Supplement: Clinical decision analysis of elective delivery versus expectant management for pregnant individuals with COVID-19-related acute respiratory distress syndrome

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Disclaimer regarding terminology

The current paper uses “pregnant individual” instead of more historically common but gendered terms such as “pregnant woman” or “mother.” However, the word “maternal” is still used as an adjective, in the absence of a more efficient gender-neutral analogue. These words were chosen to respect that not all pregnant or postpartum people are women, and recognize the importance of the experience of non-female, transgender, individuals with pregnancy and perinatal mental illness.(1)

Modelling details

The model was constructed in Treeage Pro (TP) v2021 R2 (2) (available at https://doi.org/10.5281/zenodo.6435090) and consisted of two parts: an initial portion that modelled events surrounding intensive care unit (ICU) admission and delivery and a long term portion that estimated subsequent discounted, life expectancy and discounted, quality-adjusted life expectancy for individuals who survived until hospital discharge.

Hospitalization and delivery

The initial part of the model tracked pregnant individuals from the initiation of mechanical ventilation for COVID-19 pneumonia until death, discharge or delivery and their neonate from birth until in-hospital death or discharge. Individuals progressed through model in discrete time steps each one day in duration. The model was structured as a parallel, open cohort, individual-level simulation. ‘Parallel’ refers to a structure where individuals exist simultaneously in the model in contrast to the more typical serial simulation (where a set of individuals are modelled one-at-a-time, i.e. not concurrently). This allows pregnant individuals and their children to be modelled together. The identification number of a pregnant individual was linked to the number for the neonate and vice versa using dynamic look-up tables (referred to as global matrices in TP). Furthermore, the parallel architecture allows modelling of the timing of childbirth in relation to the onset of maternal critical illness and simultaneous tracking of both maternal and fetal outcomes thereby solving a longstanding problem in obstetrical decision modelling. The model begins with a fixed number (1000) of pregnant individuals with COVID-19-related acute respiratory distress syndrome (ARDS) ventilated in ICU. The open cohort feature refers to the fact that new individuals, neonates, can enter the model via birth after the start of the simulation. For the elective delivery strategy, neonates entered the modelled cohort on the first day whereas in the expectant management strategy, they entered the model on subsequent days according to a probability based on gestational age.

Subsequent to the start of the simulation, pregnant individuals could experience several stochastic events including in-hospital death, liberation from invasive ventilation, transfer from ICU to ward, and transfer from ward to home. If a pregnant individual was discharged from hospital while still pregnant, they continued to accumulate daily time steps until they gave birth. For pregnant individuals, in-hospital death, discharge after giving birth or giving birth after discharge constituted the end of the hospitalization and delivery phase. Subsequent to birth, neonates could experience stochastic events including in-hospital mortality (including ante- and perinatal death), discharge from neonatal ICU to ward and from ward to home. Pregnancies could result in antepartum death or intrapartum death in which case fetuses entered the absorbing death state immediately upon entry into the model. For neonates, in-hospital death or discharge home constituted the end of the delivery and hospitalization phase.

Long-term outcomes

For individuals surviving the initial portion of the model, time-to-death was sampled from one of a set of Gompertz distributions depending on age at discharge (rounded to the nearest integer). The Gompertz distribution is used by demographers to model general population mortality.(3) The model makes the simplifying assumptions that life expectancy subsequent to recovery from severe COVID-19 pneumonia, or to children born to such pregnant individuals, would not differ from the general population. Further, among pregnant individuals modelled in the initial part of the model, it was assumed that a second pregnancy complicated with COVID-19 pneumonia requiring mechanical ventilation would not occur. However, the long-term quality-of-life would differ according to events experienced in the initial part of the model (see 'Quality Adjustment' below).

The Gompertz distribution can be parameterized in several ways. For time-to-death sampling in the model, the survival function, S(t) was given by

$$S(t) = \exp\left[-\left(\frac{\beta}{\eta}\right)(e^{\eta t} - 1)\right],\ \eta = \text{shape},\ \beta = \text{scale} \qquad (1).$$

β and η parameters were estimated for each integer starting age, from 0 to 110 years, yielding estimated survival curves that best fit the corresponding observed survival curves derived from Canadian life table data separately for male and female sex.(4) Observed survival curves were estimated subsequent to each integer starting age as

$$S(t) = \prod_{i=0}^{\min(t,110)} Pr(surv|t = s + i) \qquad (2)$$

where ‘s’ is the integer starting age, ‘t’ is time in integer years after the starting age, and Pr(surv|t = s + i) refers to the probability that a member of the general population would survive from age s + i until age s + i + 1. For each integer starting age and sex, the best fitting β and η parameters were found by searching their parameter space using the simulated annealing algorithm(5) for a maximum of two million iterations until a goodness-of-fit score (GoF) dropped below a target value of 0.001. The GoF score consisted of the sum of squared deviations between points on the observed survival curve and points on the estimated curve using the currently sampled β and η parameters. For this type of GoF metric, lower values indicate improved fit. The simulated annealing features are shown in the table below.

Parameter	**Value**
Maximum number of iterations	2,000,000
Target GOF	0.001
η (lower bound)	0
η (upper bound)	1
β (lower bound)	0
β (upper bound)	1
Maximum temperature	100
Minimum temperature	0.5
Boltzmann constant	0.25
Exponential cooling constant	0.01
Cooling mode	exponential

For a given integer start age, s, and sex, the simulated annealing algorithm started with random picks for the β and η parameters and computed the expected survival curve from s to 110 years using equation (1). The GoF for the current parameter set was computed as:

$$GoF(\beta_k, \eta_k) = \sum_{t=s}^{110} (S(t)_{Ek} - S(t)_O)^2 \quad (3)$$

where β_k and η_k were the Gompertz distribution parameters sampled during simulated annealing iteration k (k = 1 for the initial random picks), and $S(t)_{Ek}$ was the estimated survival function values at t years after the start age, s, calculated according to equation (1) using the current parameter set k, and $S(t)_O$ is the observed survival function at t years after the start age, s, calculated according to equation (2). If the GoF was less than the target, then the algorithm stopped and reported the initial β and η parameter values. Otherwise, new parameter values were sampled randomly from the parameter space and the GoF score was re-calculated as above. If $GoF(\beta_{k+1}, \eta_{k+1}) <= GoF(\beta_k, \eta_k)$, then the new parameter set was selected automatically as the current best set. However, if $GoF(\beta_{k+1}, \eta_{k+1}) > GoF(\beta_k, \eta_k)$, then the new parameter set could still be selected as current 'best' according to a probability equal to:

$$\Pr(accept|k+1) = exp\left(\frac{-\Delta E}{BT}\right) \quad (4)$$

where $\Delta E = GoF(\beta_{k+1}, \eta_{k+1}) - GoF(\beta_k, \eta_k)$, B = the Boltzmann constant and T was the artificial temperature. The probability of accepting a worse fitting parameter set was higher if the difference in GoF values between iteration k+1 and k was lower and/or the artificial temperature was higher. The artificial temperature was high at the beginning of the simulated annealing process but dropped exponentially to a minimum as the number of iterations increased. This feature was designed to avoid the algorithm getting trapped in a local minimum in the parameter space by allowing the process to move widely over the space initially and then becoming progressively more unlikely to accept new parameter sets with higher GoF values. This increased the chance of finding a parameter set close to the global minimum. The algorithm continued until either the GoF for the current best parameter set was lower than the threshold or the maximum number of iterations was reached. The process was repeated for each combination of starting age and sex.

