6 Appendices

6.1 Software and replication

Code for replication, including instructions on how to import the panel data and run the code, is available at the following URL and on the website of Survey Research Methods. Instructions for accessing the necessary data is detailed in the ReadMe.md file in the replication documents.

https://osf.io/n4y6w/?view_only=18eb6d46900e4c7d84175042072ff1eb

The data used in this study for each panel is referenced in the bibliography and cited as follows: The Socio-Economic Panel (SOEP) (liebig_socio-economic_2022), German Internet Panel (GIP) (ZA7878), GESIS Panel (gesis_gesis_2023), Mannheim Corona Study (MCS) (ZA7745), German Family Demography Panel Study (FREDA) (bujard_freda_2023).

6.2 Supplementary items

This section provides additional details about this study. We provide descriptive statistics about each of the panel survey datasets (Figure (Appendix) 1, Figure (Appendix) 2, Table (Appendix) 1); details about the modeling (Table (Appendix) 2), details about our definition of nonresponse (Table (Appendix) 3), a data quality checklist (Table (Appendix) 4); and further results (Figure (Appendix) 3, Figure (Appendix) 4, Figure (Appendix) 5, Figure (Appendix) 6, Figure (Appendix) 7, Figure (Appendix) 8, Table (Appendix) 5, Table (Appendix) 6).

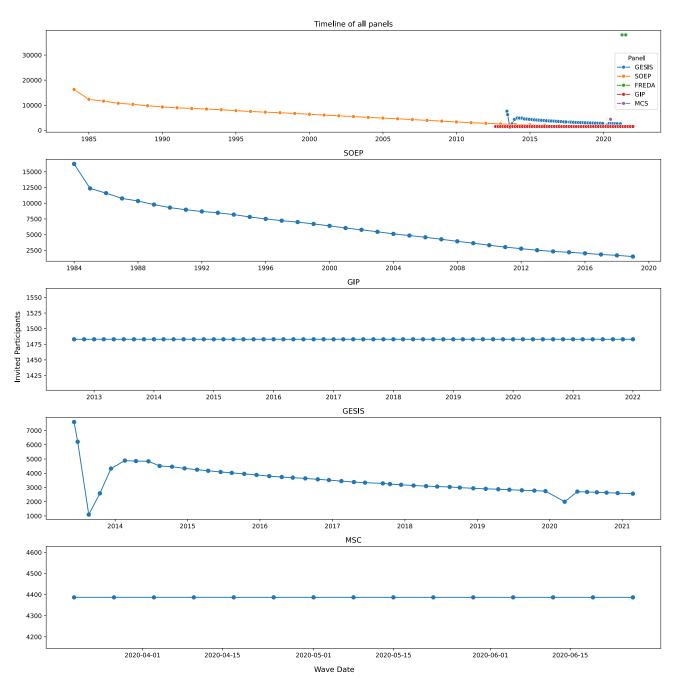


Figure (Appendix) 1. Timeline of the number of invited participants for each panel. Note that we include only those participants who were invited as of the first wave, so these values do not include any participants recruited since then. FREDA had only accumulated three waves by the time of this study, and 38,056 individuals were invited to each wave.

