

# Changes in fertility intentions due to multiple crises in Austria: A Machine Learning approach

## Extended Abstract – Do not cite

Maria Winkler-Dworak, Vienna Institute of Demography, Austrian Academy of Sciences, maria.winkler-dworak@oeaw.ac.at

### Abstract

The recent multiple crises, including the COVID-19 pandemic, a period of historically high inflation, and the repercussions of the Russian invasion of Ukraine, have contributed to economic uncertainty, heightened financial strain, and growing concerns about the future. Fertility decisions, which are inherently future-oriented, are particularly sensitive to such conditions. Previous studies show that uncertainty can lower fertility intentions or increase uncertainty about having children. However, the factors shaping these responses vary across social groups and may involve complex interactions that are difficult to capture using traditional regression models.

This study examines changes in fertility intentions during the recent crises using data from the Austrian Generations and Gender Survey (GGS-II) collected in 2022–2023. We apply a Random Forest classification model to identify the most important predictors of whether respondents revised or became unsure about their family plans due to the crises. The model accounts for class imbalance and uses permutation-based variable importance to assess predictor relevance. Preliminary results indicate that the perceived burden of the war in Ukraine and inflation are the strongest predictors of changes in fertility intentions, followed by subjective well-being and financial strain. The perceived burden of the COVID-19 pandemic, by contrast, plays a limited role in this late-pandemic period. Future work will refine the model through hyperparameter tuning, extend the outcome to distinguish between different types of change—including uncertainty in fertility intentions—and compare performance with alternative machine-learning algorithms.

**Keywords:** Fertility intentions; multiple crises; Austria, Machine learning; Random Forests

### Introduction

In recent years, Austria—like many other countries—has experienced a series of overlapping crises, starting with the COVID-19 pandemic in March 2020 and followed by the Russian invasion of Ukraine. These events triggered substantial economic disruptions, rising unemployment, historically high inflation, and a sustained recession. These multiple crises have significantly altered everyday social and working life, intensified financial pressure on households, and contributed to a widespread atmosphere of uncertainty and concern about the future (Manning et al., 2022). In such contexts, individuals often postpone or reconsider major life decisions, particularly, those involving long-term commitments, such as forming a family and having children (Guetto et al., 2022; Sobotka et al., 2011; Trinitapoli & Yeatman, 2018).

Childbearing decisions are particularly sensitive to such conditions because they are inherently oriented toward the future. In the *Narrative Framework* (Vignoli, Bazzani, et al., 2020; Vignoli, Guetto, et al., 2020), the authors argue that individuals' evaluations of their current circumstances influence their imagined futures, including whether they view the future as a feasible and supportive environment in which to raise children. Economic crises therefore influence fertility not only through reduced incomes, but also through heightened perceptions of risk of financial instability and vulnerability. Previous research consistently finds that economic crises and uncertainty are associated with declines in fertility intentions (Fiori et al., 2018; Guzzo et al., 2025; Novelli et al., 2021; Testa & Basten, 2014).

Also, the COVID-19 prompted individuals to reevaluate fertility decisions (Tasneem et al., 2023), particularly in the first wave of the pandemic, where uncertainty was particularly strong. Studies report that intended fertility often shifted toward having fewer children or later than before the pandemic (e.g., Lindberg et al., 2020; Luppi et al., 2020). Later in the pandemic, however, fertility intentions appeared comparatively

stable. For instance, Buber-Ennser et al. (2024) found largely unchanged fertility intentions as of summer 2021 in Austria.

The subsequent geopolitical and inflation crises again prompted individuals to reassess their reproductive plans. In Finland, respondents surveyed in mid-2022 were more likely to decrease their fertility preferences than to increase them (8% vs 4%) due to the Russian war in Ukraine. Evidence from a survey in Austria in late 2022 and early 2023 points in a similar direction. Buber-Ennser et al. (2025) report that about 30 percent of respondents either revised or became unsure about their fertility intentions due to the combined effects of the pandemic, inflation, and the Russian war in Ukraine.