The simulated annealing algorithm was implemented in R with the following code:

```
# Retrieve life tables from Statistics Canada

# Set file path to store downloaded life tables
fp <- "c:/users/public/downloads"

# Requires curl package or can download manually
if(!require(curl)) install.packages("curl")

## Loading required package: curl

curl::curl_download(url = "https://www150.statcan.gc.ca/pub/84-537-x/20
20001/xls/2017-2019_Tbl-eng.xlsx",
                    destfile = paste(fp,"/lifetables.xlsx",sep=""))

# Process Excel table, requires openxlsx or readxl package
# Will use Ontario life table for this example
if(!require(openxlsx)) install.packages("openxlsx")

## Loading required package: openxlsx

data <- openxlsx::read.xlsx(paste(fp,"/lifetables.xlsx",sep=""),sheet =
"Ont. - Both sexes")
```

```
# if(!require(readxl)) install.packages("readxl")
# data <- readxl::read_xlsx(paste(fp,"/lifetables.xlsx",sep=""),sheet =
"Ont. - Both sexes")
head(data)

##   Table.7c..Complete.life.tables,.both.sexes,.Ontario     X2   X3
## 1                                         2017 to 2019   <NA> <NA>
## 2                                                  Age     lx   dx
## 3                                                 <NA> number <NA>
## 4                                               0 year 100000  455
## 5                                               1 year  99545   23
## 6                                              2 years  99522   17
##                    X4                    X5                  X6
X7
## 1                <NA>                  <NA>                <NA>
<NA>
## 2                  qx             m.e.(qx)                   px
Lx
## 3         probability                  <NA>                <NA> nu
mber
## 4 4.5500000000000002E-3 2.0000000000000001E-4 0.99544999999999995  9
9583
## 5 2.3000000000000001E-4 5.0000000000000002E-5 0.99977000000000005  9
9534
## 6 1.7000000000000001E-4 4.0000000000000003E-5             0.99983  9
9513
##        X8   X9      X10
## 1    <NA> <NA>     <NA>
## 2      Tx   ex m.e.(ex)
## 3    <NA> year     <NA>
## 4 8243508 82.4        0
## 5 8143926 81.8        0
## 6 8044391 80.8        0

# Select only rows and columns required for algorithm
# - Drop first 3 rows, which are just formatted text/space
# - Need columns 1,4, and 6 for age, qx (probability of death between a
ge x and x + n), and px (probability of survival between age x and x +
n)
df <- data[4:114,c(1,4,6)]
colnames(df) <- c("age","qx","px")
# Coerce age column to sequence of integers {0,1,2,...110}
df[,"age"] <- seq(0,110,1)



# Gompertz Cumulative Probability Distribution
# x is a vector of time points
# Cumulative probability distribution function defined as 1 - exp[-(rat
e / shape) * (exp(shape * t) - 1)]
```

```
pdfGompertz <- function(x,shape,rate){
  return(1 - exp(-(rate / shape) * (exp(shape * x) - 1)))
}

# Function to estimate Gompertz goodness-of-fit
# x is a vector of time points
# s.target = target survival curve for a given age based on the life ta
ble
# Survival(t) = 1 - CDF
gofGompertz <- function(x,shape,rate,s.target){

  # s.est <- exp(-(rate / shape) * (exp(shape * t) - 1))
  s.est <- 1 - pdfGompertz(x,shape,rate)
  gof <- (s.target - s.est)^2

  return(sqrt(sum(gof)))

}



# Simulated annealing algorithm

# max.iterations is the maximum number of samples to attemt
# s.target is the target survival curve for a given age based on life t
able
# t is a vector of reference time points
# target.gof is the target goodness-of-fit threshold. Algorithm stops i
f/when this is reached.
# shape.lwr is the lower bound of the shape parameter space to search
# shape.upr is the upper bound of the shape parameter space to search
# rate.lwr is the lower bound of the rate parameter space to search
# rate.upr is the upper bound of the rate parameter space to search
# max.temp is the starting temperature of the algorithm. This is a tuni
ng parameter.
# min.temp is the lowest temperature of the algorithm. This is a tuning
parameter.
# boltzmann is a tuning parameter that influences the probability of ac
cepting a sampled parameter, depending on the current temperature
# exp.cooling.const is a tuning parameter that dictates the cooling spe
ed
simAnnealing <- function(max.iterations = 1000, s.target, t, target.gof
= 0.001, shape.lwr = 0, shape.upr = 1, rate.lwr = 0, rate.upr = 1, max.
temp = 50, min.temp = 0.5, boltzmann = 0.25, exp.cooling.const = 0.02)
{


  # initialization
  results <- list(shape=numeric(), rate=numeric(), gof=numeric(), gof.t
```

```
arget=target.gof, iterations=integer(), temperature=numeric(),best.gof=
numeric(), best.shape=numeric(), best.rate=numeric(), best.iteration=nu
meric())

  # initialize GOF with a random guess
  old.gof <- new.gof <- gofGompertz(t,runif(1,shape.lwr,shape.upr),runi
f(1,rate.lwr,rate.upr),s.target)
  iter.no <- 1
  curr.temp <- max.temp

  # pre-load max number of random variates required
  rand.shape <- runif(max.iterations, min = shape.lwr, max = shape.upr)
  rand.rate <- runif(max.iterations, min = rate.lwr, max = rate.upr)
  rand.num <- runif(max.iterations)

  # loop through iterations until target GOF is reached or max samples
are expended
  while(old.gof > target.gof & iter.no < max.iterations){

    # update current temperature
    curr.temp <- min.temp + ((max.temp - min.temp) * exp(-exp.cooling.c
onst*iter.no))
    if(curr.temp < min.temp) curr.temp <- min.temp

    # sample new parameters
    curr.shape <- rand.shape[iter.no]
    curr.rate <- rand.rate[iter.no]

    # calculate GOF of sampled parameters
    new.gof <- gofGompertz(t,curr.shape,curr.rate,s.target)

    # probability of accepting latest parameters
    delta.factor <- iter.no/(max.iterations/10) # decreases probability
of accepting worse proposal when close to max.iterations
    if(delta.factor < 1) delta.factor <- 1
    # as temperature cools, worse proposals are less likely to be accep
ted
    p.accept.move <- ifelse(new.gof < old.gof, 1, exp(-((new.gof - old.
gof)*delta.factor) / (boltzmann*curr.temp)))

    # if accept parameters, store them in output object
    if(new.gof < old.gof){

      old.gof <- new.gof
      results$best.gof <- results$gof <- new.gof
      results$best.shape <- results$shape <- curr.shape
      results$best.rate <- results$rate <- curr.rate
      results$best.iteration <- results$iterations <- iter.no
```

```r
      results$temperature <- curr.temp

    } else {

      # accept worse proposal with probability p.accept.move
      if(rand.num[iter.no] < p.accept.move){
        old.gof <- new.gof
        results$shape <- curr.shape
        results$rate <- curr.rate
        results$gof <- new.gof
        results$iterations <- iter.no
        results$temperature <- curr.temp
      }
    }

    iter.no <- iter.no + 1
  }

  results$total.iterations <- iter.no

  return(results)
}





# Run simulated annealing algorithm for each age up to 100
t.begin <- Sys.time()


# block for running in parallel
# set number of threads and export functions, variables, and data to ea
ch cluster
n.threads <- parallel::detectCores()
cl <- parallel::makeCluster(n.threads)
parallel::clusterExport(cl,varlist = c("simAnnealing","pdfGompertz","go
fGompertz","df"),envir=environment())

t.start <- Sys.time()
res <- parallel::parLapply(cl,1:101,function(x,df){

  s.target <- c(1,cumprod(df[df$age > df$age[x],"px"]))
  t <- 0:(max(df$age) - df$age[x])

  simAnnealing(max.iterations = 1e6,s.target = s.target,t = t,
               target.gof = 0.0005*max(t),
               max.temp = 50, min.temp = 0.5,
```

```
                  shape.lwr = 0, shape.upr = 0.5,
                  rate.lwr = 0, rate.upr = ifelse(df$age[x]>20,0.5,0.01),
                  boltzmann = 0.25, exp.cooling.const = 0.01)
  },df)
t.end <- Sys.time()
parallel::stopCluster(cl)

t.end - t.start

## Time difference of 8.652299 mins

# end block for running in parallel


# # block if not running in parallel
# t.start <- Sys.time()
#
# res <- lapply(1:101,function(x){
#   s.target <- c(1,cumprod(df[df$age > df$age[x],"px"]))
#   t <- 0:(max(df$age) - df$age[x])
#   simAnnealing(max.iterations = 1e6,s.target = s.target,t = t,
#                target.gof = 0.0005*max(t),
#                max.temp = 50, min.temp = 0.5,
#                shape.lwr = 0, shape.upr = 0.5,
#                rate.lwr = 0, rate.upr = ifelse(df$age[x]>20,0.5,0.01)
,
#                boltzmann = 0.25, exp.cooling.const = 0.01)
#   })
#
# t.end <- Sys.time()
# # end block for not running in parallel
#
# t.end - t.begin



# collect results for ages 0-100
df <- df[1:101,]

df$shape <- unlist(lapply(res,function(x) x$shape))
df$rate <- unlist(lapply(res,function(x) x$rate))
df$gof <- unlist(lapply(res,function(x) x$gof))


# save results to file
write.csv(df, paste(fp, "/lifetable_gompertz.csv", sep=""), row.names =
F)

# save diagnostic plots to file
```

```
def.par <- par()

pdf(paste(fp, "/lifetable_gompertz_fit.pdf",sep=""), width=5000, height
= 5000, paper = "letter")
par(mfrow=c(2,2))
for(i in 1:101){
  s.target <- c(1,cumprod(df[df$age > df$age[i],"px"]))
  t <- 0:(max(df$age) - df$age[i])
  plot(t, s.target, ylim=c(0,1), pch=20, cex=1, xlab="Years", ylab="S(t
)",
       main = paste("Age ", df$age[i], " (Shape: ", round(df$shape[i],
digits=5), ", rate: ", round(df$rate[i], digits=5), ")", sep=""),
       cex.main = 0.8)
  lines(t, 1 - pdfGompertz(t,df$shape[i],df$rate[i]), col="red", lwd=2)
  legend("topright", legend = c("Target", "Fitted"), pch=c(20, NA),lty=
c(NA,"solid"),lwd=2, col=c("black", "red"))
}
par(mfrow=def.par$mfrow)
dev.off()

## png
##   2
```

