

RESEARCH ARTICLE

Quantifying the postponement in the age at first attempt to conceive and its consequences

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ABSTRACT The substantial rise in the age at first birth in recent decades suggests that people are delaying their first attempt to have a child. The age at first birth, however, may not accurately reflect when people first attempt to conceive, given age-related declines in the ability to get pregnant and to achieve a live birth. Through a microsimulation model incorporating biological parameters and sequential Approximate Bayesian Computation, we estimate the distribution of the age at first attempt to conceive from 1960 to 1980 based on the age at first birth derived from Dutch administrative data. Over this period, the average age at first conception attempt, as inferred by the models, increases by two years. Unexpectedly, the average duration to childbirth remains stable despite later conception attempts, which is partly explained by a selection effect at advanced ages favouring couples with higher fecundity, with less fecund couples having higher rates of childlessness. We assess the influence of model assumptions on our results and underscore the promise of Approximate Bayesian Computation for future demographic and fertility research.

KEYWORDS Postponement • Age first attempt to conceive • Microsimulation • Childlessness • Selection bias • Approximate Bayesian computation

Introduction

The postponement of childbearing is both a cause and a consequence of profound social change. In many western countries, the average age at first birth now exceeds 30, compared to around 25 just 50 years ago (HFD, 2025). When researchers study this postponement, they are mostly interested in the behavioural aspect underlying the delay, namely the age at which individuals first attempt to conceive (e.g. Mills et al., 2011; Verweij et al., 2020). This is rarely measured directly, and it is often approximated by the age at first birth. However, the age at first birth is not equivalent to the moment when individuals begin attempting to conceive, but is rather the outcome of that process, and the relationship between the two is

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not straightforward. One key reason why is that the ability to have children declines with age in a non-linear fashion (Dunson et al., 2004; Noord-Zaadstra et al., 1991), in terms of both the likelihood of conception and the ability to achieve a live birth. As a result, couples who are first attempting to conceive at age 20 are more likely to quickly succeed than those same couples if they are attempting to conceive at age 30, with the gap widening further for those starting at higher ages. Consequently, as the age at which couples first try to conceive rises, the time required to achieve a successful pregnancy tends to increase, which can, in turn, accelerate the rise in the age at first birth. One important consequence of delayed child-bearing is an increase in childlessness (Beets, 2011; te Velde et al., 2012), as couples start trying to conceive at advanced reproductive ages.

Quantifying the age at which individuals first attempt to conceive is methodologically challenging, as demonstrated by the extensive literature on time to pregnancy (Bonde et al., 2006; Joffe et al., 2005; Olsen et al., 1998; Slama et al., 2006; Weinberg et al., 1993, 1994). An illustrative example is that surveys have found that parents who conceived at older ages often report shorter times to pregnancy than those who conceived at younger ages (e.g. Jensen et al., 2000; Juul et al., 2000), despite well-established findings in reproductive medicine showing that the ability to have children declines with age (Sauer, 2015). This seemingly paradoxical result is largely attributable to the retrospective sampling of those individuals who had children, for whom only time to pregnancy can be calculated. Studies that focus on parents inherently select individuals who are biologically capable of conceiving (i.e. selecting on the outcome; see also Billari and Borgoni, 2005), and only those couples who are biologically well-endowed will be able to reproduce at older ages, which skews time to pregnancy estimates downwards. Another potential concern when attempting to accurately measure time to pregnancy is that the sampled couples must make equal (full) use of their reproductive capabilities. This excludes those couples who do not try to conceive and those who use contraception, some of whom may become pregnant unintentionally. Other aspects complicating its measurement include changes in reproductive behaviour over time (e.g. frequency of intercourse and contraceptive use), as well as failure to recall when contraception was stopped and when a pregnancy occurred (Bonde et al., 2006; Slama et al., 2006; Weinberg et al., 1994). Thus, the age at first attempt to conceive cannot be easily inferred from retrospective surveys, including those focusing on recent parents.

Sophisticated sampling designs (e.g. Slama et al., 2006) and prospective studies (e.g. Bonde, Ernst, et al., 1998) can overcome some of these concerns and provide reliable estimates of time to pregnancy from which the age at first attempt to conceive can be derived, but these are relatively rare and exist only for particular populations and cohorts. In order to overcome the lack of cohort-representative prospective data and to propose an alternative to retrospective survey-based estimates of the age at first attempt to conceive (e.g. Tymicki, 2017), we employ a microsimulation approach to infer this age distribution. Specifically, we develop a microsimulation model incorporating key biological parameters from reproductive medicine, particularly the age-dependent probabilities of conception and foetal survival. The model is calibrated to reproduce the observed distribution of the age at first birth among Dutch women born between 1960 and 1980, based on comprehensive administrative records. The Netherlands has long been among the leading countries in

the postponement of childbearing, with the average age at first birth reaching 30.2 in 2023 (HFD, 2025). Through a process of sequential Approximate Bayesian Computation, we examine which distributions of the age at first attempt to conceive lead to the simulated outcomes that best match the observed age at first birth distributions.

Building a microsimulation model of fertility

Microsimulation models are particularly well-suited to studying complex processes with interacting factors underlying fertility outcomes (Ciganda and Todd, 2022; Leridon and Shapiro, 2017; van Imhoff and Post, 1998; Zagheni, 2015). In a microsimulation model of fertility, the reproductive life courses of a sample of synthetic individuals (agents) are simulated. Each individual in the synthetic population is assigned biological and behavioural characteristics based on estimates that are derived from previous research (e.g. clinical studies, survey or administrative data). These simulated individuals are then exposed to risks of certain events that vary over the life course. Whether an event occurs is determined by a random draw with a certain probability of success, a procedure known as the Monte Carlo technique (Barrett, 1969; van Imhoff and Post, 1998).

Our model has one behavioural parameter: the age at which agents first attempt to conceive. The biological parameters are fecundability, foetal survival and age at sterility. At each age, the combination of parameters stochastically determines when an individual tries to conceive, and whether an attempt to conceive leads to a conception, and subsequently to a live birth. Simulating many reproductive histories allows for the estimation of population-level metrics of fertility outcomes, which can be compared to actual population-level outcomes (see e.g. Granholm et al., 2025; Neels et al., 2024; Winkler-Dworak et al., 2021).

Microsimulation models have been used to study fertility for over five decades (Barrett, 1971; Habbema et al., 2015; Leridon, 2004; Leridon and Shapiro, 2017; Leridon and Slama, 2008; Winkler-Dworak et al., 2021; see Ciganda and Todd (2022) for an excellent review). Many such simulation models have focused on how biological processes shape fertility outcomes over the life course, typically ignoring realistic behavioural factors such as preferences or partnership trajectories. Other microsimulation models instead focus on how behaviours are related to fertility outcomes, and largely overlook biological influences (Neels et al., 2024; Thomson et al., 2019). Here, we use a microsimulation model that incorporates both biological and behavioural factors to estimate an unobserved variable of interest: the age at which people first attempt to conceive.