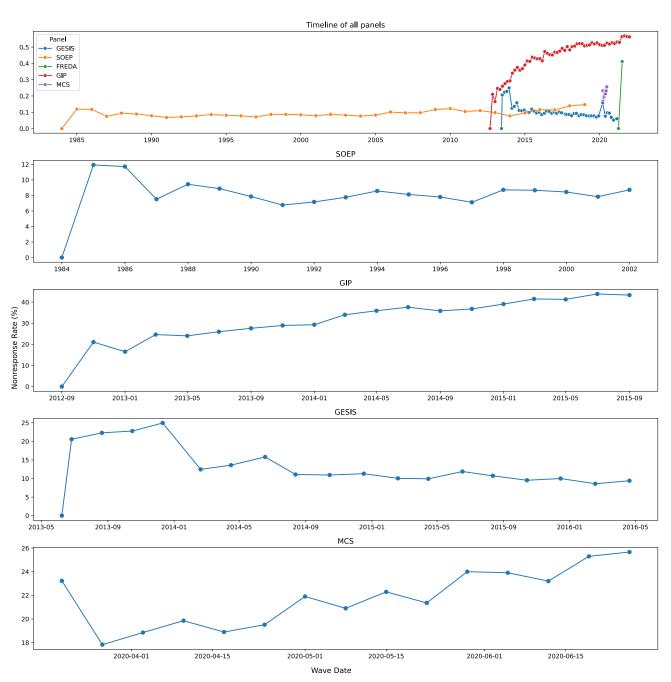


Figure (Appendix) 2. Timelines of each of the panels. FREDA is not included because only the first two waves are included in our analysis. The first wave has a nonresponse rate of zero because no nonrespondent data is retained. Nonresponse rates were 41% and 45% across the second and third FREDA waves.

Table (Appendix) 1
Distributions of predictive features across each panel

| Age Age Age Age | mean std min max mean | 46.380 18.409 0.000 102.000 | 52.058 15.605 0.000 | 49.416 14.632 | 51.661 | 33.418 |
|---------------------------|-----------------------------------|--------------------------------------|---------------------------|------------------|-----------|-------------|
| Age Age | min max | 0.000 | | 14.632 | 15.060 | |
| Age | max | | 0.000 | | 15.862 | 10.161 |
| | | 102 000 | 0.000 | 0.000 | 0.000 | 0.000 |
| TT 1 110' | mean | 102.000 | 87.000 | 78.000 | 85.000 | 68.000 |
| Household Size | | 2.957 | 2.530 | 2.622 | 2.354 | 2.897 |
| Household Size | std | 1.454 | 1.140 | 1.152 | 1.111 | 1.438 |
| Household Size | min | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Household Size | max | 17.000 | 6.000 | 5.000 | 6.000 | 20.000 |
| Household Income | mean | 1,224.505 | 2,277.657 | 1,989.130 | 2,609.574 | 999.193 |
| Household Income | std | 1,658.368 | 1,784.550 | 1,624.572 | 2,043.399 | 2,765.467 |
| Household Income | min | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Household Income | max | 29,000.000 | 7,500.000 | 6,000.000 | 7,500.000 | 250,000.000 |
| Personal Income | mean | 1,396.277 | 1,468.971 | 1,498.441 | 1,752.576 | 0.000 |
| Personal Income | std | 1,491.114 | 1,309.104 | 1,149.260 | 1,391.522 | 0.000 |
| Personal Income | min | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Personal Income | max | 51,128.000 | 7,500.000 | 5,000.000 | 7,500.000 | 0.000 |
| Invited Waves | mean | 11.984 | 29.000 | 20.455 | 8.000 | 1.500 |
| Invited Waves | std | 8.984 | 16.452 | 13.529 | 4.321 | 0.500 |
| Invited Waves | min | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Invited Waves | max | 36.000 | 57.000 | 48.000 | 15.000 | 2.000 |
| Nonresponse This Wave | mean | 0.084 | 0.438 | 0.104 | 0.218 | 0.206 |
| Historic Nonresponse Rate | mean | 0.025 | 0.330 | 0.059 | 0.207 | 0.103 |
| Historic Nonresponse Rate | std | 0.081 | 0.363 | 0.122 | 0.315 | 0.202 |
| Historic Nonresponse Rate | min | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Historic Nonresponse Rate | max | 0.857 | 0.982 | 0.857 | 1.000 | 0.500 |
| Is Married | mean | 0.581 | 0.101 | 0.618 | 0.099 | 0.124 |
| Missing Is Married | mean | 0.000 | 0.005 | 0.000 | 0.002 | 0.000 |
| Sex Female | mean | 0.511 | 0.498 | 0.518 | 0.486 | 0.431 |
| Missing Sex Female | mean | 0.000 | 0.000 | 0.000 | 0.002 | 0.000 |
| Is Unemployed | mean | 0.395 | 0.355 | 0.305 | 0.333 | 0.017 |
| Missing Is Unemployed | mean | 0.000 | 0.006 | 0.001 | 0.017 | 0.000 |
| Missing Age | mean | 0.000 | 0.000 | 0.000 | 0.002 | 0.022 |
| Missing Household Size | mean | 0.000 | 0.007 | 0.000 | 0.028 | 0.020 |
| Missing Household Income | mean | 0.516 | 0.227 | 0.066 | 0.247 | 0.752 |
| Missing Personal Income | mean | 0.232 | 0.092 | 0.000 | 0.067 | 0.000 |
| Missing Employment Status | mean | 0.000 | 0.000 | 0.000 | 0.016 | 0.012 |

