Supplementary Information for:

Massively parallel characterization of engineered transcript isoforms using direct RNA sequencing

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Supplementary Note 1: Library coverage calculation.

We estimated library coverage using the approach presented by Patrick *et al.*¹ to calculate the expected number of distinct sequences in a library chosen at random from a set of sequence variants. Given a pooled library containing *L* sequences, and a set of *V* equiprobable variants, let v_i be one of the possible variants. Since the variants are equiprobable, the mean number of occurrences of v_i in *L* is

$$\lambda = L / V. \tag{S1}$$

For $\lambda \ll L$ (i.e. $V \gg 1$), the actual number of occurrences of v_i in L is essentially independent of the number of occurrences of any other variant v_j where $j \neq i$, and therefore well-approximated by a Poisson distribution

$$P(x) = \frac{e^{-\lambda}\lambda^x}{x!},\tag{S2}$$

where P(x) gives the probability that v_i occurs exactly x times in the library. The probability that v_i occurs at least once is given by $1 - P(0) = 1 - e^{-\lambda} = 1 - e^{-L/V}$. Therefore, the number of distinct variants expected in the library is given by

$$C \approx V(1 - e^{-L/V}),\tag{S3}$$

and the fractional completeness of the library is

$$F = \frac{c}{v} \approx 1 - e^{-L/V}.$$
(S4)

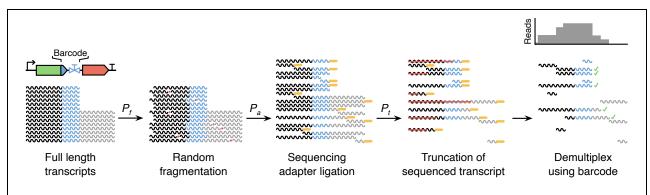
The library size required for fractional completeness F is therefore

$$L \approx -V \ln(1-F). \tag{S5}$$

In our case, V = 1183 variants and we require a fractional completeness of $F > 1 - \frac{1}{1183} = 0.99915$ to ensure with high probability the representation of all variants in the library. This necessitates a library size of at least $L \approx -V \ln(1 - 0.99915) = 8364$. To achieve this, we performed a transformation protocol that used 10 large trays with approximately 50,000 transformants per tray (**Methods**), resulting in $L \approx 500000$.

Supplementary Note 2: Modelling direct RNA sequencing

We developed a simple probabilistic model to capture the key processes impacting the reads recovered from a direct RNA sequencing (dRNA-seq) run. The following figure provides an overview of the major steps.



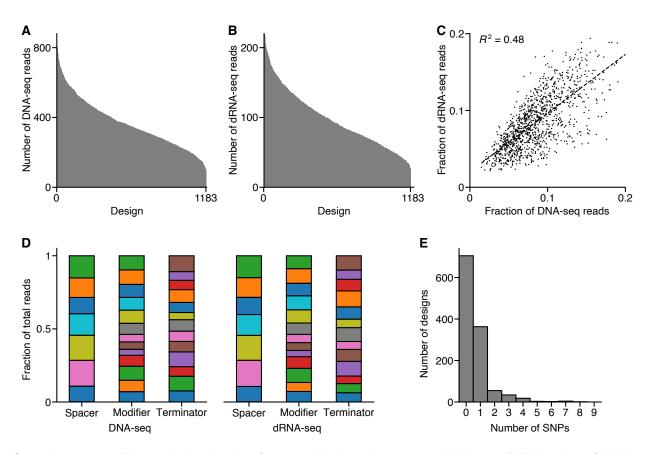
Overview of the direct RNA sequencing model. Reads are denoted by squiggles that are color coded to show core regions (e.g. blue region is the intrinsic barcode). Red dots show points of random fragmentation, orange oblongs represent sequencing adapters attached to only the 3' end of an RNA molecule, and green ticks denote reads that contain a complete barcode sequenced and which are used to generate a read depth profile. P_t , P_a , and P_t are probabilities that reads are selected for each of the modification steps (i.e. random fragmentation, adapter ligation, and truncation, respectively).