Biological parameters

The biology of human reproduction is complex and varies considerably between individuals. Attempts at estimating a set of simplified components date back to the 1950s–1960s with the work of Louis Henry (Henry, 1953, 1961, 1964), among others. These methods and estimates were later refined by scholars like Henri Leridon and John Bongaarts (Bongaarts, 1978; Leridon, 1977), and have since been implemented in various

microsimulation models of human reproduction (Bongaarts, 1977; Ciganda and Todd, 2022; Granholm et al., 2026; Habbema et al., 2015, 2015; Leridon, 2004). For the purposes of our analysis, we model the following components: fecundability, age at sterility, foetal survival and the non-susceptible period.

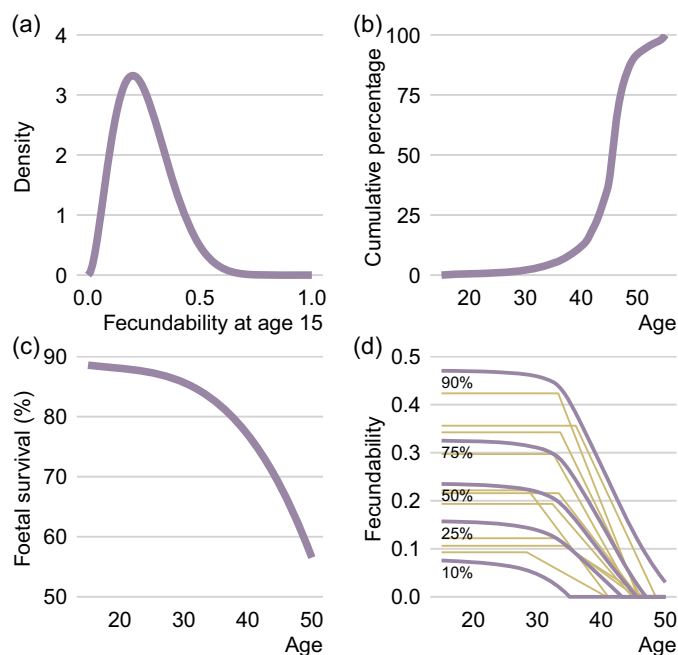
Fecundability

Fecundability refers to the monthly probability of a couple conceiving naturally when having regular intercourse while not using any contraceptive methods. We do not model male and female fecundability separately due to a lack of data on, and the limited understanding of, male fecundability (Harris et al., 2011; Wang and Swerdlhoff, 2014). We do know that within a couple, the female partner's fecundity, i.e. her biological ability to conceive children, is more important in determining the couple's fecundability than that of the male partner (Eijkemans et al., 2014). Fecundability varies greatly between couples, and we have chosen a beta distribution ($\alpha = 3$, $\beta = 9$) to model individual heterogeneity in peak fecundability. The choice of this beta distribution is based on work by Louis Henry (1961, 1964), who first empirically estimated parameters from 18th century European populations, and research by Henri Leridon (1977, 2017), who further refined these estimates based on various newer studies and his own work (Leridon, 1977, pp. 30–36; Leridon and Shapiro, 2017). This distribution yields a mean fecundability of 0.25 at the start of an individual's reproductive years, which we define as age 15 (see Figure 1a).

Female fecundability does not drop abruptly from its maximum level to sterility; rather, it declines gradually with age because both the number and the quality of the oocytes or eggs remaining in the ovaries decrease (O'Connor et al., 1998; te Velde and Pearson, 2002), alongside other age-related uterine changes (Marti-Garcia et al., 2024). We model this decline based on work by Leridon (2004), which assumes a linear decline over a period of 12.5 years prior to the age at sterility (see Figure 1d). This is in line with other attempts at modelling the decline in fecundability, which have also yielded near-linear declines (Larsen et al., 2003; Wesselink et al., 2017; Yan and Larsen, 2001).

It is important to acknowledge that fecundability, like time to pregnancy, is difficult to assess, and that considerable debate exists about its mean and variation, as well as about the extent to which it can be generalised across populations (Leridon and Shapiro, 2017). Estimates from historical populations may not be representative for contemporary Dutch couples. Indeed, some studies based on contemporary populations suggest that historical estimates of fecundability may be underestimated (Dunson, 2001; Dunson et al., 2004; Rothman et al., 2013; Wesselink et al., 2017). However, other studies point to a possible decrease in couple fecundability due to recent declines in sperm quality (Levine et al., 2017). Fecundability estimates from clinical trials in contemporary populations are also difficult to apply broadly because they often focus on specific medical conditions such as infertility, obesity or adverse pregnancy outcomes (Brink Henriksen et al., 1997; Gesink Law et al., 2007; van Eekelen et al., 2017), making samples highly selected. Here, we assume that estimates from Leridon on fecundability based on historical populations that have been used in previous studies within demography and reproductive medicine

Figure 1 Overview of the most important biological variables included in the simulation: (a) a density curve of initial fecundability at age 15, reflecting the proportion of women with a given probability of becoming pregnant within one month; (b) cumulative percentage of the age at sterility; (c) foetal survival; and (d) fecundability across the life course. The latter is the result of initial fecundability and age at sterility. The different purple lines for fecundability refer to the 10th, 25th, 50th, 75th and 90th percentiles across 100,000 agents. The yellow lines reflect trajectories for 10 individual agents



(Granholm et al., 2025; Habbema et al., 2015; Leridon, 2004; Leridon and Slama, 2008; te Velde et al., 2012) reflect the best information available to date. To get a sense of the reliability of these fecundability estimates, we also compare them to estimates derived from exemplary time to pregnancy studies.

Age at sterility

We define the age at sterility as the age at which a woman is no longer able to become pregnant naturally. The distribution of the age at sterility was taken from Leridon and Shapiro (2017), who used information on the ages at last birth in six natural fertility populations, as presented by Eijkemans and colleagues (2014; see Figure 1b). Medically assisted reproduction can, to a certain extent, help address natural sterility. However, like natural fecundability, the success rates of medically assisted reproduction decline with biological age (Alviggi et al., 2009), and certain medical conditions (e.g. severe endometriosis) cannot be overcome with such techniques (Bregaint et al., 2025; Tanbo and Fedorcsak, 2017).

Since we do not model medically assisted reproduction (but see [Granholm et al., 2026](#)), we consider natural sterility as the end of the reproductive lifespan of a woman. In our simulations, agents try to conceive up to the age at which they reach sterility, or when the simulation stops at age 50.

Foetal survival

Intrauterine mortality refers to observable foetal death during pregnancy. This includes both *miscarriage* (up to weeks 20–22 of pregnancy) and *foetal mortality* (after week 22, before or during birth). Intrauterine mortality occurs in around 15% of all pregnancies ([Andersen et al., 2000](#); [Laisk et al., 2020](#), p. 202; [Mohangoo et al., 2011](#)). To model intrauterine mortality, we use an age distribution constructed by Henri Leridon (1977) by averaging 10 different population samples ([Leridon, 1977](#), pp. 62–63). Some 80% of intrauterine deaths occur during the first trimester, which we account for when assigning the month of pregnancy in which a miscarriage occurs ([Dugas and Slane, 2023](#); [Wilcox et al., 1988](#)). The reciprocal of intrauterine mortality is foetal survival, which can be interpreted as the probability that a conception develops into a live birth (see [Figure 1c](#)).

