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Same Constraints in Changing Times? A Machine-Learning Approach to Childbearing and Fertility Intentions in Poland during and after the COVID-19 Pandemic

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Abstract: While studies highlight COVID-19's disruptive impact on fertility, whether pandemic-era childbearing predictors remain informative post-crisis is less clear. Using Polish Familydemic panel data from 2021–2024 (N = 1,925, aged 18–49), we apply theory-guided machine learning to evaluate a broad set of individual, employment, partnership, and family characteristics. Because short-term fertility intentions prove most predictive of childbearing, we model both actual births and firm positive intentions using random forest. The pandemic-trained model retained strong post-pandemic predictive performance (AUC-ROC = 0.86), demonstrating that pandemic-era drivers remain informative. Childbearing and intentions shared 16 of their top 20 predictors, highlighting common relational, demographic, and work–family factors. Relationship satisfaction, work–life balance, and domestic work division were particularly prominent, whereas prolonged school and childcare closures lowered predicted probabilities for both outcomes among parents. Ultimately, post-pandemic fertility dynamics reflect persistent constraints embedded in everyday family and working lives.

Keywords: childbearing, fertility intentions, COVID-19 pandemic, machine learning, relationship satisfaction, childcare closures

JEL codes: J13, J12, J22, C53

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Data Availability Statement: The code used for data processing and statistical analysis, together with the metadata, will be made publicly available on Zenodo/GitHub upon publication. The data that support the findings of this study are available from the corresponding author upon reasonable request.

1. Introduction

Economic recessions, wars, and other major societal disruptions - such as health crises - have repeatedly affected fertility, but their consequences differ across contexts and are rarely uniform or fully anticipated (Sobotka, Skirbekk, and Philipov 2011). The COVID-19 pandemic constituted such a disruption on an exceptional scale, producing marked but heterogeneous changes in fertility intentions and births across countries and population groups (Aassve et al. 2021; Sobotka et al. 2024). Although much of the literature documents the magnitude and timing of these changes (Sobotka et al. 2024; Winkler-Dworak, Zeman, and Sobotka 2024), a fundamental question remains: to what extent are the circumstances and mechanisms associated with childbearing during the pandemic specific to the crisis, and to what extent do they reflect constraints that also matter under non-crisis conditions? This distinction matters. If pandemic-era childbearing was shaped primarily by crisis-specific circumstances, safeguarding fertility during future disruptions calls for interventions tailored to those circumstances. If, instead, it was shaped by mechanisms that already structure reproductive decision-making more broadly, future crises call less for a distinct policy response than for strengthening the conditions on which childbearing depends at all times.

Answering this question, however, requires considering multiple aspects of individuals' lives simultaneously. The social sciences have generated a substantial body of research seeking to identify the determinants of childbearing intentions and behaviour. Yet the plethora of explanatory factors proposed in this literature are seldom assessed together in terms of how well they predict outcomes (Sivak et al. 2024). Existing studies often focus on a relatively restricted set of factors as considering a much broader set of predictors, together with potentially complex nonlinearities and interactions, requires researchers using conventional regression frameworks to make numerous a priori decisions about how these relationships should be specified in the model (Varian 2014; Verhagen 2024). Machine-learning methods provide a more flexible framework to address such challenges by accommodating large predictor spaces and learning complex nonlinear and interactive relationships from the data, while explicitly evaluating model performance out of sample (Mullainathan and Spiess 2017; Molina and Garip 2019; Delaporte, Ibbetson, and Kulu 2025).

At the same time, ML-based prediction without substantive theoretical guidance may offer limited insight into understanding of the reproductive processes. Therefore, recent methodological work emphasizes the need to integrate the predictive flexibility of machine learning with substantive social-science knowledge and theoretically informed model specification (Molina and Garip 2019; Hofman et al. 2021; Verhagen 2024). Building on this perspective, we adopt a theory-guided machine-learning approach in which existing theoretical and empirical knowledge on the determinants of childbearing informs the selection and organization of predictors as well as the sequential structure of the analysis, while machine learning is used to assess their out-of-sample predictive capacity and capture potentially complex predictive relationships. Throughout, we use 'prediction' in the machine-learning sense, i.e. as the capacity of individual-level characteristics to account for out-of-sample variation in childbearing outcomes, or in other words: their ability to generalize effectively to the unseen cases (Bishop 2006; Hastie, Tibshirani, and Friedman 2009; Goodfellow, Bengio, and Courville 2016).

We apply this approach to longitudinal data covering the COVID-19 pandemic (2021- mid 2023) and post-pandemic periods in Poland (mid 2023-2024). We first ask which of the theoretically grounded numerous individual, employment, partnership, and family characteristics - including those induced by the pandemic - best predict childbearing and whether their importance differs between the two periods. Given the central predictive role of short-term fertility intentions (Dommermuth, Klobas, and Lappegård 2015), we then examine what predicts these intentions. This sequential approach reveals whether particular circumstances are predictive primarily of births, of preceding intentions, or of both outcomes. Furthermore, in both cases (childbearing and fertility intentions) we assess whether the same model (i.e. a set of predictive variables and possible interactions) proves effective across pandemic and post-pandemic periods. Overall, our research design allows us to explore whether the circumstances and mechanisms associated with childbearing during the pandemic were specific to the crisis or rather reflected constraints that matter under more ordinary conditions.

Poland offers a particularly revealing setting for this analysis. It combines persistently low fertility with a substantial gap between reproductive intentions and realized childbearing (Brzozowska and Mynarska 2018). Moreover, the pandemic in Poland substantially disrupted employment and childcare arrangements, leading to the postponement or abandonment of pre-pandemic childbearing intentions (Malicka, Mynarska, and Świderska 2021; Kurowska, Matysiak, and Osiewalska 2023) and a decline in fertility (Tymicki, Cieślik, and Syczewska 2025; Sobotka et al., 2024).

Our study advances literature in three ways. First, by following respondents during and after the COVID-19 pandemic, we examine whether the circumstances predictive of childbearing during the crisis remain informative as it subsides. This extends the analysis beyond immediate reproductive responses to the pandemic and situates crisis-related disruptions within the broader context of work, care, and family relationships. Second, it connects the prediction of childbearing with the prediction of fertility intentions, clarifying which factors are predictive of intentions, subsequent childbearing, or both. Third, it extends the small but growing literature applying machine-learning methods to fertility outcomes (Sivak et al. 2024; Delaporte, Ibbetson, and Kulu 2025) by evaluating an unusually broad, theoretically informed set of predictors within a common framework that accommodates nonlinearities and interactions and assesses predictive performance out of sample.

2. Background

2.1. Fertility intentions as proximal predictors of childbearing

Influential theories of reproductive decision-making assign fertility intentions a proximal position in the process leading to childbearing. In Miller's Traits–Desires–Intentions–Behavior framework, relatively enduring childbearing motivations give rise to desires, which are translated into intentions and ultimately into reproductive behavior (Miller 1994; Miller 2011). A similar role is assigned to intentions in the Theory of Planned Behavior, in which behavioral intentions constitute the most immediate antecedent of reproductive action (Ajzen and Klobas 2013). These perspectives distinguish intentions from more general desires or preferences: intentions are more directly oriented toward a contemplated course of action and therefore occupy a position closer to subsequent behavior.

This theoretical proximity to behavior makes fertility intentions particularly relevant for predicting subsequent childbearing. Longitudinal demographic research has consistently found a strong correspondence between stated fertility intentions and later fertility behavior, although this relationship is far from perfect (Schoen et al. 1999; Morgan and Rackin 2010; Dommermuth, Klobas, and Lappegård 2015). Short-term intentions are particularly pertinent for predicting childbearing over a relatively short observation period because they specify whether childbearing is considered within a corresponding time horizon rather than expressing a general preference concerning eventual family size (Dommermuth, Klobas, and Lappegård 2015). At the same time, short-term intentions do not uniquely determine subsequent fertility. They may change as circumstances evolve, and their realization may be facilitated or impeded by partnership and family circumstances, employment and economic conditions, competing life-course events, and the broader institutional context (Spéder and Kapitány 2009; Ajzen and Klobas 2013; Spéder and Bálint 2024). Short-term fertility intentions can therefore be understood as a theoretically privileged, but not exhaustive, source of predictive information about subsequent childbearing. This perspective provides a rationale for considering fertility intentions jointly with a broader set of individual and contextual characteristics.

At the same time, fertility intentions, like childbearing behavior, have been linked to demographic and partnership circumstances, employment and work–family conditions, the division of unpaid work within the household, and the broader care context (Mills et al. 2008; Begall and Mills 2011; Balbo, Billari, and Mills 2013). In the following subsections, we briefly discuss the theoretical mechanisms proposed in the fertility literature through which these factors may be relevant to fertility intentions and to subsequent childbearing.

Finally, as the COVID-19 pandemic constituted one of the major exogenous shocks to the conditions under which fertility intentions were formed and childbearing decisions were made over the past decade (Luppi, Arpino, and Rosina 2020; Sobotka et al. 2024), the following discussion of factors identified in the fertility literature also considers the specific circumstances created by the pandemic. In particular, we consider changes in economic uncertainty, employment and working arrangements, work–family reconciliation, childcare availability, and caregiving demands (Aassve et al. 2020; Luppi, Arpino, and Rosina 2020).

2.2. Demographic and socioeconomic characteristics

From a life-course perspective, fertility intentions and childbearing are strongly structured by partnership circumstances, age and reproductive history (Elder 1994). Partnership status serves as the primary structural prerequisite for family formation, as union stability and legal marriage consistently elevate fertility intentions and childbearing compared to singlehood or informal cohabitation (Beets 2011; Hashemzadeh et al. 2021; Sturm, Koops and Rutigliano 2023; Kuang et al. 2025). At the same time, fertility timing is bounded by a biological window of peak fecundity, typically between ages 18 and 30, and social norms that discourage early motherhood prior to completing education and achieving economic autonomy (Beets 2011; Bratti and Tatsiramos 2012). Consequently, modern childbearing is heavily age-dependent, with first births increasingly postponed into the late twenties and early thirties as individuals negotiate socioeconomic readiness (Beets 2011; Hashemzadeh et al. 2021). Higher education further accentuates this shift by fostering distinct material and career ambitions (Beets 2011).

When expanding families, mothers generally exhibit a preference for birth spacing of two to three years. However, women who postpone their first birth often compress subsequent intervals to counteract age-related biological declines - a phenomenon recognized as the 'time squeeze' effect (Bratti and Tatsiramos 2012; Tomkinson 2019). Parity further conditions these decisions, as higher existing parity significantly depresses the likelihood of desiring or pursuing additional children (Hashemzadeh et al. 2021).

2.3. Employment-related circumstances

Employment circumstances have long been treated as central to fertility decision-making, since they shape both the economic resources available for childrearing and the time available for direct parental care (Balbo, Billari, and Mills 2013). Classical economic approaches emphasize a positive income effect of employment on fertility, particularly for men, alongside a negative substitution effect for women, whose opportunity costs of childbearing - foregone earnings and career interruptions - constitute a substantial cause of fertility postponement and decline (Becker 1991; Kravdal and Rindfuss 2008; Kreyenfeld and Andersson 2014). As the gender revolution progresses and the division of labour between partners becomes more egalitarian (Goldscheider, Bernhardt, and Lappegård 2015), these opportunity costs increasingly affect men as well. At the same time, the economic stability and earnings potential of women and men are becoming similarly important for fertility intentions and their realization, particularly where a dual-earner model is normative (Vignoli, Drefahl, and De Santis 2012; Matysiak and Vignoli 2013). Both partners' employment circumstances jointly shape fertility intentions and their realization. For instance, one partner's stable employment can partly compensate for the other's insecurity, whereas instability affecting both partners constrains fertility plans considerably more than instability affecting only one partner. This underscores the importance of allowing for such joint dependencies in empirical models (Alderotti et al. 2021; Hanappi et al. 2017).

Beyond employment status itself, the organization of paid work also matters for fertility. According to work–family conflict theory (Greenhaus and Beutell 1985), working time directly determines the time available for family and shapes the perceived compatibility of professional and family life. Stable full-time employment of both partners has increasingly become a precondition for entering parenthood in dual-earner societies (Greulich and Rendall 2026), though the picture often reverses after the first birth, when long working hours - particularly women's - become detrimental to further family development (Matysiak and Vignoli 2013).

Work-time flexibility and remote work, in turn, are typically framed as 'job resources' that ease work–family conflict by giving workers greater latitude to accommodate caregiving demands (Bakker and Demerouti 2007). Nevertheless, this benefit is not unconditional: flexibility granted alongside high job demands or an expectation of constant availability can instead intensify work–family conflict through what has been termed the ‘flexibility paradox’, whereby greater control over work is used to work more rather than to protect family time (Chung 2022). Work-family borders theory offers a related caution specific to work from home: the physical integration of work and family domains can increase role blurring and permeability, raising the risk that family time is colonized by paid work (Ashforth, Kreiner, and Fugate 2000). Consistent with this ambivalence, empirical evidence is mixed, with positive effects of flexibility and remote work concentrated among highly educated mothers, and negative effects among childless or lower-educated women (Osiewalska and Matysiak 2025; Osiewalska, Matysiak, and Kurowska 2024).

Supervisory and managerial responsibilities present a similarly two-sided case: the added earnings and autonomy they typically bring should ease economic strain, but the accompanying increase in workload, responsibility, and psychological engagement with work raises role conflict, leaving their net association with fertility ambiguous (Badawy and Schieman 2021; Yarger and Brauner-Otto 2024). Individuals' perceived work–life balance may therefore be especially informative, as it reflects how the combined effects of working hours, demands, flexibility, and personal life are evaluated by the individual (Begall and Mills, 2011).

These employment-related conditions became particularly salient during the COVID-19 pandemic, which combined heightened employment and income uncertainty with an abrupt, large-scale expansion of remote work and the disruption of established work–family arrangements (Aassve et al. 2020; Luppi, Arpino, and Rosina 2020). In Poland specifically, working from home during the pandemic was shown to be negatively associated with changes in fertility intentions among mothers, particularly when combined with increased childcare demands (Kurowska, Matysiak, and Osiewalska 2023).

2.4. Care and housework-related burden

Care responsibilities shape fertility by affecting whether individuals feel able to accommodate a(nother) child. Existing children generate not only a substantial task load - such as feeding, supervision, transportation, and help with schoolwork - but also a less visible mental load. According to Daminger’s (2019) framework of cognitive household labour, this includes anticipating children’s needs, organizing care and appointments, monitoring their health and development, and assuming responsibility for ensuring that household and family tasks are completed. Such demands may reduce parents' time and energy, intensify work–family conflict, and weaken intentions to have another child or impede their realization (Begall and Mills 2011). These consequences are likely to depend not only on the total amount of care required but also on its distribution between partners (McDonald 2000). When women carry a disproportionate share of care responsibilities, the perceived costs of further childbearing may be particularly high (Mills et al. 2008), while the resulting scarcity of discretionary time may further reduce progression to a subsequent birth (Jarosz, Matysiak, and Osiewalska 2023). Furthermore, the negative effects of the unequal division of domestic labour are shown to have the most detrimental effect on childbearing among women if they coexist with their egalitarian attitudes (Goldscheider, Bernhardt and Brandén 2013). At the same time, egalitarian attitudes combined with egalitarian sharing of domestic duties lead to higher likelihood of further childbearing (Aassve et al. 2015).

Care burdens extend beyond childcare. According to the linked-lives perspective, fertility decisions are also embedded in intergenerational exchanges (Elder 1994). Assistance provided to older, ill, or disabled relatives may compete with childbearing for time, emotional energy, and financial resources, particularly among adults in the 'sandwich generation', simultaneously responsible for children and ageing parents (Grundy and Henretta 2006). Whereas support received from relatives may facilitate childbearing, an increasing flow of care toward older generations can constrain fertility plans (Lazzari and Zurla 2024).

The COVID-19 pandemic sharply intensified both dimensions of care burden. School and childcare closures abruptly transferred education, supervision, and care into households, substantially increasing both the practical and mental demands placed on parents. At the same time, the deterioration in children's mental health observed during the pandemic may have further increased their need for parental support and monitoring (Racine et al. 2021). Although fathers often increased their participation in childcare during the pandemic, studies across Europe show that mothers generally continued to perform more childcare and frequently absorbed a larger share of the additional burden (Sevilla and Smith 2020; Fodor et al. 2021). Such re-traditionalization of care appears particularly pronounced in more gender-conservative contexts, including Poland, where pre-existing norms around maternal responsibility for childcare may have been reinforced rather than challenged by the crisis (Suwada and Karwacki 2024).

2.5. Family-related satisfaction

Subjective partnership satisfaction represents a foundational determinant in the decision to build or expand a family. Higher relationship satisfaction fosters a favorable environment for childbearing, making happier individuals and harmonious couples display a significantly greater propensity to realize first and higher-order births (Aassve, Arpino, and Balbo 2016; Cetre, Clark, and Senik 2016; Hashemzadeh et al. 2021; Parr 2010; Rijken and Thomson 2011). Within the broader framework of partnership dynamics, satisfaction with the intra-household division of labor is a specific dimension that influences fertility decision-making. As discussed earlier, allocation of domestic responsibilities directly shapes reproductive choices, as severe gender imbalances in housework can depress childbearing intentions and lead couples to forgo subsequent births (Dommermuth, Hohmann-Marriott, and Lappegård 2017; Suero 2023). Crucially, research demonstrates that the subjective evaluation of equity matters as much as the objective distribution of tasks: relationship satisfaction partially mediates the link between domestic workload and fertility, meaning that unequal task sharing primarily dampens intentions when partners perceive the arrangement as unfair (Riederer, Buber-Ennser, and Brzozowska 2019; Suero 2023). While egalitarian arrangements strengthen fertility intentions among childless individuals, experienced parents' willingness to progress to higher-order parities relies heavily on their satisfaction with domestic routines, particularly in how childcare duties are shared to absorb the demands of an expanding family (Dommermuth, Hohmann-Marriott, and Lappegård 2017; Riederer, Buber-Ennser, and Brzozowska 2019). Finally, some research suggests that satisfaction from or positive experiences with previous child(ren) or parenting in general may also positively impact childbearing decisions (Newman 2008; Parr 2010).

3. Methods

3.1. Data and Methods

We use longitudinal panel data gathered annually for Polish respondents between 2021 and 2024 as the follow-up part of the Familydemic project (Kurowska et al., 2023). The dataset thus covers both the pandemic (2021-mid 2023) and post-pandemic (mid 2023-2024) periods. The first (2021) wave of respondents was randomly sampled from the largest independent nationwide research panel in Poland (Ariadna), and was followed for the three consecutive years (2022-2024). The analytical sample initially consists of 1,925 individuals aged 18-49 in the baseline wave, generating a pooled total of 5,642 person-wave observations across the entire study period. Across all waves, the sample composition remained highly consistent: women represent approximately 61.4% to 62.0% of observations, higher-educated individuals account for 56.9% to 57.5%, and parents constitute 56.4% to 56.9% (see Table 1).

The main outcome variable, *childbirth*, is defined as either a live birth occurring between consecutive survey waves (among respondents who were not pregnant at the previous interview) or an ongoing pregnancy reported at the current interview. After reporting a birth or pregnancy, respondents were removed from all subsequent person-wave observations.

Among the *features* (in machine learning: all input variables included in the model), we first distinguish short-term fertility intentions that are measured on a 10-point scale ranging from 1 ('definitely not') to 10 ('definitely yes'), assessing the intention to have a child within the next three years. The remaining features are selected based on an extensive literature review, a summary of which was discussed in the previous section, and encompass four main domains:

1. *Demographic and socioeconomic characteristics:* respondent's age, partnership status, education, subjective material assessment, size of a place of residence, age of the youngest child and parity.
2. *Employment-related circumstances:* respondent's employment status, working hours, flexible working hours, work-from-home status, supervisory responsibilities, and satisfaction with work-life balance, together with the corresponding partner-specific factors (except for work-life balance satisfaction which was unavailable for partners).
3. *Care and housework-related burden:* time spent helping a child, the relative housework and childcare workload ratios, eldercare/family care responsibilities, mental health status of the youngest child, and time the child spent at home due to closed schools or childcare facilities during the pandemic. We also add an indicator of gender role attitudes (agreement with the statement that 'a child suffers when their mother works'), as an evidence-based moderator of the role division of domestic responsibilities plays for fertility (see Background section).
4. *Family-related satisfaction:* satisfaction with (1) the relationship with the partner, (2) relationships with children, and (3) the division of domestic responsibilities.

The exact definitions, coding levels, and descriptive statistics for all features are detailed in Table A1 in the Appendix. To preserve the sample size without artificial imputation, structurally non-applicable missing values, such as partner characteristics for single respondents, were explicitly recoded as -1.

Table 1. Sample distribution, childbirths, demographics, and fertility intentions across timeframes (main model).

Timeframe	Total Obs.	Childbirths	Childbirth rate (%)	Parents (%)	Women (%)	Higher Edu. (%)	Mean Fertility Intention	Fert. Int. 8 or higher (%)
2021→2022	1,925	47	2.4%	56.4%	62.0%	57.5%	3.3	14.4%
2022→2023	1,878	39	2.1%	56.6%	61.7%	57.1%	2.8	10.8%
2023→2024	1,839	25	1.4%	56.9%	61.4%	56.9%	2.7	9.5%
Full sample	**5,642**	**111**	**2.0%**	**56.6%**	**61.7%**	**57.2%**	**2.9**	**11.6%**

Source: Own calculations based on the 2021-2024 panel data from the Familydemic project.

