strains'

intracellular invasiveness (Mell et al., 2016) and vaccine resistance (Kress-Bennett et al., 2016;

Straume et al., 2015). Thus, understanding how different genomic regions evolve via natural

transformation processes could be used to predict the spread of pathogenic traits.

Most naturally competent bacteria that have been tested take up DNA regardless of sequence,

but species in two families, the Pasteurellaceae and the Neisseriaceae, exhibit strong

preferences for DNA containing short sequence motifs (Chen and Dubnau, 2004). Because

these motifs have become highly enriched in the corresponding genomes, these biases

effectively limit uptake to DNA from close relatives with the same uptake specificity (Dougherty

et al., 1979; Scocca et al., 1974). The distribution of the preferred sequences around the

chromosome is uneven (Smith et al., 1995), which may cause different genes to experience

quite different rates of genetic exchange.

Most steps in the natural transformation process are highly conserved among transformable

species (Chen and Dubnau, 2004). In the Pasteurellaceae, the Neisseriaceae and most other

Gram-negative bacteria, DNA uptake is initiated by binding of a type IV pilus uptake machine to

double-stranded DNA (dsDNA) at the cell surface. The DNA-binding protein has not been

identified in *H. influenzae*, but in *Neisseria* it is a minor pilin-type protein that forms part of the

pilus (Cehovin et al 2013). DNA binding is followed by retraction of the pilus, which pulls the

DNA across the outer membrane into the periplasm. Because circular DNA is taken up as

efficiently as linear DNA, uptake is thought to begin internally on DNA fragments rather than at

their ends (Barany et al., 1983). Thus, it is likely that the stiff dsDNA molecule is transiently

kinked (folded sharply back on itself) at the site of initiation to allow it to pass through the

narrow secretin pore of the uptake machinery. Forces generated by the retraction of the type

IV pilus are thought to be responsible for this kinking, which might be facilitated by strand

separation at the AT-tracts (Danner et al., 1982). Once a loop of the DNA is inside the

periplasm, a ratchet process controlled by the periplasmic protein ComEA is thought to pull the

rest of the DNA through the outer membrane (Hepp and Maier, 2016; Salzer et al., 2016).

Below we use 'DNA uptake' to refer to the combined binding and membrane-transport steps

that move DNA from the extracellular environment across the outer membrane into the

periplasm. In Gram-positive bacteria similar machinery acts to pull the DNA through the thick

cell wall (Chen and Dubnau, 2004). The next step in natural transformation is translocation of

the DNA out of the periplasm and into the cytoplasm. Only the 3'-leading strand remains intact,

passing through an inner membrane pore encoded by the *rec2/comEC* gene, while the other

strand is degraded in the periplasm and its nucleotides are dephosphorylated and imported as

nucleosides (Pifer and Smith, 1985). Circular DNA molecules are efficiently taken up across the

outer membrane but remain the periplasm because they lack free ends (Pifer and Smith, 1985).

As the single strand enters the cytoplasm it undergoes limited exonucleolytic degradation

before being complexed with cellular proteins. If sequence similarity permits the strand may

then recombine with homologous chromosomal sequences; otherwise the strand is degraded

to its constituent nucleotides (de Vries et al., 2001). Both linkage and sequencing studies

indicate that fragments much longer than the cell are readily taken up (Goodgal, 1982; Mell

and Redfield, 2014), as are fragments as short as 200 bp, although a lower limit has not been

established (Mell 2012, Maughan 2009). However, recombination of short fragments is limited

because they are usually degraded by cytoplasmic nucleases before they can recombine (Pifer

and Smith, 1985). Uptake speed has been estimated at 500-1000 bp/sec, with transformation

essentially complete by 15 min (Deich and Smith 1980).

Direct measures of DNA uptake bias: Uptake-competition experiments in the Pasteurellacean

Haemophilus influenzae and in *Neisseria gonorrhoeae* showed that genetically marked 'self-

derived' DNA competes for uptake with unmarked self-derived DNA but not with DNA from

unrelated sources (Dougherty et al., 1979; Scocca et al., 1974). Subsequent DNA uptake

experiments using cloned radiolabeled DNA fragments found that these self-preferences are

caused by the uptake machineries' strong biases for short sequence motifs, called uptake signal

sequences (USS) in *H. influenzae* and DNA uptake sequences (DUS) in *Neisseria* species (Sisco

and Smith, 1979) (Davidsen et al., 2004). Sequence comparisons and site-directed mutagenesis

initially identified the *H. influenzae* motif as an 11 bp sequence with a strong contribution by

flanking AT-rich sequences (Danner et al., 1980, 1982), and later genome sequencing identified

1465 occurrences of a 9 bp USS core in *H. influenzae* and 1892 occurrences of an unrelated 10

bp DUS motif in *N. meningitidis* (Smith et al., 1995, 1999). Subsequent motif search analyses by

Maughan *et al.* (Maughan et al., 2010) expanded this number to 2206 USSs in the genome of

the standard *H. influenzae* lab strain Rd, sharing the motif shown in Figure 1A. These genomic

analyses were later complemented by direct uptake experiments using mutated and

degenerate USS variants(Maughan, Wilson and Redfield, 2010; Mell, Hall and Redfield, 2012)..

Mell *et al.* used mutagenesis and sequencing of pools of degenerate USS-containing fragments

that had been recovered after uptake to identify the contribution to uptake of each USS

position, and found that the central GCGG bases are crucial for uptake, with much smaller

contributions made by the flanking bases and AT-rich segments. The motif in Figure 1B shows

the contribution of each base considered independently. Interaction effects between bases of

the AT-tracts and the core were also found to make important contributions to uptake, but only

a few of these have been directly measured. Although characterization of the unrelated

Neisseriacean DUS has not reached this level of detail (Mathis and Scocca, 1982), the two

uptake systems shares many features, apparently convergently evolved, including the presence

within each family of lineages with slightly different preferred motifs (Frye et al., 2013; Redfield

et al., 2006).

Evolution of uptake sequences in the genome: Alignment of homologous genomic regions

from different Pasteurellaceae species showed that USS evolve by point mutations (Redfield et

al., 2006); *i.e.* they are not inserted elements. As a mechanism for this evolution, (Danner et al.,

1980) proposed that the combination of uptake bias and genomic recombination creates an

evolutionary pressure that causes the preferred uptake sequences to accumulate throughout

the genome, with their numbers limited by their eventual interference with gene function.

Consistent with this, uptake sequences in both *Haemophilus* and *Neisseria* are

underrepresented in newly acquired segments, in rRNA genes, and in coding sequences,

especially those with strong functional constraints (Findlay and Redfield, 2009; Smith et al.,

1999). Modeling by Maughan *et al.* (Maughan et al., 2010) confirmed that this molecular drive

process could produce uptake sequence distributions like those of real genomes, with no need

for any fitness benefit from either the uptake sequences or the recombination they promote.

Thus, the presence of biased DNA uptake machinery may be sufficient in itself to explain the

abundance of uptake sequences. Such biases may be solely a consequence of direct selection

on the DNA uptake machinery for more effective DNA binding or may have been reinforced by

indirect selection for preferential uptake of conspecific DNA. These processes might be

especially important in respiratory tracts and other mucosal environments where

Pasteurellaceae and Neisseriaceae species mainly occur (Man et al., 2017). These environments

contain abundant host DNA, and transformation can only occur if the released bacterial DNA

competes successfully for binding to the uptake machinery (Lethem et al., 1990; Shak et al.,

1990).

The goal of the present study was to measure DNA uptake at every position in the *H. influenzae*

genome and to use this uptake data to characterize the effects of USS and identify any other

factors affecting uptake. To prepare a framework for interpreting uptake biases, we developed

a computational model that predicted the effect of uptake sequences on DNA uptake across

the *H. influenzae* genome. We did not attempt to build a model that accurately simulated the

actual events of DNA uptake, since too little is known about these. Instead, the initial version of

this model was 'naïve' in that its parameters and settings were based only on previously

published information. Discrepancies between the model's predictions and the observed

uptake were then used to identify features of uptake that were poorly predicted. Hypothesized

biological explanations for these discrepancies then guided changes to the model, and the

effect of each change on the discrepancy was used to confirm or refute the hypothesis. The

most important product of this recursive analysis was not the model itself, but the improved

understanding of factors affecting DNA uptake across the genome. These in turn increased the

understanding of the genomic distribution of recombination and the effects of competition

with DNA from the host or other microbiota.