The non-susceptible period

We refer to the period after a miscarriage or birth during which the woman does not ovulate as the non-susceptible period. Given that we exclusively study first births, we only include the period of non-susceptibility after miscarriage. Based on clinical data, we assume that the non-susceptible period after miscarriage is one month ([Donnet et al., 1990](#); [Schreiber et al., 2011](#)).

Behavioural parameters

The age at first attempt to conceive

There is only one behavioural parameter in the microsimulation model and that is the age at which agents first attempt to conceive. The distribution of this age is not observed, but will be estimated from the observed ages at first birth for each birth cohort through a process of Approximate Bayesian Computation ([Beaumont, 2019](#); [Csilléry et al., 2012](#)). We have chosen a particular implementation of Sequential Approximate Bayesian Computation because it is computationally efficient relative to other ABC methods ([Lenormand et al., 2013](#)).

The age at first birth

We construct the distribution of the age at first birth based on Dutch administrative data provided by Statistics Netherlands (CBS) through their System of social statistical datasets, a system of interlinked and standardised registers and surveys ([Bakker et al., 2014](#)). We obtain the date and place of birth and gender from the cumulative municipal

register (GBA) that contains data on all individuals who were legal residents of the Netherlands at any time between 1995 and 2022 (CBS, 2022). From this source data, we select individuals who were born between 1960 and 1980. Parenthood linkages are based on a table of unique (pseudonomised) individual identifiers that connect all persons who were residents of the Netherlands in 1995 and onwards to their legal parents (CBS, 1995).

Data on births are available up until 2022. Because of restrictions on the granularity of tables arising from the administrative data (if “cells” have fewer than 10 cases, e.g. women having a first birth before age 15), ages at first birth of 17 or lower are recorded as “<17” and those of 45 or higher are recorded as “>45”. The numbers of cases in these cells are too small to have a substantive impact on the averages calculated. Parenthood registers are based on legal parenthood, and we cannot distinguish between biological and non-biological parenthood in the data. Adoptions between 1960 and 1980 account for about 1.4% of the total number of births during this period (see Section S3.2 in the Supplementary material available online at <https://doi.org/10.34894/HIPZHY>, file “1_supplement.html”). Numbers on stepparent adoptions are less widely available, but such cases are far less common than other types of adoption. We do not include adoptions in our simulation model because we have no information on the age distribution of adoptions, which of these adoptions are first births or how fecundability shapes adoption.

We exclude women who were not born in the Netherlands because they may have been less exposed to the social norms around childbearing and family policies of the Netherlands, and may thus have fertility behaviour that deviates from that of the native majority (Kulu et al., 2017), and because these women may have a child that we do not observe in the data (30.76% of women from the 1960–1980 birth cohorts; this group also includes people who were in the Netherlands for a brief period only). For similar reasons, we also exclude women whose mother and father were born elsewhere (5.85%). The resulting data cover 63.8% of the cumulative Dutch female population who were born and resided in the Netherlands at any time between 1995 and 2021.

Sequential Approximate Bayesian Computation

In short, the procedure is as follows: we generate a distribution of the ages at which agents first attempt to conceive, run the simulation model and then verify how well the simulated distribution of the ages at first birth matches the actual distribution of the ages at first birth from the administrative data. Based on the similarity scores between the simulations and the actual distribution, a posterior distribution is approximated. We do not know the shape of the distribution of the age at which women first attempt to conceive and test the fit of five parametric distributions: the gamma distribution, the lognormal distribution, the Gumbel distribution, the logistic distribution and the normal distribution. All these distributions can be parametrised by a value for the mean and the variance, and we therefore specify prior distributions for the mean and the variance.

The implementation of the sequential ABC method that we use requires uniform prior distributions, as the first step applies Latin hypercube sampling, meaning that the full range

of combinations of prior values are considered with better coverage of the entire parameter space. For the prior for the mean, we have chosen a minimum that is five years below the average age at first birth for that cohort. Prior research suggests that about half of couples conceive a child within six months of starting to attempt to conceive (Juul et al., 2000; Slama et al., 2012; Wesselink et al., 2017). Assuming nine months of gestation for live births, this means that half of couples take about 15 months or fewer to have a child. Our minimum for the prior is well below this duration. As an upper boundary, we have chosen a maximum that is two years above the true average age at birth. While highly unlikely, it is not impossible that the average age at first attempting to conceive is higher than the average age at first birth when those trying to conceive a child at high ages do not succeed and those trying to conceive a child at younger ages succeed at a rapid pace (see also Figure 5). For the prior for the variance, we have selected minimum and maximum values that are nine points below and above the true variance in the age at first birth for each cohort. This range is chosen because it lies well beyond the observed minimum and maximum ages at first birth, and because the variance in the age at first attempt to conceive is unlikely to differ substantially from that of the distribution of the age at first birth. Sequential ABC occurs in multiple steps through which the evolution of the posterior distribution can be traced. The outer boundaries of the posterior distributions are not close to the minimum or maximum of the limits set on our prior distributions in any of the models, which suggests that our chosen limits are not too narrow. Selected repetitions of the models with an even wider prior distribution further show that the limits we set are appropriate, while making the range narrower leads to similar posterior distributions (see Section S6.3, file “1_supplement.html”).

Here, we will walk through an example in which the number of prior values drawn is 2000 (e.g. 2000 sets of prior values for the mean and the variance) and the number of agents in the model is 5000. In the first step of sequential ABC, the randomly selected pairs of 2000 prior values are used to run 2000 simulation models with 5000 agents. These 2000 simulations lead to 2000 distance scores between the output of the simulation model (distribution of the ages at first birth) and the true distribution of the age at first birth. As a distance score, we have chosen the Chi-square distance (see also Lenormand et al., 2013). Distances are normalised by first dividing them by the standard deviation in distance scores from the original 2000 samples (at the first step), and then by calculating the Euclidean distance of these distance measures to zero (zero distance means that there is a perfect match between the simulated and the observed age distribution). The parameter α then determines how many of these 2000 prior values are kept. As recommended by Lenormand et al (2013), we have chosen α to equal 0.5, which means that 1000 (combinations of mean and variance) prior values are kept. These prior values are assigned weights, depending on their distance scores, generating a proposal distribution. In the second step, another 1000 prior values are randomly drawn, but these values are now drawn from the proposal distribution. To arrive at novel values for the prior, randomness is added corresponding to twice the variance of the intermediate posterior distribution in the previous step (i.e. a Gaussian kernel). For these new samples, 1000 distance scores are calculated. New samples are “accepted” if they have lower distance scores than the worst distance score in the previous round. These new samples are added to the previously

accepted 1000 samples, and again, the best 1000 samples are kept for the next round and new weights are calculated.

The algorithm stops when only a small proportion of new samples have lower distance scores than the worst score from the last proposal distribution. As recommended (Lenormand et al., 2013), we set this proportion to 5%, which means that the model stops if less than 5% of the new samples fall below this worst score. Because only distance scores that are lower than the previously worst score are added, and then only the best 1000 samples are selected, the worst distance score gets progressively lower with each step, and it becomes increasingly difficult to find new samples with distance scores that fall below this threshold. An alternative way of stating this is that the algorithm stops when including the very few new samples that fall below the threshold would hardly change the posterior distribution. The final step retains 1000 sets of priors with weights, which is our final posterior distribution (see Sections S6.5 and S7.2, file “1_supplement.html”, in which we run through an example).