We estimate two random forest classification models (Breiman 2001), which were previously successfully applied to fertility outcomes (Delaporte et al. 2025; Kassaw et al. 2025; Tadese et al. 2025). Hyperparameters are selected through grid search by maximizing the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) metric on the validation set.

The main model predicts childbirths between consecutive survey waves using circumstances measured in the preceding wave. It is trained to predict 2022 outcomes from 2021 characteristics (N = 1,925) and is validated on 2023 outcomes based on 2022 characteristics (N = 1,878). Then, we evaluate the model out-of-sample on 2024 outcomes using 2023 characteristics (N = 1,839). If the model trained and validated on the pandemic data maintains its predictive performance in the post-pandemic period, this would provide evidence that the circumstances associated with childbearing during the pandemic, as well as the predictive mechanisms underlying them, remain relevant under non-crisis conditions rather than being specific to the crisis context.

In addition to identifying the most important features (predictors) of childbearing, this model is used to determine the point on the 1–10 fertility-intention scale above which fertility intentions begin to contribute positively (i.e., yield positive SHAP values) to the predicted probability of childbirth. This empirically derived threshold is then used to dichotomize fertility intentions for the second, auxiliary model. Unlike the childbearing model, the fertility-intentions model relates intentions to characteristics measured in the same survey wave, thereby treating fertility intentions as responses to the respondents' current situation (total obs. for train set = 1,925; validation set = 1,925; test set = 1,878).

Finally, eXplainable Artificial Intelligence (XAI) techniques based on SHAP (SHapley Additive exPlanations) values (Lundberg and Lee 2017) were employed to quantify features' contributions to both models, map non-linear relationships across data subspaces, and detect interaction effects between individual, domestic, and labor market factors.

3.2. Statement on the use of LLMs in this study

ChatGPT (version 5.5) was used as an auxiliary tool during the development of machine-learning models, i.e., to identify programming errors, improve code readability and structure, and assist with code comments and documentation. It was not used to generate or propose algorithms, computational methods, or scientific solutions. All scientific and methodological decisions, code, and results were developed and verified by the authors. We also acknowledge the support of ChatGPT (version 6.0 Astra) and Gemini (version 3.6 Thinking) to enhance the readability of our manuscript. Specifically, ChatGPT and Gemini assisted us with general text editing, such as rephrasing sentences, refining their structure, or checking grammar, while ensuring that the content remained entirely our own.

4. Results

4.1. Childbirth Prediction

The model achieved high predictive power, yielding a full training AUC-ROC of 0.94 and a test AUC-ROC of 0.86, indicating strong generalization ability without severe overfitting. On the test dataset, where childbirths are highly imbalanced (n = 25, or 1.4%), the model achieved a Sensitivity (Recall) of 0.64 and a Specificity of 0.89 (classification threshold optimized on the full training set using Youden's J statistic). Out of the 25 childbirth events in the test wave, the model correctly identified 16 (True Positives), missing 9 (False Negatives), while correctly classifying 1,612 non-childbirth cases (True Negatives) against 202 False Positives (see Table 2). The model identified nearly two-thirds of births while correctly classifying 88.9% of non-births, indicating good discriminatory performance for a relatively rare outcome.

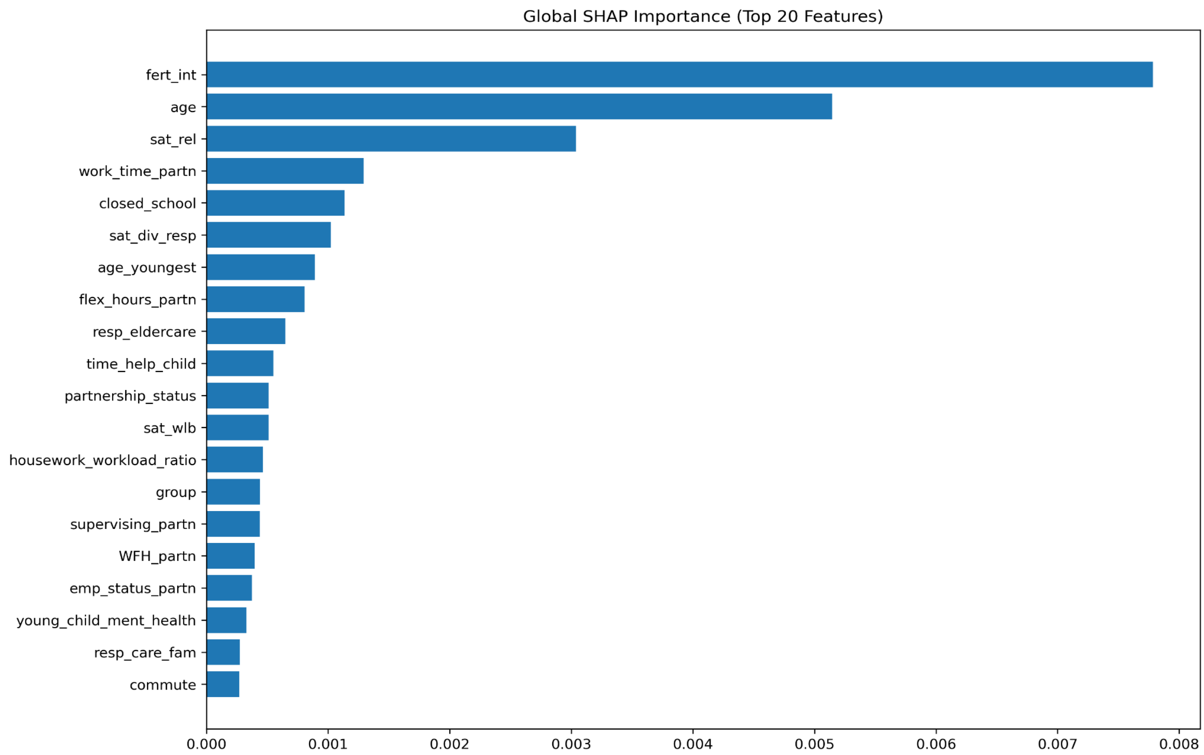
To understand which features drive these predictions, global feature importance was computed using mean absolute SHAP values across all features. Figure 1 displays the top 20 most important features (hereafter 'predictors') ranked for the train set (the corresponding predictor importance for the test set is presented in Figure A1 in the Appendix). As shown in Figure 1, fertility intentions, respondents' age, and relationship satisfaction emerge as the three most dominant predictors of childbirth. These are followed closely by partner-related work characteristics (particularly their working time), care pressures (particularly those issuing from closed schools or daycare facilities during the pandemic) and satisfaction with the division of housework.

Table 2. Test Set Confusion Matrix - Main Model (Predicting Childbirths) (N = 1,839)

	Predicted: No Childbirth	Predicted: Childbirth	Total
Actual: No Childbirth	1,612	202	1,814
Actual: Childbirth	9	16	25
Performance Metrics	**Specificity:** 88.86%	**Sensitivity:** 64.00%	**AUC-ROC:** 0.8622

Source: Own calculations based on the 2021-2024 panel data from the Familydemic project.

Figure 1. Top 20 Most Important Features (Predictors) of Childbirth on Full Training Set

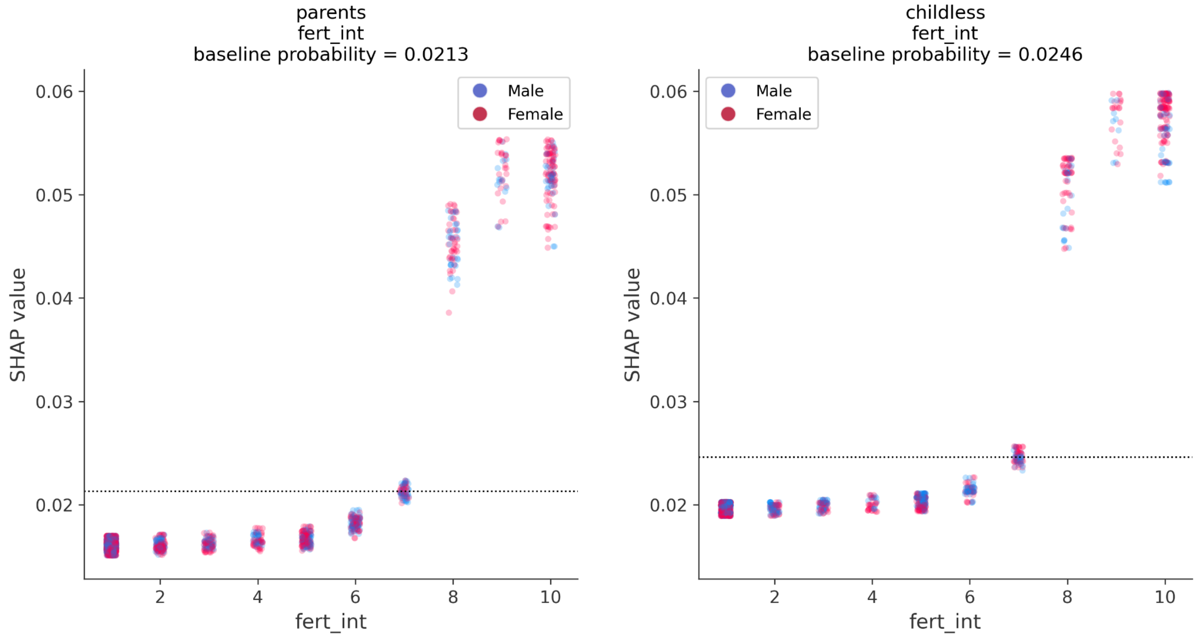


Notes: The horizontal axis represents the mean absolute SHAP value per predictor, indicating the average magnitude of each predictor's contribution to the model's predictions. Higher values correspond to greater overall predictor importance. Detailed descriptions of all variable names are included in table A1 (Appendix).

The subsequent sections focus on a selected subset of key variables from this top 20 ranking. The three most predictive features are presented on detailed SHAP dependence plots in Figures 2–4 below, while SHAP dependence plots for the remaining top-20 predictors (excluding 'group' variable as it is included only to distinguish parents from childless individuals) are provided in Figures A2–A17 in the Appendix. On all these figures, SHAP values are shifted by the baseline probability, i.e., the model's average predicted probability across the sample, representing the expected outcome before accounting for any individual predictor - so that the vertical axis reflects predicted probability rather than raw SHAP values. To account for structural baseline differences, all detailed SHAP value analyses are disaggregated across two main dimensions: parity and gender. The baseline predicted probability (base value) of a childbirth differs substantially by parity, standing at 0.0246 for childless respondents compared to 0.0213 for parents on the training data. Using these baseline probabilities as references, we analyze SHAP dependence and interaction plots to assess how individual, partner, and domestic characteristics shift the likelihood of childbirth above or below these group baseline levels. Importantly, we show results for the full training set, i.e., the dataset that uses COVID-19 circumstances to predict childbirths in 2022 and 2023, to consider the specific conditions during that period. Results for the post-pandemic 2024 test sample were very similar, suggesting good generalizability of our 'pandemic' findings and negligible overfitting.

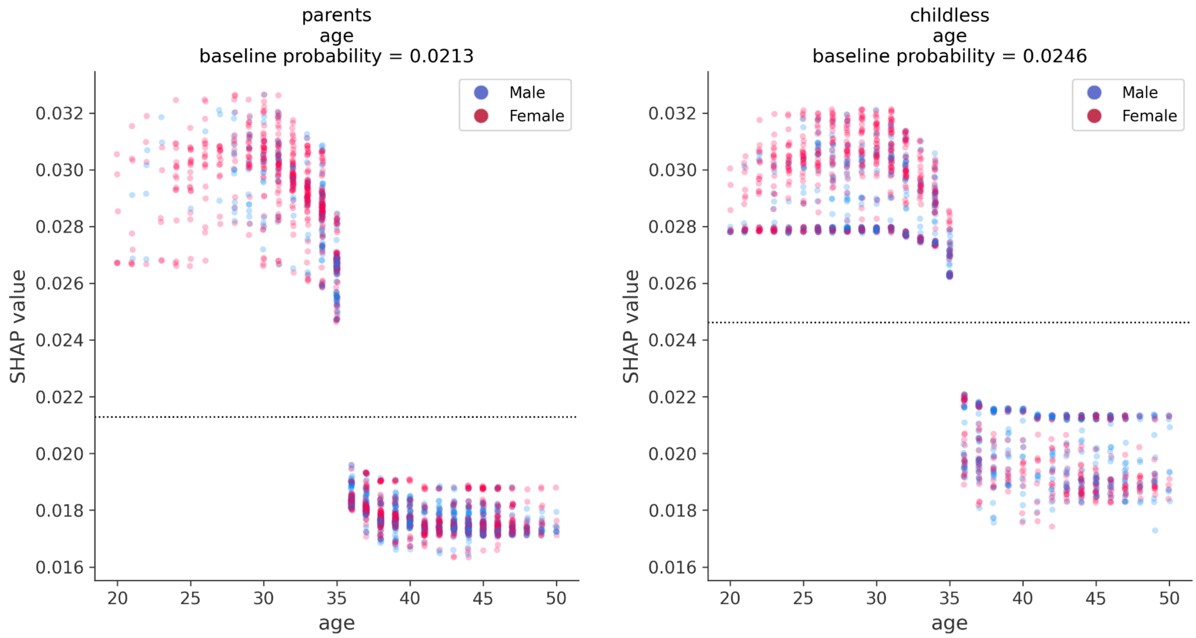
Starting with individual demographic and socioeconomic factors, short-term fertility intentions (see Fig. 2) demonstrate a clear threshold pattern regardless of parity. Stated intentions between 1 and 7 (on a 1–10 scale) exert neutral or negative SHAP contributions to childbirth. Only fertility intentions rated 8 or higher on the 10-point scale make a clear positive contribution to the model's predicted probability of childbirth. Age (see Fig. 3) exhibits a distinct, non-linear pattern with a sharp structural threshold at 35 years. Childbirth probabilities peak around age 30, after which SHAP contributions drop steeply and turn negative for individuals aged 35 and older. Partnership status (see Fig. A9) imposes strict baseline constraints. Single respondents and individuals in non-cohabiting informal relationships exhibit markedly reduced probabilities. Formal cohabitation and marriage both positively contribute to childbirth; however, cohabitation pushes probabilities above the baseline probability primarily for childless respondents, whereas formal marriage remains the dominant positive driver for higher-order births. Finally, among parents, higher childbirth probabilities are tightly concentrated in the early childhood of the youngest child, specifically when they are under 5 years old (see Fig. A5). This confirms a preference for short birth spacing among Polish couples.

Figure 2. SHAP Plot for Fertility Intentions for Childbirth Prediction on Full Training Set



Notes: The horizontal axes represent predictor values, and the vertical axes represent the predicted probability of childbirth, obtained by adding each observation's SHAP value to the model's baseline (expected) probability. The dotted horizontal line marks the baseline probability itself. Points above the dotted line indicate that the predictor's SHAP value contributes positively to the predicted probability relative to baseline, whereas points below the line indicate a negative contribution. Colors represent gender (male/female).

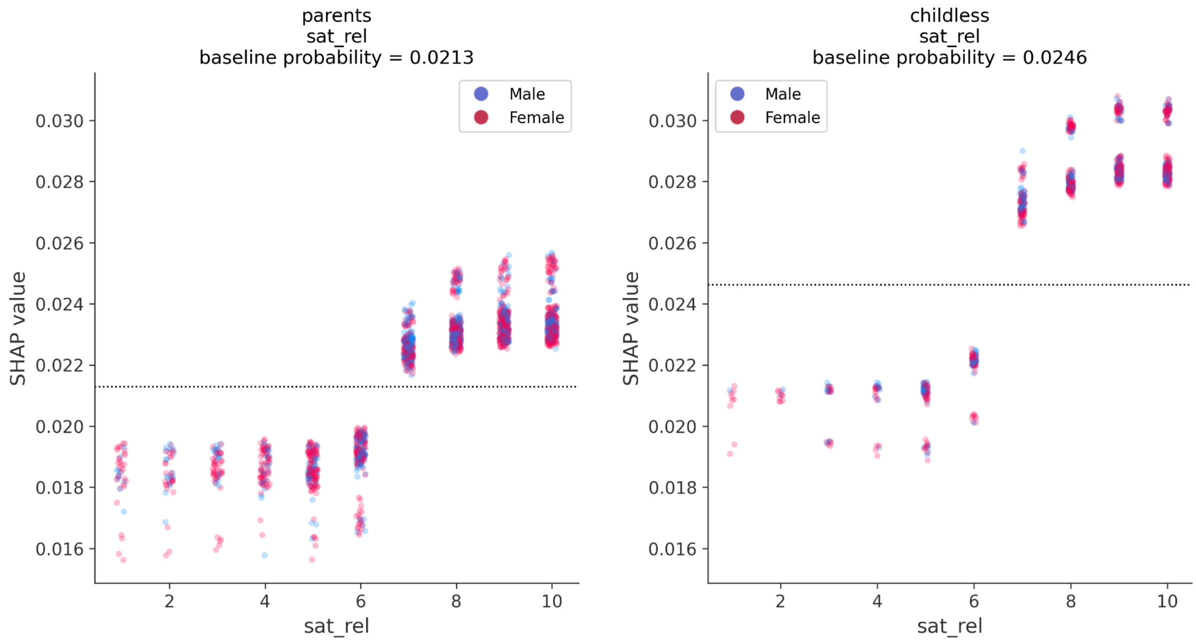
Figure 3. SHAP Plot for Age for Childbirth Prediction on Full Training Set



Notes: The horizontal axes represent predictor values, and the vertical axes represent the predicted probability of childbirth, obtained by adding each observation's SHAP value to the model's baseline (expected) probability. The dotted horizontal line marks the baseline probability itself. Points above the dotted line indicate that the predictor's SHAP value contributes positively to the predicted probability relative to baseline, whereas points below the line indicate a negative contribution. Colors represent gender (male/female).

Moving to satisfaction-related predictors, subjective partnership satisfaction - the third most important predictor in the model - operates as a ‘conditional gatekeeper’ (see Fig. 4). As with fertility intentions, probabilities of experiencing a childbirth are highest when relationship satisfaction reaches at least 7 out of 10. Perceived satisfaction with the division of domestic duties (see Fig. A4) also must reach a minimum threshold of 6 out of 10 to positively contribute to childbirth probability. This threshold pattern is particularly pronounced among men, for whom high satisfaction with domestic arrangements is associated with higher predicted fertility.

Figure 4. SHAP Plot for Satisfaction with Relationship for Childbirth Prediction on Full Training Set



Notes: The horizontal axes represent predictor values, and the vertical axes represent the predicted probability of childbirth, obtained by adding each observation's SHAP value to the model's baseline (expected) probability. The dotted horizontal line marks the baseline probability itself. Points above the dotted line indicate that the predictor's SHAP value contributes positively to the predicted probability relative to baseline, whereas points below the line indicate a negative contribution. Colors represent gender (male/female).

As for employment-related characteristics, the partner’s labor supply (see Fig. A2) makes a positive contribution to the model’s predicted probability of childbirth once specific working-hour thresholds are reached. For higher-order births among parents, childbirth likelihood is highest when a male partner works full-time or even overtime, which likely proxies his ‘income effect’: a favorable material situation and economic stability for childbearing. For childless individuals, the positive threshold occurs at lower working hours (around half-time / 20 hours per week) for both genders, suggesting that labour-market attachment, even part-time, is sufficient to support entry into parenthood. Additionally, men whose female partners are not in paid employment show slightly higher probabilities of experiencing childbirth, though this pattern is modest compared to working-hour thresholds (see Fig. A14). Next, women whose male partners do not work from home (see Fig. A13) exhibit higher probabilities of childbirth across both childless women and mothers, potentially reflecting differences in occupational stability or spatial boundaries between home and office work. Surprisingly, commute time (see Fig. A17) reveals a clear pattern: individuals with daily commutes exceeding 40 to 50 minutes have higher probabilities of childbirth. This counterintuitive finding likely reflects suburbanization and housing choices, where expanding families relocate to residential peripheries involving longer commutes. Importantly, work-life balance satisfaction (see Fig. A10) requires a baseline rating of at least 6 out of 10 to yield positive SHAP values across parities and both genders. This reflects the importance of clearly positive perception of balance between work and private life for transitions to both first and subsequent children.

Participation in domestic work (see Fig. A11) shows a similar and gendered pattern. As expected, men who contribute a very low share to housework exhibit the lowest probabilities of childbirth. This penalty for unequal domestic share is especially severe among existing parents considering higher-order births. Next, institutionally-driven shocks to childcare burden are associated with a markedly lower predicted fertility. Experiencing increased childcare burden due to closed schools or daycare facilities for more than 2 months is strongly negatively associated with childbirth probabilities (see Fig. A3). In addition, bearing additional family care duties (a burden borne disproportionately by women) is consistently associated with a lower probability of childbirth (see Fig. A16).

Importantly, several variables included in the top 20 global ranking exhibited near-zero or flat SHAP dependence distributions across their ranges, indicating little direct, independent effect once other primary drivers are controlled for. These include partners' flexible working hours (Fig. A6), eldercare responsibilities (Fig. A7), time spent helping a child with school (Fig. A8), partners' supervisory position (Fig. A12), and the youngest child's mental health assessment (Fig. A15).

Finally, none of the interactions were identified as crucial in the model. Precisely, the mean absolute SHAP interaction values across all samples were substantially smaller (at most 0.0004) than the absolute SHAP values obtained for the 20 individual features (from 0.0084 to 0.0005), indicating that the model predictions were primarily driven by main effects rather than consistent pairwise interactions. At the same time, this is a fairly common outcome for tree-based models fit on tabular data, especially with moderate sample sizes -

genuine interaction patterns need more signal to separate from noise than main patterns do, so SHAP interaction values often shrink toward zero relatively easily (Wright, Ziegler and König, 2016).