We begin by assuming that all starting RNA transcripts are all full length corresponding to either an isoform that terminates at the transcriptional valve or reads through to the end of the construct. Then, reads are chosen with probability P_t to become fragmented once at a random location along their length. This step captures the inevitable fragmentation that occurs when extracting and purifying an RNA sample. Next, a sequencing adapter is attached to each transcript or part of a fragmented RNA with probability P_a and only molecules with an adapter attached are taken forward for sequencing. Sequenced molecules are then chosen with probability P_t for possible truncation at a random position along the sequence. This step captures possible further fragmentation of the RNA during sequencing library preparation whereby only the fragment containing the adapter is sequenced, or possible truncation of reads due to premature termination during the sequencing of a molecule. Finally, we take the sequenced reads and filter out any that do not contain a complete transcriptional valve design (i.e. intrinsic barcode). Reads without a full barcode cannot be uniquely identified and so the reads are removed during the demultiplexing step. Reads that make it through these steps are then be used to generate a read depth profile.

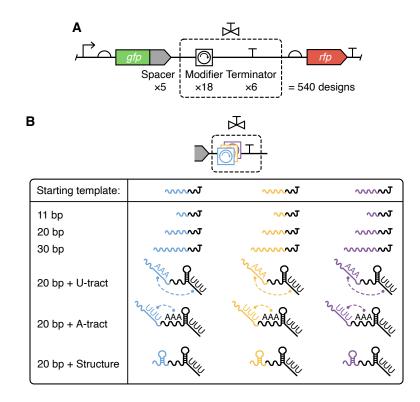
To demonstrate the model's ability to capture real read depth profiles, we made use of the RNA Control Strand (CS) that is externally 'spiked-in' to all dRNA-seq runs for Quality Control

(QC) purposes. Crucially, the RNA CS is a single known sequence unlike any other in our library and only consists of full-length RNA molecules. Fitting our model to dRNA-seq data from the two biological replicates, we found that parameter values of $P_f = 0.1$, $P_a = 0.77$ and $P_t = 0.7$ enabled a close fit in both cases, with only minor deviations at 5' and 3' ends of the RNA CS sequence (**Supplementary Figure 3A**). We also assumed the presence of an intrinsic barcode in the center of the RNA CS sequence and found that our model could also accurately predict read depth profiles recovered after demultiplexing of the real dRNA-seq data (**Supplementary Figure 3B**). This suggests that the read distribution that is generated by the model fits closely fits that recovered from sequencing and allowed us to further explore how well the observed read depth profiles matched the ground truth.

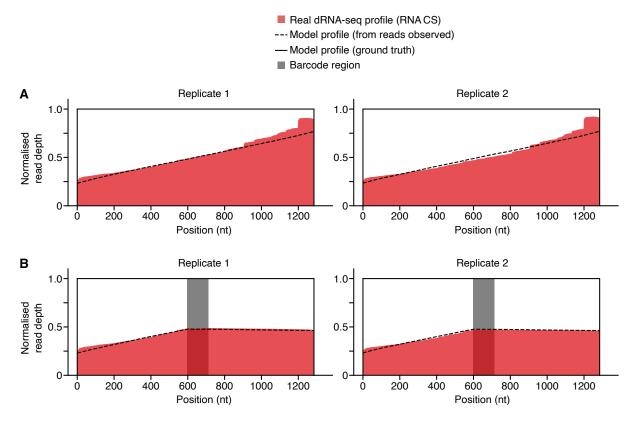
To explore this further, we used the model with parameters fitting to the real dRNA-seq data to simulate the sequencing process on synthetically generated transcripts for a hypothetical set of transcriptional valves with termination efficiencies varying between 0 and 1. By comparing the actual termination efficiency of each valve with the observed termination efficiency measured from the generated read depth profiles, we found a slight over estimation in T_e (**Supplementary Figure 4**). To ensure this didn't bias our measurements for the data from the real transcriptional valves, this deviation was corrected for by subtracting the calculated error from the observed termination efficiency seen the model simulations to give a final T_e value.



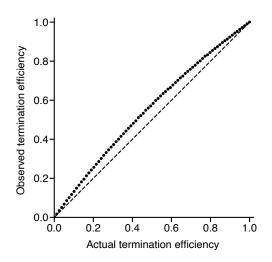
Supplementary Figure 1: Analysis of assembled and sequenced library. (**A**) Number of DNAseq reads for each design, ordered by number of reads. (**B**) Number of dRNA-seq reads for each design, ordered by number of reads. (**C**) Comparison of frequency of DNA-seq and dRNA-seq reads. Each point corresponds to a single design and R^2 is the square of the Pearson correlation coefficient. (**D**) Frequency of each part in the DNA-seq (left) and dRNA-seq (right) data. Part and design frequencies were calculated relative to the total number of annotated sequencing reads. (**E**) Number of single nucleotide polymorphisms (SNP) per design.