Table (Appendix) 2
Parameters we hypertune in the fitting process. "N settings" refers to the number of different settings for each hyperparameter.

LBFGS: Limited-memory Broyden-Fletcher-Goldfarb-Shanno.

| Model Type | Hyperparameter | Values | N settings |
|-----------------------------|---|--|------------|
| | Penalty | L1, L2 Regularization, No | |
| Logistic Regression | Optimization solver | Penalty Liblinear for Penalized, LBFGS for Unpenalized | 5 |
| | Fitting stopping tolerance | 0.0001 | |
| | C (applies to penalized) | 0.5, 1 | |
| | Number of trees in the forest | 50, 100, 500 | |
| | Function to measure split quality | Gini impurity | |
| Random Forest | Minimum samples for a split | 2 | 3 |
| | Minimum samples for a leaf | 1 | |
| | Number of features considered at each split | Square root of all features | |
| Gradient Boosted Classifier | Number of trees in the forest | 50, 100, 500 | |
| | Function to measure split quality | Gini impurity | |
| | Minimum samples for a split | 2 | 3 |
| | Minimum samples for a leaf | 1 | |
| | Number of features considered at each split | Square root of all features | |

Table (Appendix) 3 For each panel, these are the types of responses or other information used to define a given case as a nonresponse.

| Panel | Nonresponse if coded as |
|-------------|--|
| SOEP | Currently not available Cannot be found Explicit Refusal Currently not available Cannot be found Deceased |
| GIP | Implied when no response data for that participant is published |
| GESIS Panel | Nothing ever returned Explicit refusal Post: Attempted - Addressee not known at place of address Break-off: questionnaire too incomplete to process / break-off or partial with insufficient information Explicit refusal with incentive Known respondent-level refusal Logged on to survey did not complete any items Blank questionnaire mailed back implicit refusal Postal box full Implicit refusal Email Bouncer: Mailbox unknown Other person refusal Email Bouncer: Postbox full Death (including Post: Deceased) Email Bouncer: Delivery problem Physically or mentally unable/incompetent Post: Moved left no address Blank questionnaire with incentive returned Respondent language problem Explicit refusal no incentive Post: Undeliverable as addressed Post: No Mail Receptacle Refusal Blank questionnaire with no incentive returned Returned from an unsampled person Invitation returned undelivered (Email Bouncer) |
| MCS | Binary response/nonresponse variable |
| FREDA | No response Moved unknown Refused Not surveyable/deceased/permanently ill/not surveyable during field time |