4.2. Positive Fertility Intentions Prediction

Building upon the empirical findings of the main model, where childbirth was positively associated with baseline fertility intentions of 8 or higher on the 1-10 scale, the second model explicitly investigates the determinants of expressing positive fertility intentions. In this step, the binary target variable is defined as holding strong short-term fertility intentions (at least 8 on a 1-10 scale), versus lower fertility intentions (1-7). Again, the fertility-intentions model relates intentions to same-wave characteristics, treating them as responses to respondents' current situation.

The random forest model predicting high fertility intentions demonstrated solid predictive capability and generalization across waves. The model achieved an AUC-ROC of 0.80 on the full training set and an AUC-ROC of 0.74 on the test set. When evaluated on the latter, where 195 observations (10.4%) exhibited high fertility intentions, the model yielded a Sensitivity (Recall) of 0.61 and a Specificity of 0.75. Out of 195 respondents with high intentions, the model correctly identified 118 (True Positives) while missing 77 (False Negatives). Furthermore, it correctly classified 1,267 individuals with lower intentions (True Negatives) against 416 False Positives (see Table 3). These results indicate robust capacity to discriminate high-intention individuals while accommodating the broader behavioral variance inherent in subjective attitude metrics.

Table 3. Test Set Confusion Matrix - Auxiliary Model (Predicting Positive Fertility Intentions) (N = 1,878)

	Predicted: Intentions <8	Predicted: Intentions ≥8	Total
Actual: Intentions <8	1,267	416	1,683
Actual: Intentions ≥8	77	118	195
Performance Metrics	**Specificity:** 75.28%	**Sensitivity:** 60.51%	**AUC-ROC:** 0.7386

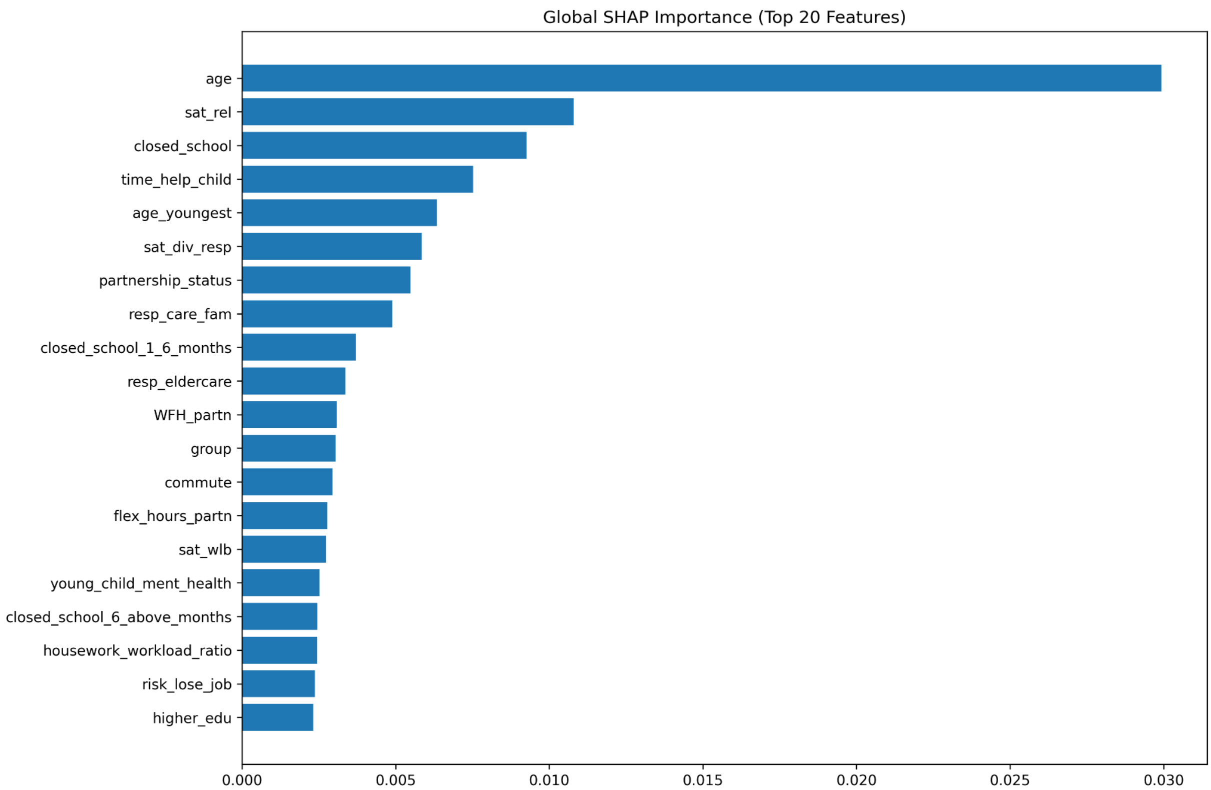
Note: Positive fertility intentions are defined as a score of ≥8 on the 10-point scale, based on the empirical threshold identified in the main model (predicting childbirth).

As in the main model, global feature importance was determined by calculating mean absolute SHAP values across all predictors. Figure 5 illustrates the top 20 most influential variables ranked for the training data (with the corresponding test-set ranking provided in Figure A18 in the Appendix).

As demonstrated in the figure, 16 of the top 20 predictors are shared with the childbirth model, albeit with slight variations in rank order. Here again respondents' age and relationship satisfaction emerge as the primary predictors of high fertility intentions. Notably, the length of the period the child stayed at home due to school or daycare closures during the pandemic emerges as the third most important predictor for childbearing intentions.

To examine how individual, household, and institutional predictors shape high fertility intentions, SHAP dependence plots were analyzed across key variable domains. As for the previous model, we present the results for the train data, separately for childless respondents and parents and distinguishing between men and women. The baseline probabilities of positive fertility intentions predicted by the model are 0.147 for childless respondents compared to 0.116 for parents. The three core predictors are highlighted in Figures 6–8 below, while plots for all remaining top 20 features are detailed in Figures A19–A34 in the Appendix.

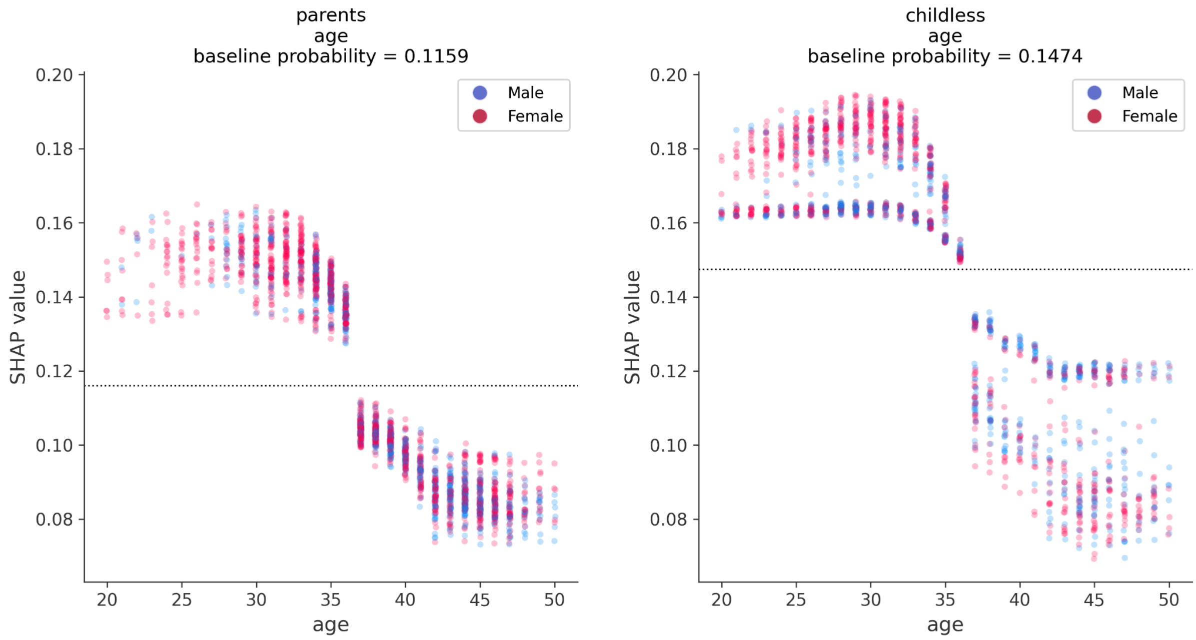
Figure 5. Top 20 Most Important Features (Predictors) of Positive Fertility Intentions on Train Data



Notes: The horizontal axis represents the mean absolute SHAP value per predictor, indicating the average magnitude of each predictor's contribution to the model's predictions. Higher values correspond to greater overall predictor importance. Detailed descriptions of all variable names are included in table A1 (Appendix).

The non-linear effect of demographic and socioeconomic anchors closely mirrors the dynamics observed in the childbirth model. Respondents' age displays a sharp drop below baseline probability around 35 years (see Fig. 6). Similarly, the age of the youngest child among existing parents exerts a strong spacing effect, with positive contributions being lowest when the youngest child is over 5 years of age (see Fig. A20). Partnership status continues to impose structural baseline constraints: single respondents and those in non-cohabiting informal relationships consistently exhibit the lowest probabilities of holding high fertility intentions (see Fig. A22). Educational attainment also emerges as a key socioeconomic correlate among childless respondents, with those who have less than higher education (a group in which men are overrepresented in our sample) showing the lowest likelihood of expressing high fertility intentions (see Fig. A34).

Figure 6. SHAP Plot for Age for Positive Fertility Intentions Prediction on Train Data

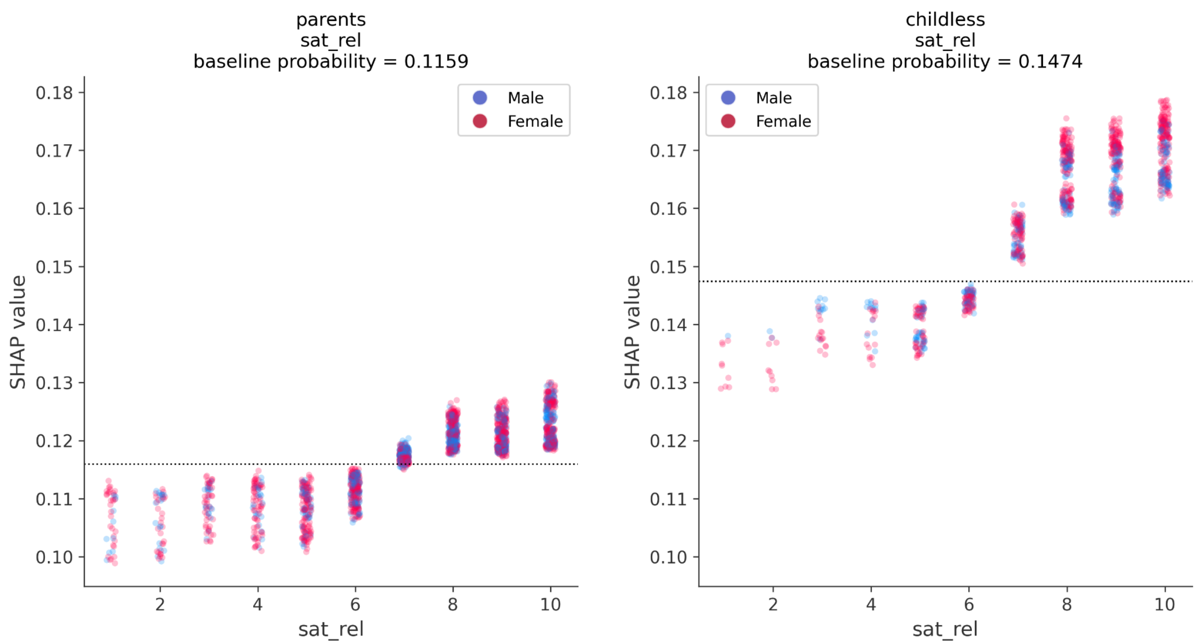


Notes: The horizontal axes represent predictor values, and the vertical axes represent the predicted probability of positive intentions, obtained by adding each observation's SHAP value to the model's baseline (expected) probability. The dotted horizontal line marks the baseline probability itself. Points above the dotted line indicate that the predictor's SHAP value contributes positively to the predicted probability relative to baseline, whereas points below the line indicate a negative contribution. Colors represent gender (male/female).

Next, subjective evaluations of partnership and domestic arrangements are also key predictors of strong fertility intentions. Consistent with birth patterns, a relationship satisfaction score of at least 7 out of 10 is necessary to exhibit the probability of positive intentions above group baselines (see Fig. 7). Regarding domestic responsibilities, the association between satisfaction with the division of household tasks and strong fertility intentions again differs by gender, whereas the housework workload ratio itself shows no clear association with these intentions (see Figs. A21 and A32).

Economic stability and flexible working arrangements show strong, nonlinear associations with fertility intentions. Perceived job insecurity is negatively associated with strong fertility intentions, particularly among childless respondents. Perceived job insecurity functions as a major ‘deterrent’, particularly among childless respondents. Individuals who report that job loss is ‘likely,’ ‘very likely,’ or who are ‘unsure’ display probabilities well below the baseline, whereas those reporting job loss as ‘very unlikely’ show significantly higher intentions (see Fig. A33). Among parents, having a partner who works from home at least half of the time is positively associated with strong fertility intentions (see Fig. A26). Commute duration replicates the spatial pattern identified in the childbirth model, with commute times exceeding approximately 40 minutes for parents and 25 minutes for childless individuals associating with above-baseline probabilities (see Fig. A27). Finally, higher satisfaction with work–life balance contributed positively to the model’s prediction of firm fertility intentions, with SHAP values rising above the baseline at scores of 7 or higher (see Fig. A29).

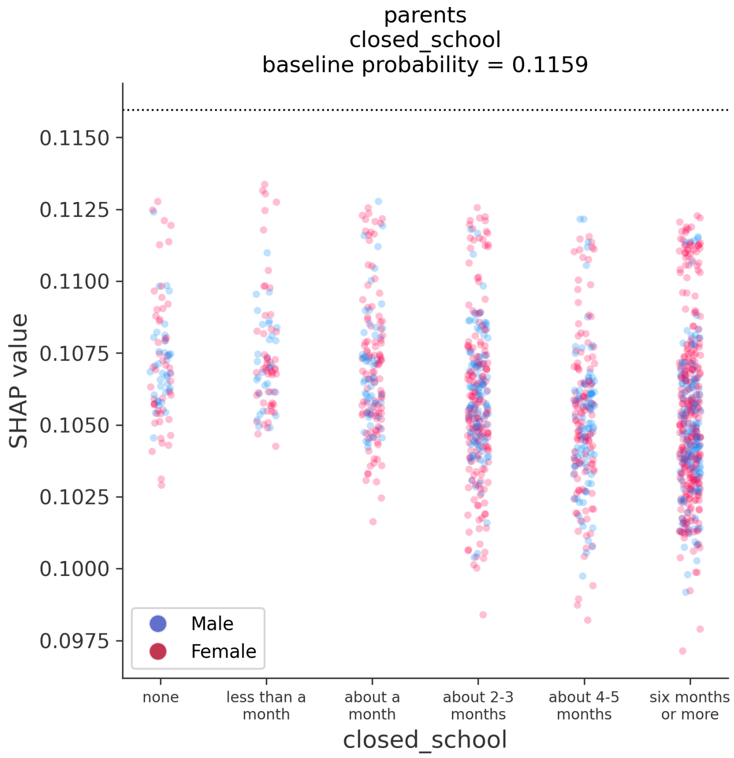
Figure 7. SHAP Plot for Satisfaction with Relationship for Positive Fertility Intentions Prediction on Train Data



Notes: The horizontal axes represent predictor values, and the vertical axes represent the predicted probability of positive intentions, obtained by adding each observation's SHAP value to the model's baseline (expected) probability. The dotted horizontal line marks the baseline probability itself. Points above the dotted line indicate that the predictor's SHAP value contributes positively to the predicted probability relative to baseline, whereas points below the line indicate a negative contribution. Colors represent gender (male/female).

Lastly, institutional shocks caused by school and daycare closures reveal nuanced effects. While an aggregate metric of closed schools links to a slight overall suppression of positive intentions (see Fig. 8), more specific, binary metrics clarify the precise threshold: school closures lasting between 1 and 6 months are actually associated with higher probabilities of positive intentions, whereas extended disruptions exceeding 6 months link to severely lower fertility intentions (see Fig. A24 and A31). Furthermore, time spent helping children with school shows a slight positive gradient, i.e., parents investing more time exhibit higher average probabilities of high fertility intentions, potentially capturing underlying family-centered orientations (see Fig. A19). Conversely, broader care responsibilities, including eldercare (see Fig. A25) and general family care duties (see Fig. A23), as well as partner's flexible working hours (see Fig. A28), and child mental health evaluations (see Fig. A30), display essentially flat SHAP distributions, demonstrating no decisive direct relationship with high fertility intentions.

Figure 8. SHAP Plot for Closed Schools Time for Positive Fertility Intentions Prediction on Train Data



Notes: The horizontal axes represent predictor values, and the vertical axes represent the predicted probability of positive intentions, obtained by adding each observation's SHAP value to the model's baseline (expected) probability. The dotted horizontal line marks the baseline probability itself. Points above the dotted line indicate that the predictor's SHAP value contributes positively to the predicted probability relative to baseline, whereas points below the line indicate a negative contribution. Colors represent gender (male/female).

5. Conclusion and discussion

In this paper, we found evidence suggesting continuity in the circumstances predictive of childbearing during and after the COVID-19 pandemic in Poland. We applied machine learning methods using an abundant set of theoretically grounded individual, employment, partnership, and family characteristics and a two-step modeling approach informed by demographic theories linking (short-term) fertility intentions and childbearing behavior (Miller 1994; Miller 2011; Ajzen and Klobas 2013). The random forest model trained on pandemic observations retained strong discriminatory performance in the post-pandemic period, with a test AUC-ROC of 0.86. This continuity supports the interpretation that the circumstances associated with childbearing during the pandemic, and mechanisms underlying them, reflected constraints that also matter under non-crisis conditions.

Short-term fertility intentions remain the strongest predictor of childbearing even when numerous other circumstances are considered simultaneously. This finding aligns with their proximal position in theories of reproductive decision-making (Miller 1994; Ajzen and Klobas 2013). At the same time, we provide evidence that the relationship is markedly nonlinear: only intentions rated at least 8 on the 10-point scale make a clearly positive contribution to childbearing predictions relative to the model's baseline. This distinction between weaker and firmly positive intentions informed our second model, which examined the circumstances associated with expressing such intentions.

Considering the two models revealed considerable overlap between the features predictive of intentions and subsequent behavior. Sixteen of the twenty highest-ranking predictors were shared, suggesting a common set of socio-demographic, work- and care-related, and relational characteristics relevant to both outcomes. Their relative importance nevertheless differed: childcare disruptions ranked more highly for intentions and perceived employment insecurity appeared among the twenty leading predictors only in the intentions model.

Relationship satisfaction proved particularly prominent, ranking immediately after fertility intentions and age for childbearing, and after age for positive intentions. In both models, it ranked far above partnership status and the partner's employment status. High satisfaction (rated at least 7 on a 10-point scale) was associated with more favorable predictions among both parents and childless respondents. This extends existing evidence on the role of relationship quality and childbearing for fertility (Aassve, Arpino, and Balbo 2016; Cetre, Clark, and Senik 2016; Hashemzadeh et al. 2021; Rijken and Thomson 2011) by demonstrating its non-linear, predictive relevance within a much broader set of variables than are usually included in regression models. Satisfaction with work-life balance had lower predictive importance, but its positive association with both outcomes was similarly clear. Only a firmly positive assessment (rated 6 or higher on a 10-point scale) contributed to a higher childbearing probability.

Domestic arrangements also mattered, although reported workloads and their subjective evaluation did not show identical patterns. Satisfaction with the division of responsibilities ranked highly in both models. Men's very low participation in housework was associated with lower childbearing probabilities, especially among parents, while the workload ratio showed no clear monotonic relationship with firm intentions. Additional family care duties were also negatively associated with subsequent childbearing among parents. These findings support attention to the gendered organization of unpaid work and to how individuals subjectively experience their domestic arrangements, consistent with previous research (Riederer, Buber-Ennser, and Brzozowska 2019; Aassve et al. 2015; Neyer, Lappegård, and Vignoli 2013).

What constituted one of the most important predictors, particularly in the intentions model, was the time spent by children in the household due to pandemic-related school and childcare closures. Increased childcare burdens associated with such closures exceeding two months contributed negatively to childbearing predictions among parents. For firm, positive intentions, the binary measures distinguished closures of one to six months, associated with higher probabilities, from longer disruptions, associated with lower probabilities. The association was therefore not uniformly negative across all closure durations. Nevertheless, prolonged disruption over 6 months was unfavorable for both outcomes, drawing attention to the reproductive implications of transferring sustained care and schooling responsibilities into households. These findings complement earlier research on working from home and changes in fertility intentions in the context of pandemic-related childcare disruptions in Poland (Kurowska, Matysiak, and Osiewalska 2023).

Employment circumstances' predictive importance was more differentiated. Perceived job insecurity had relatively low predictive importance overall, but was clearly associated with weaker intentions, particularly among childless respondents. Parents whose partners worked from home at least half the time were more likely to express firm intentions. This favorable pattern did not extend consistently to childbearing, suggesting that working from home may be linked to the two outcomes through different pathways that warrant further investigation.