Fitted Gompertz parameters (male sex)

Age	Probability of death	Probability of survival	Shape (η)	Scale (β)
0	0.0050000	0.9950000	0.0860322	0.0000545
1	0.0002400	0.9997600	0.0793399	0.0000720
2	0.0001700	0.9998300	0.0708041	0.0001652
3	0.0001300	0.9998700	0.0810591	0.0000867
4	0.0001000	0.9999000	0.0875543	0.0000611
5	0.0000800	0.9999200	0.0977807	0.0000325
6	0.0000700	0.9999300	0.1071277	0.0000240
7	0.0000700	0.9999300	0.0807308	0.0001233
8	0.0000700	0.9999300	0.1282962	0.0000062
9	0.0000700	0.9999300	0.1025841	0.0000391
10	0.0000800	0.9999200	0.0957067	0.0000739
11	0.0000900	0.9999100	0.0828527	0.0001503
12	0.0001000	0.9999000	0.1046156	0.0000471
13	0.0001200	0.9998800	0.0847556	0.0001431
14	0.0001500	0.9998500	0.1114692	0.0000375
15	0.0002000	0.9998000	0.0966479	0.0000954
16	0.0002600	0.9997400	0.0915114	0.0001263

Age	Probability of death	Probability of survival	Shape (η)	Scale (β)
17	0.0003300	0.9996700	0.0903189	0.0001868
18	0.0004000	0.9996000	0.0938692	0.0001719
19	0.0004600	0.9995400	0.1180217	0.0000438
20	0.0005200	0.9994800	0.1108221	0.0000787
21	0.0005700	0.9994300	0.1084562	0.0000906
22	0.0006100	0.9993900	0.0920685	0.0002443
23	0.0006400	0.9993600	0.0922987	0.0002695
24	0.0006500	0.9993500	0.0956676	0.0002601
25	0.0006500	0.9993500	0.0960731	0.0002616
26	0.0006500	0.9993500	0.0948924	0.0003351
27	0.0006600	0.9993400	0.0927603	0.0003585
28	0.0006800	0.9993200	0.0891320	0.0004901
29	0.0007000	0.9993000	0.0996399	0.0003414
30	0.0007200	0.9992800	0.0907855	0.0005563
31	0.0007500	0.9992500	0.1004710	0.0004111
32	0.0007700	0.9992300	0.1013710	0.0004828
33	0.0007900	0.9992100	0.1023119	0.0004573
34	0.0008000	0.9992000	0.0996031	0.0006041
35	0.0008100	0.9991900	0.1065277	0.0004758
36	0.0008200	0.9991800	0.0965349	0.0007782
37	0.0008500	0.9991500	0.1070876	0.0005254
38	0.0009000	0.9991000	0.0956056	0.0009475
39	0.0009800	0.9990200	0.1006949	0.0009844
40	0.0010800	0.9989200	0.1070000	0.0007602
41	0.0012100	0.9987900	0.0962625	0.0012692
42	0.0013500	0.9986500	0.1024079	0.0011005
43	0.0015000	0.9985000	0.1021790	0.0012924
44	0.0016700	0.9983300	0.1107790	0.0011063
45	0.0018500	0.9981500	0.1062795	0.0013738
46	0.0020400	0.9979600	0.1055993	0.0015821
47	0.0022400	0.9977600	0.1013166	0.0019042
48	0.0024600	0.9975400	0.0997214	0.0022780
49	0.0026800	0.9973200	0.1072031	0.0021419
50	0.0029300	0.9970700	0.1007665	0.0027061
51	0.0031900	0.9968100	0.1040219	0.0027190
52	0.0034700	0.9965300	0.0995798	0.0033264
53	0.0037800	0.9962200	0.1032317	0.0034001
54	0.0041300	0.9958700	0.1146094	0.0029533
55	0.0045100	0.9954900	0.1079830	0.0038774
56	0.0049200	0.9950800	0.1075083	0.0043682
57	0.0053800	0.9946200	0.1100628	0.0043216

Age	Probability of death	Probability of survival	Shape (η)	Scale (β)
58	0.0058800	0.9941200	0.1107571	0.0050325
59	0.0064400	0.9935600	0.1024058	0.0065424
60	0.0070500	0.9929500	0.1141583	0.0060133
61	0.0077300	0.9922700	0.1094066	0.0069029
62	0.0084700	0.9915300	0.1059521	0.0081828
63	0.0093000	0.9907000	0.1032518	0.0094345
64	0.0102100	0.9897900	0.1076471	0.0095692
65	0.0112200	0.9887800	0.1089279	0.0107406
66	0.0123300	0.9876700	0.1102685	0.0121161
67	0.0135700	0.9864300	0.1060628	0.0138051
68	0.0149300	0.9850700	0.1142665	0.0143868
69	0.0164500	0.9835500	0.1069476	0.0171035
70	0.0181300	0.9818700	0.1077230	0.0185663
71	0.0200000	0.9800000	0.1042804	0.0210072
72	0.0220700	0.9779300	0.1129895	0.0217532
73	0.0243800	0.9756200	0.1163918	0.0237413
74	0.0269400	0.9730600	0.1111416	0.0278128
75	0.0297900	0.9702100	0.1056635	0.0326527
76	0.0329700	0.9670300	0.1150312	0.0334381
77	0.0365000	0.9635000	0.1160895	0.0366489
78	0.0404400	0.9595600	0.1141860	0.0421600
79	0.0448400	0.9551600	0.1226838	0.0439287
80	0.0497500	0.9502500	0.1152593	0.0509941
81	0.0552300	0.9447700	0.1069599	0.0616381
82	0.0613500	0.9386500	0.1134790	0.0667637
83	0.0682000	0.9318000	0.1165385	0.0728309
84	0.0758600	0.9241400	0.1221774	0.0792484
85	0.0844300	0.9155700	0.1053543	0.0998605
86	0.0940300	0.9059700	0.1269069	0.1016651
87	0.1048000	0.8952000	0.1066067	0.1224507
88	0.1168700	0.8831300	0.1340221	0.1265262
89	0.1304200	0.8695800	0.1105598	0.1513956
90	0.1456400	0.8543600	0.1167008	0.1638274
91	0.1623200	0.8376800	0.1035348	0.1869561
92	0.1801000	0.8199000	0.1039367	0.2066612
93	0.1989500	0.8010500	0.0949319	0.2368172
94	0.2188000	0.7812000	0.1095080	0.2593342
95	0.2448100	0.7551900	0.0998220	0.2927178
96	0.2663200	0.7336800	0.0691902	0.3475282
97	0.2884400	0.7115600	0.0864980	0.3557145
98	0.3109600	0.6890400	0.0803962	0.3898665

Age	Probability of death	Probability of survival	Shape (η)	Scale (β)
99	0.3336900	0.6663100	0.0528346	0.4201627
100	0.3564200	0.6435800	0.1301212	0.4582516
101	0.3789400	0.6210600	0.0442054	0.5054725
102	0.4010300	0.5989700	0.0912491	0.4985255
103	0.4225300	0.5774700	0.0378082	0.5349600
104	0.4432500	0.5567500	0.1084083	0.5782464
105	0.4630700	0.5369300	0.1195533	0.6253554
106	0.4818500	0.5181500	0.1620850	0.6690058
107	0.4995300	0.5004700	0.0796314	0.7217357
108	0.5160500	0.4839500	0.8988835	0.4862458
109	0.5313800	0.4686200	0.8280171	0.9992005
110	1.0000000	0.0000000	0.4452554	0.7957101