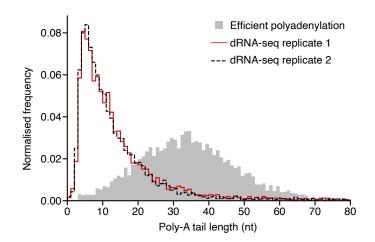
Supplementary Figure 2: Design of library used to optimize demultiplexing. (**A**) The library consists of 5 spacers (S1–S5), 18 modifiers (all parts with references beginning with M1–M3) and 6 terminators (T2–T7), resulting in 540 unique designs. For part sequences see **Supplementary Table 1**. (**B**) Modifiers were based upon 3 random starting template sequences, represented by different colored subsequences. From each template sequence 6 variants were made, each containing different proportions of the template sequence indicated by the number of base pairs: 11 bp sub-sequence, 20 bp sub-sequence, full 30 bp sequence, a 20 bp sub-sequence with U-tract interactor motif, a 20 bp sub-sequence with A-tract interactor motif, a 20 bp sub-sequence with structural motif.



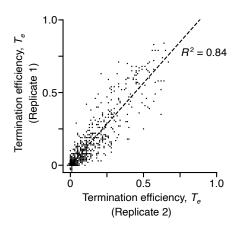
Supplementary Figure 3: Fitting model to direct RNA sequencing data. (**A**) Read depth profiles shown for all reads mapping to the RNA CS sequence for two dRNA-seq biological replicates (filled red) and fitted dRNA-seq model used to simulate the processing of 100,000 synthetic reads where $P_f = 0.1$, $P_a = 0.77$, $P_t = 0.7$ (dashed black line for observed profile, solid black line for the model ground truth). (**B**) Read depth profiles for reads that map to the grey 'intrinsic barcode' for the real dRNA-seq data and fitted model.



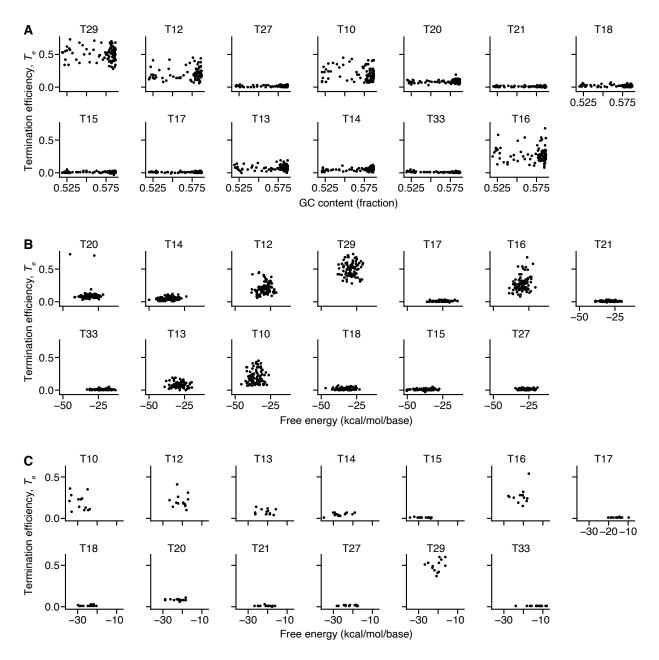
Supplementary Figure 4: Deviation between observed and actual termination efficiencies. Each point denotes a model simulation based on 100,000 artificially generated reads for transcriptional valves with varying termination efficiencies (Supplementary Note 2). Dashed line shows y = x.



Supplementary Figure 5: Polyadenylation efficiencies. Histograms showing the varying lengths of RNA poly-A tail lengths for the two biological replicates analyzed in this work (dashed black and solid red lines) and another dRNA-seq sample where efficient polyadenylation was observed (grey filled histogram).