Table (Appendix) 4

| Table (Appendix) | | |
|---|--|--|
| | ist (Seidenberg et al. 2023). | _ |
| PRICSSA | Description | Response |
| item | Describe the commendation of the control of the con | Con Firms (Amondia) 1 and |
| 1.1 Data collection dates | Describe the survey's data collection dates (e.g., range) to provide his- | See Figure (Appendix) 1 and |
| | torical context that could affect survey responses and nonresponse. | Figure (Appendix) 2. See Section 3.1. |
| 1.2 Data collection | Describe the survey's data collection mode(s). Data collection mode | see section 3.1. |
| mode(s) | can affect survey responses (e.g., to sensitive questions), including non- response, and a survey's data collection mode may change over time | |
| mode(s) | (e.g., during the COVID-19 pandemic). | |
| 1.3 Target | State the target population the survey was designed to represent and | See Table 1 and Section 3.1. |
| population | describe all weighted estimates with respect to this target population. | We use only unweighted |
| population | describe an weighted estimates with respect to this target population. | data. |
| 1.4 Sample | Describe the survey's sample design, including information about strat- | See Table 1 and Section 3.1. |
| design | ification, cluster sampling, and unequal probabilities of selection. | see Tuote 1 una section 5.1. |
| 1.5 Survey re- | State the survey's response rate and how it was calculated. | See Figure (Appendix) 2 and |
| sponse rate(s) | | Table (Appendix) 3. |
| 2.1 Missing- | Report rates of missingness for variables of interest and models, and de- | See Table (Appendix) 1. |
| ness rates | scribe any methods (if any) for dealing with missing data (e.g., multiple | , 11 |
| | imputation). | |
| 2.2 Observa- | State whether any observations were deleted from the dataset. If obser- | We included only cases from |
| tion deletion | vations were deleted, provide a justification. Note: It is best practice | the first recruitment wave to |
| | to avoid deleting cases and use available subpopulation analysis com- | avoid any impact on model |
| | mands no matter what variance estimation method is used. | results caused by the intro- |
| | | duction of fresh participants |
| | | to the training data. |
| 2.3 Sample | Include unweighted sample sizes for all weighted estimates. | See Figure (Appendix) 1. |
| sizes | | |
| | | |
| 2.4 Con- | Include confidence intervals or standard errors when reporting all esti- | Significance tests are not |
| fidence | Include confidence intervals or standard errors when reporting all estimates to inform the reliability/precision of each estimate. | applicable to our models, |
| fidence intervals/ | | applicable to our models, but instead, we provide pre- |
| fidence intervals/ standard | | applicable to our models, but instead, we provide pre- dictive performance metrics |
| fidence intervals/ standard errors | mates to inform the reliability/precision of each estimate. | applicable to our models, but instead, we provide pre- dictive performance metrics (See Section 4). |
| fidence intervals/ standard | mates to inform the reliability/precision of each estimate. State which analyses were weighted and specify which weight variables | applicable to our models, but instead, we provide pre- dictive performance metrics |
| fidence intervals/ standard errors 2.5 Weighting | mates to inform the reliability/precision of each estimate. State which analyses were weighted and specify which weight variables were used in analysis. | applicable to our models, but instead, we provide pre- dictive performance metrics (See Section 4). Not applicable. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance | mates to inform the reliability/precision of each estimate. State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and spec- | applicable to our models, but instead, we provide pre- dictive performance metrics (See Section 4). |
| fidence intervals/ standard errors 2.5 Weighting | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were | applicable to our models, but instead, we provide pre- dictive performance metrics (See Section 4). Not applicable. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopu- | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses | applicable to our models, but instead, we provide pre- dictive performance metrics (See Section 4). Not applicable. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppres- | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppres- | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules 2.9 Software | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). Report which statistical software was used, comprehensively describe | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules 2.9 Software and code | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). Report which statistical software was used, comprehensively describe data management and analysis in the manuscript, and provide all statistical software code. | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules 2.9 Software and code | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). Report which statistical software was used, comprehensively describe data management and analysis in the manuscript, and provide all statis- | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. See Section 6.1. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules 2.9 Software and code 2.10 Single- | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). Report which statistical software was used, comprehensively describe data management and analysis in the manuscript, and provide all statistical software code. Taylor Series Linearization requires at least two PSUs per stratum for | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. See Section 6.1. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules 2.9 Software and code 2.10 Singleton problem | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). Report which statistical software was used, comprehensively describe data management and analysis in the manuscript, and provide all statistical software code. Taylor Series Linearization requires at least two PSUs per stratum for variance estimation. Sometimes an analysis is being performed and | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. See Section 6.1. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules 2.9 Software and code 2.10 Singleton problem (as needed) | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). Report which statistical software was used, comprehensively describe data management and analysis in the manuscript, and provide all statistical software code. Taylor Series Linearization requires at least two PSUs per stratum for variance estimation. Sometimes an analysis is being performed and there is only a single PSU in a stratum. There are several possible fixes to this problem, which should be detailed if the singleton problem is encountered. | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. See Section 6.1. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules 2.9 Software and code 2.10 Singleton problem | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). Report which statistical software was used, comprehensively describe data management and analysis in the manuscript, and provide all statistical software code. Taylor Series Linearization requires at least two PSUs per stratum for variance estimation. Sometimes an analysis is being performed and there is only a single PSU in a stratum. There are several possible fixes to this problem, which should be detailed if the singleton problem is | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. See Section 6.1. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules 2.9 Software and code 2.10 Singleton problem (as needed) | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). Report which statistical software was used, comprehensively describe data management and analysis in the manuscript, and provide all statistical software code. Taylor Series Linearization requires at least two PSUs per stratum for variance estimation. Sometimes an analysis is being performed and there is only a single PSU in a stratum. There are several possible fixes to this problem, which should be detailed if the singleton problem is encountered. | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. See Section 6.1. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules 2.9 Software and code 2.10 Singleton problem (as needed) 2.11 Public/ restricted data (as needed) | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). Report which statistical software was used, comprehensively describe data management and analysis in the manuscript, and provide all statistical software code. Taylor Series Linearization requires at least two PSUs per stratum for variance estimation. Sometimes an analysis is being performed and there is only a single PSU in a stratum. There are several possible fixes to this problem, which should be detailed if the singleton problem is encountered. If applicable, state whether the public use or restricted version of the dataset was analyzed. | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. See Section 6.1. See Section 6.1. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules 2.9 Software and code 2.10 Singleton problem (as needed) 2.11 Public/ restricted data (as needed) 2.12 Em- | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). Report which statistical software was used, comprehensively describe data management and analysis in the manuscript, and provide all statistical software code. Taylor Series Linearization requires at least two PSUs per stratum for variance estimation. Sometimes an analysis is being performed and there is only a single PSU in a stratum. There are several possible fixes to this problem, which should be detailed if the singleton problem is encountered. If applicable, state whether the public use or restricted version of the dataset was analyzed. | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. See Section 6.1. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules 2.9 Software and code 2.10 Singleton problem (as needed) 2.11 Public/ restricted data (as needed) 2.12 Embedded | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). Report which statistical software was used, comprehensively describe data management and analysis in the manuscript, and provide all statistical software code. Taylor Series Linearization requires at least two PSUs per stratum for variance estimation. Sometimes an analysis is being performed and there is only a single PSU in a stratum. There are several possible fixes to this problem, which should be detailed if the singleton problem is encountered. If applicable, state whether the public use or restricted version of the dataset was analyzed. If applicable, provide information about split sample embedded experiments (e.g., mode of data collection or varying participant incentives) | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. See Section 6.1. See Section 6.1. |
| fidence intervals/ standard errors 2.5 Weighting 2.6 Variance estimation 2.7 Subpopulation analysis 2.8 Suppression rules 2.9 Software and code 2.10 Singleton problem (as needed) 2.11 Public/ restricted data (as needed) 2.12 Em- | State which analyses were weighted and specify which weight variables were used in analysis. Describe the variance estimation method used in the analysis and specify which design variables (e.g., PSU/stratum, replicate weights) were used. Describe the procedures used for conducting subpopulation analyses (e.g., Stata's "subpop" command, SAS's "domain" command). State whether or not a suppression rule was followed (e.g., minimum sample size or relative standard error). Report which statistical software was used, comprehensively describe data management and analysis in the manuscript, and provide all statistical software code. Taylor Series Linearization requires at least two PSUs per stratum for variance estimation. Sometimes an analysis is being performed and there is only a single PSU in a stratum. There are several possible fixes to this problem, which should be detailed if the singleton problem is encountered. If applicable, state whether the public use or restricted version of the dataset was analyzed. | applicable to our models, but instead, we provide predictive performance metrics (See Section 4). Not applicable. Not applicable. Not applicable. See Section 6.1. See Section 6.1. |