Given that we have to repeat these analyses for all 21 cohorts, and that each analysis is computationally expensive, smaller sample sizes (of either agents or priors drawn) that are large enough to avoid compromising the quality of the posterior distribution are preferred. Two adjustments can be made that co-depend on one another: changing the number of agents in the simulation model (a lower number of agents will lead to more variance in the simulated age distributions, and thus to more variation in the distance scores) and changing the number of priors sampled. Running a model for one of the birth cohorts with different sets of numbers of agents and priors drawn reveals that the number of agents has a larger impact on the width of the posterior distribution than the number of priors drawn. A combination of 50,000 agents per simulation and 1000 initially drawn priors leads to satisfactory results (see Sections S6.1 and S6.2, file “1_supplement.html”), and these numbers are chosen for all the models we present here.

To examine to what extent the choice of priors has an impact on the posterior distributions, we also vary the range of our priors and show that wider or narrower prior ranges lead to similar results (see Section S6.3, file “1_supplement.html”). We further examine whether sequential ABC is able to retrieve the correct means and variances from known (simulated) distributions, and whether it is able to find the correct parametric distribution from which the data are generated. Using simulated distributions of the age at first attempt to conceive based on different parametric distributions, and using these to simulate the ages at first birth, we show that sequential ABC based on the age at first birth retrieves the correct means and variances of the age at first attempt distribution, and finds the correct parametric distribution from which the data are generated (see Section S6.6, file “1_supplement.html”).

Estimate uncertainty and posterior predictions

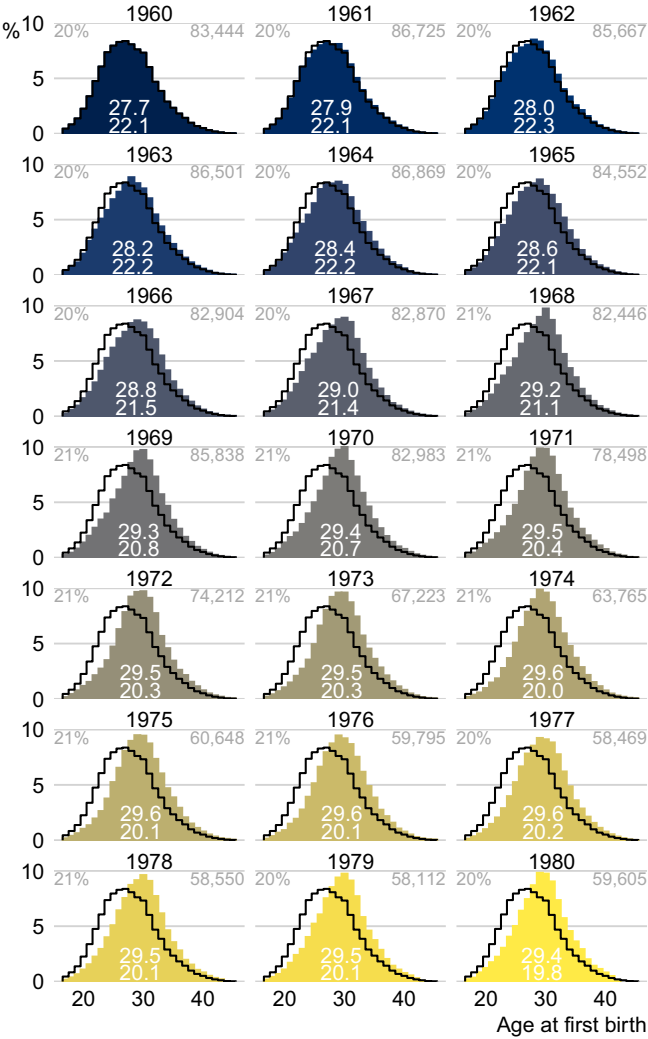
From the posterior distributions, we calculate a posterior mean as our best point estimate for the posterior distribution and similarly calculate a 95% credible interval. We are also interested in other measures for which no posterior distribution is estimated, for instance

levels of childlessness among our agents (all of whom try to have children) or the average age at first attempt to conceive for agents who have had a child. Note that the biological parameters are the only cause of childlessness among our agents in the simulations, and that agents continue to attempt to have a child up until the age at sterility or age 50; thus, all agents who do not give birth to a child by age 50 are considered childless. For such quantities of interest without a posterior distribution, we calculate the mean and 95% posterior prediction intervals: we sample 100 posterior values from the posterior distribution (combinations of means and variances) and run simulation models with 50,000 agents on the basis of these values. For each simulation, we calculate childlessness among agents and determine the ages at first attempt to conceive for the agents who have had a child. We then calculate the mean of those quantities across the 100 draws, plus the interval corresponding to the middle 95% of all values. For the sake of consistency between measures, we only show 95% posterior prediction intervals. We also verify how the posterior predictions match the true distributions and observe rather close matches (see Section S8.1.1.1, file “1_supplement.html” for these posterior predictive checks for each birth cohort and each distribution).

Arriving at the distribution for the age at first attempt to conceive

To examine which distributions representing the age at first attempt to conceive result in a close fit to the data, we first run sequential ABCs with 5000 agents and 1000 initially drawn priors for each birth year, for each of the five distributions (gamma, lognormal, normal, Gumbel, logistic), and arrive at posterior distributions. We then sample 100 draws from this posterior distribution and generate the age at first birth distributions resulting from each of the five types of distributions and compare them to the true age at first birth distribution. We calculate three measures of correspondence: the chi-square distance, the Kullback–Leibler Divergence and the Earth Mover’s Distance. Using these different measures of fit, we assess which distribution produces the best fit (on average) for each year of birth (see Section S8.1, file “1_supplement.html”), and arrive at a log-normal distribution for the 1960 cohort, a gamma distribution for the 1961–1966 cohorts and a normal distribution for the 1967–1980 cohorts. This seems to mirror the skewness and symmetry from the observed age at first birth distributions (see Figure 2). The Gumbel distribution is a poor fit and we do not consider it in further analyses. While it is clear that some distributions are a better fit to the observed age distribution than others, the choice of distribution has little influence on the posterior mean for the age at first attempt to conceive (the largest observed difference across all cohorts and distributions is three months; see Section S8.1.0.2, file “1_supplement.html”). Here, for purposes of consistency and comparability, we only present results based on the gamma distribution. We have chosen the gamma distribution because it is often a good fit, and it is a flexible distribution that better accommodates the skewness at lower ages at starting to conceive in earlier cohorts (Figure 2) than the normal distribution (which is also often a good fit). In Section S8.2.4, file “1_supplement.html”, we present results based on all of the different distributions as well as the results based on the best fit for each cohort.