RESULTS

A computational model of DNA uptake

As a framework for interpreting DNA uptake data we developed a simulation model of USS-

dependent DNA uptake. It takes as input the locations and strengths of USSs in the DNA whose

uptake is to be simulated, the fragment-size distribution of this DNA, and binding and uptake

functions that specify how uptake probability depends on USS presence and strength. The

output is the expected relative uptake of every position in the genome.

Development of the model was guided by basic principles of sequence-specific protein-DNA

interactions (Halford and Marko, 2004; Rohs et al., 2010). The first step in these interactions is

thought to be a random encounter between a DNA fragment and the binding site of the

protein, usually at a DNA position that does not contain the protein's preferred sequence. This

non-specific binding dramatically increases the probability that the protein will subsequently

encounter any preferred sequence, either by sliding along the DNA or by transient dissociation

and reassociation, leading to specific binding between DNA and protein. In the case of the USS

this specific binding then enables uptake of the DNA fragment across the cell's outer

membrane.

The model did not explicitly simulate the first step, non-specific binding, since this is expected

to be equally probable for all DNA positions. The specific binding and DNA uptake steps were

separately modeled since they are expected to depend on the properties of the DNA uptake

machinery and on the length and sequence of the DNA fragment. Although in real cells both

steps may depend on the quality of the USS, for simplicity the initial version of the model

assumed that specific binding required only a threshold similarity to the USS consensus and

that the subsequent probability of uptake depended on the strength of this similarity.

Simulating these steps required first specifying the genomic sequences that should be treated

as USS. This was not straightforward because genomes contain many USS variants that differ in

how well they promote DNA uptake (Findlay and Redfield, 2009; Maughan and Redfield, 2009).

Our strategy was to score the information content (in bits) of every genome position, using the

Position-Specific Scoring Matrix (PSSM) from Mell *et al.*'s degenerate-sequence uptake

experiment (Mell et al., 2012) (Table S1), and to use overrepresentation of high-scoring

sequences as the USS criterion. We scored every genome position in the three *H. influenzae*

strains used for the experiments described below (Table 1), and in four randomly generated

sequences with the same length and base composition (Figure S1 shows the score

distributions). In the *H. influenzae* genomes, overrepresentation of high-scoring sequences was

detectable above a score of 7.0 bits and became dramatic above 10.0 bits, where the numbers

of high-scoring positions increased in *H. influenzae* genomes but became vanishingly small in

the random-sequence controls, (see inset in Figure S1). Since the slight overrepresentation of

scores between 7 and 10 bits was hypothesized to be not a direct effect of DNA uptake but an

indirect consequence of mutational degeneration of high scoring USSs, the model initially used

a USS cut-off score of 10 bits ('USS_{10}', n=1941 in strain 86-028NP). This was later reduced to a

less stringent 9.5 bits after weak uptake effects had been examined ('$USS_{9.5}$', n=2248 in strain

86-028NP).

The computational model used these USS scores to predict DNA uptake for every position in the

genome, summing the contributions of binding and uptake probabilities from DNA fragments of

different sizes (Figure 2A gives an overview). Each fragment under consideration was first

checked for the locations of any USS_{10}s, and the maximum fragment length (20 kb) and the

mean length of USS-free segments (*mean_gap*) were used to calculate the probability that a

DNA receptor protein initially encountering a random location in the fragment would then

encounter and bind specifically to a USS_{10} rather than disassociating from the fragment: *p_bind*

= 1 – mean_gap/20000). Fragments with no USS were initially assigned a baseline *p_bind* of 0.1.

The probability that this specific binding led to uptake of the DNA fragment was then calculated

from the USS_{10} score (or the mean score if the fragment contained more than one USS_{10}), using

the function *p_uptake = 0.1 + (1 - 0.1)/(1 + exp(-5 * (score – 11))),* where *0.1* specifies the

baseline uptake of USS-free fragments and *-5* is an arbitrarily chosen coefficient specifying the

slope at the inflection point. The score of 11 bits specifying the inflection point of the function

was chosen because this score was the midpoint of the range of increasing USS overabundance

in the genomes (see Figure S1). When combined with the baseline *p_bind* of 0.1, the *p_uptake*

baseline assigned fragments with no USS_{10} a net uptake probability of 0.01.

Once the contributions of every size of fragment had been calculated for each position (Figure

2A), the model combined all the contributions, taking into account the frequency of each size in

the input DNA. The position-specific uptake predictions were then normalized to a genome-

wide mean uptake probability of 1.0. Except in simple test cases, for computational efficiency

DNA fragment lengths were specified as the median lengths of bins (10 bp bins for short

fragments, 200 bp bins for long fragments) rather than each being considered separately (e.g.

101-120 bp, 121-140 bp).

Model results: Figures 2B and 2C show examples of model predictions for simple situations.

Figure 2B shows the uptake predictions for an 800-bp simulated genome containing a single

USS with score 12.0 bits, considering three different input DNA fragment sizes (100, 200 and

300 bp). The peaks at the USS have straight sides, a basal width twice the length of the

fragments being taken up, and 31-bp flat tops arising from the model's requirement for a full-

length USS. When the DNA fragment sizes were evenly distributed between 25-300 bp in length

(Figure 2C), the peak had steep sides at its tops and gradually flattened at the base; maximum

width at the base equalled twice the maximum fragment length. In simulated mini-genomes

with more than one USS (Figures 2D, E and F), isolated peaks were only seen when the DNA

fragments being taken up were substantially shorter than the spacing of the USSs (Figure 2D),

and peaks disappeared entirely when the fragments were long enough that almost all

contained at least one USS (Figure 2F).

Figure 2G and H show the predicted uptake maps when this model analyzed a 50kb segment of

the *H. influenzae* 86-028NP genome, using the short-fragment and long-fragment length

distributions from the actual uptake experiments described below (Figures S2A and B), and

Figure 2.I shows the distribution of USSs over this segment. Because the 'short' DNA fragments

are shorter than the typical separation between USSs, the model predicts that uptake will be

restricted to sharp peaks at each USS. In contrast, uptake of long DNA fragments is predicted to

be much more uniform, since most of these will contain at least one USS.

Generation of experimental DNA uptake data

To obtain high-resolution measurements of actual DNA uptake, we sequenced *H. influenzae*

genomic DNA that had been taken up by and recovered from competent *H. influenzae* cells.

Competent cells of the standard laboratory strain Rd were first incubated with genomic DNA

preparations from strains 86-028NP and PittGG, whose core genomes are readily differentiated

from Rd (and each other) because they differ at ~3% of orthologous positions (Hogg et al.,

2007). To allow efficient recovery of the taken-up DNA, the Rd strain in which competence was

induced carried a *rec2* mutation that blocks translocation of taken-up DNA fragments, causing

the DNA to be trapped intact in the periplasm (16). The 86-028NP and PittGG genomic DNAs

were pre-sheared to give short (50-800 bp) and long (1.5-17 kb) DNA preparations (size

distributions are shown in Figure S2), and three replicate uptake experiments were done with

each DNA preparation. After 20 min incubation with competent cells, the taken-up DNA was

recovered from the cell periplasm using the cell-fractionation procedure of Kahn *et al.* (Barouki

and Smith, 1985; Kahn et al., 1983; Mell et al., 2012). Taken-up DNA samples were sequenced

along with samples of the input 86-028NP and PittGG DNAs and of the recipient Rd DNA. The

input and uptake reads were then aligned to the corresponding 86-028NP and PittGG reference

sequences and coverage at every position was calculated. Table S2 provides detailed

information about the four input samples, the twelve uptake samples, and the Rd sample.

Removal of contaminating Rd DNA: Preparations of DNA recovered from the periplasm after

uptake always included some contaminating DNA from the recipient Rd chromosome. The

divergence between the Rd and donor genomes allowed us to estimate the extent of this

contamination by competitively aligning the taken-up reads from each sample to an artificial

reference 'genome' consisting of both recipient and donor genomes as separate

'chromosomes'. Reads that uniquely aligned to only one chromosome could then be

unambiguously assigned to either donor (taken-up) or recipient (contamination). The resulting

estimates of Rd chromosomal contamination were between 3.2% and 19.3% of reads; sample-

specific values are listed in Table S2.