Methodologically, the study contributes to fertility research by: (i) combining an extensive, theoretically informed predictor selection with a novel modeling approach based on machine-learning algorithms, (ii) taking into account interactions and nonlinearities without the need for their a priori specification, (iii) simultaneously considering models of intentions and childbearing, and (iv) leveraging the longitudinal nature of panel data for model evaluation. This approach identifies predictive regularities for further explanatory investigation, allowing interpretation of the model-derived predictive patterns via SHAP values, opening new avenues for future family research (Sivak et al. 2024; Delaporte et al. 2025).

From the perspective of reproductive autonomy, these findings direct attention to the conditions under which people can pursue their own reproductive plans. Relationship satisfaction and the gendered distribution of unpaid work deserve consideration alongside material and economic circumstances. The unfavorable associations with prolonged childcare disruptions also point to continuity of childcare and schooling as a priority in preparations for future health emergencies.

This study, like any other, has limitations. The predictor set, although extensive, is not exhaustive, and predictive associations do not establish causal pathways or intervention effects. Intentions were measured approximately a year before the subsequent birth or pregnancy observation; other predictors may partly capture intervening changes in intentions. Measurement relatively close to conception may limit, but cannot eliminate, this possibility. Moreover, intentions concerned a three-year horizon, whereas outcomes were observed between annual waves. Finally, our post-pandemic evidence is based on a single wave of a Polish panel, and generalization to future periods, other populations, or other health crises should be made with caution. Longer follow-up and comparative evidence from other contexts would help establish whether the regularities identified here persist beyond the present study and extend to crises of a different nature.

References

Aassve, A., Fuochi, G., Mencarini, L., Mendola, D., 2015. What is your couple type? Gender ideology, housework sharing, and babies. Demographic Research, 32(30), 835–858. https://doi.org/10.4054/DemRes.2015.32.30

Aassve, A., Arpino, B., Balbo, N., 2016. It takes two to tango: Couples' happiness and childbearing. European Journal of Population, 32(3), 339–354. https://doi.org/10.1007/s10680-016-9385-1

Aassve, A., Cavalli, N., Mencarini, L., Plach, S., Livi Bacci, M., 2020. The COVID-19 pandemic and human fertility. Science, 369(6502), 370–371. https://doi.org/10.1126/science.abc9520

Aassve, A., Cavalli, N., Mencarini, L., Plach, S., Sanders, S., 2021. Early assessment of the relationship between the COVID-19 pandemic and births in high-income countries. Proceedings of the National Academy of Sciences, 118(36), Article e2105709118. https://doi.org/10.1073/pnas.2105709118

Ajzen, I., Klobas, J., 2013. Fertility intentions: An approach based on the theory of planned behavior. Demographic Research, 29(8), 203–232. https://doi.org/10.4054/DemRes.2013.29.8

Alderotti, G., Vignoli, D., Baccini, M., Matysiak, A., 2021. Employment instability and fertility in Europe: A meta-analysis. Demography, 58(3), 871–900. https://doi.org/10.1215/00703370-9164737

Ashforth, B.E., Kreiner, G.E., Fugate, M., 2000. All in a day's work: Boundaries and micro role transitions. Academy of Management Review, 25(3), 472–491. https://doi.org/10.5465/amr.2000.3363315

Badawy, P.J., Schieman, S., 2021. With greater power comes greater stress? Authority, supervisor support, and work-family strains. Journal of Marriage and Family, 83(1), 40–56. https://doi.org/10.1111/jomf.12714

Bakker, A.B., Demerouti, E., 2007. The Job Demands–Resources model: State of the art. Journal of Managerial Psychology, 22(3), 309–328. https://doi.org/10.1108/02683940710733115

Balbo, N., Billari, F.C., Mills, M., 2013. Fertility in advanced societies: A review of research. European Journal of Population, 29(1), 1–38. https://doi.org/10.1007/s10680-012-9277-y

Becker, G.S., 1991. A treatise on the family (Enlarged ed.). Harvard University Press.

Beets, G., 2011. The demography of the age at first birth: The close relationship between having children and postponement. In G. Beets, J. Schippers, & E. R. te Velde (Eds.), The future of motherhood in Western societies: Late fertility and its consequences (pp. 61–90). Springer. https://doi.org/10.1007/978-90-481-8969-4_6

Begall, K., Mills, M., 2011. The impact of subjective work control, job strain and work–family conflict on fertility intentions: A European comparison. European Journal of Population, 27(4), 433–456. https://doi.org/10.1007/s10680-011-9244-z

Bishop, C.M., 2006. Pattern recognition and machine learning. Springer.

Bratti, M., Tatsiramos, K., 2012. The effect of delaying motherhood on the second childbirth in Europe. Journal of Population Economics, 25(1), 291–321. https://doi.org/10.1007/s00148-010-0341-9

Breiman, L., 2001. Random forests. Machine Learning, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

Brzozowska, Z., Mynarska, M., 2018. Short-term fertility intentions and their realisation in Poland. Studia Demograficzne, 2018(2), 25–36.

Cetre, S., Clark, A.E., Senik, C., 2016. Happy people have children: Choice and self-selection into parenthood. European Journal of Population, 32(3), 445–473. https://doi.org/10.1007/s10680-016-9389-x

Chung, H., 2022. The flexibility paradox: Why flexible working leads to (self-)exploitation. Policy Press. https://doi.org/10.51952/9781447354796

Daminger, A., 2019. The cognitive dimension of household labor. American Sociological Review, 84(4), 609–633. https://doi.org/10.1177/0003122419859007

Delaporte, I., Kulu, H., Ibbetson, A., 2025. Analysing migrant fertility using machine learning techniques. Demographic Research, 53, 629–660. https://doi.org/10.4054/DemRes.2025.53.21

Dommermuth, L., Klobas, J., Lappegård, T., 2015. Realization of fertility intentions by different time frames. Advances in Life Course Research, 24, 34–46. https://doi.org/10.1016/j.alcr.2015.02.001

Dommermuth, L., Hohmann-Marriott, B., Lappegård, T., 2017. Gender equality in the family and childbearing. Journal of Family Issues, 38(13), 1803–1824. https://doi.org/10.1177/0192513X15590686

Elder, G.H., Jr., 1994. Time, human agency, and social change: Perspectives on the life course. Social Psychology Quarterly, 57(1), 4–15. https://doi.org/10.2307/2786971

Fodor, É., Gregor, A., Koltai, J., Kováts, E., 2021. The impact of COVID-19 on the gender division of childcare work in Hungary. European Societies, 23(S1), S95–S110. https://doi.org/10.1080/14616696.2020.1817522

Goldscheider, F., Bernhardt, E., Brandén, M., 2013. Domestic gender equality and childbearing in Sweden. Demographic Research, 29(40), 1097–1126. https://doi.org/10.4054/DemRes.2013.29.40

Goldscheider, F., Bernhardt, E., Lappegård, T., 2015. The gender revolution: A framework for understanding changing family and demographic behavior. Population and Development Review, 41(2), 207–239. https://doi.org/10.1111/j.1728-4457.2015.00045.x

Goodfellow, I., Bengio, Y., Courville, A., 2016. Deep learning. MIT Press.

Greenhaus, J.H., Beutell, N.J., 1985. Sources of conflict between work and family roles. Academy of Management Review, 10(1), 76–88. https://doi.org/10.5465/amr.1985.4277352

Greulich, A., Rendall, M.S., 2026. An ongoing gender revolution in Europe: Women's stable employment as a precondition for partnered first births. Population Research and Policy Review, 45(1), Article 8. https://doi.org/10.1007/s11113-026-09990-6

Grundy, E., Henretta, J.C., 2006. Between elderly parents and adult children: A new look at the intergenerational care provided by the 'sandwich generation'. Ageing & Society, 26(5), 707–722. https://doi.org/10.1017/S0144686X06004934

Hanappi, D., Ryser, V.-A., Bernardi, L., Le Goff, J.-M., 2017. Changes in employment uncertainty and the fertility intention–realization link: An analysis based on the Swiss Household Panel. European Journal of Population, 33(3), 381–407. https://doi.org/10.1007/s10680-016-9408-y

Hashemzadeh, M., Shariati, M., Mohammad Nazari, A., Keramat, A., 2021. Childbearing intention and its associated factors: A systematic review. Nursing Open, 8(5), 2354–2368. https://doi.org/10.1002/nop2.849

Hastie, T., Tibshirani, R., Friedman, J., 2009. The elements of statistical learning: Data mining, inference, and prediction (2nd ed.). Springer.

Hofman, J.M., Watts, D.J., Athey, S., Garip, F., Griffiths, T.L., Kleinberg, J., Margetts, H., Mullainathan, S., Salganik, M.J., Vazire, S., Vespignani, A., Yarkoni, T., 2021. Integrating explanation and prediction in computational social science. Nature, 595(7866), 181–188. https://doi.org/10.1038/s41586-021-03659-0

Jarosz, E., Matysiak, A., Osiewalska, B., 2023. Maternal free time: A missing element in fertility studies. Population and Development Review, 49(4), 801–828. https://doi.org/10.1111/padr.12589

Kassaw, E.A., Abate, B.B., Enyew, B.M., Sendekie, A.K., 2025. The application of machine learning approaches to classify and predict fertility rate in Ethiopia. Scientific Reports, 15(1), Article 2562. https://doi.org/10.1038/s41598-025-85695-8

Kravdal, Ø., Rindfuss, R.R., 2008. Changing relationships between education and fertility: A study of women and men born 1940 to 1964. American Sociological Review, 73(5), 854–873. https://doi.org/10.1177/000312240807300508

Kreyenfeld, M., Andersson, G., 2014. Socioeconomic differences in the unemployment and fertility nexus: Evidence from Denmark and Germany. Advances in Life Course Research, 21, 59–73. https://doi.org/10.1016/j.alcr.2014.01.007

Kuang, B., Berrington, A., Vasireddy, S., Kulu, H., 2025. The changing inter-relationship between partnership dynamics and fertility trends in Europe and the United States: A review. Demographic Research, 52, 179–228. https://doi.org/10.4054/DemRes.2025.52.7

Kurowska, A., Barardehi, I.H., Fuller, S., Petts, R.J., Kaufman, G., Doucet, A., Engeman, C., Matysiak, A., Guetto, R., Reimer, T., Kasegn, T.D., Vignoli, D., Duvander, A.-Z., Gabel, S.G., 2023. Familydemic Cross Country and Gender Dataset on work and family outcomes during COVID-19 pandemic. Scientific Data, 10(1), 2. https://doi.org/10.1038/s41597-022-01880-8

Kurowska, A., Matysiak, A., Osiewalska, B., 2023. Working from home during COVID-19 pandemic and changes to fertility intentions among parents. European Journal of Population, 39(1), Article 32. https://doi.org/10.1007/s10680-023-09678-z

Lazzari, E., Zurla, V., 2024. The effect of parental caregiving on the fertility expectations of adult children. European Journal of Population, 40(1), Article 35. https://doi.org/10.1007/s10680-024-09724-4

Lundberg, S.M., & Lee, S.-I., 2017. A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 30, 4765–4774. https://doi.org/10.48550/arXiv.1705.07874

Luppi, F., Arpino, B., Rosina, A., 2020. The impact of COVID-19 on fertility plans in Italy, Germany, France, Spain, and the United Kingdom. Demographic Research, 43(47), 1399–1412. https://doi.org/10.4054/DemRes.2020.43.47

Malicka, I., Mynarska, M., Świderska, J., 2021. Perceived consequences of the COVID-19 pandemic and childbearing intentions in Poland. Journal of Family Research, 33(3), 674–702. https://doi.org/10.20377/jfr-666

Matysiak, A., Vignoli, D., 2013. Diverse effects of women's employment on fertility: Insights from Italy and Poland. European Journal of Population, 29(3), 273–302. https://doi.org/10.1007/s10680-013-9287-4

McDonald, P., 2000. Gender equity in theories of fertility transition. Population and Development Review, 26(3), 427–439. https://doi.org/10.1111/j.1728-4457.2000.00427.x

Miller, W.B., 1994. Childbearing motivations, desires, and intentions: A theoretical framework. Genetic, Social, and General Psychology Monographs, 120(2), 223–258.

Miller, W.B., 2011. Differences between fertility desires and intentions: Implications for theory, research and policy. Vienna Yearbook of Population Research, 9, 75–98. https://doi.org/10.1553/populationyearbook2011s75

Mills, M., Begall, K., Mencarini, L., Tanturri, M.L., 2008. Gender equity and fertility intentions in Italy and the Netherlands. Demographic Research, 18(1), 1–26. https://doi.org/10.4054/DemRes.2008.18.1

Molina, M., & Garip, F. (2019). Machine learning for sociology. Annual Review of Sociology, 45, 27–45. https://doi.org/10.1146/annurev-soc-073117-041106

Morgan, S.P., Rackin, H., 2010. The correspondence between fertility intentions and behavior in the United States. Population and Development Review, 36(1), 91–118. https://doi.org/10.1111/j.1728-4457.2010.00319.x

Mullainathan, S., Spiess, J., 2017. Machine learning: An applied econometric approach. Journal of Economic Perspectives, 31(2), 87–106. https://doi.org/10.1257/jep.31.2.87

Newman, L., 2008. How parenthood experiences influence desire for more children in Australia: A qualitative study. Journal of Population Research, 25(1), 1–27. https://doi.org/10.1007/BF03031938

Neyer, G., Lappegård, T., Vignoli, D., 2013. Gender equality and fertility: Which equality matters? European Journal of Population, 29(3), 245–272. https://doi.org/10.1007/s10680-013-9292-7

Osiewalska, B., Matysiak, A., Kurowska, A., 2024. Home-based work and childbearing. Population Studies, 78(3), 525–545. https://doi.org/10.1080/00324728.2023.2287510

Osiewalska, B., Matysiak, A., 2025. Two sides of a coin: The relationship between work autonomy and childbearing. Journal of Marriage and Family, 1–22. https://doi.org/10.1111/jomf.13066

Parr, N., 2010. Satisfaction with life as an antecedent of fertility: Partner + Happiness = Children? Demographic Research, 22(21), 635–662. https://doi.org/10.4054/DemRes.2010.22.21

Racine, N., McArthur, B.A., Cooke, J.E., Eirich, R., Zhu, J., Madigan, S., 2021. Global prevalence of depressive and anxiety symptoms in children and adolescents during COVID-19: A meta-analysis. JAMA Pediatrics, 175(11), 1142–1150. https://doi.org/10.1001/jamapediatrics.2021.2482

Riederer, B., Buber-Ennser, I., Brzozowska, Z., 2019. Fertility intentions and their realization in couples: How the division of household chores matters. Journal of Family Issues, 40(13), 1860–1882. https://doi.org/10.1177/0192513X19848794

Rijken, A.J., Thomson, E., 2011. Partners' relationship quality and childbearing. Social Science Research, 40(2), 485–497. https://doi.org/10.1016/j.ssresearch.2010.10.001

Schoen, R., Astone, N.M., Kim, Y.J., Nathanson, C.A., Fields, J.M., 1999. Do fertility intentions affect fertility behavior? Journal of Marriage and the Family, 61(3), 790–799. https://doi.org/10.2307/353578

Sevilla, A., Smith, S., 2020. Baby steps: The gender division of childcare during the COVID-19 pandemic. Oxford Review of Economic Policy, 36(S1), S169–S186. https://doi.org/10.1093/oxrep/graa027

Sivak, E., Pankowska, P., Mendrik, A., et al., 2024. Combining the strengths of Dutch survey and register data in a data challenge to predict fertility (PreFer). Journal of Computational Social Science, 7(2), 1403–1431. https://doi.org/10.1007/s42001-024-00275-6

Sobotka, T., Skirbekk, V., Philipov, D., 2011. Economic recession and fertility in the developed world. Population and Development Review, 37(2), 267–306. https://doi.org/10.1111/j.1728-4457.2011.00411.x

Sobotka, T., Zeman, K., Jasilioniene, A., Winkler-Dworak, M., Brzozowska, Z., Alustiza-Galarza, A., Németh, L., Jdanov, D.A., 2024. Pandemic roller-coaster? Birth trends in higher-income countries during the COVID-19 pandemic. Population and Development Review, 50(S1), 23–58. https://doi.org/10.1111/padr.12544

Spéder, Z., Kapitány, B., 2009. How are time-dependent childbearing intentions realized? Realization, postponement, abandonment, bringing forward. European Journal of Population, 25(4), 503–523. https://doi.org/10.1007/s10680-009-9189-7

Spéder, Z., Bálint, L., 2024. Realization of short-term fertility intentions in a comparative perspective: Which macro-level conditions matter? Population Research and Policy Review, 43(5), Article 72. https://doi.org/10.1007/s11113-024-09913-3

Sturm, N., Koops, J.C., Rutigliano, R., 2023. The influence of partnership status on fertility intentions of childless women and men across European countries. European Journal of Population, 39(1), Article 20. https://doi.org/10.1007/s10680-023-09664-5

Suero, C., 2023. Gendered division of housework and childcare and women's intention to have a second child in Spain. Genus, 79(1), Article 3. https://doi.org/10.1186/s41118-023-00182-0

Suwada, K., Karwacki, A., 2024. Women's domestic multitasking: The phenomenon of feminization of unpaid work in Polish households during the COVID-19 pandemic. Journal of Family Studies, 30(6), 1013–1037. https://doi.org/10.1080/13229400.2024.2371139

Tadese, Z.B., Nimani, T.D., Mare, K.U., Gubena, F., Wali, I.G., Sani, J., 2025. Exploring machine learning algorithms for predicting fertility preferences among reproductive age women in Nigeria. Frontiers in Digital Health, 6, Article 1495382. https://doi.org/10.3389/fdgth.2024.1495382

Tomkinson, J., 2019. Age at first birth and subsequent fertility: The case of adolescent mothers in France and England and Wales. Demographic Research, 40(27), 761–798. https://doi.org/10.4054/DemRes.2019.40.27

Tymicki, K., Cieślik, B., Syczewska, E.M., 2025. Short-term impact of the COVID-19 pandemic on age-specific fertility rates in Poland. Studia Demograficzne, 185(1–2), 31–48. https://doi.org/10.33119/SD.2024.1-2.2

Varian, H.R., 2014. Big data: New tricks for econometrics. Journal of Economic Perspectives, 28(2), 3–28. https://doi.org/10.1257/jep.28.2.3

Verhagen, M.D., 2024. Incorporating machine learning into sociological model-building. Sociological Methodology, 54(2), 217–268. https://doi.org/10.1177/00811750231217734

Vignoli, D., Drefahl, S., De Santis, G., 2012. Whose job instability affects the likelihood of becoming a parent in Italy? A tale of two partners. Demographic Research, 26(2), 41–62. https://doi.org/10.4054/DemRes.2012.26.2

Winkler-Dworak, M., Zeman, K., Sobotka, T., 2024. Birth rate decline in the later phase of the COVID-19 pandemic: The role of policy interventions, vaccination programmes, and economic uncertainty. Human Reproduction Open, 2024(3), Article hoae052. https://doi.org/10.1093/hropen/hoae052

Wright, M.N., Ziegler, A., König, I.R., 2016. Do little interactions get lost in dark random forests?. BMC bioinformatics, 17(1), Article 145. https://doi.org/10.1186/s12859-016-0995-8

Yarger, J., Brauner-Otto, S.R., 2024. Women's work characteristics and fertility expectations. Population Research and Policy Review, 43(2), Article 26. https://doi.org/10.1007/s11113-024-09866-7

Appendixes

Table A1. Full List and Description of Explanatory Variables in Prediction Models

Variable Name	Description / Label	Levels / Type
Individual demographic characteristics		
fert_int	Fertility Intentions	Continuous (1-10)
age	Age	Continuous (scale 0-49)
age_youngest	Age of the Youngest Child	Continuous (scale 0-18)
female	Female	0 = male; 1 = female
group	Parity	0 = childless; 1 = parents
partnership_status	Partnership Status	1 = formal relationship, living together; 2 = formal relationship, living apart; 3 = informal relationship, living together; 4 = informal relationship, living apart; 5 = single
higher_edu	Having Higher Education	0 = less than higher education; 1 = higher education
inc_abs	Subjective Material Assessment	1 = living comfortably on present income; 2 = coping on present income; 3 = finding it difficult on present income; 4 = finding it very difficult on present income
fin_sit_change	Change of Financial Situation	1=improved a lot; 2=somewhat improved; 3=did not change; 4=somewhat deteriorated; 5=deteriorated a lot
rising_liv_costs	Perception of Rising Costs of Living	1 = definitely not; 2 = rather not; 3 = neither nor; 4 = rather yes; 5 = definitely yes
place_res	Place of Residence	1 = city; 2 = town or suburb; 3 = rural area

Variable Name	Description / Label	Levels / Type
Employment-realated circumstances		
emp_status	Employment Status	1 = an employee; 2 = self-employed; 3 = employee/self-employed but not working; 4 = not employed, looking for work; 5 = not employed, not looking for work
emp_status_partn	Employment Status - Partner	1 = an employee; 2 = self-employed; 3 = employee/self-employed but not working; 4 = not employed, looking for work; 5 = not employed, not looking for work
work_time	Work Time, Weekly	Continuous (scale 0-60)
work_time_partn	Work Time, Weekly - Partner	Continuous (scale 0-60)
flex_hours	Having Flexible Hours	1 = yes; 2 = no, no such option at work; 3 = no, but have such option at work
flex_hours_partn	Having Flexible Hours - Partner	1 = no; 2 = yes
WFH_freq	Frequency of WFH	1 = daily; 2 = several times a week; 3 = several times a month; 4 = less often; 5 = never
WFH_partn	Frequency of WFH - Partner	1 = always from home; 2 = usually from home; 3 = half of the time from home; 4 = usually elsewhere; 5 = always elsewhere
supervising	Having Supervisory Responsibilities	1 = no; 2 = yes
supervising_partn	Having Supervisory Responsibilities - Partner	1 = no; 2 = yes
contract_type	Type of Contract	1 = permanent; 2 = temporary; 3 = seasonal; 4 = casual/on call; 5 = temporary help agency; 6 = other temporary