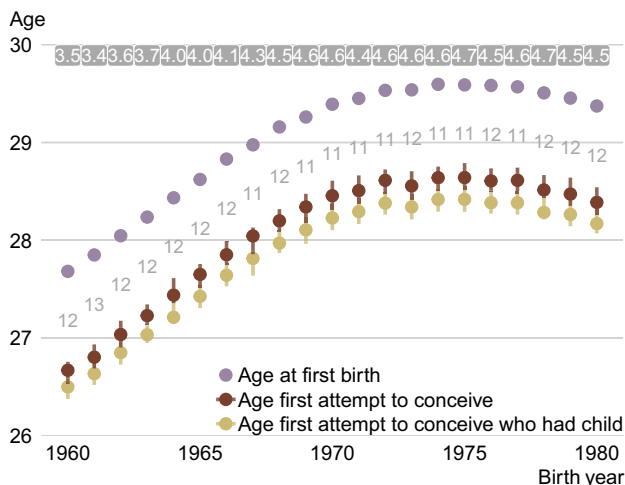
Figure 2 Age at first birth across cohorts of Dutch women born between 1960 and 1980. The top number in white refers to the mean and the bottom number in white refers to variance; the number in grey refers to population size; and the percentage refers to the rate of childlessness in the population. The histogram of 1960 is shown in black in all panels



Simulating scenarios for the average age at first attempt to conceive

To evaluate the consequences of further postponement, we run simulation models in which we vary the average age at first attempt to conceive from 20 to 35, simulating the age at first birth outcomes for 50,000 agents for each age. We have to make assumptions about the

Figure 3 Model estimates for the average age at which women first attempt to conceive and for childlessness (white numbers in the grey tags; %). Grey numbers reflect the number of months between the average age at first attempt to conceive and the average age at first birth. Bars represent 95% posterior prediction intervals. The upper purple dots are observed averages from the administrative data



variance associated with those ages that we base on the association between the estimated average age at first attempt to conceive and the estimated variance across birth cohorts (see Section S8.3.1, file “1_supplement.html”). For the average ages at first attempt to conceive of 27 and 28 that were observed for the 1962 and 1967 cohorts, respectively (see Figure 3), we use the estimates of variance for those cohorts (22.4 and 22.2; see Section S8.3.1, file “1_supplement.html”). For the average ages at first attempt to conceive below 27, we use the variance that is estimated for 1960 (22.0), when the lowest average age at first attempt is observed. For the starting ages above 28, we use the estimated variance from 1974 (20.3), as it is in this cohort that the highest average age at first attempt is observed (Figure 3). This latter estimate for the variance is likely an overestimate for situations with higher average ages at first attempt to conceive, because a higher average age will “compress” the age range, leading to lower variance due to limits on the reproductive lifespan. Because there is no way of establishing the fit to the observed distributions in our hypothetical examples, we have chosen the gamma distribution to represent the age at first attempt to conceive. Results using different distributions are remarkably similar (see Section S8.3.4.1.1, file “1_supplement.html”).

Validating fecundability and robustness checks

Given the importance of fecundability in our model and the difficulty of assessing this quantity, we compare the durations of attempts to conceive a child through simulations

based on our biological parameters to the findings of a series of empirical studies. In these studies, such durations are presented for people trying to have their first child, and for whom (aggregate) information is available on their ages at first attempt to conceive (Bonde, Ernst, et al., 1998; Bonde, Hjollund, et al., 1998; Eisenberg et al., 2021; Karmaus et al., 1999; Schwartz and Mayaux, 1982; Slama et al., 2012). This comparison shows that our simulation model captures well the age-related decline in pregnancy rates observed in these studies, although our agents have higher chances of conceiving (see Section S6.8, file “1_supplement.html”). Differences across these studies and differences between these studies and our study may be attributed to variation in methodological approaches, e.g. lower chances of fertilisation with artificial insemination than with natural conception (in the case of Schwartz and Mayaux (1982); see also Bongaarts (1982)), inappropriate censoring, differences in the ability of couples to detect a pregnancy in the first month or less consistency in attempts to conceive (actual couples, as opposed to agents, may not have had consistent opportunities for intercourse for months on end). Nonetheless, given that our agents have slightly increased chances of conception facilitated by uninterrupted attempts to conceive, which may be harder to maintain in real life, our estimates of the ages at first attempt to conceive a child may be on the high side (i.e. actual couples may need longer to conceive and might therefore be younger at their first attempt to conceive; see Section S6.8.8, file “1_supplement.html” for further discussion). To further examine the effect of fecundability, a key parameter in our model, we run sensitivity analyses in which we either increase or decrease fecundability by 20%. These analyses show that 20% higher fecundability would, on average across cohorts, increase the estimated age at first attempt to conceive by 1.3 months, whereas 20% lower fecundability would decrease it by 2.5 months (see Section S6.7, file “1_supplement.html”).

All models have been programmed in R (R Core Team, 2018), with the most important packages used being tidyverse (Wickham, 2017) and EasyABC (Jabot et al., 2013). See <https://doi.org/10.34894/HIPZHY> for all code, walkthroughs and supplementary materials.

Results

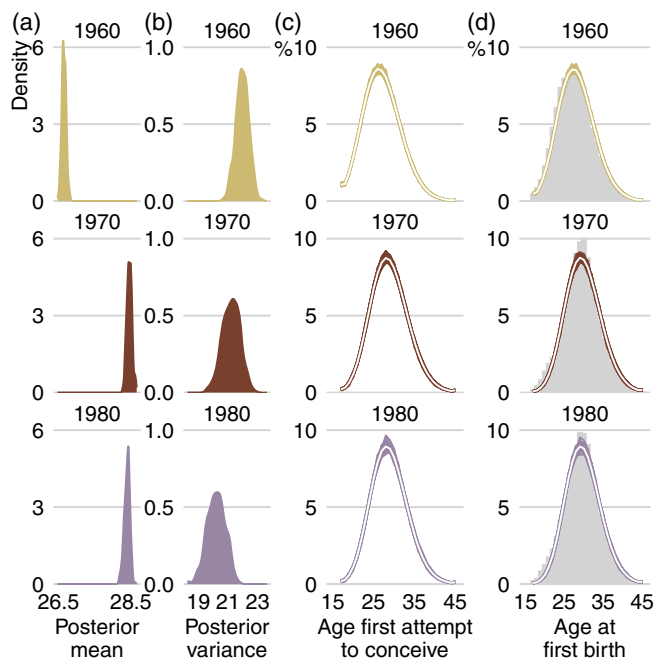
Descriptive statistics

The age at first birth increases steadily between the 1960 and 1970 cohorts, but levels off after 1970 (Figures 2 and 3). Women born in 1970 have their first child on average at around 27.7 years, and this age increases to about 29.6 years for women born in 1975, after which it decreases slightly. Some of the levelling off is due to the fact that women in the later cohorts may still have a child at higher ages, which would raise the age at first birth (2022 is the last observed year, when women born in 1980 were 42 years old). The variance in the age at first birth decreases in the younger cohorts, and the age distributions go from relatively broad, right-skewed distributions to narrower, symmetrical distributions in the younger cohorts (Figure 2).