Supplementary Figure 6: Comparison of termination efficiencies calculated from biological replicates. Each point represents a single transcriptional valve design and dotted line shows the linear regression. R^2 is the square of the Pearson correlation coefficient.



Supplementary Figure 7: Analysis of possible predictors of termination efficiency. (A) Scatter plot for each terminator showing T_e against percentage GC content of each design. Calculation based on 80 nucleotides upstream of 3'-end of design. (B) Scatter plot for each terminator showing T_e against the thermodynamic minimum free energy of each design. Calculation based on 120 nt upstream of 3'-end of design. (C) Scatter plot for each valve showing T_e against the thermodynamic minimum free energy of each valve showing T_e against the thermodynamic minimum free energy of each valve showing T_e against the thermodynamic minimum free energy of each valve showing T_e against the thermodynamic minimum free energy of each valve sequence.

ID	Forward strand oligonucleotide sequence	Reverse strand oligonucleotide sequence
pT7	CTAATACGACTCACTATAGGGAGAG	CTAGCTCTCCCTATAGTGAGTCGTATTAGACGT
S10	AATTCCTGTGTACCGGGAACCAGCCAGACTACACAGGGT AA	GCTCTTACCCTGTGTAGTCTGGCTGGTTCCCGGTACACA GG
S16	AATTCGTGCAGAGACAAGCGTTTGGGGCACCAGCACAGT AA	GCTCTTACTGTGCTGGTGCCCCAAACGCTTGTCTCTGCA CG
S18	AATTCTTCAAAGCTACGAGCGCTAGAGATGTGAGACCCT AA	GCTCTTAGGGTCTCACATCTCTAGCGCTCGTAGCTTTGA AG
S19	AATTCCTAATTATGTCTCAAAAGCTCGAAGATTACACCT AA	GCTCTTAGGTGTAATCTTCGAGCTTTTGAGACATAATTA GG
S20	AATTCTTGTCGCTAAAGAAACCTTTCCCAATTAATACAT AA	GCTCTTATGTATTAATTGGGAAAGGTTTCTTTAGCGACA AG
S21	AATTCGGAATCGCTGATCTACAGAACGGTCCTTATGGGT AA	GCTCTTACCCATAAGGACCGTTCTGTAGATCAGCGATTC CG
S22	AATTCATCACTCACACATCGCTCGAGATCGGTACGGGGT AA	GCTCTTACCCCGTACCGATCTCGAGCGATGTGTGAGTGA TG
M10	GAGCTTTCTCCGAAGTGTAGTAAAAAAAAAAAAAAAAA	GGCATTTTTATTTTTTTTTTACTACACTTCGGAGAAA
M11	GAGCGATTACAGAAGCGTGGTATTTTTTATTTT	GGCAAAAAATAAAAAATACCACGCTTCTGTAATC
M12	GAGCCAGGAACTTATCAATAGTCGCCCGAAAGGG	GGCACCCTTTCGGGCGACTATTGATAAGTTCCTG
M13	GAGCCCTATTTACCTCAGT	GGCAACTGAGGTAAATAGG
M14	GAGCTAGACAGTAATACCC	GGCAGGGTATTACTGTCTA
M15	GAGCCTATCTGGTGCTACA	GGCATGTAGCACCAGATAG
M16	GAGCTTATCGGTTACCAGA	GGCATCTGGTAACCGATAA
M17	GAGCGTATCCAGACTTATTGAGGTTTACGCACTA	GGCATAGTGCGTAAACCTCAATAAGTCTGGATAC
M18	GAGCATTCGCTGAGAGTTACACGATACTGACTAT	GGCAATAGTCAGTATCGTGTAACTCTCAGCGAAT
M19	GAGCTTGAAATCGGATACTTCCTGAACTGCGAAT	GGCAATTCGCAGTTCAGGAAGTATCCGATTTCAA
M20	GAGCATAGACTTTCGTGGATTATTACCTTACAACTGATA GGACGGACTC	GGCAGAGTCCGTCCTATCAGTTGTAAGGTAATAATCCAC GAAAGTCTAT
M21	GAGCATAGCCGAGATTATCCACCAGCAACAGTTCGTTAT TGTAGTGATT	GGCAAATCACTACAATAACGAACTGTTGCTGGTGGATAA TCTCGGCTAT
M22	GAGCAAGGCGTGACTACAACCAATCTTCTATTCTGCGAG AGTAAAGTTT	GGCAAAACTTTACTCTCGCAGAATAGAAGATTGGTTGTA GTCACGCCTT
T10	TGCCGCTGATGCCAGAAAGGGTCCTGAATTTCAGGGCCC TTTTTTTACATGGATTGA	CTAGTCAATCCATGTAAAAAAAGGGCCCTGAAATTCAGG ACCCTTTCTGGCATCAGC