However, responses to crises are far from being uniform. Individual fertility decisions may vary markedly, depending on personal resources, coping capacities, and structural inequalities (Berrington et al., 2022; Vignoli, Mencarini, et al., 2020). Understanding changes in fertility intentions during periods of overlapping crises requires therefore an approach that can simultaneously account for a wide range of demographic, economic, family-related, and subjective variables and capture how these dimensions interact with each other.

Traditional regression frameworks, however, are limited in this regard, as they typically require assumptions about functional forms and face constraints when including many, correlated variables. Machine learning (ML) methods, by contrast, can incorporate numerous predictors with no or low risk of overfitting or multicollinearity issues, inherently accommodate nonlinearities and interactions effects, and identify complex interaction patterns. In addition, Machine Learning provides measures of variable importance that help identify the most influential determinants of an outcome.

Applications of machine learning in demographic research are still rare. Early work by De Rose and Pallara (1997) used tree-based models to analyze marriage formation in Italy, while Billari et al. (2006) applied decision trees and classifications to transitions to adulthood in Austria and Italy. More recently, ML methods have been used to predict under-five mortality (Bitew et al., 2020), union instability in Germany (Arpino et al., 2022), parity progression among immigrants in France (Delaporte & Kulu, 2022), fertility behaviour in Austria (Bordone et al., 2024) and fertility intentions in China and Korea (Guo et al., 2025; Kim, 2023; Li & Xu, 2022).

Building on this emerging literature, we use ML to examine changes in fertility intentions during the recent multiple crisis in Austria. To this end, we use data from the Austrian GGS-II (Neuwirth et al., 2024), which includes a dedicated module on crises perceptions and related changes in family planning. Our aim is to identify the main predictors of crises-induced changes in fertility intentions and to investigate the complex ways in which socio-demographic characteristics, family status, individuals' or couples' employment and financial conditions, and subjective perceptions of strain and uncertainty interact. By applying machine learning methods, we seek to uncover nonlinearities and complex interaction patterns that are difficult to model with conventional regression techniques.

## **Data and Methods**

The analysis draws on data from the Austrian Generations and Gender Survey-II (Neuwirth et al., 2024), collected between October 2022 and March 2023. Poststratification weights adjust for age, sex, education, region, marital status, parity and household size. The key question for this study asks whether respondents had changed their family plans or became unsure about their plans due to prevailing global crises (inflation, COVID-19 pandemic, and war in Ukraine). This question was only asked to respondents of childbearing age, i.e., women age below 50, single men (irrespective of age, i.e., aged 18-59) and men with female partner below age 50, who indicated to be biologically able to have children.

For the present analysis, we include respondents who indicated either (1) having revised their fertility intentions due to the crises, (2) having become unsure about their family plans, (3) having maintained their existing fertility intentions. Respondents who declared not having thought about it, as well as those having completed their family plans and non-respondents were excluded. In follow-up questions, respondents who had revised their fertility intentions due to crises were asked to indicate the direction of the change, both in terms of the intended number of children and the timing of the prospective birth. Similarly, respondents who had become unsure about their fertility intentions to the crises were asked to indicated

the most likely direction of a change. The reported (likely) direction of change was overwhelmingly in the direction of fewer children or having them later in life. Very few respondents indicated intentions to have more children or to accelerate childbearing; these cases were not included in this analysis.

For the outcome variable we combined respondents with revised family plans and respondents who became unsure into one category versus those with unchanged family plans. The independent variables (i.e., features) include socio-demographic and family characteristics, region, education, individuals' or couples' financial and employment variables, subjective measures on wellbeing, health, and perceived burden of crises. Observations with missing values in any of the selected variables were excluded. The final sample consists of observation from 1,684 women and men. Table 1 provides details about the sample characteristics.