The effects of this contamination were not expected to be uniform across each donor genome,

since segments of the 86-028NP and PittGG genomes with high divergence from or with no

close homolog in Rd would be free of contamination-derived reads. We used the competitive-

alignment described above to create contamination-corrected uptake coverages by discarding

all reads that could not be uniquely mapped to the donor genome; in addition to removing Rd

contamination this also removed reads from segments that are identical between the donor

and recipient strains ('double-mapping reads') and reads that mapped to repeats, such as the

six copies of the rRNA genes. For consistency, the same changes were applied to the input

samples although they did not experience any contamination. This correction removed an

average of 18.6% of reads (range 8.9%-28.3%), left some segments of the 86-028NP and PittGG

genomes with no coverage in all samples (2.3% and 2.1% respectively), and reduced coverage

adjacent to these segments. Figure S3 shows the locations of the missing data. Contamination

details for each sample are provided in Table S2, and the impacts are considered below. The

uptake analysis described below showed this correction to be effective.

Uptake ratios: To control for position-specific differences in sequencing efficiency,

contamination-corrected read coverage at each position in each uptake sample was divided by

read coverage at that position in the corresponding input sample (*e.g.* coverages of each 86-

028NP-short uptake sample were divided by 86-028NP-short input coverages). Normalizing the

mean of the three replicates to a genome-wide mean ratio of 1.0 then gave a mean 'uptake

ratio' measurement for each genome position for each DNA type. Finally each position's uptake

ratio was smoothed using a USS-length (31 bp) window. Figures 2.5 and 2.6 show the resulting

uptake ratio maps.

Figure 3A shows the short-fragment uptake ratio map for the first 50kb of the 86-028NP

genome; the ticks in Figure 3C indicate locations and scores of USS_{10}s. The pattern is strikingly

similar to that predicted for the same DNA segment by the model (Figure 2G). Sharp uptake

peaks are seen at USS_{10} positions, some separated by flat-bottomed valleys and others

overlapping. Figure S4A, B and C show similar analysis for the first 50 kb of strain PittGG's

genome, and Figure S5A and B show expanded maps for two examples of the 86-028NP peaks.

The full-genome maps of these uptake ratios are provided in Figure S4D (86-028NP) and S4G

(PittGG;) they display the consistency of the peak heights across each genome.

As expected, the long-fragment DNA samples (Figure 3B and Figure S4B, E and H) had much less

variation in uptake ratio than the short-fragment samples; 90% of positions had uptake ratios

within two-fold of the mean, and there were few high peaks or low valleys. The few extended

segments with low or no uptake coincided with large gaps between USS_{10}s. The largest gap was

in the 86-028NP segment between 95 and 145kb —the site of a genomic island that is absent

from the PittGG and Rd strains, has few USS and has high similarity to an *H. influenzae* plasmid

(Harrison et al., 2005). However, uptake ratios did exhibit substantial short-range variation not

predicted by the model, which is considered further below.

Sensitivity is limited by low sequencing coverage: At some genome positions our ability to

detect USS-dependent uptake biases and possible USS-independent biases in uptake coverage

was limited by low sequencing coverage. Although some of this low coverage arose from the

contamination-correction step described above, segments of low coverage were also seen in

the raw data, likely arising from biases in the library preparation and sequencing steps. Figure

S6 compares the raw coverage of short and long input samples for a 50 kb segment of the 86-

028NP genome, illustrating the strong variation in sequencing coverage that was both broadly

reproducible and sequence dependent. Low coverage had similar effects in all samples,

precluding calculation of uptake ratios where input coverage was zero and generating high

levels of stochastic variation where coverage was low (segments with no coverage and

positions with coverage below 20 reads are indicated in uptake ratio maps by gaps and grey

dots respectively).

We used the low uptake ratios of positions at least 1000 bp from the nearest $USS_{9.5}$ to assess

the effectiveness of the contamination correction described above, since these positions are

where contamination would have had its largest effects. This peak-separation distance was

chosen because a peak-shape analysis of uptake around 158 $USS_{10}s$ that were separated by at

least 1200 bp from other $USS_{10}s$ and had uptake ratios of at least 3.0 found that mean uptake

ratio had fallen to baseline at positions 600 bp from the USS (Figure S7). Figure 4 compares

uptake ratios between the valley positions that received the contamination correction

described above (those with a Rd homolog) and the positions where no correction was needed

(those with no Rd homolog). The two distributions had nearly identical medians (0.0022 and

0.0020 respectively), indicating that the correction was sufficient but not excessive. These low

values also confirm that the DNase I treatment and washing steps removed at least 99.99% of

the donor DNA that had not been taken up.

Uptake ratios show no periodicity across the genome: Bacterial genomes show periodicity for

several features related to DNA curvature and codon usage biases (Mrazek, 2010), so we

examined the distribution of uptake ratios across each genome by Fourier analysis, using the R

package TSA. The log-log plots in Figure S8 show that this found no strong influence of any

specific repeat period on either the variation in input-sample coverage (panels A-D) or the

variation in uptake ratios (panels E-H). Instead, to explain the observed variation, the analysis

needed to invoke small contributions from almost every possible repeat period.

Uptake of short-fragment 86-028NP DNA

To investigate how USSs contribute to the DNA uptake process, our strategy was to first analyze

discrepancies between model predictions and observed uptake ratio peaks in the 86-028NP

short-fragment dataset, since these would reveal ways in which the simple assumptions

underlying the model mischaracterized the actual steps of DNA uptake. Model changes that

improved the predictions were considered to better reflect the true constraints on uptake of

short DNA fragments. The refined model's predictions were then compared to the real uptake

ratios for 86-028NP long-fragment DNA, allowing additional refinement, and finally to the

short- and long-fragment uptake ratios for PittGG DNA.

Figure 5 compares predicted and measured uptake (orange and blue lines respectively) of

short-fragment 86-028NP DNA for the first 50kb of the genome. The close correspondence

between the model's predictions and observed peak locations and shapes confirmed that

almost all of the variation in uptake was due to USSs. (The Pearson correlation coefficient over

all positions was 0.92). However, the more detailed analyses below identified components of

the model that could be improved.

First, the predicted low-uptake valleys were too high. This is not easily seen in Figure 5, but the

log-scale inset in Figure 3 and the analysis in Figure 4 show that most valley-bottom positions

had uptake ratios between 0.01 and 0.001, well below the model's predicted baseline uptake of

0.052 (dashed orange line in Figure 4).

Second, the score cutoff of 10.0 bits was too high. Analysis of score-subsets within the uptake-

valley dataset showed that 9.5 bits was a better cutoff. For the 78 positions with scores

between 9.5 and 10.0 bits, the correlation between score and uptake ratio was 0.27. Although

a similar correlation (0.27) was seen for the 136 positions with scores between 9.0 and 9.5 bits,

it was driven mainly by very small effects, and only 4 positions had uptake ratios higher than

0.1. For the 461 positions with USS scores between 8.5 and 9.5 bits the correlation was only

0.09.

Third, most of the predicted peaks were too high. Figure 6 complements Figure 4's analysis of

uptake valleys with an analysis of similarly isolated uptake peaks. The blue dots show the

uptake ratio at every $USS_{9.5}$ position in the genome that is at least 1000 bp from the nearest

USS_{10} (n=209), and the small orange dots show predicted uptake at the same positions. The lack

of scatter in the orange points confirms that the separation distance was sufficient to avoid

predicted effects of nearby USS; the least-squares difference between predicted and observed

uptake ratios at these 209 USS positions was 0.521.

In the original-version of the uptake model, the sigmoidal parameters of the *p_uptake* function

(baseline and location and slope of inflection point) were set using the frequencies of USS

scores in the 86-028NP genome; as expected, the same parameters were obtained when a

sigmoidal function was fit to the uptake points predicted by this model (orange line in Figure 6).

To improve the predictions we replaced these *p_uptake* parameters with those of a sigmoidal

function fitted to the real uptake data (blue line in Figure 6), changed the *p_uptake* baseline to

0.005, lowered the USS score cutoff from 10.0 bits to 9.5 bits, and ran the model again. The

purple points in Figure 6 show that, although peak-height predictions for low-scoring USS were

somewhat improved by the changed *p_uptake* function, those for USS with scores > 11.5 bits

became slightly worse; the least-squares difference for the 209 positions was modestly reduced

from 0.521 to 0.420.