Fitted Gompertz parameters (female sex)

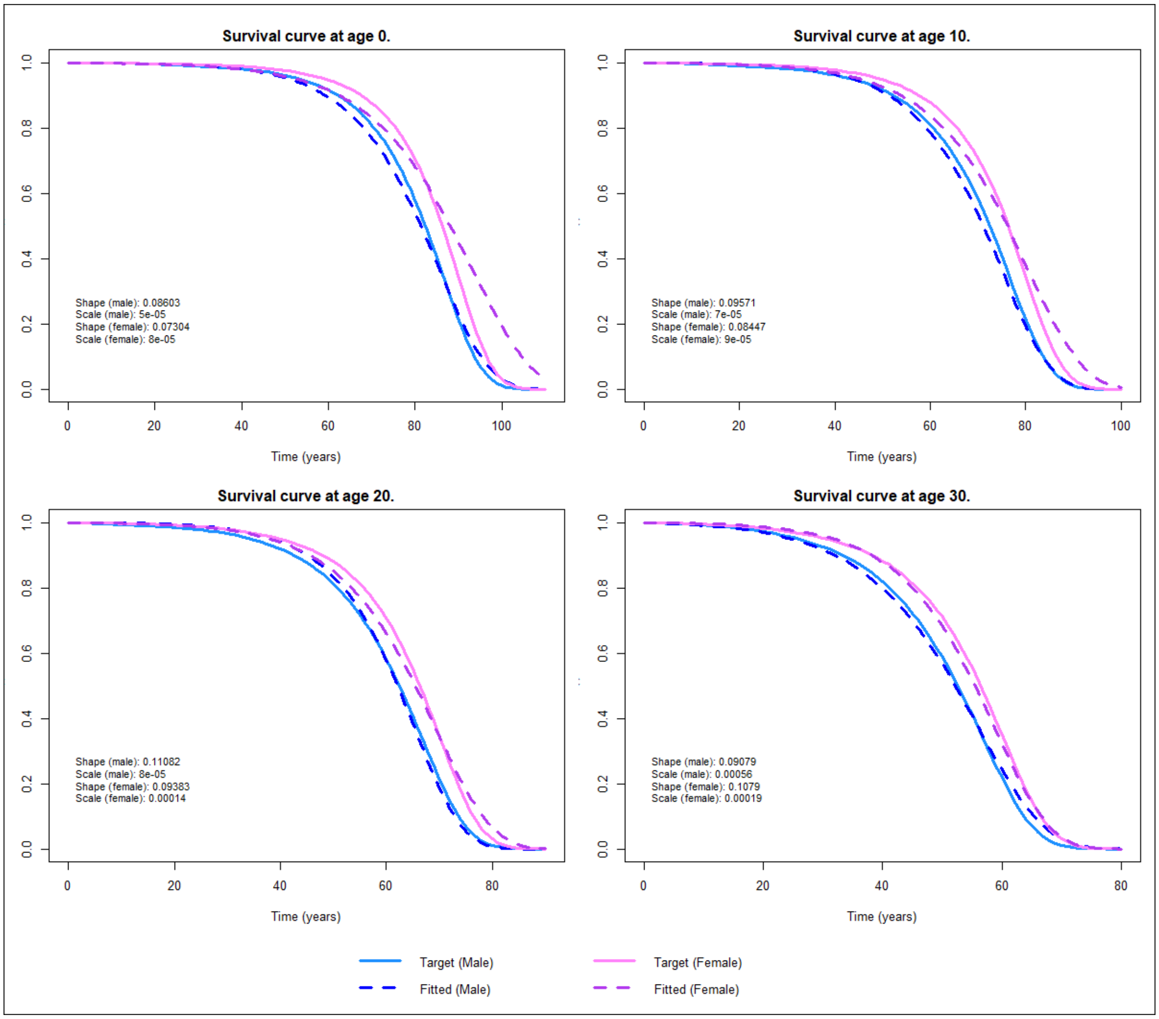
Age	Probability of death	Probability of survival	Shape (η)	Scale (β)
0	0.0042600	0.9957400	0.0730392	0.0000810
1	0.0002200	0.9997800	0.0742192	0.0001215
2	0.0001500	0.9998500	0.0992084	0.0000161
3	0.0001100	0.9998900	0.1307227	0.0000016
4	0.0000900	0.9999100	0.0822641	0.0000632
5	0.0000800	0.9999200	0.0996789	0.0000288
6	0.0000700	0.9999300	0.1064841	0.0000178
7	0.0000600	0.9999400	0.0906049	0.0000492
8	0.0000700	0.9999300	0.0866073	0.0000600
9	0.0000700	0.9999300	0.0943840	0.0000486
10	0.0000800	0.9999200	0.0844693	0.0000943
11	0.0000900	0.9999100	0.0920387	0.0000640
12	0.0001000	0.9999000	0.0949269	0.0000608
13	0.0001100	0.9998900	0.0944318	0.0000582
14	0.0001300	0.9998700	0.1007436	0.0000500