Table 1 Sample characteristics (unweighted)

| Variables                                     | Total<br>N=1,684 | Variables continued         | Total<br>N=1,684 |
|---|------------------|-----------------------------|------------------|
| Crises-induced change in fertility intentions |                  | Region of current residence |                  |
| Changed or unsure                             | 285 (16.9%)      | Burgenland                  | 51 (3.0%)        |
| Unsure  | 402 (23.9%)      | Carinthia                   | 100 (5.9%)       |
| Unchanged                                     | 997 (59.2%)      | Lower Austria               | 283 (16.8%)      |
| Sex of Respondent                             |                  | Upper Austria               | 252 (15.0%)      |
| Male  | 768 (45.6%)      | Salzburg                    | 100 (5.9%)       |
| Female  | 916 (54.4%)      | Styria                      | 236 (14.0%)      |
| Age   |                  | Tyrol                       | 156 (9.3%)       |
| 18-24   | 373 (22.1%)      | Vorarlberg                  | 72 (4.3%)        |
| 25-29   | 407 (24.2%)      | Vienna                      | 434 (25.8%)      |
| 30-34   | 362 (21.5%)      | Make ends meet              |                  |
| 35-39   | 249 (14.8%)      | With great difficulty       | 81 (4.8%)        |
| 40-44   | 123 (7.3%)       | With difficulty             | 201 (11.9%)      |
| 45-49   | 97 (5.8%)        | With some difficulty        | 277 (16.4%)      |
| 50-59   | 73 (4.3%)        | Fairly easily               | 491 (29.2%)      |
| Number of children                            |                  | Easily                      | 350 (20.8%)      |
| Childless                                     | 1,012 (60.1%)    | Very easily                 | 284 (16.9%)      |
| One child                                     | 319 (18.9%)      | Life Satisfaction           | 7.71 (1.73)      |
| 2+ children                                   | 353 (21.0%)      | Happiness Scale             | 7.76 (1.67)      |
| Partnership status                            |                  | Subjective health           |                  |
| LAT   | 246 (14.6%)      | Very good                   | 639 (37.9%)      |
| Coresident partner                            | 1,028 (61.0%)    | Good                        | 801 (47.6%)      |
| No partner                                    | 410 (24.3%)      | Fair                        | 210 (12.5%)      |
| Marital status                                |                  | (Very) bad                  | 34 (2.0%)        |
| Married                                       | 540 (32.1%)      | Burden of inflation         | 6.33 (2.68)      |
| Registered partnership                        | 12 (0.7%)        | Burden of Covid             | 5.19 (3.22)      |
| Unmarried                                     | 722 (42.9%)      | Burden war in Ukraine       | 5.01 (2.91)      |
| No partner                                    | 410 (24.3%)      | Partner's educational level |                  |
| Education Level                               |                  | Low (ISCED 0-2)             | 60 (3.6%)        |
| Low (ISCED 0-2)                               | 109 (6.5%)       | Medium (ISCED 3-4)          | 658 (39.1%)      |
| Medium (ISCED 3-4)                            | 892 (53.0%)      | High (ISCED 5-8)            | 556 (33.0%)      |
| High (ISCED 5-8)                              | 683 (40.6%)      | No partner                  | 410 (24.3%)      |
| Employment status                             |                  | Partner's employment status |                  |
| In education or training                      | 293 (17.4%)      | In education or training    | 131 (7.8%)       |
| Employed                                      | 1,045 (62.1%)    | Employed                    | 918 (54.5%)      |
| Self Employed                                 | 106 (6.3%)       | Self Employed               | 100 (5.9%)       |
| Unemployed                                    | 38 (2.3%)        | Unemployed                  | 23 (1.4%)        |