We initially suspected that the over-prediction of peak heights might be due to overestimating

the proportion of very short fragments in the input DNA, but eliminating the contributions of

fragments shorter than 80 bp had very little effect on predicted peak heights. (This is likely

because these fragments contribute little DNA and rarely contain USS.) We then considered an

alternative explanation, that USS might be ineffective when they were very close to fragment

ends. The red dots in Figure 6 shows that requiring USS to be at least 50 bp from fragment ends

lowered predicted peak heights to the mean observed height while maintaining a low baseline

uptake. Distances of 30 bp and 70 bp were also tested, but gave peaks that were, respectively,

too high and not high enough. Incorporating this modification into the model barely changed

the least-squares difference of its predictions with the observed uptake ratios (0.93, up from

0.92), but dramatically reduced the least-squares difference from 0.420 to 0.052. This revised

model was used by the analyses described below.

The above analyses do not explain why many uptake ratio peaks were substantially higher or

lower than predicted by their USS score. The scatter is unlikely to be due to noise alone, since

more extreme smoothing of the uptake ratio data with windows as large as 150 bp improved

the correlation by only 0.001. Below we consider three other factors that might influence DNA

uptake: weak non-USS uptake biases, effects of interactions between bases at different

positions in the USS, and effects of DNA shape.

Weak uptake biases could arise from either low-scoring USS or non-USS sequence factors. Since

weak biases would only be detectable in genome segments that lack strong USSs, we searched

for them using a far-from-USS$_{10}$ dataset containing only DNA segments whose ends were at

least 0.6kb from the closest USS$_{10}$ and that had input coverage of at least 20 reads. This dataset

contained 513 segments where weak uptake effects could in principle be detected (22% of the

genome); their mean uptake ratio over the 428678 positions was 0.0102. In these segments,

the only positions with distinct uptake ratio peaks >0.2 were 9 weak USSs with scores between

9.5 and 9.9 bits (an example is shown in panel C of Figure S5). Since this analysis did not find

any non-USS positions giving uptake higher than 0.2, it suggests that other sequence factors do

not detectably promote uptake in the absence of a USS.

The degenerate-USS analysis of Mell *et al.* (Mell et al., 2012) found that pairwise interactions

between the AT-tract bases and core bases of a USS made substantial contributions to uptake

of a 200 bp synthetic fragment. To evaluate the effects of these interactions in predicting

uptake of genomic DNA, the USS scores used by our revised model were raised or lowered in

proportion to the interaction effects reported in Figure 6 of Mell *et al*. Figure 7 shows that, for

the same 209 isolated USS$_{9.5}$s used above (Figure 6), this adjustment had little effect on high-

scoring USS but further reduced the scores of low-scoring USS. The data points are coloured by

their uptake ratios, showing that weak USS giving unusually high or low uptake were equally

likely to have their scores reduced. However, these scoring changes had no effect on the short-

fragment uptake predictions of the revised model (both Pearson correlations 0.93), probably

because (i) the scores of strong USS were not significantly changed and (ii) the scores of weak

USS already gave near-baseline uptake.

DNA shape effects: Most of the interactions in Figure 7 were between bases separated by 10

bp or more, so we complemented that analysis with analysis of DNA shape, which reflects both

pairwise and more complex interactions over a 5 bp range. The major shape features that can

be predicted from DNA sequence are the minor groove width, the propeller twist between two

paired bases, the helix twist between one base pair and the next, and the roll of one base pair

relative to the next. In Figure 8, the wide grey line reproduced in each panel shows these

feature predictions for the consensus USS. The USS inner core (orange shading) has a relatively

wide minor groove and high propeller twist, which would facilitate sequence recognition by

proteins (Rohs et al., 2009). To the left of this and in both AT-tracts (yellow shading) the minor

groove is narrow with low propeller twist and negative roll, predicting that these segments are

both rigid and slightly bent.

To see if shape features affect uptake in ways that were not captured by scores alone, we

compared the shape features of subsets of the 209 isolated USS with similar scores but

different uptake ratios. Panels A-D of Figure 8 compare the shape features of very weak USS

(USS$_{9.5-10}$) whose uptake ratios were either low (<0.6, blue lines) or high (>2.0, orange lines).

Similarly, panels E-H and I-L show the same comparisons for USSs with low and moderate

scores (USS$_{10-10.5}$ and USS$_{10.5-11}$ respectively). USSs with scores higher than 11 bits were not

analyzed since they did not exhibit enough uptake variation to reveal correlations between

uptake and DNA shape.

In all three score subsets the inner-core shape features were very similar for low-uptake and

high-uptake subsets (blue and orange lines), probably because this sequence perfectly matches

the consensus in 206 of the 209 USS$_{9.5}$. (The other three had otherwise-perfect core sequences

and good AT tracts but had only baseline uptake ratios.) However, the AT-tract shapes had

marked differences, with low-uptake USSs having no distinctive shape features and high-uptake

USSs resembling the USS consensus shape. This suggests that the predicted rigidity and slight

bend caused by interactions within the consensus AT tracts facilitate DNA uptake.

Uptake of fragments with more than one USS: Many genomic USSs are sufficiently close that

they will co-occur even on short DNA fragments; 23% of 86-028NP USS$_{10}$s are within 100 bp of

another USS$_{10}$, and 17% are within 30 bp (Figure S9A**)**. Fragments with multiple USS might be

expected to have relatively high uptake, since they provide more targets to which the uptake

machinery receptor could bind, but only one of the two previous studies in *Neisseria* found this

effect (Ambur et al., 2007; Goodman and Scocca, 1991).

Visual examination of uptake ratio maps around the 230 pairs of 86-028NP USS$_{10}$s within 100

bp found only single peaks; Figure S9B shows that the midpoints of these USS pairs (red and

green points) have very similar uptake ratios to those of the 209 isolated USSs (pale blue

points). Figure S5 panels E and F show examples of peaks at USS pairs separated by 69 bp and

230 bp.

A special subclass of USS pairs consists of oppositely oriented pairs that are so close that they

overlap; these can form RNA hairpins and are usually located at the ends of genes where they

act as transcriptional terminators (Kingsford et al., 2007; Smith et al., 1995, 1999). Figure S9A

shows that the 86-028NP genome has 109 USS$_{10}$ pairs whose centers are within 14 bp: 69 in the

-/+ orientation, all 0-3 bp apart, and 40 in the +/- orientation, all 10-14 bp apart. The green

points in Figure S9B shows that midpoint uptake ratios of these pairs were very similar to those

of other pairs or at isolated USS$_{10}$s with similar scores.

Overall, these results indicate that the presence of two USS$_{10}$s within 100 bp does not

detectably increase the probability of the receptor binding to a USS, a result consistent with

that of Ambur *et al.* for pairs of closely spaced DUS in *Neisseria meningitidis* (Ambur et al.,

2007). Because individual fragments were not tracked, we cannot make any conclusions about

uptake of fragments with more widely separated USS.

Uptake of long-fragment 86-028NP DNA

Figure 9A compares the revised model's predictions for long-fragment 86-028NP DNA with the

uptake ratios observed over the same 50kb genome segment as in Figure 3B. In contrast to

predictions for short-fragment uptake (correlation of 0.93), it seriously underpredicted the

variation in long-fragment uptake ratios (correlation of 0.60). Although 51% of 86-028NP

positions had long-fragment uptake ratios lower than 0.8 or higher than 1.2, only 13% had

predicted uptake outside these limits.

Because long-fragment uptake ratios lacked the dramatic peaks and valleys seen for short-

fragments, stochastic noise arising at the regions of low sequencing coverage described earlier

was expected to play a larger role. To estimate the magnitude of this effect, we compared the

effects of adding different amounts of artificially generated noise to simulated (noise-free)

uptake data (Figure S10A shows examples of noise-free and noise-added coverages). Figure

S10B shows that, as expected, the correlation between noisy and noise-free data worsened as

the arbitrary level of noise increased for both short-fragment (blue) and long-fragment (red)

simulations, and that increasing noise had a much stronger effect on the long-fragment

simulations. For short DNA fragments, simulations with noise levels of 2 and 2.5 gave

correlations of 0.94 and 0.92, very close to the 0.93 correlation between the revised model and

the real data. (dashed blue line in Fig. S9B) For long DNA fragments with the same noise levels,

more noise was needed, with a 3.0 multiplier giving a correlation of 0.56, slightly lower than the

observed correlation of 0.60 (dashed red line in Fig. S9B). This confirms that the disparities

between measured uptake ratios and USS-based predictions were at least partially due to noise

in the sequencing data. However, these correlations are still 21% and 10% higher than the best

correlation obtained between the revised model's predictions and real data.