Variable Name	Description / Label	Levels / Type
contract_type_partn	Contract Type - Partner	1 = permanent; 2 = temporary; 3 = seasonal; 4 = casual/on call; 5 = temporary help agency; 6 = other temporary
work_sector	Sector of Occupation	1 = public sector; 2 = private sector; 3 = other, ngo
commute	Commute Time	Continuous (scale 0-200 minutes)
irreg_schedule	Having Irregular Schedule	1 = no; 2 = yes
irreg_schedule_partn	Having Irregular Schedule - Partner	1 = no; 2 = yes
quit_job	Quit Job	1 = no; 2 = yes
lost_job	Lost Job	1 = no; 2 = yes
reduced_hours	Had Reduced Hours	1 = no; 2 = yes
reduced_hours_emp	Had Reduced Hours by Employer	1 = no; 2 = yes
res_not_work	Reason for not Working	1 = temporary disability/illness leave; 2 = parental/paternity/maternity leave; 3 = leave to care for children or family members; 4 = other leave; 5 = other reasons
risk_lose_job	Perceived Risk of Losing Job	1 = very likely; 2 = likely; 3 = neither likely nor unlikely; 4 = unlikely; 5 = very unlikely
risk_lose_job_self_emp	Perceived Risk of Losing Job, Self-Employed	1 = very likely; 2 = likely; 3 = neither likely nor unlikely; 4 = unlikely; 5 = very unlikely
career_prospects_change	Perception of Changing Career Prospects	1 = improved a lot; 2 = somewhat improved; 3 = did not change; 4 = somewhat deteriorated; 5 = deteriorated a lot

Variable Name	Description / Label	Levels / Type
att_enjoy_work	Enjoying Work	1 = strongly agree; 2 = agree; 3 = neither agree nor disagree; 4 = disagree; 5 = strongly disagree
Care and housework-related burden		
childcare_workload_ratio	Division of Childcare	Continuous (0-1)
housework_workload_ratio	Division of Housework	Continuous (0-1)
resp_eldercare	Eldercare Responsibility	1 = always; 2 = usually me; 3 = my partner and me about equally; 4 = usually my partner; 5 = always my partner; 6 = always or usually someone else; 7 = does not apply
resp_care_fam	Family Care Responsibilities	1 = always; 2 = usually me; 3 = my partner and me about equally; 4 = usually my partner; 5 = always my partner; 6 = always or usually someone else; 7 = does not apply
childcare_unavailable	Duration of Unavailable Childcare	1 = none; 2 = less than a month; 3 = about a month; 4 = about 2-3 months; 5 = about 4-5 months; 6 = six months or more
time_help_child	Time Spent Helping Child with School	Continuous (scale 0-12)
closed_school	Duration of School Closure	1 = none; 2 = less than a month; 3 = about a month; 4 = about 2-3 months; 5 = about 4-5 months; 6 = six months or more
closed_school_1_6_months	Schools Were Closed Less Than 6 Months	0 = no; 1 = yes
closed_school_6_above_months	Schools Were Closed More Than 6 Months	0 = no; 1 = yes

Variable Name	Description / Label	Levels / Type
young_child_ment_health	Mental Health of the Youngest Child	1 = very well; 2 = well; 3 = neither well nor poorly; 4 = poorly; 5 = very poorly
Satisfaction from relationship and intra-household division of labour		
sat_rel_child	Satisfaction with Relationship with Children	Continuous (1-10)
sat_wlb	Satisfaction with Work-Life Balance	Continuous (1-10)
sat_rel	Satisfaction with Relationship	Continuous (1-10)
sat_div_resp	Satisfaction with Division of Responsibilities	Continuous (1-10)
gr_child_suffer	Child Suffering with Working Mother	1 = strongly agree; 2 = agree; 3 = neither agree nor disagree; 4 = disagree; 5 = strongly disagree

Figure A1. Top 20 Most Important Predictors of Childbirth on Test Data

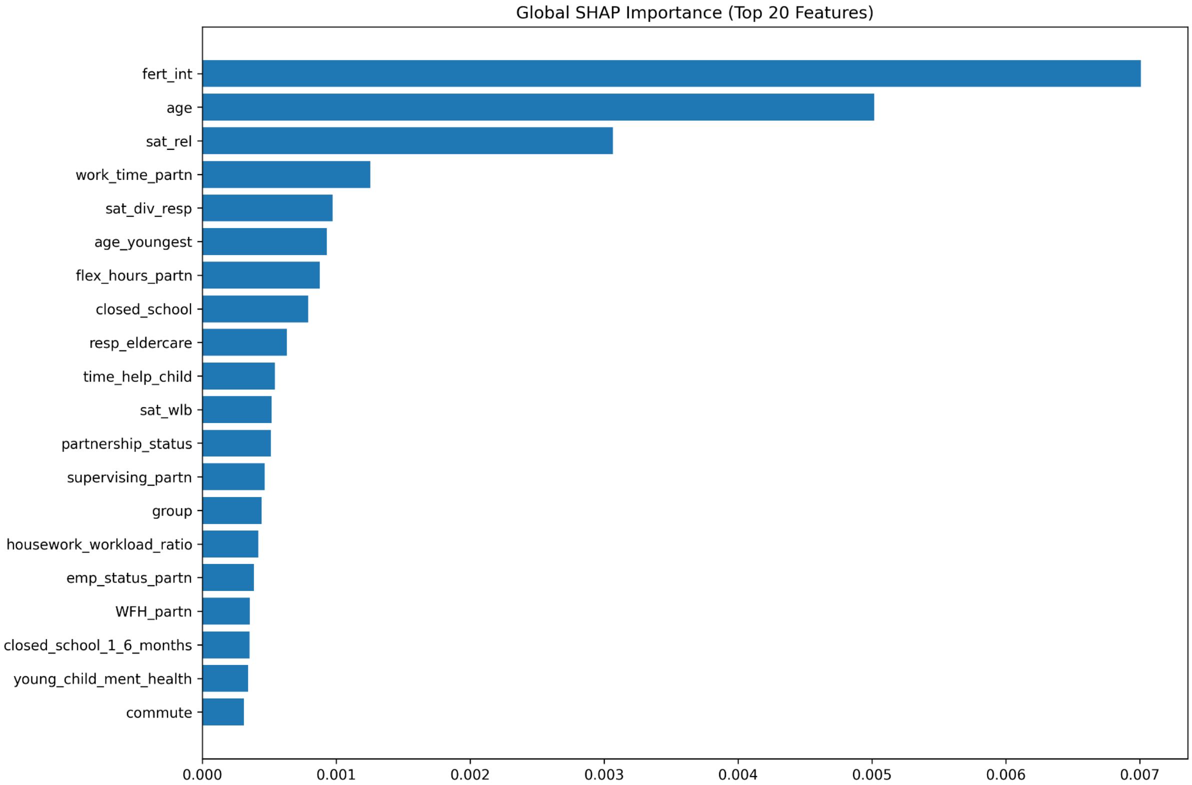


Figure A2. SHAP Plot for Working Time of a Partner for Childbirth Prediction

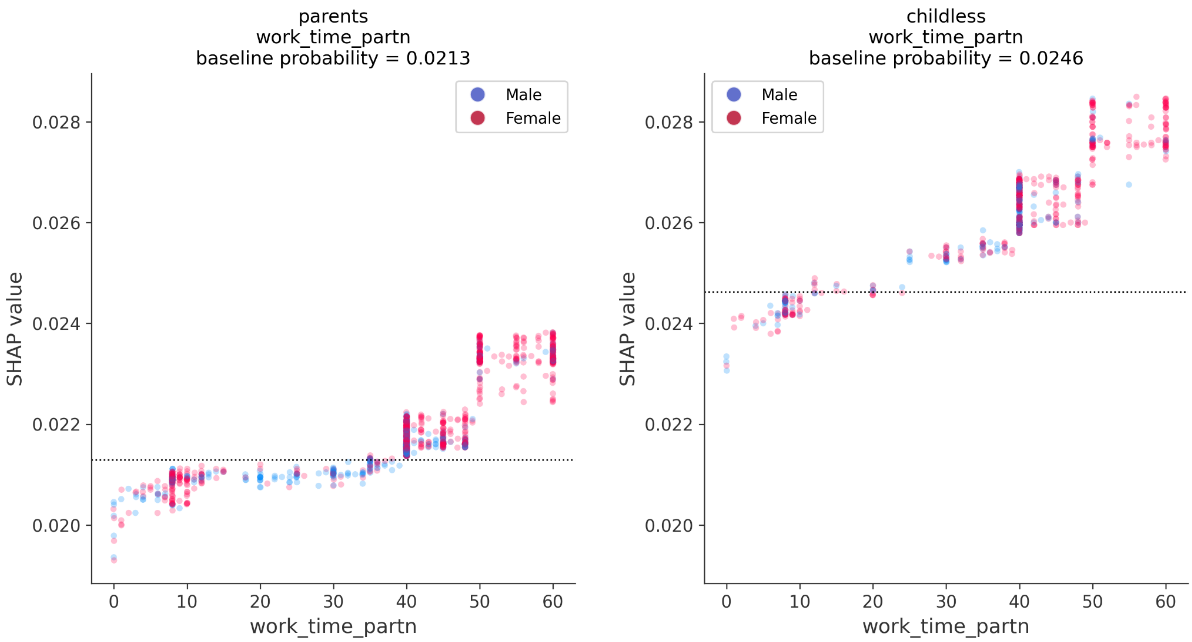


Figure A3. SHAP Plot for Closed Schools Time for Childbirth Prediction

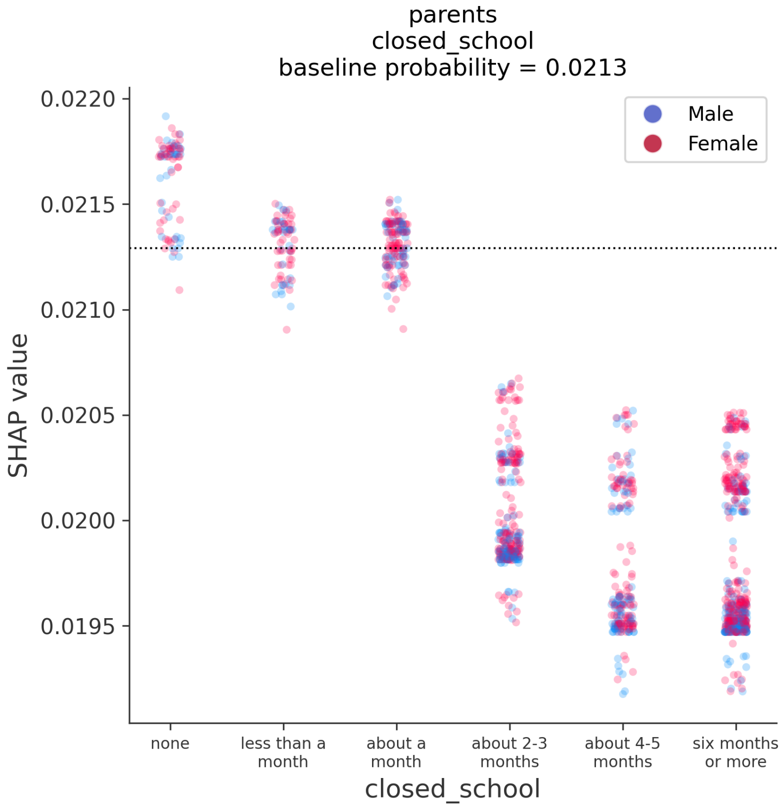


Figure A4. SHAP Plot for Satisfaction with the Division of Household Responsibilities for Childbirth Prediction

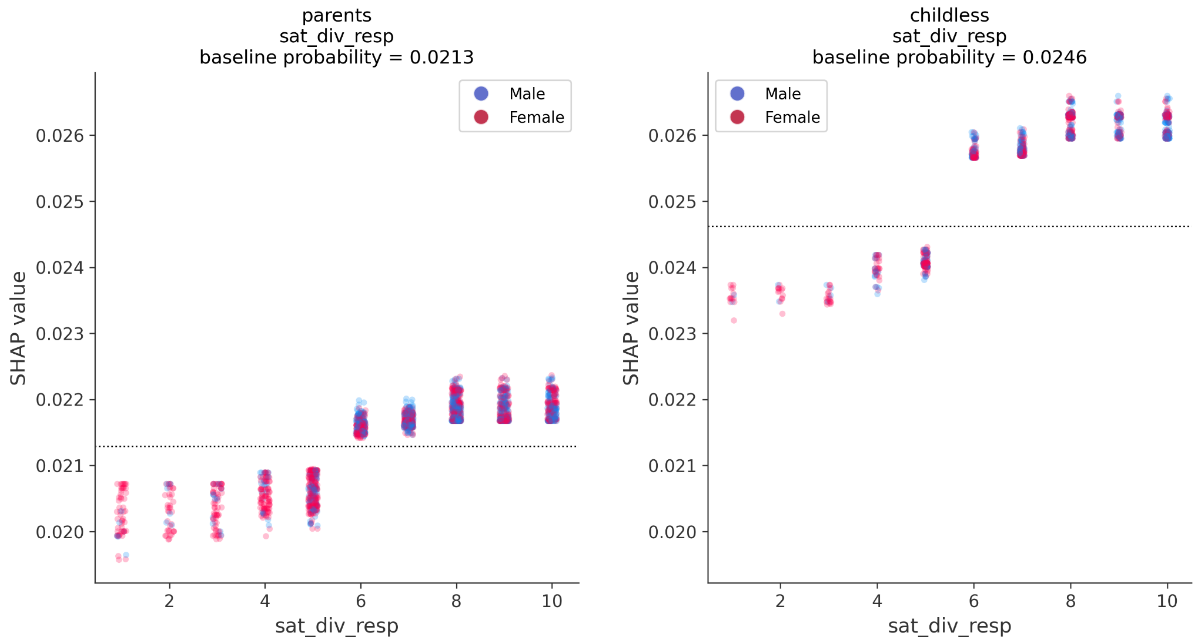


Figure A5. SHAP Plot for Age of the Youngest Child for Childbirth Prediction

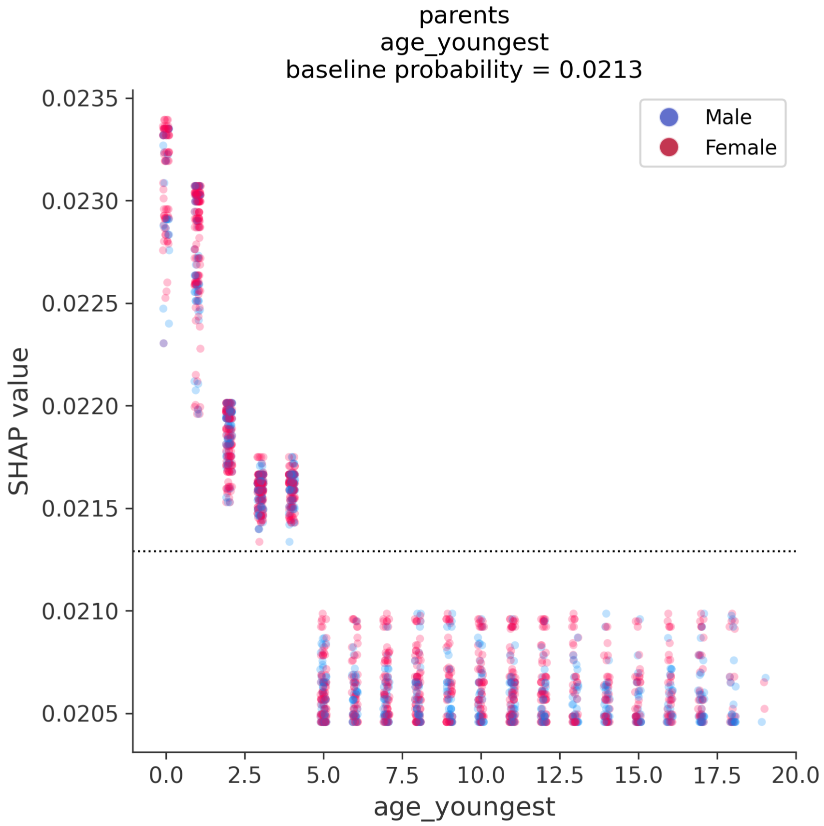


Figure A6. SHAP Plot for Flexible Working Hours of a Partner for Childbirth Prediction

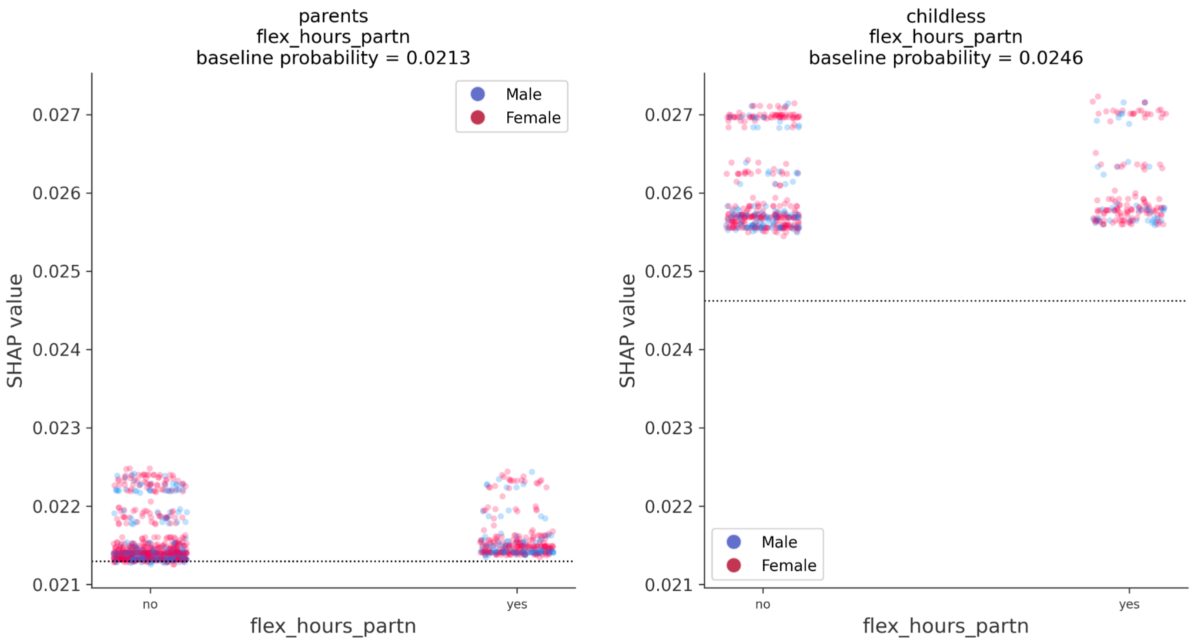


Figure A7. SHAP Plot for Responsibility for Eldercare for Childbirth Prediction

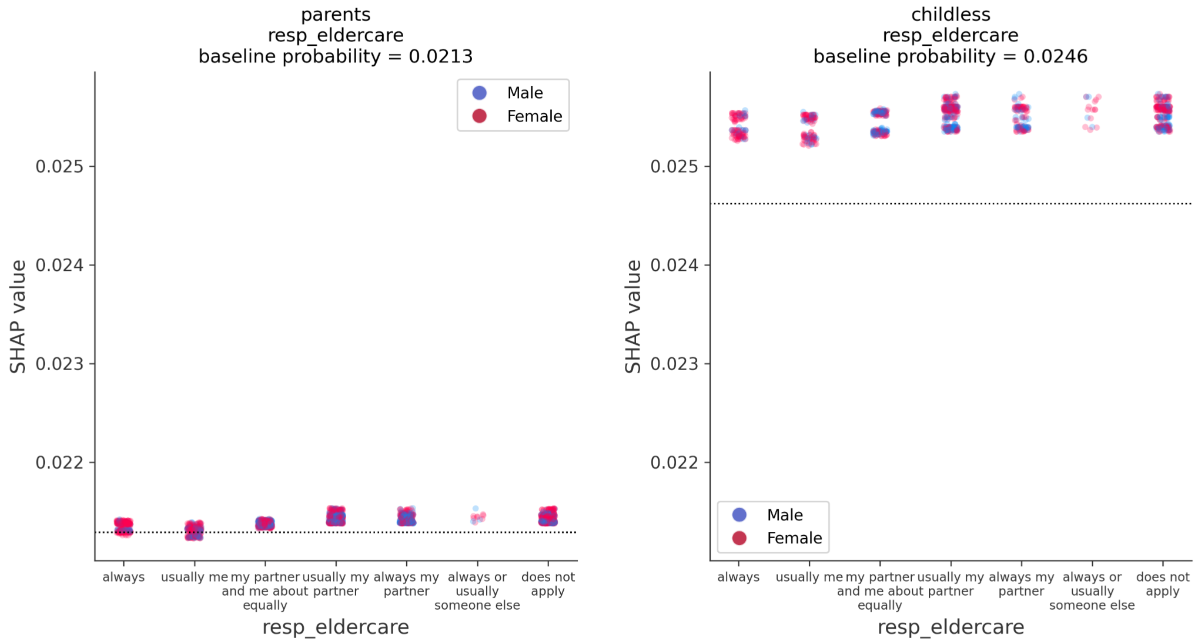


Figure A8. SHAP Plot for Time Helping Child with School for Childbirth Prediction