6.3 Additional Results



Figure (Appendix) 3. Model performance over time, but with Recall instead of AUROC.



Figure (Appendix) 4. Model performance over time, but with Precision instead of AUROC.

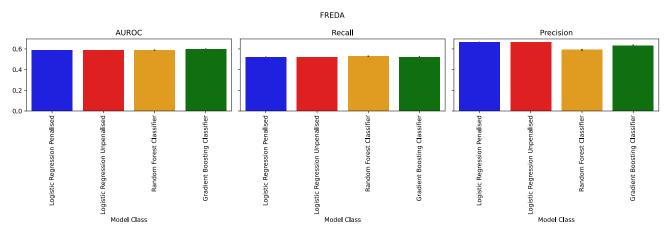


Figure (Appendix) 5. Performance metrics for the second wave of FREDA for which we can make predictions with a model trained on the first FEDA wave.



Figure (Appendix) 6. Models trained on other surveys but applied to the SOEP Panel. The 'Baseline' subplot shows performance results when models are trained using training data of the same panel as the target wave. Auras around the lines indicate the range of performance values across different hyperparameter settings.

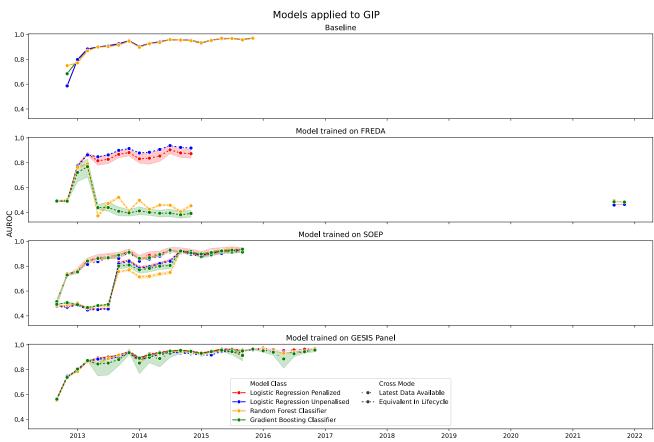


Figure (Appendix) 7. Models trained on other surveys but applied to the GIP Panel. The 'Baseline' subplot shows performance results when models are trained using training data of the same panel as the target wave. Auras around the lines indicate the range of performance values across different hyperparameter settings.

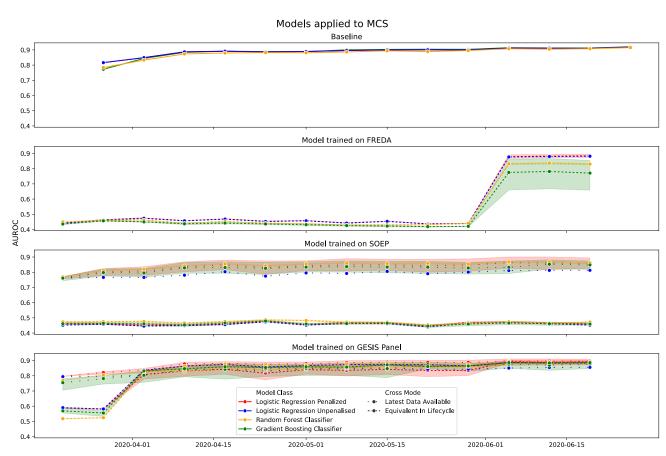


Figure (Appendix) 8. Models trained on other surveys but applied to the MCS. The 'Baseline' subplot shows performance results when models are trained using training data of the same panel as the target wave. Auras around the lines indicate the range of performance values across different hyperparameter settings.