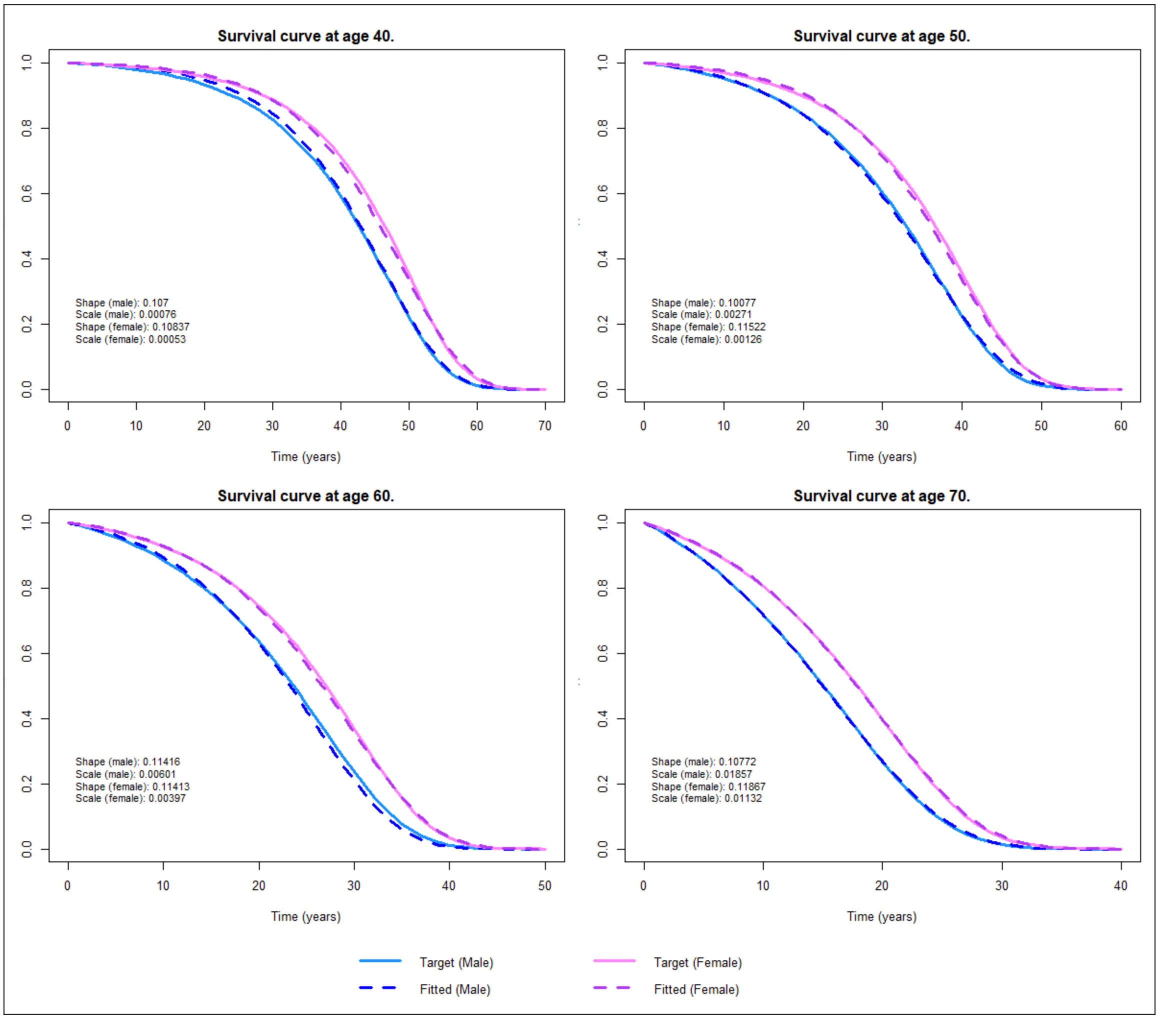
Age	Probability of death	Probability of survival	Shape (η)	Scale (β)
15	0.0001400	0.9998600	0.0884306	0.0001180
16	0.0001600	0.9998400	0.0840226	0.0001728
17	0.0001700	0.9998300	0.1048025	0.0000605
18	0.0001900	0.9998100	0.1020751	0.0000691
19	0.0002000	0.9998000	0.1077616	0.0000472
20	0.0002100	0.9997900	0.0938306	0.0001396
21	0.0002200	0.9997800	0.0949874	0.0001438
22	0.0002300	0.9997700	0.1120429	0.0000612
23	0.0002500	0.9997500	0.1103099	0.0000851
24	0.0002600	0.9997400	0.1272694	0.0000315
25	0.0002800	0.9997200	0.1022068	0.0001471
26	0.0002900	0.9997100	0.0872755	0.0003509
27	0.0003100	0.9996900	0.1180241	0.0000838
28	0.0003200	0.9996800	0.1179363	0.0000895
29	0.0003400	0.9996600	0.1051216	0.0001664
30	0.0003500	0.9996500	0.1078950	0.0001885
31	0.0003700	0.9996300	0.0980732	0.0002771
32	0.0003800	0.9996200	0.1095594	0.0002047
33	0.0004000	0.9996000	0.1025359	0.0002993
34	0.0004300	0.9995700	0.1129198	0.0002027
35	0.0004600	0.9995400	0.1146138	0.0002393
36	0.0004900	0.9995100	0.1191215	0.0001896
37	0.0005300	0.9994700	0.1163440	0.0002622
38	0.0005800	0.9994200	0.1039551	0.0004917
39	0.0006400	0.9993600	0.1153944	0.0003563
40	0.0007100	0.9992900	0.1083717	0.0005285
41	0.0008000	0.9992000	0.1081255	0.0005487
42	0.0008900	0.9991100	0.1079652	0.0006423
43	0.0009800	0.9990200	0.1192616	0.0004600
44	0.0010900	0.9989100	0.1073603	0.0007904
45	0.0012000	0.9988000	0.1149900	0.0006896
46	0.0013200	0.9986800	0.1183261	0.0007285
47	0.0014400	0.9985600	0.1064191	0.0010931
48	0.0015700	0.9984300	0.1110140	0.0010746
49	0.0017100	0.9982900	0.1097750	0.0013125
50	0.0018600	0.9981400	0.1152189	0.0012650
51	0.0020100	0.9979900	0.1147319	0.0014530
52	0.0021900	0.9978100	0.1146736	0.0015118
53	0.0023800	0.9976200	0.1114540	0.0018705
54	0.0025800	0.9974200	0.1132694	0.0020032
55	0.0028100	0.9971900	0.1148960	0.0022101

Age	Probability of death	Probability of survival	Shape (η)	Scale (β)
56	0.0030700	0.9969300	0.1137318	0.0025719
57	0.0033400	0.9966600	0.1180214	0.0024276
58	0.0036500	0.9963500	0.1206742	0.0026683
59	0.0040000	0.9960000	0.1189152	0.0031026
60	0.0043700	0.9956300	0.1141322	0.0039749
61	0.0047900	0.9952100	0.1200166	0.0038610
62	0.0052600	0.9947400	0.1125905	0.0049155
63	0.0057800	0.9942200	0.1224327	0.0046877
64	0.0063500	0.9936500	0.1147249	0.0060495
65	0.0069900	0.9930100	0.1185712	0.0063180
66	0.0077100	0.9922900	0.1233590	0.0068129
67	0.0085000	0.9915000	0.1211863	0.0077068
68	0.0093900	0.9906100	0.1237435	0.0082691
69	0.0103800	0.9896200	0.1190406	0.0099570
70	0.0114900	0.9885100	0.1186677	0.0113168
71	0.0127300	0.9872700	0.1308563	0.0116204
72	0.0141300	0.9858700	0.1187461	0.0144685
73	0.0156900	0.9843100	0.1237664	0.0152653
74	0.0174400	0.9825600	0.1260669	0.0165732
75	0.0194100	0.9805900	0.1144674	0.0213994
76	0.0216300	0.9783700	0.1240198	0.0217355
77	0.0241300	0.9758700	0.1401038	0.0210216
78	0.0269400	0.9730600	0.1288753	0.0268964
79	0.0301200	0.9698800	0.1223477	0.0323904
80	0.0337100	0.9662900	0.1422448	0.0306060
81	0.0377600	0.9622400	0.1327674	0.0384967
82	0.0423500	0.9576500	0.1208982	0.0468981
83	0.0475600	0.9524400	0.1232046	0.0525163
84	0.0534600	0.9465400	0.1234954	0.0594794
85	0.0601600	0.9398400	0.1249835	0.0672782
86	0.0677700	0.9322300	0.1310730	0.0734192
87	0.0764300	0.9235700	0.1010697	0.0919157
88	0.0862900	0.9137100	0.1130455	0.0979238
89	0.0975300	0.9024700	0.1160139	0.1136079
90	0.1103600	0.8896400	0.1233786	0.1253244
91	0.1246600	0.8753400	0.1052736	0.1455774
92	0.1401900	0.8598100	0.0904810	0.1722428
93	0.1569600	0.8430400	0.1102550	0.1888674
94	0.1749400	0.8250600	0.1205484	0.2046073
95	0.1990200	0.8009800	0.1080330	0.2311890
96	0.2198900	0.7801100	0.0931611	0.2658987