Supplementary Table 1: Oligonucleotide sequences

T12	TGCCACTGATTTTTAAGGCGACTGATGAGTCGCCTTTTT TTTGTCTA	CTAGTAGACAAAAAAAAGGCGACTCATCAGTCGCCTTAA AAATCAGT
T13	TGCCAGTTAACCAAAAAGGGGGGGATTTTATCTCCCCTTT AATTTTTCCTA	CTAGTAGGAAAAATTAAAGGGGAGATAAAATCCCCCCTT TTTGGTTAACT
T14	TGCCCGTGTTCCTGAACGCCCGCATATGCGGGCGTTTTG CTTTTTGA	CTAGTCAAAAAGCAAAACGCCCGCATATGCGGGCGTTCA GGAACACG
T15	TGCCTCTGAATGCGTGCCCATTCCTGACGGAATGGGCAT TTCTGCGCAA	CTAGTTGCGCAGAAATGCCCATTCCGTCAGGAATGGGCA CGCATTCAGA
T16	TGCCGTTATTAAATAGCCTGCCATCTGGCAGGCTTTTTT TATCGA	CTAGTCGATAAAAAAAGCCTGCCAGATGGCAGGCTATTT AATAAC
T17	TGCCCGTCTGCGTATGGAACGTGGTAACGGTTCTACTGA AGATTTA	CTAGTAAATCTTCAGTAGAACCGTTACCACGTTCCATAC GCAGACG
T18	TGCCTACTTCTTACTCGCCCATCTGCAACGGATGGGCGA ATTTATACCCA	CTAGTGGGTATAAATTCGCCCATCCGTTGCAGATGGGCG AGTAAGAAGTA
T20	TGCCCTGAAATATCCAGCGGATCAAGAAAATTCGTTGGA TATTTTTTA	CTAGTAAAAAATATCCAACGAATTTTCTTGATCCGCTGG ATATTTCAG
T21	TGCCAAACACGTAGGCCTGATAAGCGAAGCGCATCAGGC AGTTTTGCGTA	CTAGTACGCAAAACTGCCTGATGCGCTTCGCTTATCAGG CCTACGTGTTT
T27	TGCCTTTCAGCAAAAAACCCCTCAAGACCCGTTTAGAGG CCCCAAGGGGTTATGCTAGGA	CTAGTCCTAGCATAACCCCTTGGGGGCCTCTAAACGGGTC TTGAGGGGTTTTTTGCTGAAA
T29	TGCCCAGAAATCATCCTTAGCGAAAGCTAAGGATTTTTT TTATCTGAAA	CTAGTTTCAGATAAAAAAAATCCTTAGCTTTCGCTAAGG ATGATTTCTG
T33	TGCCCAGCGTTGAACCTACGACAGTCTCTTATTGACGAG TAAAGTGCTA	CTAGTAGCACTTTACTCGTCAATAAGAGACTGTCGTAGG TTCAACGCTG
S1	AATTCGACTTTCACGTGAACCTGTTCCCAATATAA	GCTCTTATATTGGGAACAGGTTCACGTGAAAGTCG
S2	AATTCAATGTGGAACTCTTCGCTCATGTAGAATAA	GCTCTTATTCTACATGAGCGAAGAGTTCCACATTG
S3	AATTCGGTGCAGCGGAGAAAAGATTTGCTACCTAA	GCTCTTAGGTAGCAAATCTTTTCTCCGCTGCACCG
S4	AATTCCTTGATATAAAACTTCCGGGAGTAGGATAA	GCTCTTATCCTACTCCCGGAAGTTTTATATCAAGG
S5	AATTCCAAGAACTCGTTTTCCTATATGGCGTCTAA	GCTCTTAGACGCCATATAGGAAAACGAGTTCTTGG
M1N	GAGCTTTCTCCGAAGTGTAGTAAATAAAGCGTCC	GGCAGGACGCTTTATTTACTACACTTCGGAGAAA
M1A	GAGCTTTCTCCGAAGTGTAGTAAATTTTATTTTT	GGCAAAAAATAAAATTTACTACACTTCGGAGAAA