One notable feature of the long-fragment uptake ratio maps in Figure 3B and 9A is the presence

of occasional spikes of unusually high uptake, *e.g.* at position 18,540 (examples are shown in

panels G and H of Figure S5). These spikes were much narrower than expected for true uptake

biases acting on long DNA fragments, so they were likely due to stochastic differences between

input and uptake coverage in regions of low coverage, not to true differences in uptake.

Consistent with this explanation, 70.4% of positions with uptake ratios greater than 2.0 had

coverage less than 100 reads, compared to only 8% of positions with more typical uptake ratios

between 0.5 and 2. Table S3 shows analysis of the distribution of uptake extremes at positions

with different levels of sequencing coverage, and panels I and J of Figure S5 show the low

coverage at the example spikes. However, this explanation did not apply to most positions with

very low uptake, which were in broad segments with few or weak USS, not in narrow spikes at

low coverage positions, and thus likely reflect genuinely low uptake.

Prediction of uptake of PittGG DNA

Since the uptake model was refined using uptake data for DNA of strain 86-028NP, the revised

model's predictions were assessed using uptake data for DNA of a different strain, PittGG,

which differs from 86-028NP DNA by SNPs and indels affecting about 11% of its genome. Figure

S11 compares the uptake predictions with the observed PittGG uptake ratios. For short-

fragment data the peak heights and valley depths were similar to those for 86-028NP, as was

the Pearson correlation between predicted and observed uptake (0.92). Although the model

predicted similar long-fragment variation for 86-028NP and PittGG, the PittGG experimental

data showed more extreme variation, and the correlation was only 0.41, substantially worse

than the 0.60 obtained for 86-028NP. As with the 86-028NP data, much of this discrepancy may

be due to noise in regions of low sequencing coverage. However this may not fully explain

PittGG's lower correlation, because input samples of the two strains had similar frequencies of

low-coverage positions (Table 2.2).

Predicted competition with other DNAs in the human respiratory tract

H. influenzae's natural environment is the human respiratory tract, where its DNA must

compete for uptake with DNAs from other bacteria, and with host-derived DNA whose

concentration in respiratory mucus of healthy individuals can exceed 300 µg/ml (Lethem et al.,

1990; Shak et al., 1990). The revised model was used to investigate this competition.

Table 2 lists the frequencies of USS_{10} and USS_{11} in the genomes of various species.

Pasteurellaceae species that share *H. influenzae*'s *Hin*-type USS (*e.g. H. parainfluenzae* and

Aggregatibacter actinomycetemcomitans) typically have about 1000 USS_{10}s per Mb (Redfield

2006); most of these are strong USS with scores ≥ 11. Pasteurellaceae with the *Apl*-type USS

(*e.g. H. ducreyi* and *Mannheimia haemolytica*) have about tenfold fewer *Hin*-type USS_{10}s, and

fewer than 20% of these are strong. Other common respiratory tract bacteria (*e.g. N.*

meningitidis, Streptococcus pneumonia and *Pseudomonas aeruginosa*) have USS only at the

frequencies expected for their base compositions. The human genome is exceptional in having

about 5-fold *fewer* USS_{10} per Mb than expected from simulated sequences with the 41% GC

content of human DNA (observed frequency 4.6/Mb, simulated frequency 30/Mb, both with

mean scores of only 10.3 bits). Since the USS inner-core motif includes a CpG, the

underrepresentation of USS_{10} in human DNA relative to simulated sequences is probably a

consequence of the 4-5 fold depletion of CpGs in the human genome caused by deamination of

methylated cytosines (Babenko et al., 2017; Bird, 1986).

To estimate how strongly these DNAs would compete with *H. influenzae* DNA for uptake by *H.*

influenzae cells, we concatenated the 86-028NP genome with each of two Pasteurellacean

genomes and with three 1.9 Mb segments of the human genome, and used the revised uptake

model to predict relative uptake. The respiratory pathogen *H. parainfluenzae* was used as the

Hin-type USS representative. The genital pathogen *H. ducreyi* was used as a representative

species with *Apl*-type USSs, since none occur in the human respiratory tract, and segments of

human DNA also served to represent non-Pasteurellacean bacteria. To approximate the lengths

of DNA fragments in the respiratory tract (Lethem et al., 1990; Shak et al., 1990), the model was

run using fixed fragment lengths of 1kb and 10kb, and because human DNA will contain many

fragments lacking USSs, the predictions were made with and without the model's *p_uptake*

baseline binding probability of 0.005. For each genome in the concatenated sequence, the

predicted uptake at every position was then summed to get a total genome uptake value for

each fragment length and baseline assumption.

Table 3 shows the relative amounts of *H. influenzae* DNA predicted to be taken up under the

various competition conditions. As expected from published uptake-competition experiments

(Albritton et al., 1984; Redfield et al., 2006), *H. influenzae* and *H. parainfluenzae* DNAs were

taken up with equal efficiency in all simulated conditions, and *H. ducreyi* DNA was much less

competitive, contributing only 5% of the 1 kb fragments and only 12% of the 10 kb fragments.

With human DNA as the 1:1 competitor, more than 99% of the DNA taken up was predicted to

be from *H. influenzae*. For all competing DNAs, baseline uptake of fragments containing no USS

made only a tiny contribution.

DISCUSSION

DNA uptake by competent *H. influenzae* Rd cells was measured at every position in the

genomes of two divergent *H. influenzae* strains, using short-fragment and long-fragment DNA

preparations. Differences between observed uptake and that predicted by a computational

model of USS-dependent uptake revealed the strength of the uptake machinery's bias towards

USS and the absence of other sequence biases. These findings increased our understanding of

DNA uptake bias and its potential effects on the distribution of recombination.

Implications for DNA uptake

The USS motif: The measured discrimination' for USS was very strong; with short DNA

fragments, valleys at USS-free segments had ~1000-fold lower uptake ratios than peaks at high-

scoring USS. This non-zero baseline is unlikely to be due to residual contamination by recipient

DNA, since valley depths were similar for segments with and without Rd homology (Figure 4).

One surprising finding of Mell et al.'s (2012) work was the difference between the inner-core

uptake motif identified by their degenerate-USS experiments (Figure 1A) and the extended

motif of USS sequences in the *H. influenzae* genome (Figure 1B). Our analysis confirmed that

uptake absolutely requires a perfect match to the inner core, but found that this was not

sufficient to raise uptake above baseline, even if the rest of the core was perfectly matched.

Effect of USS shape: The predicted shape differences between similarly-scoring USSs that gave

strong or weak uptake (Figure 8) suggest a preference for USS that are rigidly bent at AT-tracts

and the outer core (Harteis and Schneider, 2014; Rohs et al., 2009). Similar preferences have

been described for several DNA binding proteins and have been associated with specific binding

by arginine or lysine residues to narrow minor grooves (Rohs et al., 2009; Stella et al., 2010).

These features have been integrated successfully in some transcription factor binding models

(Li et al., 2017), but using them to improve uptake prediction will require more comprehensive

investigation into the effects of DNA shape on uptake. The stiffness also suggests that the initial

passage of DNA through the secretin pore may be facilitated by transient strand melting at or

beside the USS rather than by bending (Danner et al., 1982).

Other USS effects on DNA uptake: Comparison of predicted and measured heights of uptake

peaks suggested that USSs were ineffective when located very close to fragment ends. This

would be consistent with experimental evidence that uptake initiates internally rather than at

fragment ends(Barany et al., 1983), but would need to be experimentally investigated. The

presence of two USSs within 100 bp did not detectably increase uptake, a finding consistent

with Ambur *et al.*'s (Ambur et al., 2007) study of very close uptake sequences in *Neisseri*a.

Lack of USS-independent effects: The very low valleys between short-fragment uptake peaks

allowed us to examine more than 400,000 positions for USS-independent increases in uptake.

None were found; the only positions with distinct uptake ratio peaks >0.2 were 9 weak USSs.

Implications for genetic exchange

Preferential uptake of USS can create variation in recombination at all levels: across a single

genome, between strains of one species, and between both closely related and unrelated

species. Pifer & Smith showed that transformation frequency in *H. influenzae* decreased

exponentially when fragments were smaller than 3.5 kb*.* This decrease was attributed to

exonuclease degradation of fragments from their 3' ends, since similar numbers of short and

long fragments were taken up, only 5'-end label was incorporated into the chromosome, short

fragments transformed more efficiently when the selected marker was far from one end*.* Mell

(2014) used genome sequencing of inter-strain recombinants to examine the distribution of

recombination tract lengths; despite the presence of 2-3% SNPs, the mean tract length was 6.9

kb and the longest was 43 kb. The efficient uptake and recombination of long fragments allows

fragments containing non-homologous segments to still recombine well, provided both

fragment ends are homologous. Fragments with only one homologous end recombine much

less efficiently ('homology-facilitated recombination' (de Vries and Wackernagel, 2002)), and

integration of fragments with no homology is very rare.