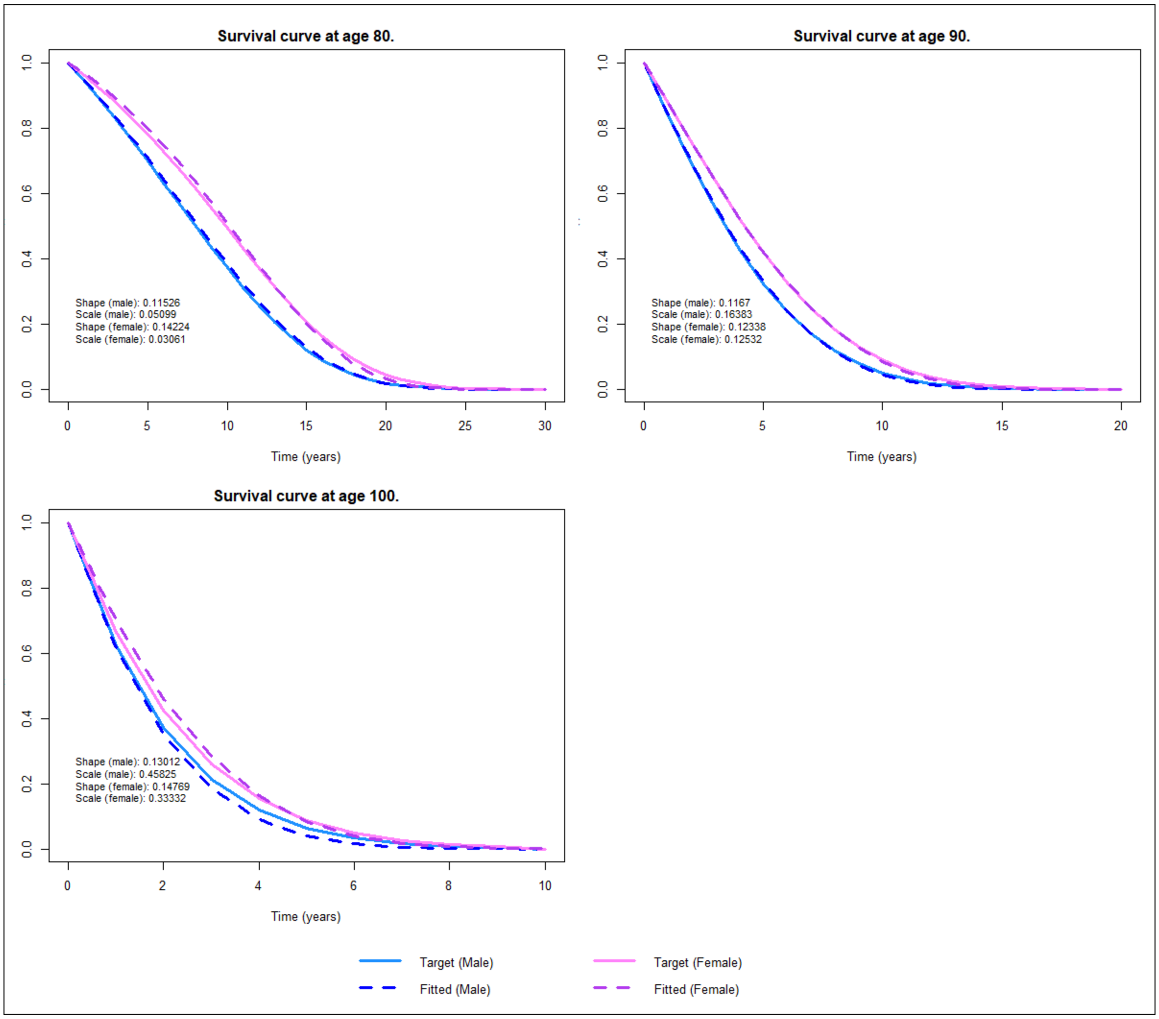
Age	Probability of death	Probability of survival	Shape (η)	Scale (β)
97	0.2418200	0.7581800	0.1370253	0.2689299
98	0.2646300	0.7353700	0.1124392	0.3146941
99	0.2881400	0.7118600	0.0104545	0.3950946
100	0.3121200	0.6878800	0.1476933	0.3333236
101	0.3363200	0.6636800	0.1547931	0.3971246
102	0.3604800	0.6395200	0.0228388	0.4939976
103	0.3843700	0.6156300	0.2922922	0.4400734
104	0.4077300	0.5922700	0.0923933	0.5733933
105	0.4303400	0.5696600	0.1631831	0.5852797
106	0.4520200	0.5479800	0.2826936	0.5351306
107	0.4726000	0.5274000	0.4984257	0.4290466
108	0.4919800	0.5080200	0.9173890	0.5263410
109	0.5100600	0.4899400	0.9797783	0.9393380
110	1.0000000	0.0000000	0.1738668	0.2405948

Fitted Gompertz versus observed survival curves by starting age





Survival curve at age 40.
Shape (male): 0.107
Scale (male): 0.00076
Shape (female): 0.10837
Scale (female): 0.00053
Time (years)
Survival curve at age 50.
Shape (male): 0.10077
Scale (male): 0.00271
Shape (female): 0.11522
Scale (female): 0.00126
Time (years)
Survival curve at age 60.
Shape (male): 0.11416
Scale (male): 0.00601
Shape (female): 0.11413
Scale (female): 0.00397
Time (years)
Survival curve at age 70.
Shape (male): 0.10772
Scale (male): 0.01857
Shape (female): 0.11867
Scale (female): 0.01132
Time (years)
Target (Male)
Fitted (Male)
Target (Female)
Fitted (Female)



In the model, an individual's sex and integer age was used to locate the correct row in the fitted tables displayed above. The corresponding β and η parameters were then supplied to the Treeage Pro's Gompertz distribution sampler and a time-to-death sampled from the distribution.

The corresponding number of discounted life years from the time of discharge (unrounded) until the sampled time of death was calculated as the area under the continuous discounting function, exp(-ρt), where ρ is the continuous discounting coefficient equal to ln(1+r), with ‘r’ being the discrete annual discount rate of 1.5% (i.e. 0.015) as per the Canadian Agency for Drugs and Technology in Health (CADTH).(6)

The area under the continuous discounting function was calculated as:

$$LE_{disc} = \frac{e^{-\rho t_1} - e^{-\rho t_2}}{-\rho} \tag{5}$$

where t_1 is the model time at discharge, and t_2 is the sampled time-to-death from the Gompertz distribution.

Quality adjustment

Discounted, quality-adjusted life expectancy was calculated by multiplying discounted life expectancy by health utility weights determined by events occurring in the initial part of the model (see the main text, Table 1).

Additional model outputs

In addition to discounted life expectancy and discounted, quality-adjusted life expectancy, for pregnant individuals, the model reported proportion of ventilator duration, proportion of hospital survival, mean hospital survival hospital length-of-stay, and proportion with long term complications. Additional outcomes for neonates and children included, mean gestational age, mean with vertical COVID-19 infection, proportion with NICU admission, mean NICU length-of-stay, proportion of hospital survival and proportion with long-term complications. In addition, there were joint outcomes: the proportion of pairs where both pregnant individual and neonate survive and the proportion of pairs where both pregnant individual and child is born at term.

Model repetitions and credible intervals

A model run consisted of simulating 1000 pregnant individuals. Uncertainty in the model outcomes was assessed by repeating the model run 1000 times (for a total of 1 million pregnant individuals). We estimated 95% credible intervals for each model output by finding the 2.5th and 97.5th percentile among the 1000 repetitions.

Supplemental Tables

Table E1: Differences in outcomes by gestational age

	GA 28 weeks	GA 30 weeks	GA 32 weeks (base)	GA 34 weeks
Both survive	-0.009 (-0.043 to 0.025)	0.02 (-0.01 to 0.053)	0.019 (-0.012 to 0.049)	0.015 (-0.016 to 0.047)
Both survive, term birth	-0.7 (-0.727 to -0.672)	-0.707 (-0.736 to -0.679)	-0.716 (-0.742 to -0.688)	-0.765 (-0.793 to -0.737)
Maternal hospital survival	-0.009 (-0.039 to 0.019)	-0.003 (-0.033 to 0.025)	-0.002 (-0.031 to 0.027)	-0.003 (-0.031 to 0.025)
Maternal long-term complication	-0.003 (-0.032 to 0.026)	-0.002 (-0.032 to 0.028)	-0.001 (-0.03 to 0.027)	-0.001 (-0.03 to 0.028)
Maternal life-years	-0.3 (-1.6 to 0.8)	-0.1 (-1.3 to 1.1)	-0.1 (-1.3 to 1.1)	-0.1 (-1.3 to 1)
Maternal QALYs	-0.4 (-1.6 to 0.6)	-0.2 (-1.3 to 1)	0 (-1.3 to 1.2)	-0.1 (-1.3 to 1)
Maternal survival, neonatal death	0 (-0.018 to 0.016)	-0.024 (-0.036 to -0.011)	-0.021 (-0.035 to -0.008)	-0.019 (-0.032 to -0.006)
Neonatal COVID-19	0.115 (0.094 to 0.138)	0.116 (0.094 to 0.138)	0.111 (0.089 to 0.133)	0.111 (0.087 to 0.134)
Neonatal hospital survival	0.024 (0.003 to 0.045)	0.055 (0.037 to 0.074)	0.052 (0.035 to 0.07)	0.048 (0.032 to 0.066)
Neonatal long-term complication	0.035 (0.023 to 0.049)	0.037 (0.024 to 0.051)	0.004 (-0.001 to 0.01)	0.005 (-0.001 to 0.01)
Neonatal life-years	0 (-1.1 to 1.1)	1.5 (0.5 to 2.5)	1.3 (0.4 to 2.3)	1.7 (0.8 to 2.6)
Neonatal QALYs	-0.3 (-1.5 to 0.8)	1.1 (0.1 to 2.1)	1.3 (0.3 to 2.3)	1.6 (0.7 to 2.6)

The outcomes show the difference between elective delivery and expectant management (eg, elective delivery QALYs – expectant management QALYs), so positive numbers denote outcomes where that outcome was numerically greater for elective delivery than expectant management.

