From Concurrent to Push-To-Web Mixed-Mode: Experimental Design Change in the German Social Cohesion Panel

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Abstract

Research shows that concurrent and sequential self-administered mixed-mode designs both have advantages and disadvantages in terms of panel survey recruitment and maintenance. Since concurrent mixed-mode designs usually achieve higher initial response rates at lower bias than sequential mixed-mode designs, the former may be ideal for panel recruitment. However, concurrent designs produce a high share of paper respondents relative to web respondents. Since these paper respondents have been found to be at higher risk of attrition, cause higher data collection costs, and slow down the field-work process, sequential mixed-mode designs may be more practical in the regular course of the panel study after recruitment. Our study provides experimental evidence on the effect of switching a panel study from concurrent to sequential mixed-mode design after the panel recruitment. Results show that this switch significantly increases the share of online respondents without harming response rates. Respondents who are pushed to the web by the design change differ significantly from respondents who continue to participate via paper questionnaires with regard to a number of socio-digital inequality correlates. This suggests that, while the share of online respondents can be increased through mode sequencing, keeping the paper mail mode option is vital for ensuring continued representation od societal subgroups.

Keywords: mixed-mode, longitudinal data, experiment, push-to-web, sequential mode design, concurrent mode design

1 Introduction

Recent years have seen an increase in the use of mixed-mode design strategies in both cross-sectional (see e.g., Wolf et al., 2021) and longitudinal surveys (see e.g., Burton et al., 2020). Reasons for this development include declining response rates and increasing costs of many single-mode surveys as well as the rise of the internet to a global mass medium (see e.g., De Leeuw et al., 2018; Schonlau & Couper, 2017). According to Eurostat (2022), 93% of households across the European Union (EU) had internet access in 2022, compared to only 53% in 2007. Moreover, 84% of EU citizens between ages 16 and 74 used the internet every day in 2022, compared to 54% in 2011. The omnipresence of the internet in many lives helps explain the success of online surveys in providing critical data in a speedy manner during the COVID-19 pandemic (see e.g., Cornesse, Krieger, et al., 2022; Kreuter et al., 2020).

When examining the steep rise in internet access and use, it needs to be acknowledged, however, that a non-negligible part of the population still either does not use the internet or may at least not feel comfortable with certain digital tasks, such as providing survey data online. Reasons for this can be structural disadvantages related to internet access and skills or personal choices regarding internet use and attitudes (see Helsper, 2021). In Germany, 17% of people between 65 and 74 had never actively used the internet in their life by 2022 and are thereby excluded from digital information and public services (see Destatis, 2023). Moreover, many people use the internet selectively for certain tasks either by choice or due to a lack of skills in a particular area. For example, the vast majority of people in Germany use the internet to send and receive email (80%), but only half the population is active on social media (48%) or engages in online banking (49%, see Destatis, 2022).

Regarding data collection, research shows that non-internet users are often willing to participate in surveys if they are given the chance (see e.g., Blom et al., 2017), in particular if they are offered an alternative participation mode (see e.g., Bosnjak et al., 2016). Moreover, even among internet users, a significant proportion prefers to be surveyed offline rather than online (see e.g., Bosnjak et al., 2018). These findings indicate that it may be useful to mix traditional offline and faster, more cost-efficient online modes for survey data collection (for a critical discussion see e.g., Couper, 2017). This notion is supported by studies which show that mixing modes can indeed increase response rates and reduce bias as well as costs and speed up fieldwork processes (see e.g., Luiten et al., 2020). This is particularly true when comparing self-administered mixed-modes to online-only surveys (see e.g., Cornesse & Bosnjak, 2018), but may also apply in comparison to face-to-face surveys, at least in some countries (see Luijkx et al., 2021 for a cross-national evaluation).

2 Self-Administered Mixed-Mode Survey Designs

While many options for mixing self-administered modes exist, two strategies are particularly prevalent: a) concurrent mode designs, where survey participants are offered a choice of an offline and an online survey option concurrently, and b) sequential push-to-web designs, where survey participants are asked to respond online and only nonrespondents are followed up with a choice of offline and online survey options (see Dillman, 2017). Ideally, researchers would want to combine modes in a way which achieves the best cost-benefit ratio. Cost-efficiency is maximized if many people participate online, because offline modes are more expensive and slow. Benefits of the mixed-mode strategy are maximized if the people who participate offline improve the respondent sample in both size (i.e., higher response rate) and quality (e.g., reduced bias) compared to other designs.

The majority of research on cross-sectional self-administered surveys shows that push-to-web designs maximize cost-efficiency while concurrent mode designs maximize response rates and minimize bias (for an overview see DeLeeuw, 2018). Evidence on longitudinal panel surveys is less conclusive. On the one hand, concurrent mode designs lead to higher recruitment survey response rates than push-to-web designs (see e.g., Christmann et al., 2024; Cornesse, Felderer, et al., 2022). On the other hand, panel consent seems to be lower and panel attrition higher among offline respondents than online respondents, at least if the offline mode option is paper mail-back questionnaires (see e.g., Cornesse & Schaurer, 2021b; Genoni et al., 2021). Thus, the initial response rate advantage of concurrent mode designs may be lost over time while the financial cost disadvantage due to low shares of online respondents is upheld.

A useful compromise might, therefore, be to apply a concurrent mode design in the panel recruitment to maximize initial response rates, but to subsequently switch to a sequential push-to-web design to reduce the risk of attrition and increase the number of cost-efficient online respondents. A possible concern with such a design switch after panel recruitment may be that panel respondents could react negatively to the change. For example, they could gain the impression that their participation is becoming less important to the researchers after recruitment, because the survey invitation contains less options than it used to have. The resulting backlash may be particularly strong among population subgroups typically known to not or only selectively use the internet.