Age at first attempt to conceive

The estimated average age at first attempt to conceive closely follows the trend of the age at first birth, shifted by about 11.7 months (Figure 3), and increasing from about 26.7 in 1960 to 28.4 in 1980. The models are able to reproduce the observed age at first birth, as the estimated average age at first birth is on average about 0.3 months below or above the actual average age at first birth. Figure 4 shows more detailed outcomes from our models for three birth cohorts with respect to the posterior distribution for the mean (panels a) and the variance (panels b), the resulting distribution of the age at first attempt to conceive (panels c) and the fit between the observed and the simulated distributions of the age at first birth (panels d). The distribution of the age at first birth arising from the simulations fits the true age distributions reasonably well (see Figure 4d and Section S8.1.3.4, file “1_supplement.html” for all years of birth). The estimated average age at first attempt to conceive includes both women who will have a child (which results in the distribution of the age at first birth) and women who will not have a child (which results in the rates of childlessness). Across the birth cohorts, agents who end up having children start attempting to conceive slightly earlier

Figure 4 Model outcomes and validation for three selected cohorts (1960, 1970, 1980). Panels (a) and (b) represent the posterior distributions for the mean and the variance, which lead to the distribution of the age at first attempt to conceive in panel (c), which in turn leads to the simulated age at first birth distribution (d). The coloured lines represent 100 distributions from posterior draws, and the white line represents the average of those distributions. The true distribution of the age at first birth is shown in grey



than the average, by about 2.6 months (Figure 3). This means that it takes about 14.2 months on average to conceive a child.

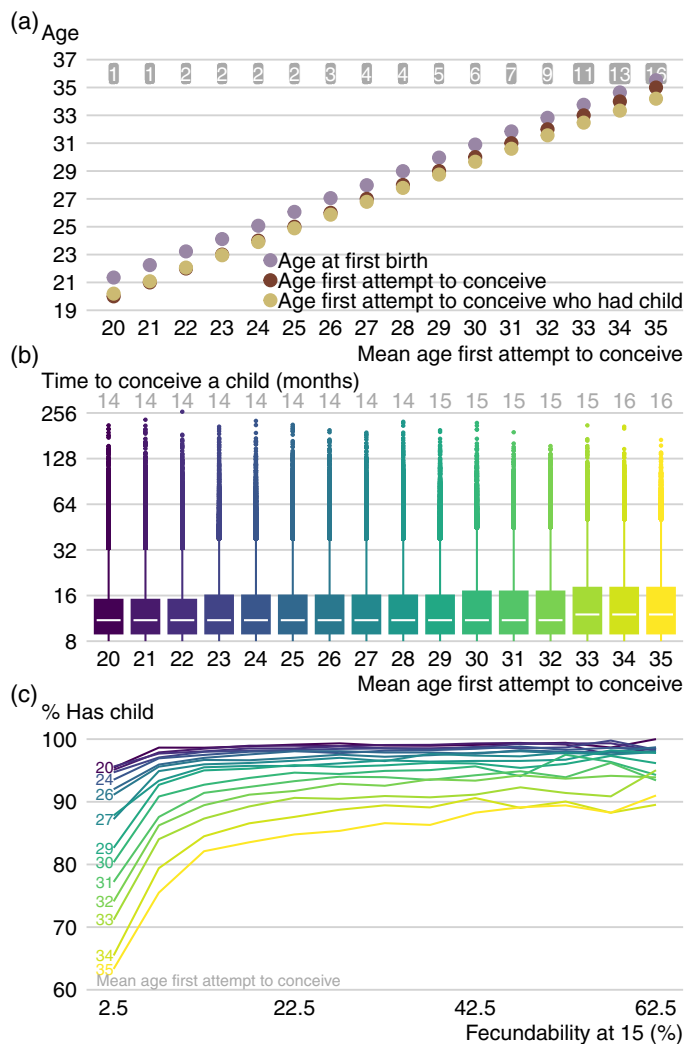
Similar to the trend in the age at first attempt to conceive, the rates of estimated childlessness among agents also increase, and then level off, although the differences between cohorts are minimal (Figure 3). Across the cohorts, the average rate of estimated childlessness is about 4%, which is much lower than the observed population rates of about 20%, reflecting both voluntary and involuntary childlessness (Figure 2).

Different scenarios for the average age at first attempt to conceive

To better understand the effects of the age at first attempt to conceive on the age at first birth and childlessness, we run models in which we vary the mean age at first attempt from 20 to 35 (see Figure 5). A striking pattern arises whereby the mean age at starting to attempt to conceive gets closer to the average age at first birth with increasing ages at first attempt to conceive (Figure 5a). At an average age at first attempt of 35, the average age at first birth is only six months later. This pattern can be explained by shifts in the age composition of agents and the marked increase in childlessness (Figure 5a; grey boxes). As the average age at first attempt to conceive rises, a growing share of agents begin trying to conceive at relatively advanced ages, when the probability of remaining childless is high. For instance, at an average age at first attempt of 35, over 15% of the agents start attempting to conceive at age 40 or higher, and these agents have childlessness rates close to 50% (see Section S8.3.5, file “1_supplement.html”). These childless agents who start late therefore raise the average age at first attempt to conceive, but do not have an impact on the average age at first birth. In this scenario, agents who begin attempting to conceive at younger ages are much more likely to have children and thus contribute more to the average age at first birth.

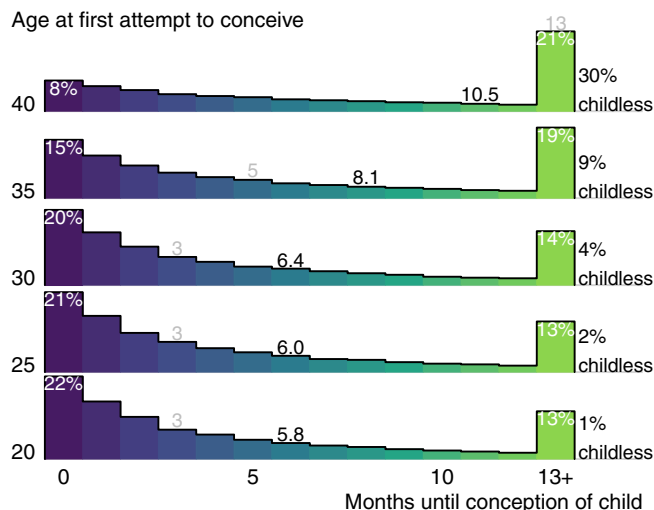
Examining only agents who have children, we observe that the difference between the average age at first attempt to conceive and the age at first birth is on average 15 months and varies little regardless of the average age at first attempt to conceive (from 14 months at age 20 to 16 months at age 35; Figure 5b). Given the decline in fecundability and foetal survival with age, we would not expect that the population of agents who first attempt to conceive at older reproductive ages (on average) need a similar amount of time to conceive a child as the population of agents who start at much younger ages (on average). In addition to the changes in the age composition and the rates of childlessness, another reason for this finding is a selection effect on fecundability. An agent with low fecundability at age 15, who has a low monthly probability of getting pregnant, will nonetheless have a high probability of giving birth to a child if the agent starts trying to conceive at a young age (Figure 5c). Although the monthly probability is low, the chance of eventually conceiving a child is high given many attempts. The fecundability of all agents declines with age, which means that agents with low fecundability at younger ages may not be able to conceive if they postpone their first attempt to conceive to later reproductive years. Agents with high fecundability have high probabilities of conceiving a child, even with increasing age (Figure 5c). This means that if the ages at first attempt to conceive are higher, there will be a stronger bias towards the agents with higher fecundability being the ones who go on to have a child than would