Across the genome: Across the genome of a *H. influenzae* strain, the genetic consequences of

USS-dependent DNA uptake depend on USS locations and on the lengths of the available DNA

fragments. If only short fragments are available, the limitation to positions close to a USS may

be obscured by limitation caused by degradation of incoming DNA in the cytoplasm. If most

fragments are long, recombination will be both more frequent and more evenly distributed

across the genome, because long fragments are more likely to both contain USS and

recombine. The result will be that almost all recombination is caused by fragments long enough

to usually contain at least one strong USS. This situation is caused by the high abundance and

relatively even distribution of genomic USS, itself an expected consequence of the functionally

neutral accumulation of USS under a molecular drive caused by USS-biased DNA uptake

(Danner et al., 1982; Maughan et al., 2010).

Recombination between _H. influenzae_ strains: On average about 85% of the genomes of _H._

influenzae strains are homologous, with sequence divergence low enough to have only a

modest effect on recombination frequencies (Mell et al., 2011). On average, genome segments

that are absent from other strains have lower density of USS (0.58/kb vs 1.08/kb for sequences

present in 86-028NP but absent from Rd. Only some of these will be segments newly acquired

from species without USS. If a non-homologous segment introduced into one strain by

conjugation or transduction is beneficial, the USSs in adjacent DNA will help it efficiently spread

to other strains by transformation.

Recombination between Pasteurellaceae species: Uptake of DNA from related species can also

influence recombination, either directly if the DNA is sufficiently similar to recombine with the

H. influenzae genome, or indirectly if it successfully competes with _H. influenzae_ DNA for

uptake or, once inside the cell, for access to nucleases or recombination machinery. For _H._

influenzae the most important competition will be with other Pasteurellaceae that share both

the respiratory tract niche and the _Hin_-type USS, but similar effects are expected for

Pasteurellaceae in other host species.

Competition with DNAs from human cells and other respiratory bacteria:

In the respiratory tract, the most important source of competing DNA is human cells. However,

our analysis suggests that _H. influenzae_'s uptake specificity allows its DNA to outcompete

human and other foreign DNAs even if these are in 100-fold excess, a combined effect of the

low number of USS_{10}s and their poor match to the uptake motif. Note that efficient self-uptake

does not necessarily imply a selective advantage, since USS accumulation in *H. influenzae*'s

genome may simply be due to the molecular drive process.

Uptake of DNA in the respiratory track could also be influenced by the presence of chromatin

and nucleoid proteins stably bound to the DNA. Although laboratory experiments typically use

highly purified DNA, DNA released by cell death will be coated with these proteins, which can

contribute significantly to biofilm stability (Brockman et al., 2018). Because such proteins could

interfere with uptake both directly, by blocking binding to the USS, and indirectly, by blocking

sliding of non-specifically bound uptake machinery along the DNA, it will be important to re-

examine DNA uptake using DNA that retains its bound proteins.

LIMITATIONS OF THE STUDY

Three factors limited measurements of uptake ratios: low sequencing read coverage,

contamination of recovered donor DNA with recipient DNA, and segments of sequence identity

between donor and recipient. Many reads had to be excluded at the contamination-correction

step, because they were in segments that were either identical between donor and recipient or

were repeated within the donor genome. Strong sequence-dependent variation in read

coverage caused other positions to be excluded from analysis because they had no coverage in

the control input sample. Overall, 2.3% of the genome was excluded from analysis, and an

additional 1.7% was flagged as unreliable due to low coverage. In addition, the stochastic

variation at low coverage positions introduced substantial noise into the calculation of

experimental uptake ratios, especially at uptake valleys. On the other hand, the model

predictions for long-fragment may be more accurate than indicated by their modest correlation

with the noisy measured uptake ratios.

RESOURCE AVAILABILITY

Lead Contact:

Further information and requests should be directed to and will be fulfilled by the Lead Contact.

Rosemary J. Redfield (redfield@zoology.ubc.ca)

Materials Availability:

All bacterial strains are available from Joshua Chang Mell (joshua.mell@drexelmed.edu).

Data and Code Availability:

All fastQ files have been deposited at NCBI under BioProject PRJNA387591. The corresponding

BioSamples are listed in Table S2. FastQ files were also deposited at Mendeley data

(DOI:10.17632/hcxp9d4zkf.1. Available at https://data.mendeley.com/datasets/hcxp9d4zkf/1).

The PacBio-sequenced PittGG genome reference was deposited into Genbank under SRA

number SRR10207558. Full calculations, and R scripts are available

at: https://github.com/mamora/DNA_uptake.

ACKNOWLEDGEMENTS

Financial support for this work was provided by the National Science and Engineering Research

Council of Canada (to RJR) and by the National Institutes of Health (to GDE (5R01DC002148-

21)). We thank the Drexel Genomic Core Facility for DNA sequencing, Rachel Simister for her

assistance with the bioanalyzer fragment analysis, and Matt Pennell, Sally Otto, Stephen Hallam

and David Baltrus for advice on the manuscript. We also thank two anonymous reviewers for

their very helpful comments, and the Editor for their patience during the revisions.

AUTHOR CONTRIBUTIONS

MM, JCM and RJR designed the experiments and analysis. MM performed the experiments and

most of the analyses; JCM and RJR performed the remaining analyses. Sequencing was done in

the laboratory of GDE; data curation by RLE, JCM and MM. RJR and MM wrote the manuscript

with input from the other authors.

DECLARATIONS OF INTERESTS

The authors declare no competing interests.

REFERENCES

Albritton, W.L., Setlow, J.K., Thomas, M., Sottnek, F., and Steigerwalt, A.G. (1984).
Heterospecific transformation in the genus Haemophilus. Mol. Gen. Genet. 193, 358–363.

Ambur, O.H., Frye, S.A., and Tønjum, T. (2007). New functional identity for the DNA uptake
sequence in transformation and its presence in transcriptional terminators. J. Bacteriol. 189,
2077–2085.

Babenko, V.N., Chadaeva, I. V, and Orlov, Y.L. (2017). Genomic landscape of CpG rich elements
in human. BMC Evol. Biol. 17, 19.

Bae, J., Oh, E., and Jeon, B. (2014). Enhanced transmission of antibiotic resistance in
Campylobacter jejuni biofilms by natural transformation. Antimicrob. Agents Chemother. 58,
7573–7575.

Barany, F., Kahn, M.E., and Smith, H.O. (1983). Directional transport and integration of donor
DNA in Haemophilus influenzae transformation. Proc Natl Acad Sci U S A 80, 7274–7278.

Barouki, R., and Smith, H.O. (1985). Reexamination of phenotypic defects in rec-1 and rec-2
mutants of Haemophilus influenzae Rd. J. Bacteriol. 163, 629–634.

Bird, A.P. (1986). CpG-rich islands and the function of DNA methylation. Nature 321, 209–213.

Brockman, K.L., Azzari, P.N., Taylor Branstool, M., Atack, J.M., Schulz, B.L., Jen, F.E.-C., Jennings,
M.P., and Bakaletz, L.O. (2018). Epigenetic regulation alters biofilm architecture and
composition in multiple clinical isolates of Nontypeable Haemophilus influenzae. MBio 9,
e01682-18.

Chen, I., and Dubnau, D. (2004). DNA uptake during bacterial transformation. Nat. Rev.
Microbiol. 2, 241–249.

Danner, D.B., Deich, R. a, Sisco, K.L., and Smith, H.O. (1980). An eleven-base-pair sequence
determines the specificity of DNA uptake in Haemophilus transformation. Gene 11, 311–318.

Danner, D.B., Smith, H.O., and Narang, S.A. (1982). Construction of DNA recognition sites active
in Haemophilus transformation. Proc. Natl. Acad. Sci. U. S. A. 79, 2393–2397.

Davidsen, T., Rødland, E.A., Lagesen, K., Seeberg, E., Rognes, T., and Tønjum, T. (2004). Biased
distribution of DNA uptake sequences towards genome maintenance genes. Nucleic Acids Res.
32, 1050–1058.