|                                      |               |                                       |             |
|--------------------------------------|---------------|---------------------------------------|-------------|
| On parental leave or childcare leave | 159 (9.4%)    | On parental leave or childcare leave  | 84 (5.0%)   |
| Other                                | 43 (2.6%)     | Other                                 | 18 (1.1%)   |
| Part/full-time employment            |               | No partner                            | 410 (24.3%) |
| Part-time employment                 | 433 (25.7%)   | Part/full-time employment of partner  |             |
| Full-time employment                 | 875 (52.0%)   | Part-time employment                  | 319 (18.9%) |
| Not working                          | 376 (22.3%)   | Full-time employment                  | 734 (43.6%) |
| Work from home                       |               | No partner/partner not working        | 631 (37.5%) |
| Yes, twice or more per week          | 305 (18.1%)   | Partner works from home               |             |
| Yes, less than twice per week        | 127 (7.5%)    | Yes, twice or more per week           | 309 (18.3%) |
| No                                   | 869 (51.6%)   | Yes, less than twice per week         | 146 (8.7%)  |
| Not working                          | 383 (22.7%)   | No                                    | 590 (35.0%) |
| Sector                               |               | No partner/partner not working        | 639 (37.9%) |
| Private                              | 584 (34.7%)   | Sector of partner's employment        |             |
| Public                               | 579 (34.4%)   | Private                               | 459 (27.3%) |
| Unknown                              | 145 (8.6%)    | Public                                | 433 (25.7%) |
| Not working                          | 376 (22.3%)   | Unknown                               | 161 (9.6%)  |
| Type of contract                     |               | No partner/partner not working        | 631 (37.5%) |
| Permanent                            | 986 (58.6%)   | Type of partner's contract            |             |
| Fixed term                           | 119 (7.1%)    | Permanent                             | 795 (47.2%) |
| Temporary                            | 67 (4.0%)     | Fixed term                            | 100 (5.9%)  |
| No written contract                  | 28 (1.7%)     | No written contract                   | 19 (1.1%)   |
| Unknown                              | 108 (6.4%)    | Unknown                               | 139 (8.3%)  |
| Not working                          | 376 (22.3%)   | No partner/partner not working        | 631 (37.5%) |
| Flexible work arrangements           |               | Flexible work arrangements of partner |             |
| Flexible                             | 826 (49.0%)   | Flexible                              | 515 (30.6%) |
| Non-flexible                         | 298 (17.7%)   | Non-flexible                          | 316 (18.8%) |
| Unknown                              | 184 (10.9%)   | Unknown                               | 222 (13.2%) |
| Not working                          | 376 (22.3%)   | No partner/partner not working        | 631 (37.5%) |
| Home language                        |               |                                       |             |
| German                               | 1,461 (86.8%) |                                       |             |
| Other                                | 223 (13.2%)   |                                       |             |

Source: Austrian GGS-II (Neuwirth et al., 2024)

We split the analytical sample into a training dataset of 70 percent of observations, used for model estimation, and a test dataset with the remaining observations, used for model evaluation. To model changes in fertility intentions, we employ a Random Forest classification algorithm (Breiman, 2001). Random Forests consist of an ensemble of decision trees that are grown on different bootstrap samples of the training data, with a random subset of predictors considered at each split. The final prediction is obtained by aggregating the predictions across all trees, which reduces variance and improves predictive performance. To account for the complex sample design, we incorporate survey (case) weights. In addition, as respondents who changed or became uncertain about their family plans constitute a minority in the sample, class weights are applied to counteract class imbalance and prevent the model from disproportionately favoring the majority class.

Model performance is evaluated using the out-of-bag (OOB) error rate generated internally by the Random Forest as an estimate of prediction error, as well as the area under the receiver operating characteristic curve (ROC) and overall accuracy on the test dataset. The ROC curve plots the true positive rate against the false positive rate across a range of classification thresholds. A model with no discriminatory ability would follow the diagonal line, indicating that it performs no better than random guessing, and the area under the ROC curve (AUC-ROC) would correspond to a value of 0.5. In contrast, an AUC-ROC value closer to one indicates strong predictive power.

To assess how well the model distinguishes between respondents who changed or became unsure about their family plans and those who did not, we also report class-specific precision, recall, and F1-scores. Precision reflects the proportion of predicted positive cases that are correct, recall measures the

proportion of actual positive cases that are correctly identified, and the F1-score summarizes the balance between precision and recall in a single metric.

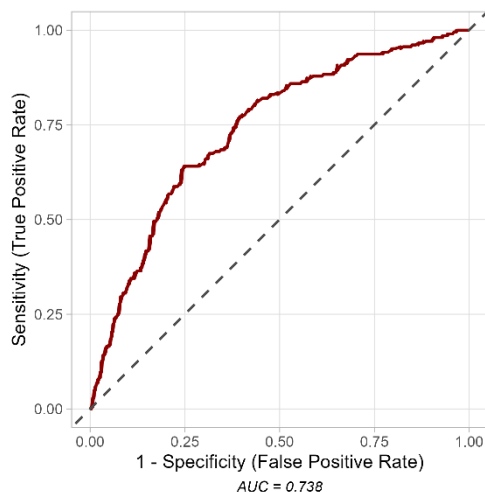
To identify the most influential predictors, we compute variable importance based on permutation importance, which evaluates the decrease in predictive accuracy when the values of a given variable are randomly permuted in the test data; a larger drop indicates a stronger contribution of that variable to model performance.