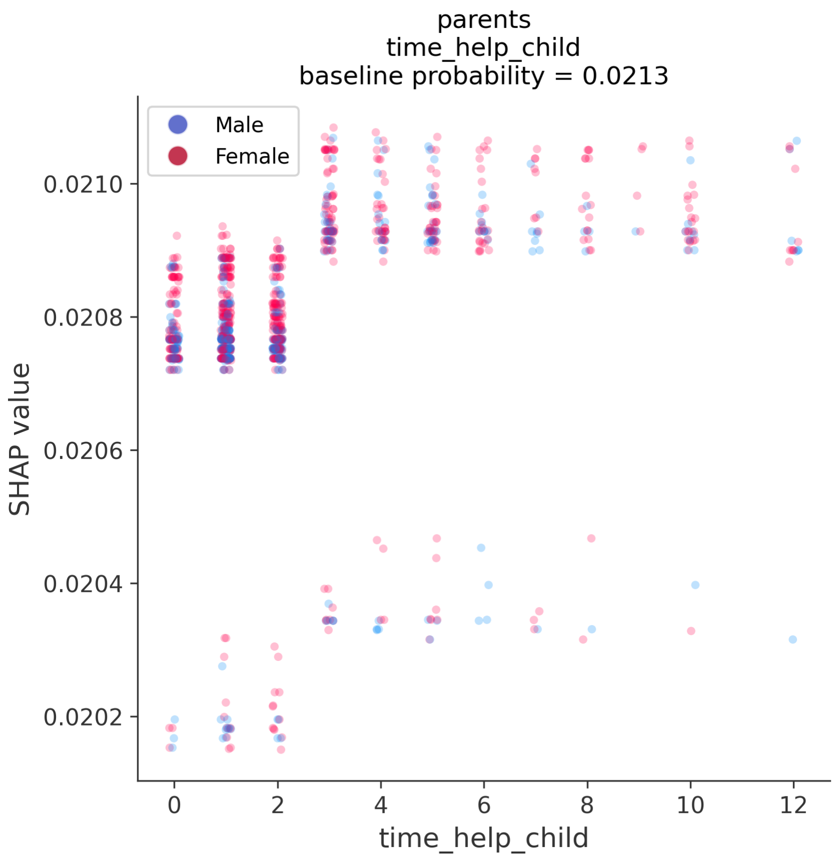


Figure A9. SHAP Plot for Partnership Status for Childbirth Prediction

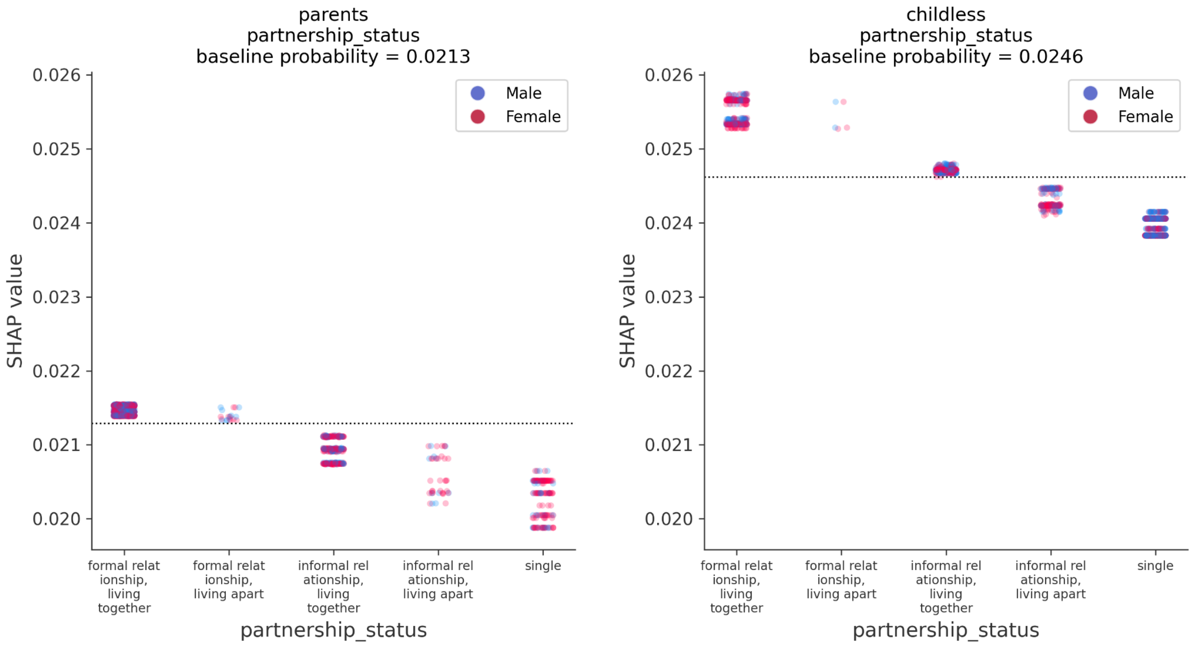


Figure A10. SHAP Plot for Satisfaction with Work-Life Balance for Childbirth Prediction

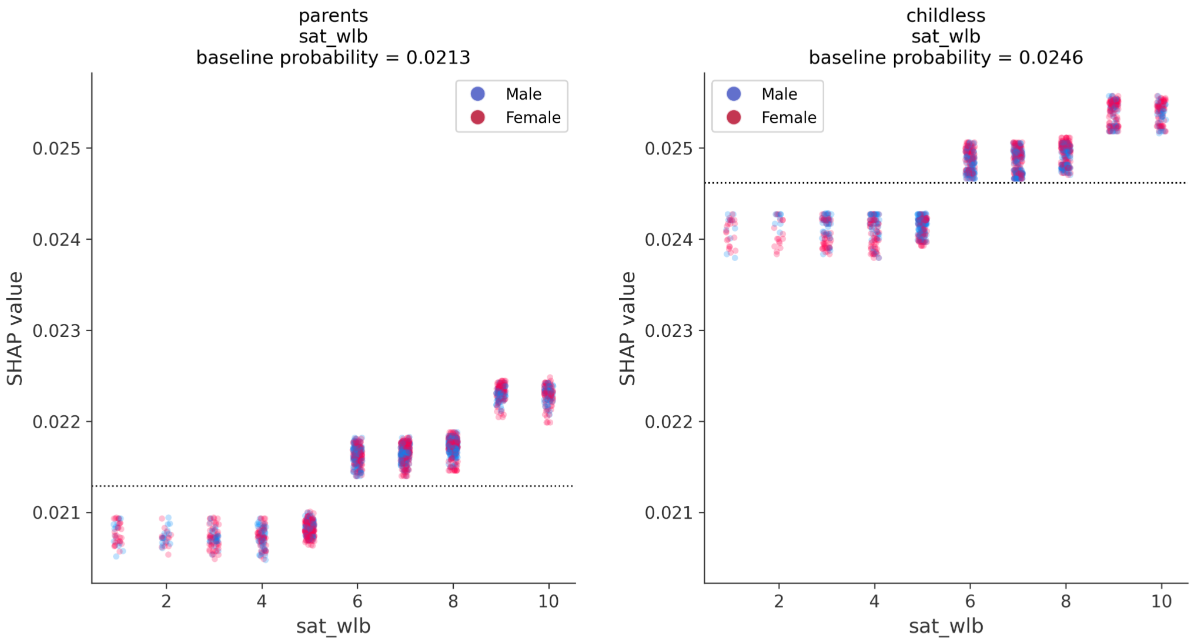


Figure A11. SHAP Plot for Housework Division for Childbirth Prediction

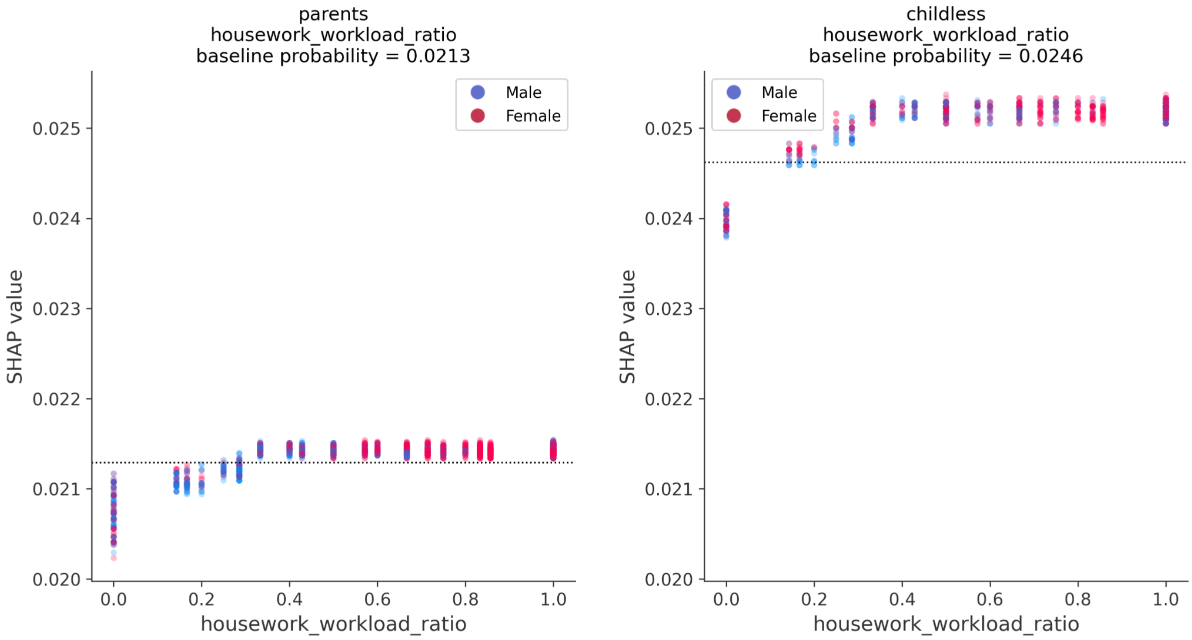


Figure A12. SHAP Plot for Supervising Responsibility at Work of a Partner for Childbirth Prediction

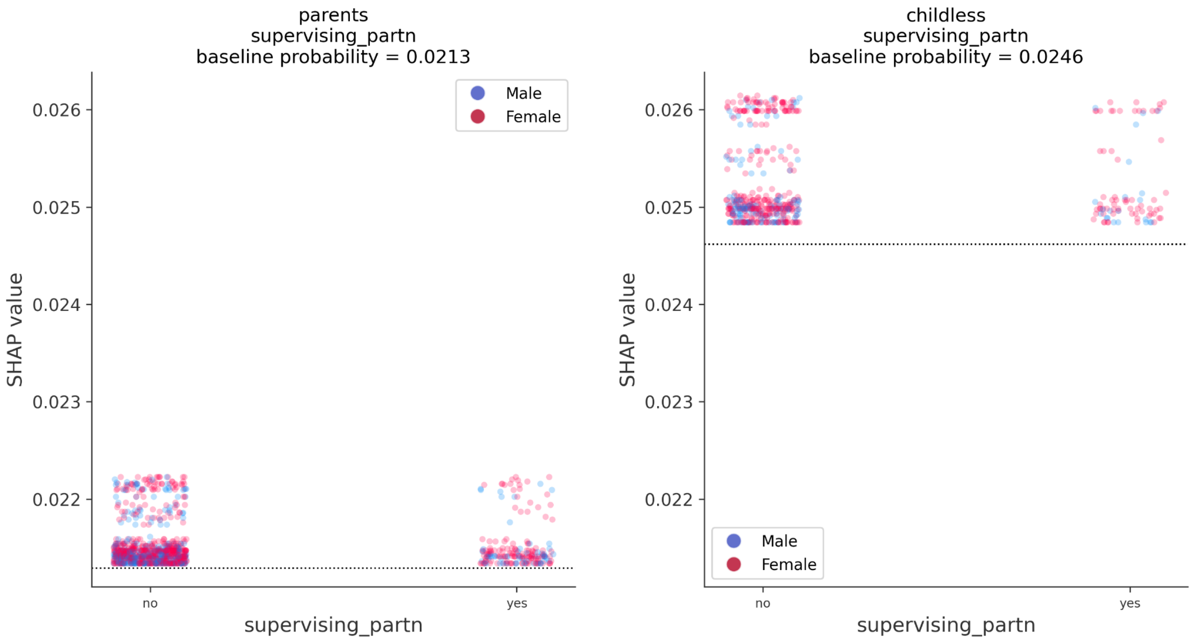


Figure A13. SHAP Plot for Work from Home of a Partner for Childbirth Prediction

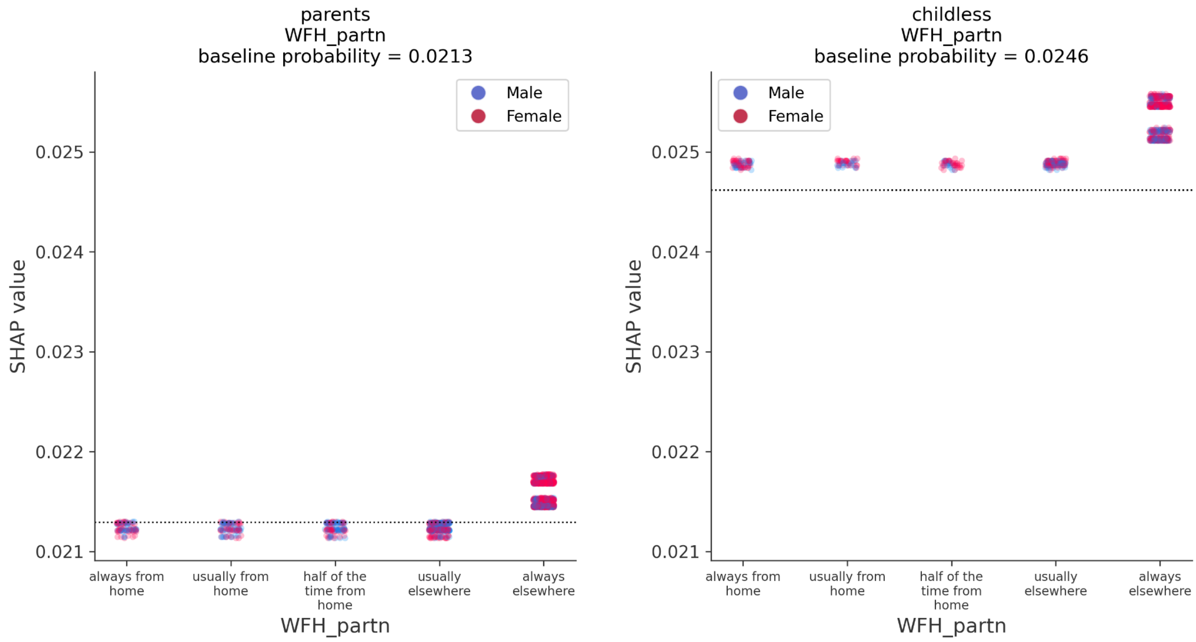


Figure A14. SHAP Plot for Employment Status of a Partner for Childbirth Prediction

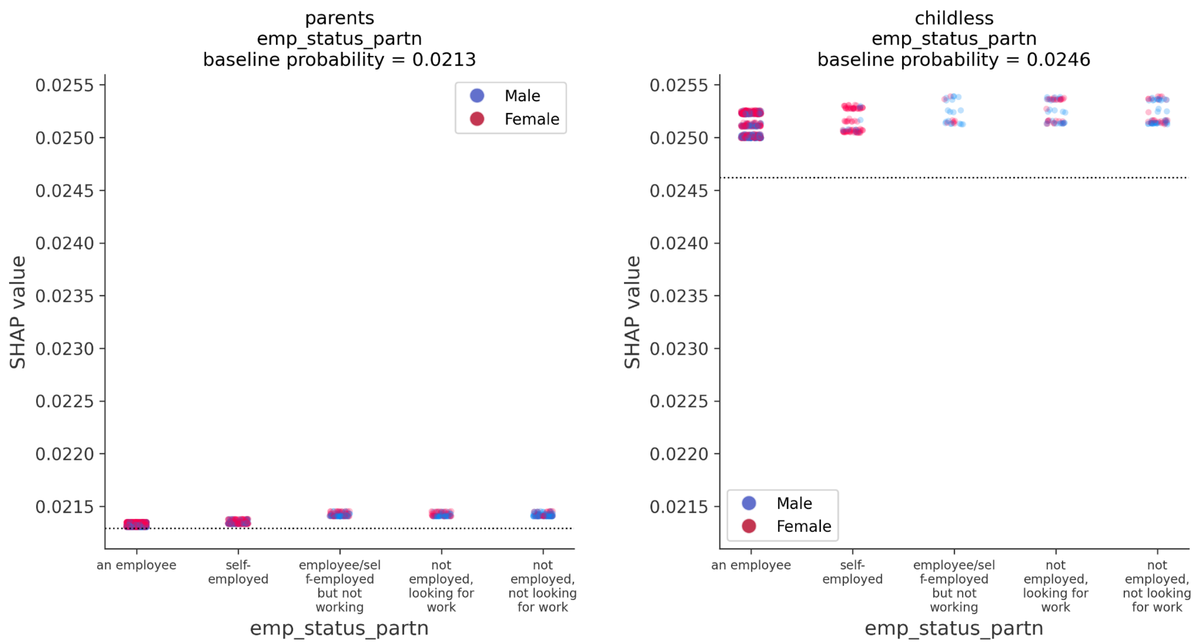


Figure A15. SHAP Plot for Youngest Child's Mental Health Assessment for Childbirth Prediction

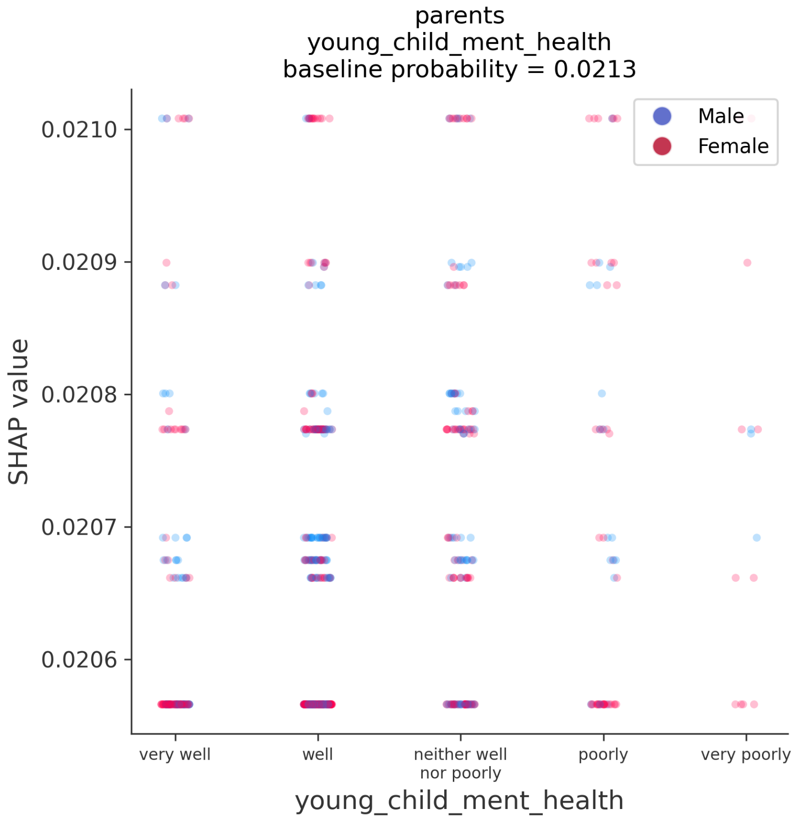


Figure A16. SHAP Plot for Care Responsibilities for Family Members for Childbirth Prediction