Dougherty, T.J., Asmus, A., and Tomasz, A. (1979). Specificity of DNA uptake in genetic
transformation of gonococci. Biochem. Biophys. Res. Commun. 86, 97–104.

Findlay, W.A., and Redfield, R.J. (2009). Coevolution of DNA uptake sequences and bacterial
proteomes. Genome Biol. Evol. 1, 45–55.

Frye, S.A., Nilsen, M., Tønjum, T., and Ambur, O.H. (2013). Dialects of the DNA uptake sequence
in Neisseriaceae. PLOS Genet. 9, e1003458.

Goodgal, S.H. (1982). DNA uptake in Haemophilus transformation. Annu. Rev. Genet. 16, 169–
192.

Goodman, S.D., and Scocca, J.J. (1991). Factors influencing the specific interaction of Neisseria
gonorrhoeae with transforming DNA. J. Bacteriol. 173, 5921–5923.

Halford, S.E., and Marko, J.F. (2004). How do site-specific DNA-binding proteins find their
targets? Nucleic Acids Res. 32, 3040–3052.

Harrison, A., Dyer, D.W., Gillaspy, A., Ray, W.C., Mungur, R., Carson, M.B., Zhong, H., Gipson, J.,
Gipson, M., Johnson, L.S., et al. (2005). Genomic sequence of an otitis media isolate of
nontypeable Haemophilus influenzae: Comparative study with H. influenzae serotype d, strain
KW20. J. Bacteriol. 187, 4627–4636.

Harteis, S., and Schneider, S. (2014). Making the bend: DNA tertiary structure and protein-DNA
interactions. Int. J. Mol. Sci. 15, 12335–12363.

Hepp, C., and Maier, B. (2016). Kinetics of DNA uptake during transformation provide evidence
for a translocation ratchet mechanism. Proc. Natl. Acad. Sci. U. S. A. 113, 12467–12472.

Hogg, J.S., Hu, F.Z., Janto, B., Boissy, R., Hayes, J., Keefe, R., Post, J.C., and Ehrlich, G.D. (2007).
Characterization and modeling of the Haemophilus influenzae core and supragenomes based
on the complete genomic sequences of Rd and 12 clinical nontypeable strains. Genome Biol. 8,
R103.

Kahn, M.E., Barany, F., and Smith, H.O. (1983). Transformasomes: specialized membranous
structures that protect DNA during Haemophilus transformation. Proc. Natl. Acad. Sci. U. S. A.
80, 6927–6931.

Kingsford, C.L., Ayanbule, K., and Salzberg, S.L. (2007). Rapid, accurate, computational discovery
of Rho-independent transcription terminators illuminates their relationship to DNA uptake.
Genome Biol. 8, 1–12.

Kress-Bennett, J.M., Hiller, N.L., Eutsey, R.A., Powell, E., Longwell, J., Hillman, T., Blackwell, T.,
Byers, B., Mell, J.C., Post, J.C., et al. (2016). Identification and characterization of msf , a novel
virulence factor in Haemophilus influenzae. PLoS One 11, e0149891.

Lethem, M., James, S.L., Marriott, C., and Burke, J.F. (1990). The origin of DNA associated with
mucus glycoproteins in cystic fibrosis sputum. Eur. Respir. J. 3, 19–23.

Li, J., Sagendorf, J.M., Chiu, T.P., Pasi, M., Perez, A., and Rohs, R. (2017). Expanding the
repertoire of DNA shape features for genome-scale studies of transcription factor binding.
Nucleic Acids Res. 45, 12877–12887.

Lorenz, M.G., and Wackernagel, W. (1994). Bacterial gene transfer by natural genetic

transformation in the environment. Microbiol. Rev. 58, 563–602.

Man, W.H., De Steenhuijsen Piters, W.A.A., and Bogaert, D. (2017). The microbiota of the

respiratory tract: Gatekeeper to respiratory health. Nat. Rev. Microbiol. 15, 259–270.

Mathis, L.S., and Scocca, J.J. (1982). Recognize different specificity determinants in the DNA

uptake step of genetic transformation. J. Gen. Microbiol. 128, 1159–1161.

Maughan, H., and Redfield, R.J. (2009). Extensive variation in natural competence in

haemophilus influenzae. Evolution. 63, 1852–1866.

Maughan, H., Wilson, L.A., and Redfield, R.J. (2010). Bacterial DNA uptake sequences can

accumulate by molecular drive alone. Genetics 186, 613–627.

Mell, J.C., and Redfield, R.J. (2014). Natural competence and the evolution of DNA uptake

specificity. J. Bacteriol. 196, 1471–1483.

Mell, J.C., Shumilina, S., Hall, I.M., and Redfield, R.J. (2011). Transformation of natural genetic

variation into Haemophilus Influenzae genomes. PLoS Pathog. 7, e1002151.

Mell, J.C., Hall, I.M., and Redfield, R.J. (2012). Defining the DNA uptake specificity of naturally

competent Haemophilus influenzae cells. Nucleic Acids Res. 40, 8536–8549.

Mell, J.C., Viadas, C., Moleres, J., Sinha, S., Fernández-Calvet, A., Porsch, E.A., St. Geme, J.W.,

Nislow, C., Redfield, R.J., and Garmendia, J. (2016). Transformed recombinant enrichment

profiling rapidly Identifies HMW1 as an intracellular invasion locus in Haemophilus influenza.

PLoS Pathog. 12, e1005576.

Mrazek, J. (2010). Comparative analysis of sequence periodicity among prokaryotic genomes

points to differences in nucleoid structure and a relationship to gene expression. J. Bacteriol.

192, 3763–3772.

Pifer, M.L., and Smith, H.O. (1985). Processing of donor DNA during Haemophilus influenzae

transformation: analysis using a model plasmid system. Proc. Natl. Acad. Sci. U. S. A. 82, 3731–

3735.

Redfield, R.J., Findlay, W.A., Bossé, J., Kroll, J.S., Cameron, A.D.S., and Nash, J.H.E. (2006).

Evolution of competence and DNA uptake specificity in the Pasteurellaceae. BMC Evol. Biol. 6,

1–15.

Rohs, R., West, S.M., Sosinsky, A., Liu, P., Mann, R.S., and Honig, B. (2009). The role of DNA

shape in protein-DNA recognition. Nature 461, 1248–1253.

Rohs, R., Jin, X., West, S.M., Joshi, R., Honig, B., and Mann, R.S. (2010). Origins of specificity in

protein-DNA recognition. Annu. Rev. Biochem. 79, 233–269.

Salzer, R., Kern, T., Joos, F., and Averhoff, B. (2016). The Thermus thermophilus comEA / comEC

operon is associated with DNA binding and regulation of the DNA translocator and type IV pili.

Environ. Microbiol. 18, 65–74.

Scocca, J.J., Poland, R.L., and Zoon, K.C. (1974). Specificity in deoxyribonucleic acid uptake by

transformable Haemophilus influenzae. J. Bacteriol. 118, 369–373.

Shak, S., Capon, D.J., Hellmiss, R., Marsters, S.A., and Baker, C.L. (1990). Recombinant human

DNase I reduces the viscosity of cystic fibrosis sputum. Proc. Natl. Acad. Sci. U. S. A. 87, 9188–

9192.

Sisco, K.L., and Smith, H.O. (1979). Sequence-specific DNA uptake in Haemophilus

transformation. Proc. Natl. Acad. Sci. U. S. A. 76, 972–976.

Smith, H.O., Tomb, J.F., Dougherty, B.A., Fleischmann, R.D., and Venter, J.C. (1995). Frequency

and distribution of DNA uptake signal sequences in the Haemophilus influenzae Rd genome.

Science. 269, 538–540.

Smith, H.O., Gwinn, M.L., and Salzberg, S.L. (1999). DNA uptake signal sequences in naturally

transformable bacteria. Res. Microbiol. 150, 603–616.

Stella, S., Cascio, D., and Johnson, R.C. (2010). The shape of the DNA minor groove directs

binding by the DNA-bending protein Fis. Genes Dev. 24, 814–826.

Straume, D., Stamsås, G.A., and Håvarstein, L.S. (2015). Natural transformation and genome

evolution in Streptococcus pneumoniae. Infect. Genet. Evol. 33, 371–380.

de Vries, J., and Wackernagel, W. (2002). Integration of foreign DNA during natural

transformation of Acinetobacter sp. by homology-facilitated illegitimate recombination. Proc.