Figure 5 Different scenarios of the average age at first attempt to conceive and its impact on (a) the average age at first birth and (b) the time to conception. Numbers in grey boxes (a) represent estimated percentages of childlessness and numbers in grey (b) represent average times to conception leading to birth in months. Panel (c) shows the association between an agent's fecundability and the probability of having a child, given different mean ages at first attempt to conceive



be the case if the ages at first attempt to conceive were lower (see Sections S8.3.5 and S8.4.3, file “1_supplement.html”). The proposed mechanism is thus the following: when an entire birth cohort of agents has lower ages at first attempt to conceive, many agents with low fecundability will still have children, although it will take them longer on average than

Figure 6 Outcomes for the same set of 50,000 agents who all try to conceive at the same age, where this age is varied across simulations. The heights of the bars (and the percentages in white) represent relative frequency, the black numbers on top of the bars represent the average time and the grey numbers indicate the Kaplan–Meier median survival time



agents with high fecundability. These agents raise the average time to conception. In contrast, in populations in which the average age at first attempt to conceive is higher, agents with low fecundability will have low probabilities of having children, and their long durations of attempting to have children will not be included in the cohort average time to conception and age at first birth. Thus, the duration of the time to conception is shaped by two opposing forces as age increases. On the one hand, advanced reproductive age is associated with longer times to conception due to age-related declines in fecundability and foetal survival. On the other hand, durations may appear shorter at higher ages because agents who are still able to conceive at those ages are a selected group with relatively high fecundity.

In the above model, only the average age at first attempt to conceive and the variation in that age is fixed, meaning that in the population of agents there is substantial variation in the age at starting to attempt to conceive. To understand the effect of age on the probability of conceiving a child and the duration of attempting to conceive, we also run simulations in which we fix the ages at first attempt to conceive to the same value for all agents. Thus, we generate a sample of 50,000 agents with randomly assigned biological features and then fix the ages at first attempt to conceive for that same group of agents in one-year increments from age 20 to age 40 (see Section S8.4, file “1_supplement.html”). Here, we present results for the starting ages 20, 25, 30, 35 and 40. Between the ages of 20 and 30 there are some minor differences in outcomes (Figure 6): compared to 30-year-old agents, 20-year-old agents have a slightly higher chance of having a successful conception that leads to a birth in the first month of trying and take on average one month less to conceive, with 1%

remaining childless at age 50, instead of 4%. If we compare 30-year-olds to older agents, we find that the percentage who remain childless at age 50 increases from 4% in 30-year-old agents to 9% in 35-year-old agents and then to 30% in 40-year-old agents. The increase in the average time until conception is less pronounced, with 40-year-olds taking on average four months longer to conceive than 30-year-olds. The differences across the ages at first attempt to conceive become much more pronounced when examining the Kaplan–Meier median survival – the point at which half of the agents have had a child. This measure takes into account the conception attempts of agents who ultimately do not have children. The median time to conception is three months for ages at first attempt to conceive up to age 30 and increases to five months at age 35 and to 13 months at age 40.

Discussion

This paper set out to quantify the age at which women in the Netherlands first attempt to conceive, focusing on the cohorts born between 1960 and 1980. This age is rarely measured directly and is typically proxied by the age at first birth or inferred from studies on the time to pregnancy – both of which have significant limitations. We infer the distribution of the ages at first attempt to conceive from the distribution of the ages at first birth based on administrative data by combining a simulation model that integrates biological parameters related to the age-dependent ability to have children with sequential Approximate Bayesian Computation. Our simulations indicate that the most likely average age at which women first attempt to conceive increases from 26.7 in the 1960 cohort to 28.6 in the 1975 cohort, after which it plateaus, reaching 28.4 in the 1980 cohort. Across these cohorts, the difference between the average age at first birth and the average age at first attempt to conceive is about 11.6 months, with relatively limited differences across birth cohorts (12.1 months for 1960 and 11.8 for 1980). When we restrict our analysis to agents who have had a child, the time it takes them to conceive a child and give birth is about 14 months, again with small differences across birth cohorts (14.0 months for 1960 and 14.4 for 1980). It is important to clarify that these are simulation-based estimates derived from the behaviour of agents for whom we apply strong – though well-justified – assumptions regarding the biological parameters influencing reproduction, and who engage in uninterrupted, continuous attempts to conceive over successive months.

At first glance, it is surprising that the difference between the average age at first birth and the average age at first attempt to conceive remains rather similar despite increasing ages at first attempt to conceive across birth cohorts. The simulations even show that further increases in the average age at first attempt to conceive among all agents decrease the difference between their *average* age at first attempt to conceive and their *average* age at first birth. Increasing levels of childlessness and changes in the age composition account for this pattern. As the mean age at first attempt to conceive increases, a growing share of agents begin attempting to conceive at advanced ages (e.g. over 40), with many ending up childless. These childless agents count towards the average age at first attempt to conceive but not towards the average age at first birth. By contrast, agents who begin attempting to conceive at younger ages are more likely to achieve

a live birth, and, due to their earlier starting ages, will also have relatively young ages at first birth.

Another surprising finding is that despite the age-related declines in fecundability and foetal survival, the average duration to conception remains nearly identical in our study period, and large increases in the average age at first attempt to conceive would lead to only small increases in this duration (from 14 to 16 months, including nine months pregnancy). This result fits well with empirical findings showing that, among women who recently gave birth, those who did so at older ages required less time to conceive than their younger counterparts (Jensen et al., 2000; Juul et al., 2000). Substantive explanations for this pattern have been proposed, including the possibility that older women may be more motivated to conceive, more deliberate in their efforts or more likely to adopt healthier lifestyles. However, our analyses, following the pioneering work by Juul et al. (2000), point towards a selection effect: only highly fecund women are able to conceive at older ages, while those with lower fecundity who attempt to conceive at older ages are more likely to remain childless, and thus are excluded from such retrospective samples. In contrast, women with lower fecundity who attempt to conceive at younger ages have a longer time window in which conception can occur. While age-related declines in fecundability and foetal survival increase the duration between the first attempt to conceive and the birth of a child, the selection of highly fecund individuals who are able to conceive a child even at relatively high ages may decrease this duration or slow its increase.

Such selection effects may similarly account for other empirical patterns. For example, shorter interbirth intervals are observed among older mothers in low-fertility contexts (Berg and Rotkirch, 2014; Compans et al., 2023). Compans et al. (2023), for example, report that while women over age 30, and especially those over age 35, are less likely to have a second child, those who do tend to have it within a shorter interval. Although various substantive interpretations exist – for example, that older mothers plan shorter spacing between births due to their awareness of age-related fertility decline – this finding fits well with our results on the selection on fecundity (see also Billari and Borgoni, 2005). Another related finding is that the time to conception is often lower for second births than for first births (Boldsen and Schaumburg, 1990), further illustrating how fecundity-related selection shapes observed fertility behaviours.