Table E2: Differences in outcomes for scenarios relevant to maternal QALYs

	Delivery worsens maternal outcome (RR 1.4)	Higher mortality rate of cesarean delivery (0.5% vs 0.1%)	Lower maternal utility of neonatal outcomes (0.5 vs 0.95)	Delivery improves maternal outcome (RR 0.7)
Both survive	-0.029 (-0.062 to 0.003)	0.015 (-0.016 to 0.046)	0.019 (-0.012 to 0.052)	0.056 (0.025 to 0.087)
Both survive, term birth	-0.717 (-0.746 to -0.689)	-0.717 (-0.745 to -0.689)	-0.716 (-0.743 to -0.687)	-0.716 (-0.744 to -0.689)
Maternal hospital survival	-0.052 (-0.083 to -0.022)	-0.007 (-0.038 to 0.025)	-0.003 (-0.032 to 0.026)	0.035 (0.007 to 0.062)
Maternal long-term complication	-0.001 (-0.033 to 0.03)	-0.002 (-0.032 to 0.03)	-0.001 (-0.03 to 0.028)	-0.007 (-0.036 to 0.022)
Maternal life-years	-1.9 (-3.1 to -0.7)	-0.3 (-1.4 to 1)	-0.1 (-1.3 to 1.1)	1.3 (0.2 to 2.3)
Maternal QALYs	-1.8 (-3 to -0.6)	-0.2 (-1.4 to 1)	0.2 (-1 to 1.4)	1.4 (0.3 to 2.4)
Maternal survival, neonatal death	-0.022 (-0.035 to -0.01)	-0.021 (-0.036 to -0.008)	-0.022 (-0.035 to -0.008)	-0.021 (-0.034 to -0.007)
Neonatal COVID-19	0.111 (0.089 to 0.134)	0.111 (0.089 to 0.133)	0.111 (0.088 to 0.133)	0.111 (0.09 to 0.135)
Neonatal hospital survival	0.052 (0.036 to 0.069)	0.052 (0.035 to 0.069)	0.052 (0.035 to 0.07)	0.052 (0.034 to 0.069)
Neonatal long-term complication	0.004 (-0.002 to 0.01)	0.004 (-0.002 to 0.01)	0.004 (-0.001 to 0.01)	0.004 (-0.002 to 0.01)
Neonatal life-years	1.3 (0.4 to 2.3)	1.3 (0.4 to 2.3)	1.4 (0.4 to 2.3)	1.3 (0.4 to 2.2)
Neonatal QALYs	1.3 (0.4 to 2.2)	1.3 (0.3 to 2.2)	1.3 (0.4 to 2.3)	1.3 (0.4 to 2.2)

The outcomes show the difference between elective delivery and expectant management (eg, elective delivery QALYs – expectant management QALYs), so positive numbers denote outcomes where that outcome was numerically greater for elective delivery than expectant management.

Table E3: Differences in outcomes for maternal scenarios relevant to neonatal QALYs

	Intrauterine death rate lower (1% vs 5%)	Lower ARDS mortality (7% vs 13%)	Fetal loss rate higher (10% vs 5%)	Higher ARDS mortality (24% vs 13%)
Both survive	-0.007 (-0.038 to 0.023)	0.02 (-0.006 to 0.046)	0.014 (-0.024 to 0.052)	0.05 (0.019 to 0.081)
Both survive, term birth	-0.741 (-0.769 to -0.714)	-0.767 (-0.793 to -0.74)	-0.627 (-0.657 to -0.598)	-0.687 (-0.714 to -0.658)
Maternal hospital survival	-0.002 (-0.032 to 0.026)	-0.003 (-0.024 to 0.02)	-0.005 (-0.044 to 0.033)	-0.003 (-0.031 to 0.024)
Maternal long-term complication	-0.001 (-0.029 to 0.027)	-0.001 (-0.033 to 0.03)	-0.001 (-0.031 to 0.032)	-0.001 (-0.03 to 0.028)
Maternal life-years	-0.1 (-1.2 to 1.1)	-0.1 (-1 to 0.9)	-0.2 (-1.6 to 1.2)	-0.1 (-1.2 to 1)
Maternal QALYs	-0.1 (-1.2 to 1.1)	-0.1 (-1 to 1)	-0.1 (-1.5 to 1.3)	0 (-1.2 to 1.1)
Maternal survival, neonatal death	0.005 (-0.004 to 0.013)	-0.023 (-0.037 to -0.009)	-0.019 (-0.031 to -0.006)	-0.053 (-0.071 to -0.036)
Neonatal COVID-19	0.111 (0.09 to 0.134)	0.117 (0.096 to 0.139)	0.101 (0.077 to 0.124)	0.111 (0.091 to 0.133)
Neonatal hospital survival	0.025 (0.011 to 0.04)	0.039 (0.023 to 0.055)	0.076 (0.057 to 0.095)	0.085 (0.066 to 0.107)
Neonatal long-term complication	0.004 (-0.002 to 0.01)	0.004 (-0.001 to 0.011)	0.004 (-0.002 to 0.01)	0.004 (-0.001 to 0.01)
Neonatal life-years	0.1 (-0.8 to 0.9)	0.7 (-0.3 to 1.6)	2.6 (1.6 to 3.6)	2.9 (1.9 to 3.9)
Neonatal QALYs	0 (-0.8 to 0.9)	0.6 (-0.3 to 1.5)	2.5 (1.6 to 3.5)	2.8 (1.8 to 3.9)

The outcomes show the difference between elective delivery and expectant management (eg, elective delivery QALYs – expectant management QALYs), so positive numbers denote outcomes where that outcome was numerically greater for elective delivery than expectant management.

Table E4: Differences in outcomes by perinatal and neonatal scenario

	Higher mortality risk in ex-preterm (RR 2)	Higher NICU mortality risk (RR 2)	Base case	Perimortem delivery survival lower (50% vs 75%)
Both survive	0.018 (-0.016 to 0.049)	0.007 (-0.027 to 0.04)	0.019 (-0.012 to 0.049)	0.019 (-0.012 to 0.05)
Both survive, term birth	-0.717 (-0.744 to -0.688)	-0.717 (-0.744 to -0.69)	-0.716 (-0.742 to -0.688)	-0.716 (-0.742 to -0.688)
Maternal hospital survival	-0.003 (-0.033 to 0.027)	-0.004 (-0.034 to 0.025)	-0.002 (-0.031 to 0.027)	-0.003 (-0.032 to 0.026)
Maternal long-term complication	-0.001 (-0.031 to 0.03)	-0.002 (-0.032 to 0.028)	-0.001 (-0.03 to 0.027)	-0.002 (-0.032 to 0.027)
Maternal life-years	-0.1 (-1.3 to 1.1)	-0.1 (-1.2 to 1)	-0.1 (-1.3 to 1.1)	-0.1 (-1.2 to 1.1)
Maternal QALYs	-0.1 (-1.2 to 1.1)	-0.1 (-1.1 to 1.1)	0 (-1.3 to 1.2)	-0.1 (-1.1 to 1.1)
Maternal survival, neonatal death	-0.021 (-0.034 to -0.007)	-0.011 (-0.025 to 0.004)	-0.021 (-0.035 to -0.008)	-0.022 (-0.035 to -0.008)
Neonatal COVID-19	0.111 (0.089 to 0.134)	0.111 (0.09 to 0.134)	0.111 (0.089 to 0.133)	0.111 (0.089 to 0.133)
Neonatal hospital survival	0.052 (0.035 to 0.07)	0.041 (0.021 to 0.059)	0.052 (0.035 to 0.07)	0.082 (0.063 to 0.1)
Neonatal long-term complication	0.004 (-0.001 to 0.01)	0.004 (-0.002 to 0.01)	0.004 (-0.001 to 0.01)	0.005 (-0.001 to 0.011)
Neonatal life-years	-0.1 (-1.1 to 0.8)	0.8 (-0.2 to 1.8)	1.3 (0.4 to 2.3)	2.7 (1.6 to 3.7)
Neonatal QALYs	-0.2 (-1.1 to 0.7)	0.8 (-0.2 to 1.8)	1.3 (0.3 to 2.3)	2.6 (1.6 to 3.7)

The outcomes show the difference between elective delivery and expectant management (eg, elective delivery QALYs – expectant management QALYs), so positive numbers denote outcomes where that outcome was numerically greater for elective delivery than expectant management.