Natl. Acad. Sci. 99, 2094–2099.

de Vries, J., Meier, P., and Wackernagel, W. (2001). The natural transformation of the soil

bacteria Pseudomonas stutzeri and Acinetobacter sp. by transgenic plant DNA strictly depends

on homologous sequences in the recipient cells. FEMS Microbiol. Lett. 195, 211–215.

FIGURES:

Figure 1. The *H. influenzae* uptake signal sequence.

Legend: A. Sequence logo showing the individual contributions to genomic abundance of bases

in the USS motif (Maughan 2010). **B.** Sequence logo showing the individual contributions to

uptake of bases in the USS motif, as measured by Mell *et al*. **C.** Conserved USS segments. See

also Figure S1.

Figure 2. A computational model to predict DNA uptake.

Legend: A. Components of the DNA uptake model (see Transparent Methods and Results for

details). **B. & C.** Model predictions for uptake centered at a 12-bit USS for: **B**. 100, 200, and 300

bp fragments, **C**. a mixed distribution of fragments between 25-300 bp with and without

baseline uptake. **D. E. & F.** Model predictions for uptake of a 3000 bp region with 3 USSs (red

squares, scores in black) using different fragment-length distributions: **D**. 50-300 bp fragments,

E. 50-2000 bp fragment, **F.** 1-14 kb fragments. **G. & H.** Predicted DNA uptake of a 50 kb

segment of the 86-028NP genome using **G.** short and **H.** long fragment-length distributions: **I.**

Locations and scores of USS_{10}s in this 50 kb segment. See also Table S1 and Figures S1 and S2.

Figure 3. Experimentally determined uptake ratios for a 50 kb segment.

Legend: The X-axis is the same 50 kb segment of the 86-028NP genome as Figure 2G and H.

Grey points indicate positions with input coverage lower than 20 reads. Gaps indicate

unmappable segments. **A.** Uptake ratios of short-fragment DNA. **Inset:** Same data with a

logarithmic-scale Y-axis. **B.** Uptake ratios of long-fragment DNA. **C.** Locations and scores of

USS_{10}s. See also Figures S3 and S4.

Figure 4. Depths of uptake ratio valleys with and without contamination correction.

Legend: Uptake ratios of positions in the 86-028NP short-fragment dataset that were at least

1kb from the nearest $USS_{9.5}$ and whose uptake coverages were either corrected for

contamination with homologous Rd sequences (left, 272,547 positions) or not corrected for

contamination because they had no Rd homology (right, 89,418 positions). Orange and red

dashed lines indicate valley uptake predicted by the original and revised models respectively.

See also Figure S6.

Figure 5. Predicted and observed DNA uptake analysis for short fragments of 86-028NP DNA.

Legend: A. Map of uptake ratios and initial model predictions. The blue points show the same

uptake ratio map as in Figure 3A. The orange points show the same predicted uptake as in

Figure 2G. **B.** Locations and scores of USS$_{9.5}$s.

Figure 6. Short-fragment uptake ratios and predicted DNA uptake at isolated 86-028NP USS as a

function of USS score.

Legend: Predicted or measured DNA uptake at 209 $USS_{9.5}$ positions separated by at least 1000

bp from the nearest $USS_{10}s$. The blue dots show the measured uptake ratios; grey bars show

the ranges of the three replicates at each position. The blue line shows a sigmoidal function fit

to these points. The small orange dots and line show uptake predicted by the original model at

the same positions, and the small purple and red dots show uptake predicted by the

intermediate and revised model versions discussed in the text. See also Figure S6.

Figure 7. Effects of within-USS interactions on USS scores.

Legend: USS scores calculated with and without interactions effects for 209 isolated 86-028Np

$USS_{9.5}s$ (see Methods for details). Red line shows expected scores if the interactions had no

effect. Point color indicates the uptake ratios at the USS: yellow, <0.01; red, 0.01-0.1; purple,

0.1-0.5; blue 0.5-1.5; green, >1.5.

Figure 8. Predicted shape features of USS.

Legend: The thick grey line reproduced in each box shows shape analysis of the consensus USS sequence. Blue and orange lines in each box show shape analysis of genomic USS separated by at least 500 bp, grouped by score and coloured by uptake ratio. The orange and yellow bars below each box indicate components of the USS (see Figure 1): light orange: outer core; dark orange: inner core; yellow: AT tracts. **Panels A-D** USS$_{9.5-10}$: Blue: uptake ratios <0.2 (n=68, mean USS score =9.7). Orange: uptake ratios >0.2 (n = 10, mean USS score =9.8). **Panels E-H:** USS$_{10.0-10.5}$: Blue: uptake ratios <0.6 (n=47, mean USS score=10.22). Orange: uptake ratios >2.0 (n=10, mean USS score=10.26). **Panels I-L:** USS$_{10.5-11.0}$: Blue: uptake ratios <0.6 (n=14, mean USS score=10.64). Orange: uptake ratios >2.0 (n=59, mean USS score=10.79). **A, E and I.** Minor groove width, in Å. **B, F and J**. Propeller twist, in degrees. **C, G and K**. Helix twist, in degrees. **D, G and L**. Base pair roll, in degrees. See also Figure S6. Grey bars for each point show the standard error. Dots indicate significant differences by Kolmogorov-Smirnov between high-uptake and low-uptake positions with (red dots) and without (black dots) Bonferroni correction.

Figure 9. Predicted and observed uptake of long 86-028NP DNA fragments.

Legend: A. and C. Uptake maps for 86-028NP long-fragment DNA. Orange points: USS-

dependent uptake predicted by the revised model. Blue points: mean uptake ratios from 3

replicate experiments (grey indicates input coverage <20 reads, gaps indicate unmappable

positions). **B.** and **D.** $USS_{9.5}$ positions and scores. **A. and B.** The same 50 kb genome segment

shown in previous figures. **C. and D.** Whole genome.

885
886

 TABLES:

890 **Table 1. Bacterial strains used in this study**

Strain number	Strain name	Phenotype	Source
RR3117	*rec2::spec*	Spectinomycin resistant Rd derivative. No translocation of taken-up fragments to the cytoplasm	Sinha *et al.* 2012
RR3125	*Rd Δrec2*	Unmarked Rd derivative. No translocation of taken-up fragments to the cytoplasm	Sinha *et al.* 2012
RR3133	86-028NP NalR	Otitis media clinical isolate. Nalidixic acid resistant	Mell *et al.* 2011
RR1361	*PittGG*	Nontypeable clinical isolate	G. Ehrlich
RR722	*Rd*	Rd KW20, rough (unencapsulated) derivative of type d	H. O. Smith

894   **Table 2. Frequencies of *Hin*-type USS in genomes of other species**

Species	Genome size	USS$_{10}$/Mb	USS$_{11}$/Mb
H. influenzae 86-028NP	1.914	1014	754
H. parainfluenzae T3T1	2.087	867	683
Aggregatibacter actino-mycetemcomitans VT1169	2.129	970	737
H. ducreyi 35000HP	1.699	102	16
Mannheimia haemolytica M42584	2.732	96	18
N. meningitidis	2.272	52	4
Streptococcus pneumoniae	2.039	16	1
Pseudomonas aeruginosa	6.264	8	0
Homo sapiens[1]	3 x 1.9 Mb	6.6	0.1
Random-sequence DNA[2]*, 41% G+C*	3 x 1.9 Mb	29.5	0.3

895   1. Means for three 1.9 Mb segments of human chromosomes 1, 3 and 12.

896   2. Means for three 1.9 Mb 'genomes' with the same base composition as human

897   DNA.

898 **Table 3. Predicted relative uptake[1] of *H. influenzae* DNA in simulated competition**

899 **with DNAs of other species[2].**

Assumptions:	1 kb fragments, *p_uptake*=0	1 kb fragments, *p_uptake*=0.005	10 kb fragments, *p_uptake*=0	10 kb fragments, *p_uptake*=0.005
86-028NP DNA in competition with:				
H. parainfluenzae DNA (*Hin*-type USS)	0.500	0.500	0.475	0.475
H. ducreyi DNA (*Apl*-type USS)	0.952	0.951	0.884	0.883
Homo sapiens DNA[3] (no USS enrichment)	0.998	0.997	0.991	0.990

900   [1] *H. influenzae* DNA as a fraction of the total DNA predicted to be taken up.

901   [2] Competitions were genome:genome

902   [3] Means for the three genome 1.9 Mb segments described in Transparent Methods.