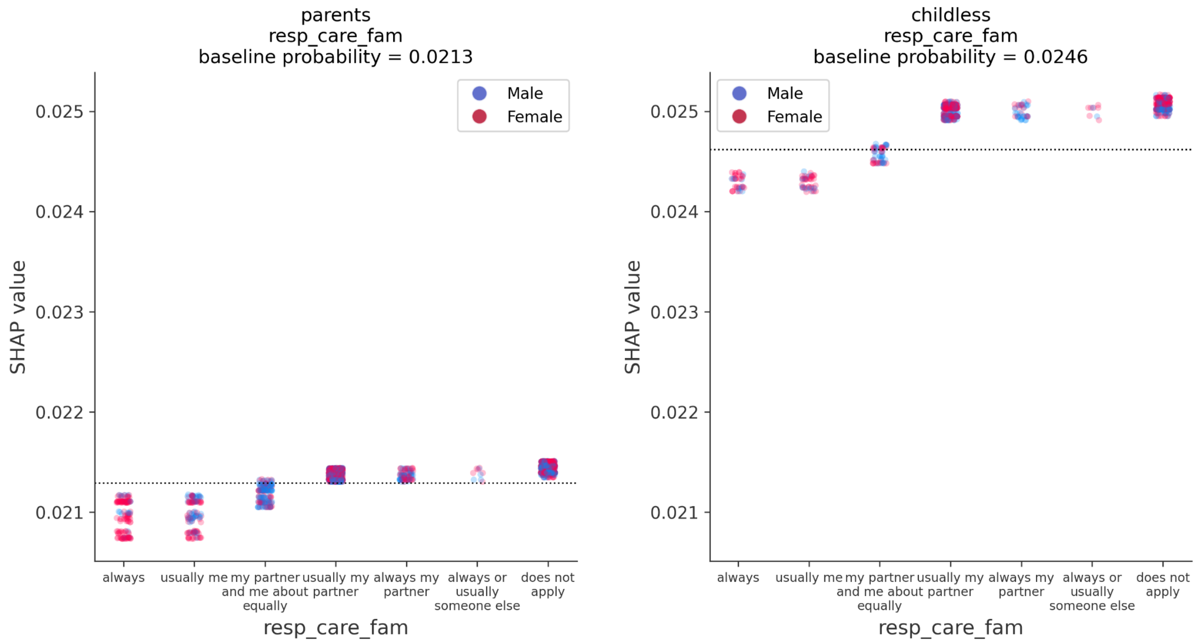


Figure A17. SHAP Plot for Commuting Time of a Partner for Childbirth Prediction

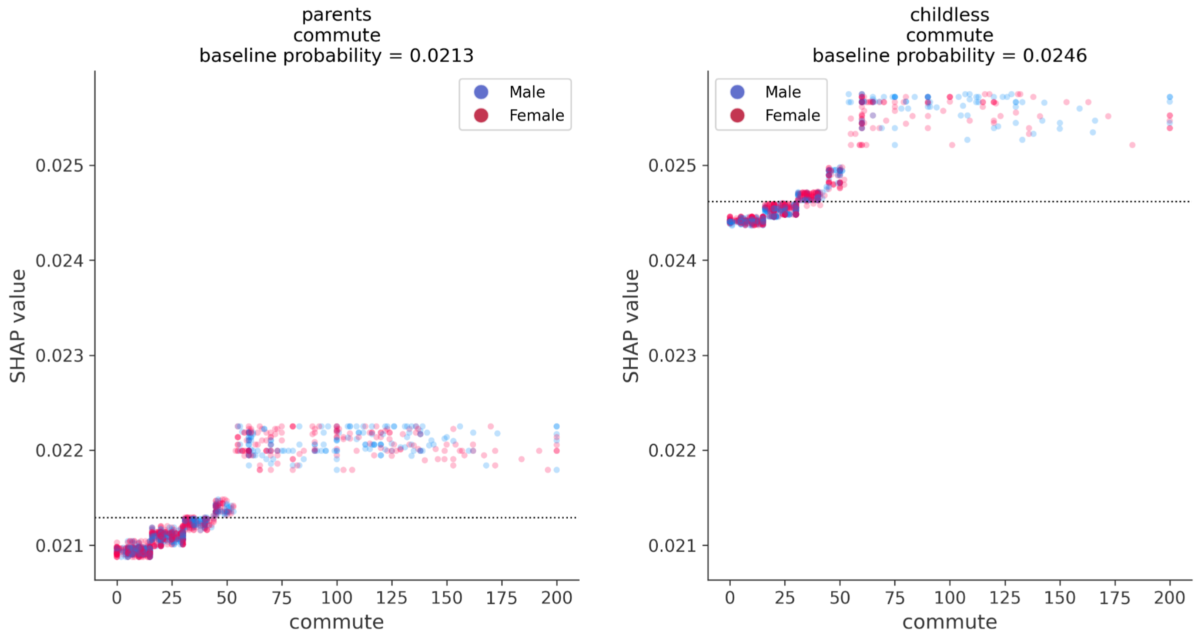


Figure A18. Top 20 Most Important Predictors of High Fertility Intentions on Test Data

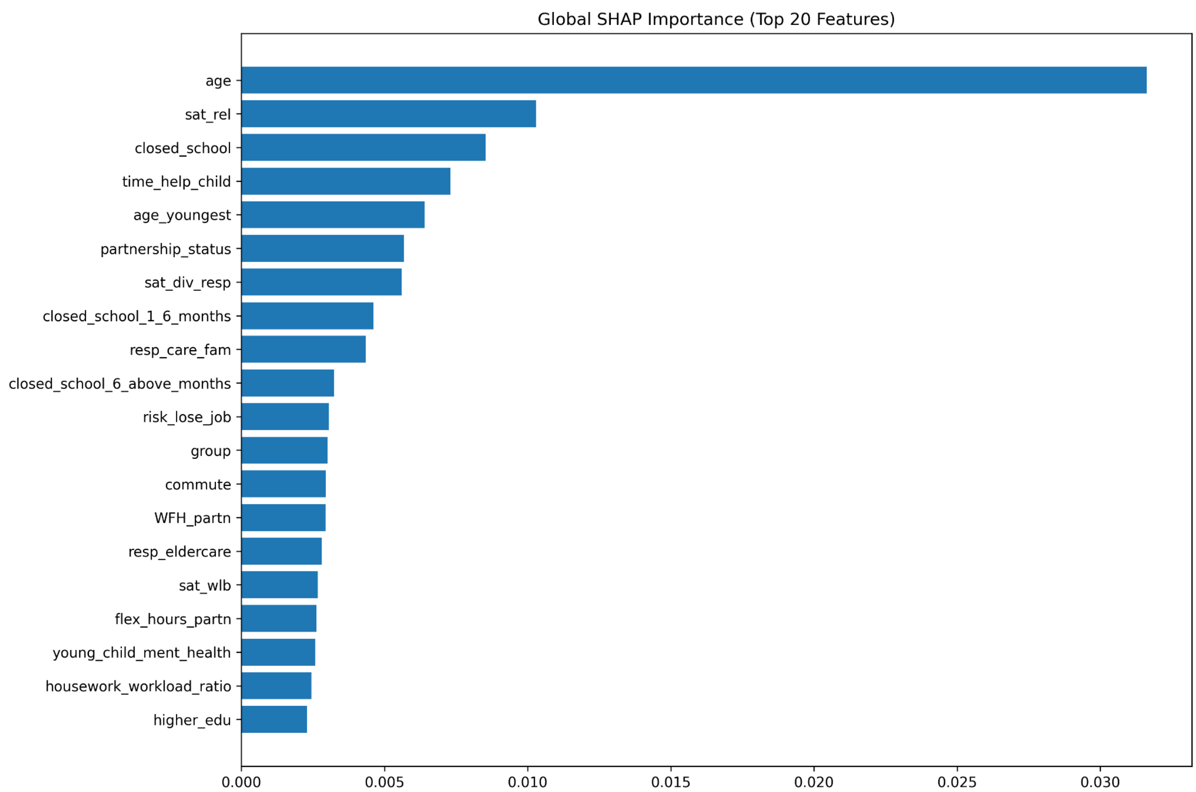


Figure A19. SHAP Plot for Time Helping Child with School for Positive Fertility Intentions Prediction

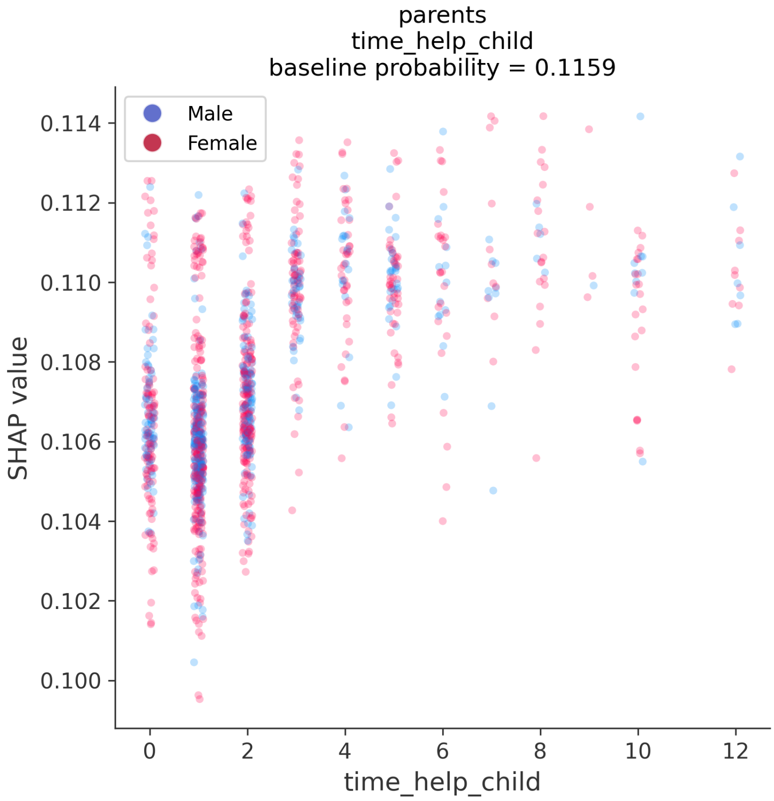


Figure A20. SHAP Plot for Age of the Youngest Child for Positive Fertility Intentions Prediction

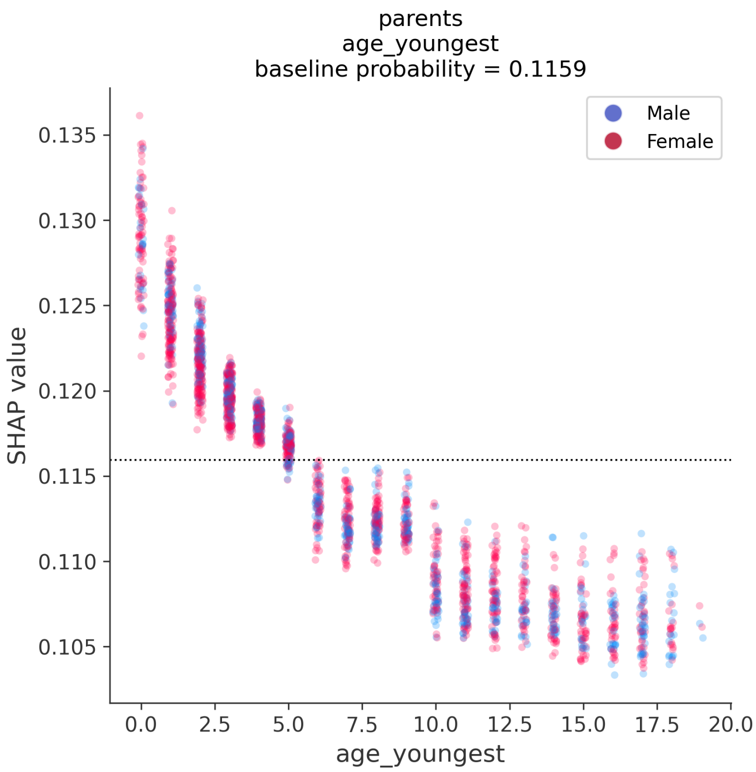


Figure A21. SHAP Plot for Satisfaction with the Division of Household Responsibilities for Positive Fertility Intentions Prediction

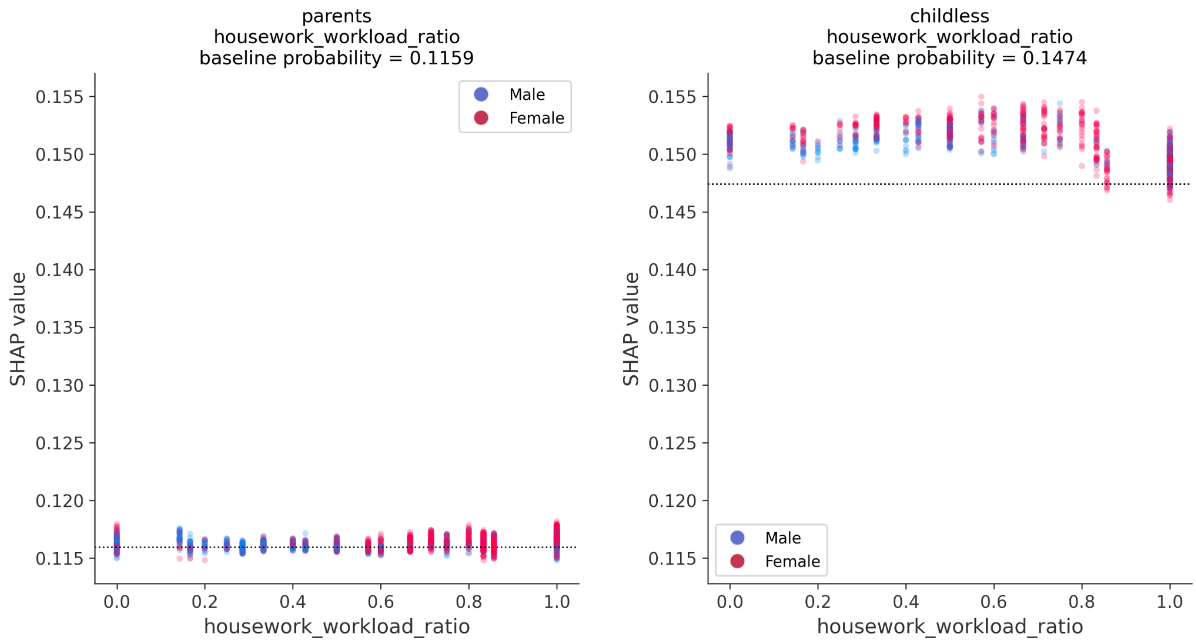


Figure A22. SHAP Plot for Partnership Status for Positive Fertility Intentions Prediction

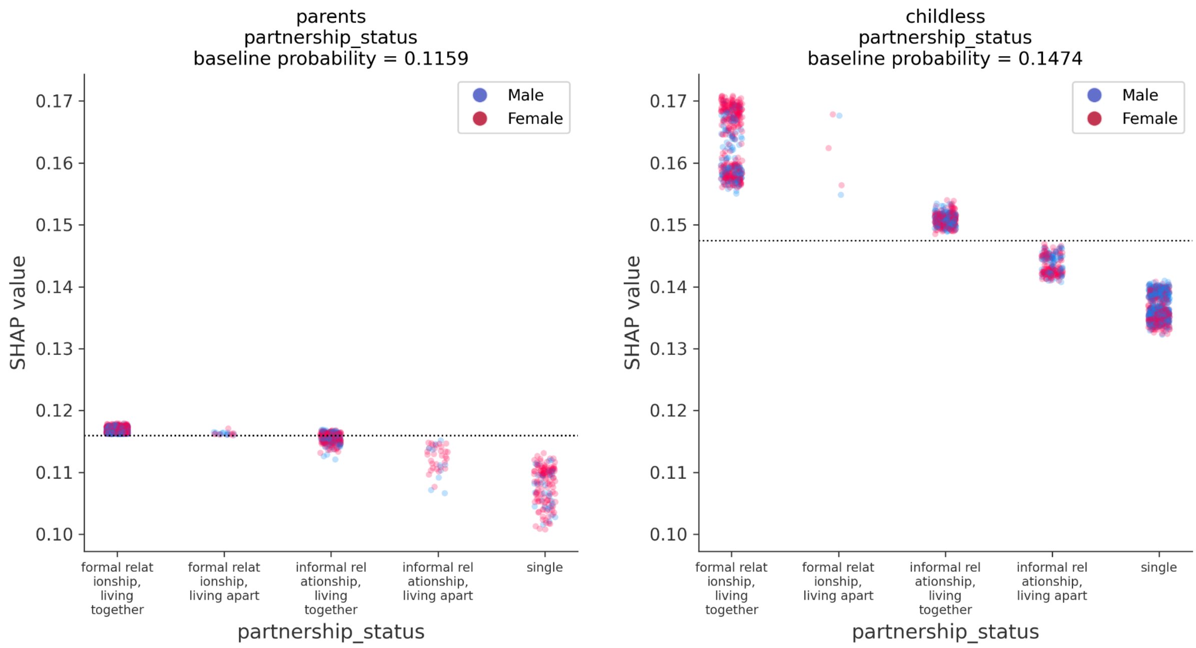


Figure A23. SHAP Plot for Care Responsibilities for Family Members for Positive Fertility Intentions Prediction

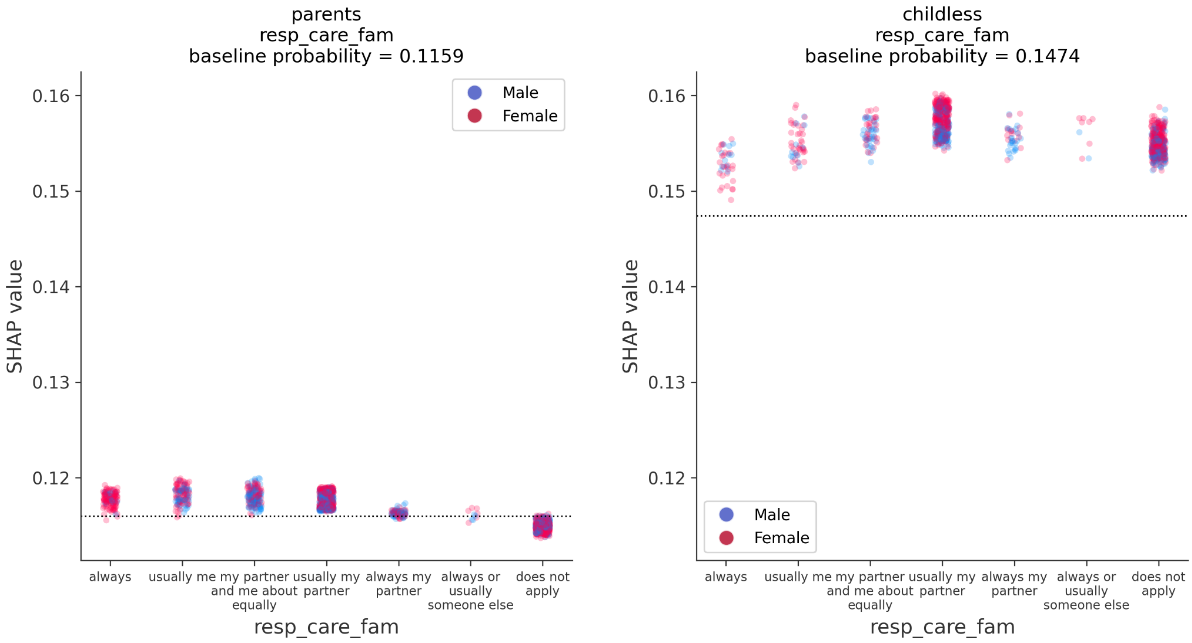


Figure A24. SHAP Plot for Closed School for Between 1 and 6 Months Binary Variable for Positive Fertility Intentions Prediction

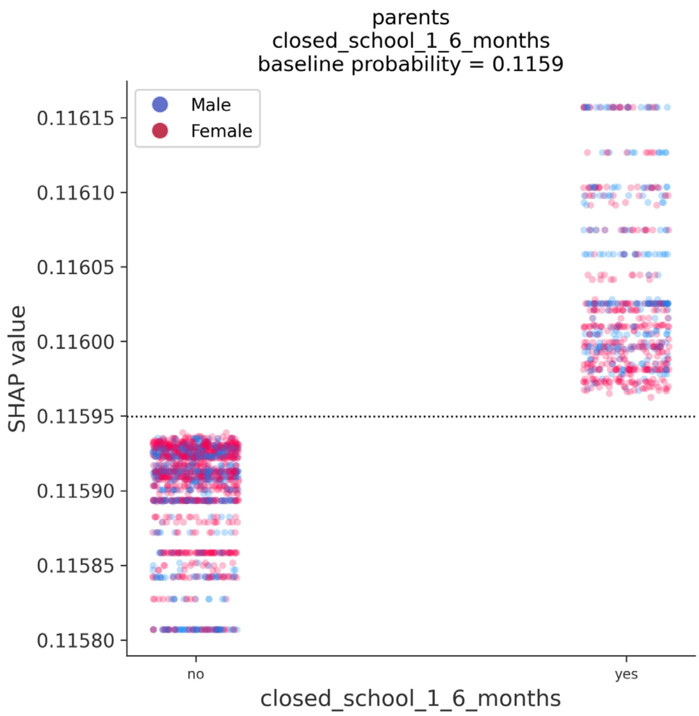


Figure A25. SHAP Plot for Responsibility for Eldercare for Positive Fertility Intentions Prediction

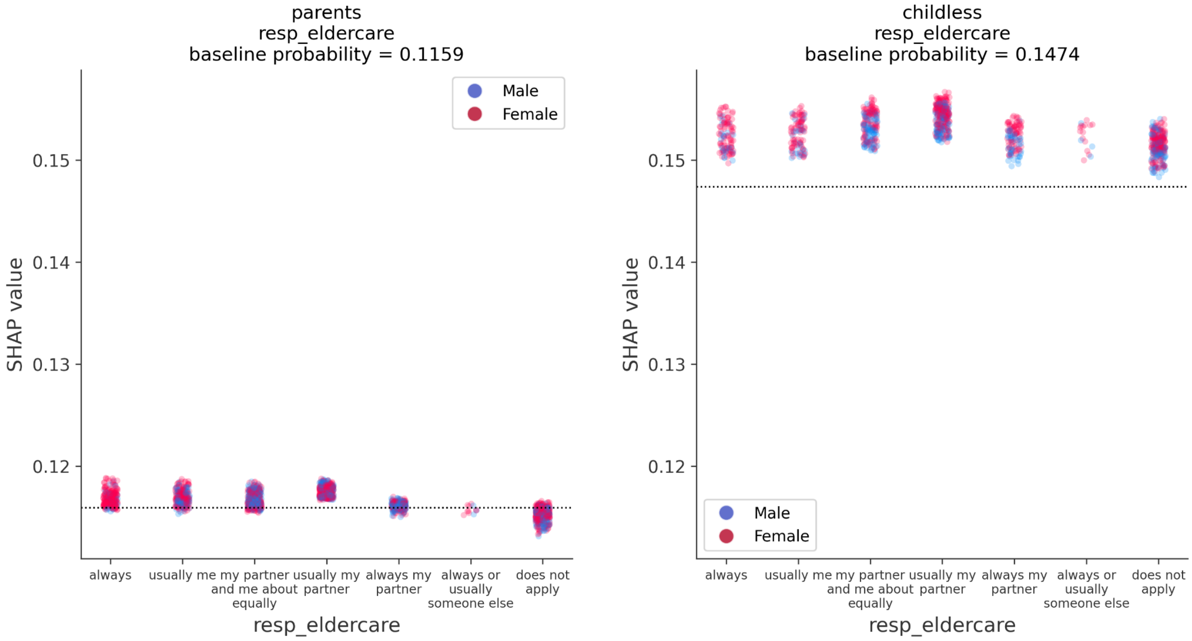


Figure A26. SHAP Plot for Work from Home of a Partner for Positive Fertility Intentions Prediction