The following section presents first results of the Random Forest model, including overall model performance, class-specific prediction accuracy, and the relative importance of the predictors, and gives an outlook on the further analytical strategy.

### First results and outlook

Preliminary results provide an initial indication of the factors most strongly associated with predicting crisis-related changes in fertility intentions. The Random Forest model performs reasonably well in distinguishing between respondents who changed or became unsure about their family plans and those whose intentions remained unchanged. The model yields an out-of-bag error rate of 0.216 and an overall accuracy of 0.695. The ROC curve in Figure 1 with an AUC-ROC value of 0.734 indicates acceptable discriminative ability, suggesting that the model captures meaningful variation in fertility intention responses during the crisis period. Table 2 reports performance for each outcome class. Evidently, the model performs better for the majority group (Unchanged family plans) with higher precision and recall compared to the group that revised or became unsure about their fertility intentions due to the crises. We plan to use grid search to tune the hyperparameters to improve predictive performance in the further analysis.

Figure 1 ROC curve for the Random Forest model predicting crisis-related changes in fertility intentions.



Source: Own computations based on Austrian GGS-II.

Table 2 Classification performance of the Random Forest model by outcome category.

| Metrics   | Changed or unsure fertility intentions | Unchanged intentions |
|-----------|--|----------------------|
| Precision | 0.50                                   | 0.83                 |
| Recall    | 0.67                                   | 0.71                 |
| F1        | 0.57                                   | 0.76                 |

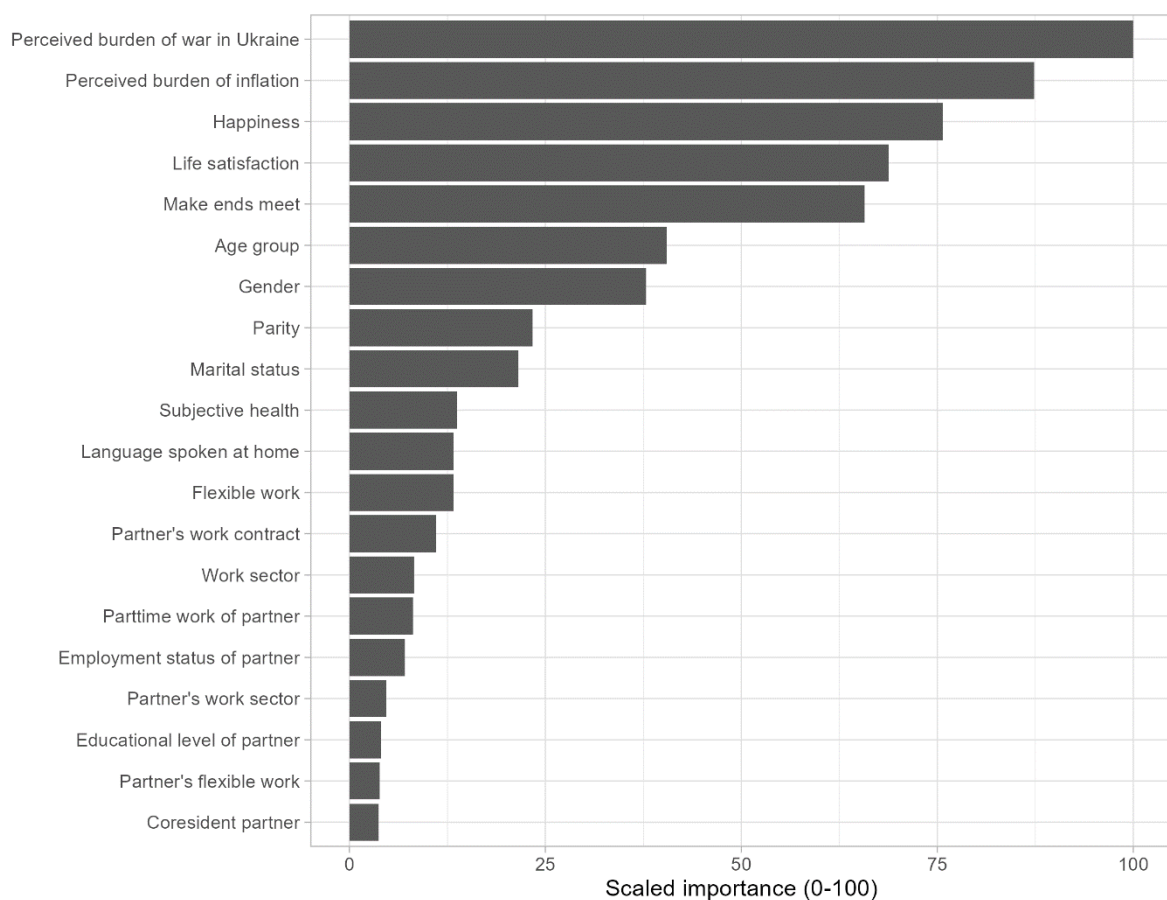
Source: Own computations based on Austrian GGS-II.