M1U	GAGCTTTCTCCGAAGTGTAGTAAAAAAAAAAAAAAAA	GGCATTTTTATTTTTTTTTTTTCTACACTTCGGAGAAA
M1S	GAGCTTTCTCCGAAGTGTAGTAAACCCGAAAGGG	GGCACCCTTTCGGGTTTACTACACTTCGGAGAAA
M1T	GAGCTTTCTCCGAAGTGTAGTAAA	GGCATTTACTACACTTCGGAGAAA
M1X	GAGCTTTCTCCGAAG	GGCACTTCGGAGAAA
M2N	GAGCAAGGACTTTCTCTACTGATTGTAAGACCGA	GGCATCGGTCTTACAATCAGTAGAGAAAGTCCTT
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M2A	GAGCAAGGACTTTCTCTACTGATTTTTTATTTT	GGCAAAAAATAAAAAATCAGTAGAGAAAGTCCTT
M2U	GAGCAAGGACTTTCTCTACTGATTAAAATAAAAA	GGCATTTTTATTTTAATCAGTAGAGAAAGTCCTT
M2S	GAGCAAGGACTTTCTCTACTGATTCCCGAAAGGG	GGCACCCTTTCGGGAATCAGTAGAGAAAGTCCTT
M2T	GAGCAAGGACTTTCTCTACTGATT	GGCAAATCAGTAGAGAAAGTCCTT
M2X	GAGCAAGGACTTTCT	GGCAAGAAAGTCCTT
M3N	GAGCCAGGAACTTATCAATAGTCGTTGTGACACT	GGCAAGTGTCACAACGACTATTGATAAGTTCCTG
МЗА	GAGCCAGGAACTTATCAATAGTCGTTTTATTTTT	GGCAAAAAATAAAACGACTATTGATAAGTTCCTG
M3U	GAGCCAGGAACTTATCAATAGTCGAAAATAAAAA	GGCATTTTTATTTTCGACTATTGATAAGTTCCTG
M3S	GAGCCAGGAACTTATCAATAGTCGCCCGAAAGGG	GGCACCCTTTCGGGCGACTATTGATAAGTTCCTG
МЗТ	GAGCCAGGAACTTATCAATAGTCG	GGCACGACTATTGATAAGTTCCTG
МЗХ	GAGCCAGGAACTTAT	GGCAATAAGTTCCTG
T2	TGCCCGTAAAAACCCGCCGAAGCGGGTTTTTACGTAACA	CTAGTGTTACGTAAAAACCCGCTTCGGCGGGTTTTTACG
Т3	TGCCAGTAAAAACCCGCCGAAGCGGGTTTTTACGTAACA	CTAGTGTTACGTAAAAACCCGCTTCGGCGGGTTTTTACT
T4	ТСССААААААААСАСССТААССССТАТТТТТТТТТТТТТ	CTAGTAAAAAAAAAAAAACACCCGTTAGGGTGTTTTTTT
Т5	TGCCAGAATTCAGTCAAAAAGCCTCCGACCGGAGGCTTTT GACTATTACTACTAGA	CTAGTCTAGTAGTAATAGTCAAAAGCCTCCGGTCGGAGG CTTTTGACTGAATTCT
Т6	TGCCAGAATTCAGCCCGCCTAATGAGCGGGCTTTTTTT ACTAA	CTAGTTAGTAAAAAAAAGCCCGCTCATTAGGCGGGCTGA ATTCT
Т7	TGCCAGAAAAGAGGCCTCCCGAAAGGGGGGGCCTTTTTTC GTTTTA	CTAGTAAAACGAAAAAAGGCCCCCCTTTCGGGAGGCCTC TTTTCT

Supplementary References

 Patrick, Wayne M., Andrew E. Firth, and Jonathan M. Blackburn. User-Friendly Algorithms for Estimating Completeness and Diversity in Randomized Protein-Encoding Libraries. *Protein Engineering* 16 (6): 451–57 (2003).