From the 1970s onwards, the rise in the average age at first birth levels off and enters a period of stagnation among these Dutch cohorts, perhaps suggesting that there are limits to further postponement. Indeed, one might attribute this stagnation to biological constraints, given that the ability to have children declines with age and ultimately reaches zero. Our analyses suggest otherwise. First, the age at first attempt to conceive exhibits the same levelling-off pattern over this period. It is unlikely that biology accounts for these behavioural patterns of trying to have a child. Second, biological constraints become significant only after the mid-thirties and thus cannot fully explain the stagnation in the average age at first birth, which remains well below 30. Further evidence that biological factors have not yet become major constraints for our agents during this period comes from childlessness rates. Despite the increased postponement, the childlessness rate among our agents, all of whom attempt to conceive, remains relatively stable at around 4%. This estimate is close to estimates found in American women for whom the rates of involuntary childlessness could be

determined through survey answers (between 3.1–5.4% for different groups of women; [Poston and Cruz, 2016](#)). This estimate of 4% is well below the 20% childlessness rate observed in these Dutch women, which implies that, if our model assumptions hold, biological infertility can explain only about 20% of the observed childlessness in these cohorts. While our model cannot account for the large remaining share, prior research suggests that factors such as the absence of a suitable partner, a weak socioeconomic position and voluntary childlessness are likely responsible for it ([Granholm et al., 2025](#); [Miettinen and Szalma, 2014](#)).

Although biological constraints related to delayed attempts at childbearing have only a modest impact on childlessness among the cohorts studied, continued postponement is increasingly pushing the age at first attempt to conceive into a range where biological limitations become more pronounced. Our findings indicate that attempting to conceive for the first time after the age of 30, and particularly after age 35, is associated with a significant rise in the risk of childlessness. This result is consistent with a wide range of sources, including clinical studies showing a marked decline in fecundability at advanced reproductive ages ([Schwartz and Mayaux, 1982](#)), findings on marital fertility in historical natural fertility populations ([Committee Opinion, 2014](#)), evidence indicating decreased transitions to first births at higher ages based on demographic life tables ([Beaujouan and Neels, 2025](#)) and survey results showing increased rates of childlessness among couples that have formed at higher ages ([Toulemon, 1996](#)). Despite this, public awareness of the age-related decline in fertility remains limited. Studies have shown that individuals often underestimate the extent to which fecundity declines after the early thirties ([Lampic et al., 2006](#)), and tend to overestimate the effectiveness of medically assisted reproduction ([Devroe et al., 2020](#); [McMahon et al., 2024](#)) in overcoming these biological barriers. In reality, the success rates of assisted reproductive technologies also decrease with age, and they are unlikely to fully compensate for age-related reductions in natural fecundity ([Gu et al., 2021](#)). As a result, the continued trend towards later childbearing may contribute to rising rates of involuntary childlessness in future cohorts unless there is greater awareness of reproductive ageing and its limits.

A central strength of our microsimulation model lies in its integration of biological parameters that are widely studied in reproductive medicine. However, estimates based on historical samples remain subject to debate ([Leridon and Shapiro, 2017](#)). There are, for example, arguments that fecundability is higher in contemporary populations ([Dunson, 2001](#); [Dunson et al., 2004](#); [Rothman et al., 2013](#); [Wesselink et al., 2017](#)), but also arguments that it could be lower ([Levine et al., 2017](#)). Our comparison to earlier studies suggests that our fecundability estimates based on the work by Leridon are, if anything, on the high end (i.e. with couples getting pregnant more easily), which implies that the ages at first attempt to conceive may be lower than our models currently suggest. Similarly, increases in the average age at menopause and decreases in the average age at menarche may have extended the reproductive window of women over the 20th century compared to historical populations ([Appiah et al., 2021](#); [Gottschalk et al., 2020](#)). A shift towards an earlier start to reproduction is unlikely in light of the strong and global increasing trends in the age at first birth. An extension of the reproductive window increases the probability of having a child, although levels of fecundability would still be low at high ages. Moreover, facilitated

by widespread access to contraception, women often end their reproductive phase earlier for social reasons, reinforcing cultural norms around “appropriate” ages for childbearing (Billari et al., 2011; Eijkemans et al., 2014). Finally, people in contemporary societies can benefit from medically assisted reproductive technologies that can help couples to have children or to have them sooner. Taking such technologies and their effects into account in our simulations would be a non-trivial undertaking because it would require data on when people use these technologies, which specific technologies they use and what the outcomes are (Granhölm et al., 2026). Nonetheless, doing so would likely change the estimated age at first attempt to conceive.

Behavioural factors also influence fecundability and pose challenges for our simulations. Intercourse frequency and timing can influence fecundability (Rothman et al., 2013; Weinstein et al., 1990), which may be optimised by highly motivated couples. Other couples may cease to use contraception without actively trying, have fluctuations in periods of sexual activity or abandon attempts after a prolonged period of failure (Basso et al., 2000). Couples may conceive despite contraceptive use, and while some of these couples may have exceptionally high fecundity, others might have reason to believe they are subfecund and therefore use more error-prone contraceptive methods. Future studies could further address the role of fecundability and additional pathways to birth that are difficult to estimate reliably from existing data by explicitly modelling them (e.g. unplanned births, behaviours changing fecundability, fecundability itself), treating them as additional quantities to be estimated (e.g. Ciganda and Lorenti, 2019; Ciganda and Todd, 2024).

A related limitation of our model is the assumption that all agents behave uniformly. In reality, different population groups may exhibit distinct reproductive behaviours (Hruschka et al., 2019; Stulp et al., 2016), resulting in a distribution of the age at first birth that is actually a composite of group-specific distributions. Education is a particularly salient factor, as it strongly influences demographic behaviour. Substantial differences in the age at first birth are observed across educational groups (e.g. Vasireddy et al., 2023), which may reflect variation in social norms regarding acceptable ages for childbearing, different partnership trajectories, differences in health and exposure to healthier environments impacting fecundability, as well as unequal access to medically assisted reproduction. Future research could examine such differences in educational groups and investigate how they shape the age at first attempt to conceive.

Facilitated by advances in computing power, there has been a rise in the use of micro-simulation models in demographic research. These models focus on individual-level behaviours, simulating how such micro-level dynamics aggregate to shape population-level patterns. One of the key strengths of microsimulation is its ability to incorporate knowledge from diverse bodies of research (e.g. biological features from genetics and reproductive medicine, behavioural features such as partnership trajectories and preferences). Microsimulation models also allow for non-linearity (e.g. the accelerating decrease in fecundability with age), which make them flexible tools for analysing social phenomena (Ciganda and Lorenti, 2019; Ciganda and Todd, 2022). The integration of computational methods such as Approximate Bayesian Computation (ABC) has expanded the analytical capabilities of microsimulation. These techniques allow researchers not only to simulate forward from individual behaviour to macro outcomes, but also to infer the underlying distributions of

individual behaviour that are most consistent with observed or projected population-level characteristics (Ciganda and Todd, 2024). As such, microsimulation serves as a valuable tool for bridging the micro–macro divide in demographic analysis (Billari and Borgoni, 2005; Neels et al., 2024).

Supplementary material

Available online at <https://doi.org/10.34894/HIPZHY>



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