Figure 2 displays the permutation-based variable importance for the Random Forest model predicting crises-induced changes in fertility intentions among Austrian GGS-II respondents. Higher bars indicate a larger decrease in model accuracy when the variable is permuted, reflecting greater predictive contribution. The variable importance bars indicate that the perceived burden of the war in Ukraine and of inflation are the strongest predictors of changes in fertility intentions. These are followed by indicators of subjective well-being, such as general happiness and life satisfaction, and by the ability to making ends meet. This pattern aligns with previous findings showing that better overall life satisfaction is associated with intending a child rather than being uncertain or not intending one, while greater economic stress is linked to heightened uncertainty regarding childbearing (Guzzo et al., 2025). However, while the current analysis identifies the importance of these predictors, the nature of their associations still remains to be examined in more detail. In the next phase of the study, we will

investigate functional relationships and potential interaction effects using partial dependence plots (Friedman, 2001) and SHAP values (Lundberg & Lee, 2017). Partial dependence plots can show whether the relationship between the outcome and the independent variables are linear, monotonic or more complex, while SHAP show how each variable influences individual predictions and into which direction.

By contrast, the perceived burden of the COVID-19 pandemic does not emerge as a decisive predictor of changes in fertility intentions in this late-pandemic period. This finding is consistent with Buber-Ennser et al. (2024), who reported largely stable fertility intentions in Austria in 2021. Although a renewed COVID-19 wave occurred during GGS-II fieldwork, excess mortality remained limited and containment measures had largely been relaxed due to widespread immunity from vaccination and prior infections. These conditions may have reduced the salience of the pandemic relative to the more acute economic and geopolitical crises.

Figure 2 Permutation-based variable importance for the Random Forest model predicting crisis-induced changes in fertility intentions.



Source: Own computations based on Austrian GGS-II.

In the next stage of the analysis, we will follow several routes to improve the present analysis, both methodologically and substantively. Firstly, we will refine the Random Forest model through hyperparameter tuning using grid search to improve predictive performance. Secondly, we will extend the binary outcome used here to a multiclass categorical variable that distinguishes between respondents who revised their plans, those who became uncertain, and those who had not considered their plans or did not know how they would respond to the crises. This will allow us to capture not only the direction of change in fertility intentions, but also the growing prevalence of uncertainty in reproductive decision-making (Guzzo et al., 2025). Because moving to a multiclass outcome will further

accentuate class imbalance, we will evaluate strategies for addressing imbalance, including improved class weighting and Synthetic Minority Oversampling (SMOTE). In addition, we will compare the performance of Random Forests with alternative machine learning algorithms, such as Extreme Gradient Boosting, to assess robustness across modeling frameworks.

Overall, these preliminary results underscore the central role of financial strain, subjective well-being and perceived burden of crises in shaping fertility decision-making during periods of overlapping crises. Further analyses will investigate how these dimensions interact and shape the conditions under which fertility intentions become uncertain.

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