Table (Appendix) 5
Models trained on other surveys but applied to FREDA Panel. Part one: Latest Data Available method.

| Cross Mode | Test Wave | Model Class | Train Data | AUROC |
|-------------------------|-----------|---------------------------------|--------------------|-------|
| Baseline | 7/07/2021 | Gradient Boosting Classifier | - | 0.60 |
| | | Logistic Regression Penalised | - | 0.59 |
| | | Logistic Regression Unpenalised | - | 0.59 |
| | | Random Forest Classifier | - | 0.59 |
| Equivalent In Lifecycle | 7/04/2021 | Gradient Boosting Classifier | GESIS Panel | 0.51 |
| | | | GIP | 0.49 |
| | | | MCS | 0.50 |
| | | | SOEP | 0.53 |
| | | Logistic Regression Penalized | GESIS Panel | 0.53 |
| | | | GIP | 0.52 |
| | | | MCS | 0.49 |
| | | | SOEP | 0.51 |
| | | Logistic Regression Unpenalised | GESIS Panel | 0.49 |
| | | | GIP | 0.52 |
| | | | MCS | 0.50 |
| | | | SOEP | 0.51 |
| | | Random Forest Classifier | GESIS Panel | 0.51 |
| | | | GIP | 0.51 |
| | | | MCS | 0.51 |
| | | | SOEP | 0.54 |
| | 7/07/2021 | Gradient Boosting Classifier | GESIS Panel | 0.87 |
| | | | GIP | 0.80 |
| | | | MCS | 0.86 |
| | | | SOEP | 0.74 |
| | | Logistic Regression Penalized | GESIS Panel | 0.88 |
| | | | GIP | 0.88 |
| | | | MCS | 0.87 |
| | | | SOEP | 0.57 |
| | | Logistic Regression Unpenalised | GESIS Panel | 0.88 |
| | | | GIP | 0.88 |
| | | | MCS | 0.87 |
| | | | SOEP | 0.53 |
| | | Random Forest Classifier | GESIS Panel | 0.87 |
| | | | GIP | 0.86 |
| | | | MCS | 0.86 |
| | | | MCS | 0.00 |

Table (Appendix) 6

Models trained on other surveys but applied to FREDA Panel. Part two: Equivalent In Lifecycle.

| Cross Mode | Test Wave | Model Class | Train Data | AUROC |
|-----------------------|-----------|---------------------------------|--------------------|-------|
| Latest Data Available | 7/04/2021 | Gradient Boosting Classifier | GESIS Panel | 0.51 |
| | | - | GIP | 0.51 |
| | | | MCS | 0.49 |
| | | | SOEP | 0.49 |
| | | Logistic Regression Penalized | GESIS Panel | 0.49 |
| | | | GIP | 0.51 |
| | | | MCS | 0.48 |
| | | | SOEP | 0.51 |
| | | Logistic Regression Unpenalised | GESIS Panel | 0.49 |
| | | | GIP | 0.51 |
| | | | MCS | 0.49 |
| | | | SOEP | 0.51 |
| | | Random Forest Classifier | GESIS Panel | 0.51 |
| | | | GIP | 0.53 |
| | | | MCS | 0.53 |
| | | | SOEP | 0.50 |
| | 7/07/2021 | Gradient Boosting Classifier | GESIS Panel | 0.87 |
| | | | GIP | 0.87 |
| | | | MCS | 0.86 |
| | | | SOEP | 0.87 |
| | | Logistic Regression Penalized | GESIS Panel | 0.86 |
| | | | GIP | 0.88 |
| | | | MCS | 0.87 |
| | | | SOEP | 0.87 |
| | | Logistic Regression Unpenalised | GESIS Panel | 0.86 |
| | | | GIP | 0.87 |
| | | | MCS | 0.87 |
| | | | SOEP | 0.87 |
| | | Random Forest Classifier | GESIS Panel | 0.87 |
| | | | GIP | 0.87 |
| | | | MCS | 0.86 |
| | | | SOEP | 0.87 |