Probability Tables

Maternal Age

Maternal Age	Probability
18	0.013143
19	0.013143
20	0.013143
21	0.013143
22	0.013143
23	0.013143
24	0.013143
25	0.0592
26	0.0592
27	0.0592
28	0.0592
29	0.0592
30	0.075
31	0.075
32	0.075
33	0.075
34	0.075
35	0.0384
36	0.0384
37	0.0384
38	0.0384
39	0.0384
40	0.009
41	0.009
42	0.009
43	0.009
44	0.009

Money, 2021. Based on Canadian COVID positive pregnant patients.(7)

Delivery

	Week	Day	P(delivery today)	P(no delivery prior to today)	P(delivery today | no delivery prior to today)
0	28	0	6.68E-04	0.9932	6.72E-04
1	28	1	6.68E-04	9.93E-01	6.73E-04
2	28	2	6.68E-04	9.92E-01	6.73E-04
3	28	3	6.68E-04	9.91E-01	6.74E-04
4	28	4	6.68E-04	9.91E-01	6.74E-04
5	28	5	6.68E-04	9.90E-01	6.75E-04
6	28	6	6.68E-04	9.89E-01	6.75E-04
7	29	0	6.68E-04	9.89E-01	6.76E-04
8	29	1	6.68E-04	9.88E-01	6.76E-04
9	29	2	6.68E-04	9.87E-01	6.77E-04
10	29	3	6.68E-04	9.87E-01	6.77E-04
11	29	4	6.68E-04	9.86E-01	6.77E-04
12	29	5	6.68E-04	9.85E-01	6.78E-04
13	29	6	6.68E-04	9.85E-01	6.78E-04
14	30	0	6.68E-04	9.84E-01	6.79E-04
15	30	1	6.68E-04	9.83E-01	6.79E-04
16	30	2	6.68E-04	9.83E-01	6.80E-04
17	30	3	6.68E-04	9.82E-01	6.80E-04
18	30	4	6.68E-04	9.81E-01	6.81E-04
19	30	5	6.68E-04	9.81E-01	6.81E-04
20	30	6	6.68E-04	9.80E-01	6.82E-04
21	31	0	6.68E-04	9.79E-01	6.82E-04
22	31	1	6.68E-04	9.79E-01	6.83E-04
23	31	2	6.68E-04	9.78E-01	6.83E-04
24	31	3	6.68E-04	9.77E-01	6.83E-04
25	31	4	6.68E-04	9.77E-01	6.84E-04
26	31	5	6.68E-04	9.76E-01	6.84E-04
27	31	6	6.68E-04	9.75E-01	6.85E-04
28	32	0	4.13E-03	9.75E-01	4.24E-03
29	32	1	4.13E-03	9.70E-01	4.25E-03
30	32	2	4.13E-03	9.66E-01	4.27E-03
31	32	3	4.13E-03	9.62E-01	4.29E-03
32	32	4	4.13E-03	9.58E-01	4.31E-03
33	32	5	4.13E-03	9.54E-01	4.33E-03
34	32	6	4.13E-03	9.50E-01	4.35E-03
35	33	0	4.13E-03	9.46E-01	4.37E-03
36	33	1	4.13E-03	9.41E-01	4.39E-03
37	33	2	4.13E-03	9.37E-01	4.40E-03
38	33	3	4.13E-03	9.33E-01	4.42E-03
39	33	4	4.13E-03	9.29E-01	4.44E-03

40	33	5	4.13E-03	9.25E-01	4.46E-03
41	33	6	4.13E-03	9.21E-01	4.48E-03
42	34	0	4.13E-03	9.17E-01	4.50E-03
43	34	1	4.13E-03	9.13E-01	4.52E-03
44	34	2	4.13E-03	9.08E-01	4.54E-03
45	34	3	4.13E-03	9.04E-01	4.57E-03
46	34	4	4.13E-03	9.00E-01	4.59E-03
47	34	5	4.13E-03	8.96E-01	4.61E-03
48	34	6	4.13E-03	8.92E-01	4.63E-03
49	35	0	4.13E-03	8.88E-01	4.65E-03
50	35	1	4.13E-03	8.84E-01	4.67E-03
51	35	2	4.13E-03	8.80E-01	4.69E-03
52	35	3	4.13E-03	8.75E-01	4.72E-03
53	35	4	4.13E-03	8.71E-01	4.74E-03
54	35	5	4.13E-03	8.67E-01	4.76E-03
55	35	6	4.13E-03	8.63E-01	4.78E-03
56	36	0	4.13E-03	8.59E-01	4.81E-03
57	36	1	4.13E-03	8.55E-01	4.83E-03
58	36	2	4.13E-03	8.51E-01	4.85E-03
59	36	3	4.13E-03	8.47E-01	4.88E-03
60	36	4	4.13E-03	8.42E-01	4.90E-03
61	36	5	4.13E-03	8.38E-01	4.93E-03
62	36	6	4.13E-03	8.34E-01	4.95E-03
63	37	0	1.91E-02	8.30E-01	2.30E-02
64	37	1	1.91E-02	8.11E-01	2.35E-02
65	37	2	1.91E-02	7.92E-01	2.41E-02
66	37	3	1.91E-02	7.73E-01	2.47E-02
67	37	4	1.91E-02	7.54E-01	2.53E-02
68	37	5	1.91E-02	7.35E-01	2.60E-02
69	37	6	1.91E-02	7.15E-01	2.67E-02
70	38	0	1.91E-02	6.96E-01	2.74E-02
71	38	1	1.91E-02	6.77E-01	2.82E-02
72	38	2	1.91E-02	6.58E-01	2.90E-02
73	38	3	1.91E-02	6.39E-01	2.99E-02
74	38	4	1.91E-02	6.20E-01	3.08E-02
75	38	5	1.91E-02	6.01E-01	3.18E-02
76	38	6	1.91E-02	5.82E-01	3.28E-02
77	39	0	3.55E-02	5.63E-01	6.31E-02
78	39	1	3.55E-02	5.27E-01	6.73E-02
79	39	2	3.55E-02	4.92E-01	7.22E-02
80	39	3	3.55E-02	4.56E-01	7.78E-02
81	39	4	3.55E-02	4.21E-01	8.44E-02
82	39	5	3.55E-02	3.85E-01	9.22E-02

83	39	6	3.55E-02	3.50E-01	1.02E-01
84	40	0	3.55E-02	3.14E-01	1.13E-01
85	40	1	3.55E-02	2.79E-01	1.27E-01
86	40	2	3.55E-02	2.43E-01	1.46E-01
87	40	3	3.55E-02	2.08E-01	1.71E-01
88	40	4	3.55E-02	1.72E-01	2.06E-01
89	40	5	3.55E-02	1.37E-01	2.60E-01
90	40	6	3.55E-02	1.01E-01	3.51E-01
91	41	0	9.38E-03	6.57E-02	1.43E-01
92	41	1	9.38E-03	5.63E-02	1.67E-01
93	41	2	9.38E-03	4.69E-02	2.00E-01
94	41	3	9.38E-03	3.75E-02	2.50E-01
95	41	4	9.38E-03	2.81E-02	3.33E-01
96	41	5	9.38E-03	1.88E-02	5.00E-01
97	41	6	9.38E-03	9.38E-03	1.00E+00

Based on Allotey 2021, Chawanpaiboon 2019, Ananth 2018.(8–10)

ARDS outcomes (extubation, mortality)

Day	Probability of extubation	Probability of mortality
1	0.030101	0.008734
2	0.034732	0.026201
3	0.039942	0.015721
4	0.009551	0.015721
5	0.030391	0.023581
6	0.031693	0.00262
7	0.036903	0.01048
8	0.018669	0.015721
9	0.031259	0.020961
10	0.022142	0.015721
11	0.024313	0.020961
12	0.037337	0.0131
13	0.009117	0.028821
14	0.01259	0.0131
15	0.015195	0.00786
16	0.006078	0.01048
17	0.01259	0.00262
18	0.009551	0.00786
19	0	0.0131
20	0.015195	0.00524
21	0.01563	0.00524
22	0.006512	0.00262

23	0.005644	0.002166
24	0.009117	0.003074
25	0.012156	0.003297
26	0.006946	0.001943
27	0.012156	0

From the Kaplan-Meier curves of the invasively ventilated patients in the RECOVERY dexamethasone study. (11)

Neonatal

NICU discharge and survival

Gestational Age at birth	Discharge Rate	Probability of Survival at discharge
28	0.013862944	0.957711
29	0.018733708	0.961303
30	0.023901627	0.986011
31	0.03150669	0.986011
32	0.038508177	0.986011
33	0.046209812	0.986011
34	0.06301338	0.986011

Based Risnes 2021.(12) Rates are based on the median time to discharge.

Longterm complications

GA at birth	Probability of complication
28	0.04315
29	0.04315
30	0.04315
31	0.04315
32	0.00675
33	0.00675
34	0.00675
35	0.00675
36	0.00675
37	0.00135
38	0.00135
39	0.00135
40	0.00135
41	0.00135

From Oskoui 2013.(13)

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