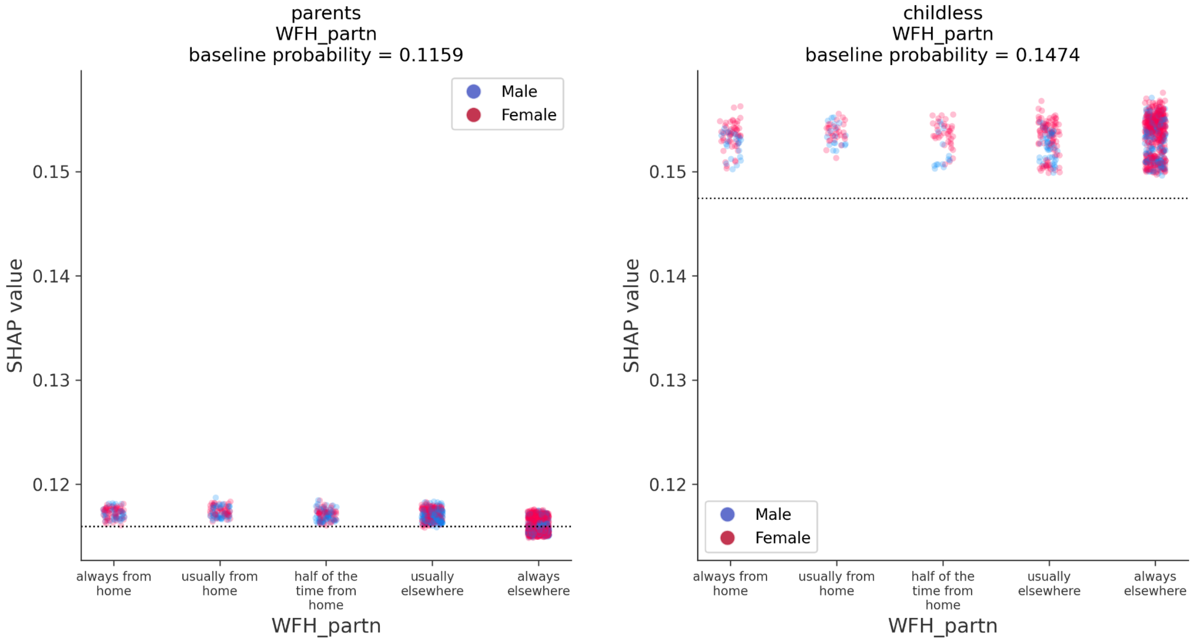


Figure A27. SHAP Plot for Commuting Time for Positive Fertility Intentions Prediction

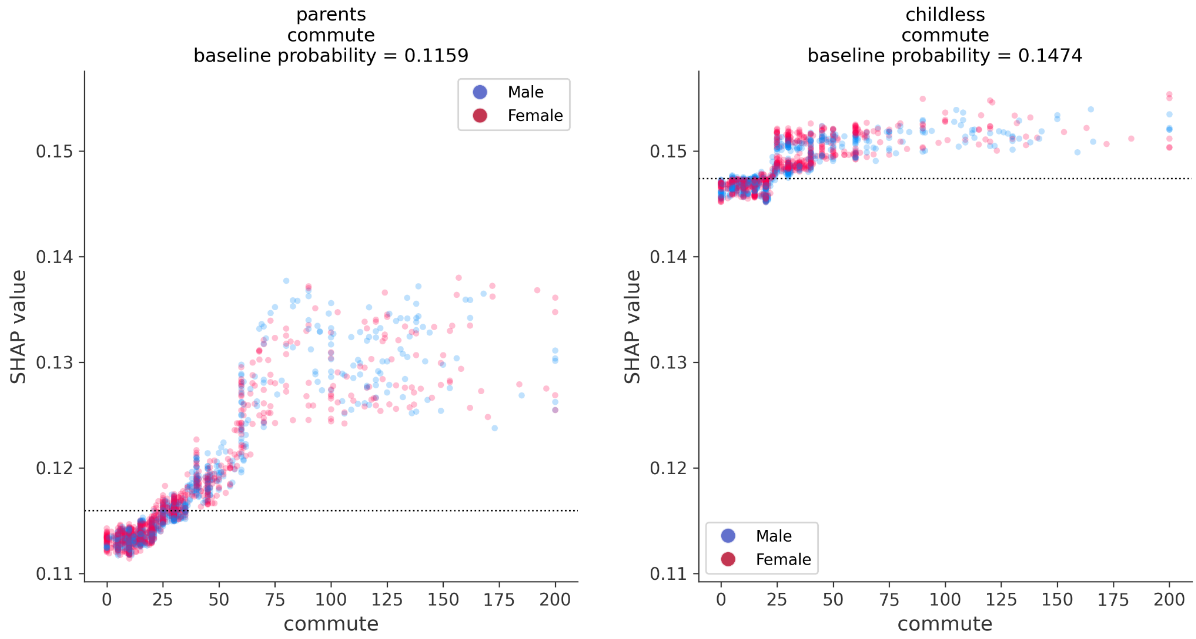


Figure A28. SHAP Plot for Flexible Working Hours of a Partner for Positive Fertility Intentions Prediction

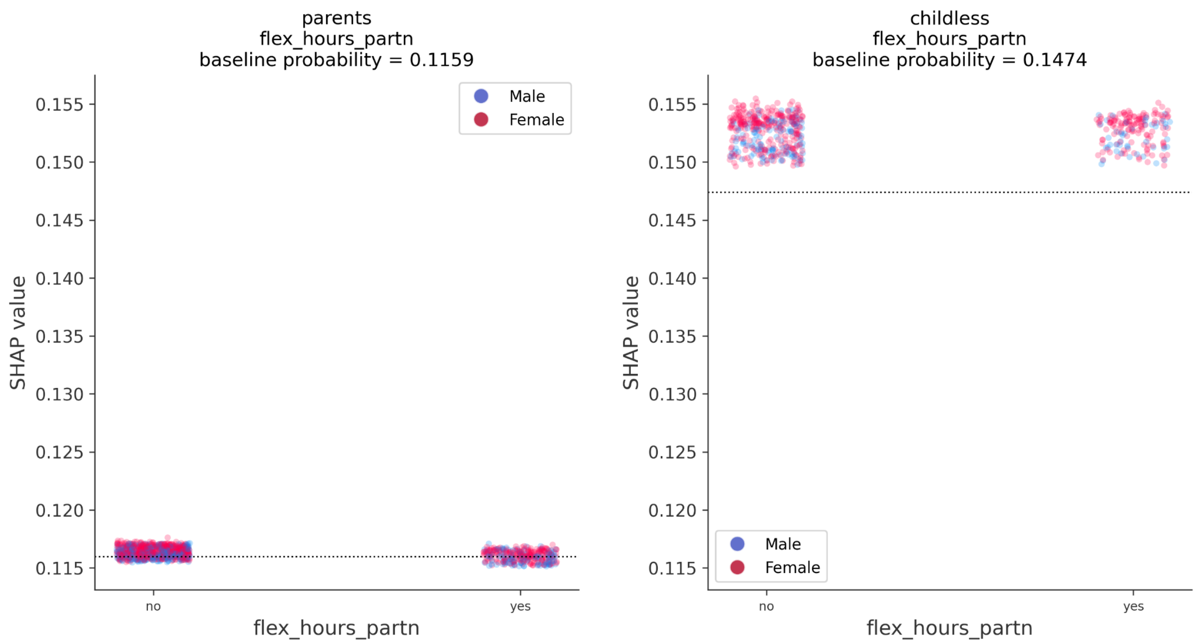


Figure A29. SHAP Plot for Satisfaction with Work-Life Balance for Positive Fertility Intentions Prediction

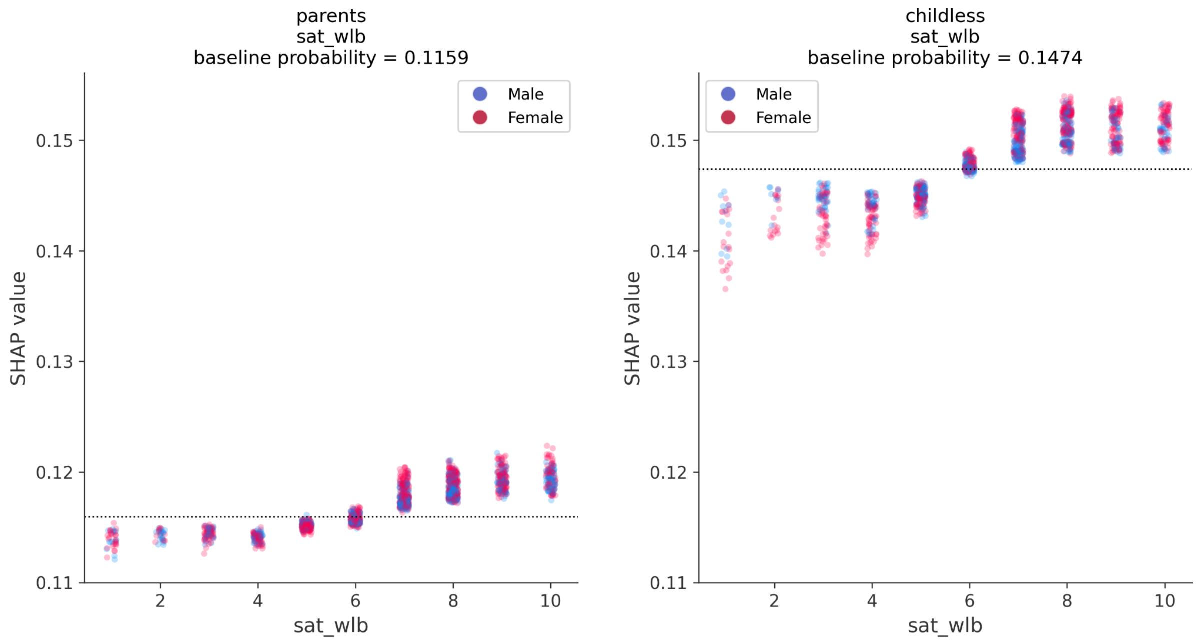


Figure A30. SHAP Plot for Youngest Child's Mental Health Assessment for Positive Fertility Intentions Prediction

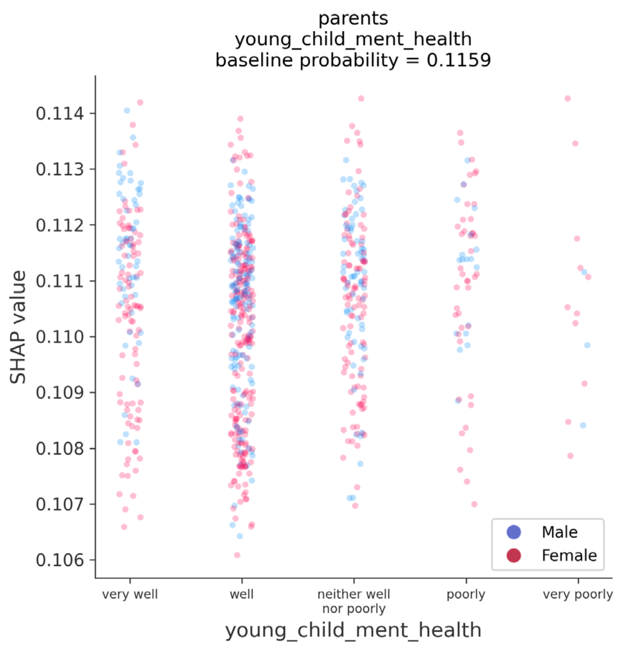


Figure A31. SHAP Plot for Closed School for More than 6 Months Binary Variable for Positive Fertility Intentions Prediction

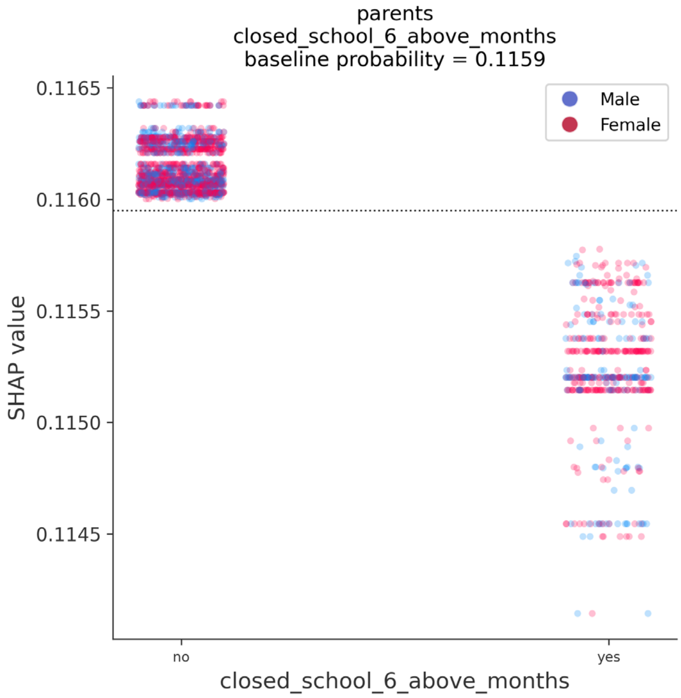


Figure A32. SHAP Plot for Housework Division for Positive Fertility Intentions Prediction

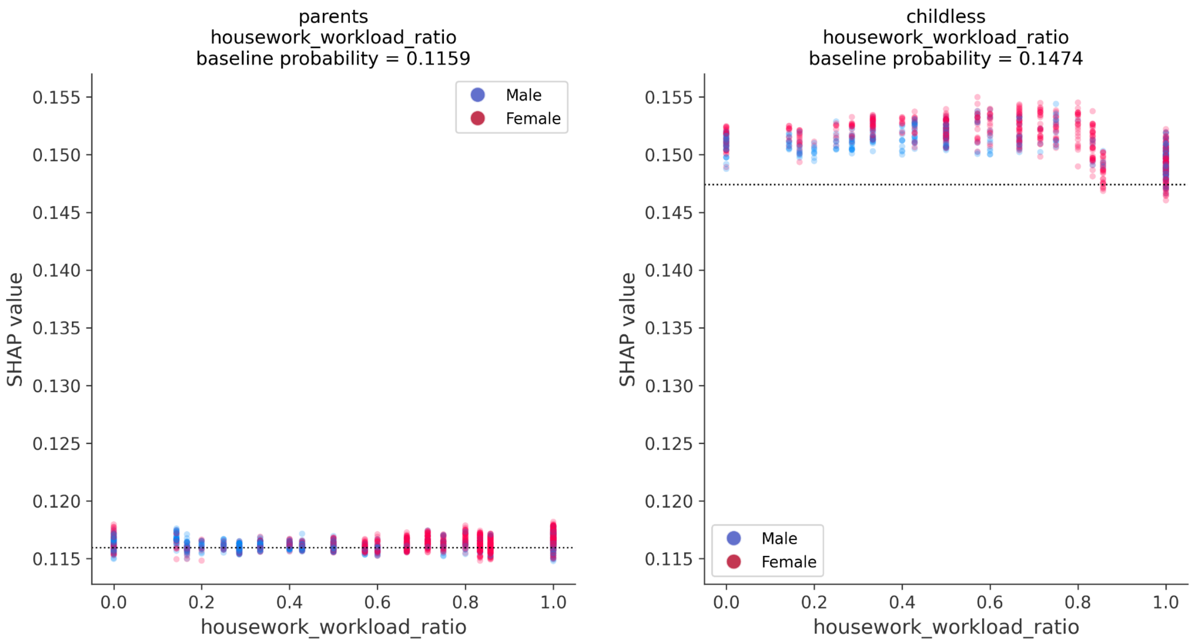


Figure A33. SHAP Plot for Perceived Risk of Losing Job for Positive Fertility Intentions Prediction

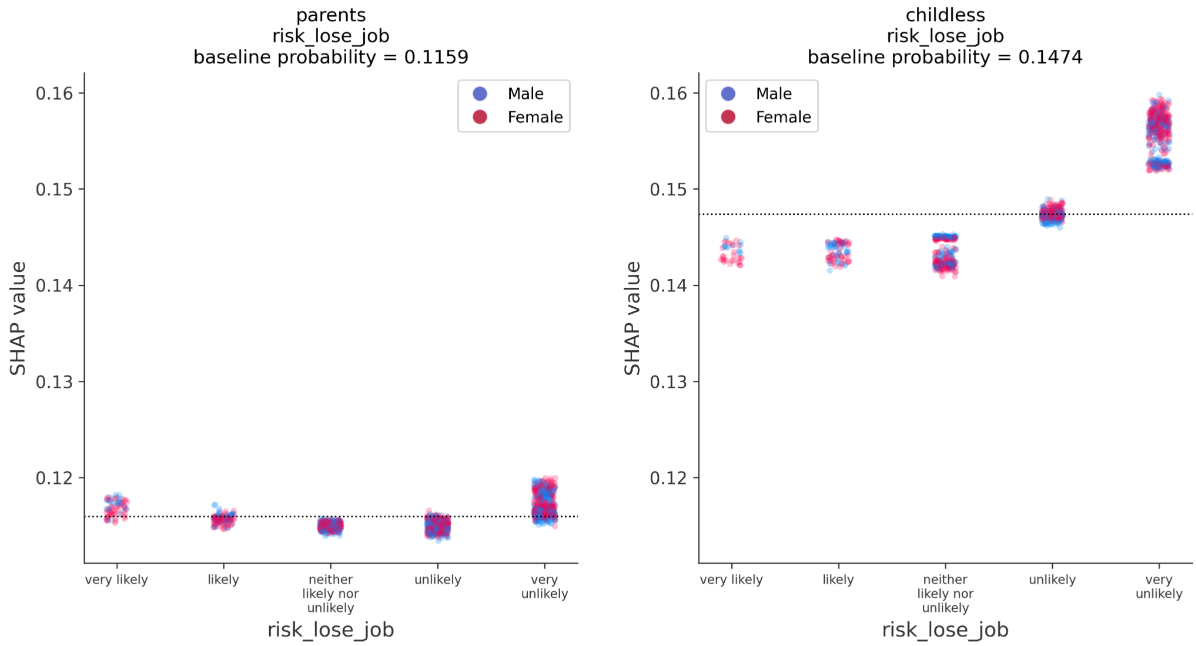
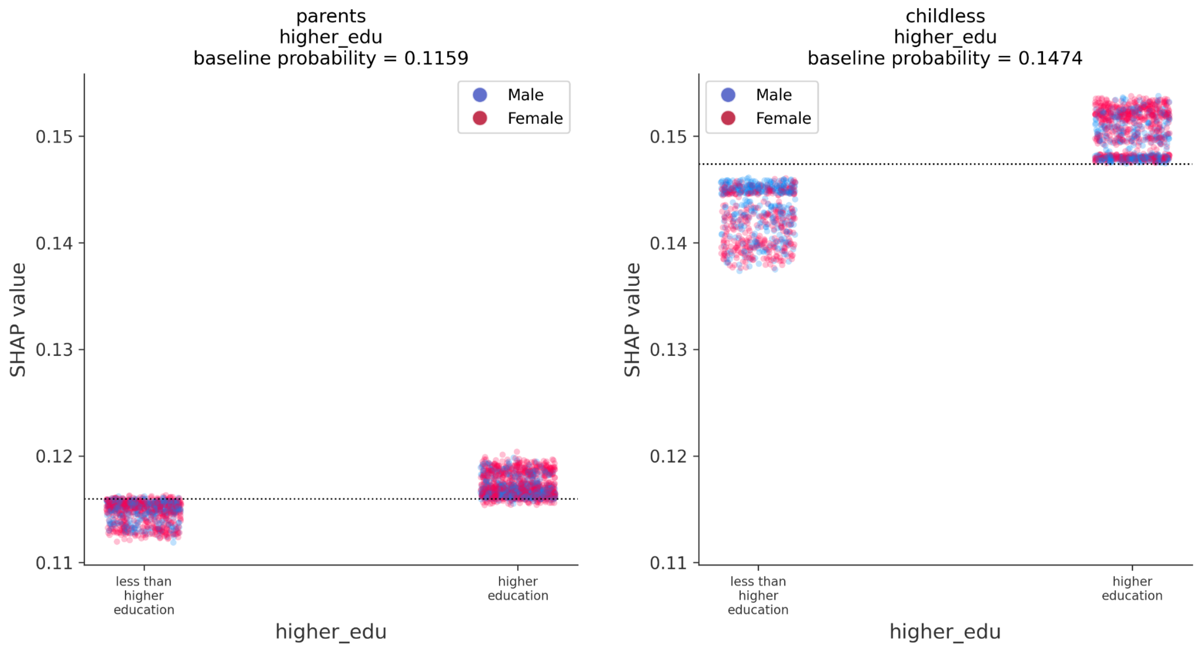


Figure A34. SHAP Plot for Higher Education for Positive Fertility Intentions Prediction



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