In our experimental study implemented in the second data collection wave of the German Social Cohesion Panel (SCP, see Gerlitz et al., 2024), we aim to contribute to the literature on the possibilities and consequences of mixed-mode design changes in panel studies by answering the following question:

Which consequences does switching a mixed-mode panel survey from a concurrent to a sequential push-to-web design have?

3 Experimental Evidence

Some studies have examined the impact of switching the data collection mode over the course of a panel study experimentally (see e.g., Voorpostel et al., 2021). For studies switching face-to-face surveys to mixed-mode designs, most evidence suggests that the design change decreases response rates (see e.g., Jäckle et al., 2015; Lynn, 2013). Moreover, these studies show that some population subgroups (e.g., younger people, urban dwellers, highly educated people) are more likely than others to take up the online survey option for all or at least some panel data collection waves subsequent to the design change (for an analysis of web participation patterns see e.g., Cernat & Sakshaug, 2021).

Few studies have explored the impact of changing data collection modes in self-administered panel studies. An exception is a study by Bretschi et al. (2023), which experimentally evaluates strategies for increasing the share of online respondents in a web-and-paper mixed-mode survey. The authors find that a significant share of panel respondents who previously participated via paper mail-back questionnaires can be converted to the online mode for at least one survey wave by offering mode conversion incentives.

These results suggest that a significant share of offline respondents both generally use the internet and would be willing to provide survey data online given the right circumstances. This is in line with experimental evidence from cross-sectional and panel recruitment contexts. These studies show that concurrent mode designs generally lead to higher response rates than push-to-web designs, but that the share of online respondents, and thereby the cost-efficiency, is higher in push-to-web designs (see Cornesse, Felderer, et al., 2022; Mauz et al., 2018; Millar & Dillman, 2011; Wolf et al., 2021). Furthermore, the more strongly respondents are pushed to the web (e.g., without mentioning that follow-up mailings will contain paper questionnaires), the more likely will they be to respond online (see e.g., Freedman et al., 2018; Patrick et al., 2018).

4 Theory and Hypotheses

In this section we derive hypotheses on how switching from concurrent mode to a push-to-web design after recruitment may impact a self-administered panel study. Generally, social exchange theory proposes that the more options for addressing different preferences are offered in a request, the stronger will a person's wish be to comply (see e.g., Dillman, 2011). For mixed-mode surveys, this may mean that offering all available survey modes directly in the survey invitation rather than withholding a mode will be beneficial for respondents' participation likelihood. This should be particularly true for respondents who perceive the burden of participating online as relatively high (i.e., cost dimension of social exchange) or who are concerned about providing data online (i.e., trust dimension of social exchange). Switching from a design with direct access to the maximum available number of participation options from the start to a design with initially less options should consequently decrease panel participants' willingness to continue responding.

The reasoning is in line with the leverage-salience theory of survey participation (see Groves et al., 2000), which suggests that adding the offline mode option to the survey request from the start will increase the perceived importance of the survey (i.e., the offline mode provides more "leverage" to the request). This leverage is smaller in push-to-web designs, because less options are provided. Consequently, the perceived importance of participating in the panel will decrease when switching from concurrent mode to push-to-web. These considerations are in line with the empirical evidence described above. We therefore derive the following hypothesis for our panel survey setting:

H1: Respondents will be more likely to respond to a survey if they remain in the concurrent mode design rather than being pushed to the web.

Leverage-salience theory also provides a framework for thinking about the development of mode choices among respondents when being switched to a sequential push-to-web design. By making the online mode more prominent (and thus more salient to most respondents), respondents will be more inclined to use it. This consideration is again in line with previous research, which shows that pushing respondents to the web significantly increases the share of online respondents among all respondents. For our study setting, we therefore derive the following hypothesis:

H2: Respondents will be more likely to participate in a survey online rather than via paper mail-back questionnaire when they are pushed to the web rather than remaining in the concurrent mode design.

Average response propensities and shares of respondents per mode are aggregate statistics. To understand the impact of switching a panel study to a sequential push-to-web design it is crucial to also examine who the people are who participate online, and whether societal subgroups may react differently to the design change. As a framework, it may be beneficial to view online versus offline survey participation as an expression of digital inequality. Digital inequality manifests in differences in access, skills, and use of information and communication technologies (ICTs, see Scheerder et al., 2017). According to Helsper (2012)'s corresponding fields model, inequalities in the online and offline world mutually influence one another. For example, highly educated people may find it easier to develop strong ICT skills and these skills may help them to improve their education (e.g., through educational resources offered on the internet). In that sense, access, skills, and use of ICTs are both cause and effect of people's available general economic, cultural, social, and personal resources (see Helsper, 2021). Consequently, barriers to participate in a survey online should be higher for people with fewer resources in the offline world. This is in line with the common finding, that offline respondents in mixed-mode surveys often have lower socio-digital status Herzing & Blom (2019). Based on this reasoning, we derive the following three sub-hypotheses:

H3: Compared to people with lower socio-digital status, people with higher socio-digital status will be…

H3.1: … less likely to participate online from the start.

H3.2: … less likely to switch from the offline to the online mode of data collection.

H.3.3: … more likely to become survey wave nonrespondents.

5 Data

The data for our analyses come from an experiment implemented in the second wave of the SCP. The SCP was recruited in 2021. It is based on a sample of individuals drawn from German population registers. The sampling process consisted of two stages: First, municipalities in Germany were sampled proportional to their population size, but with an oversampling of municipalities in Eastern Germany. Second, individuals were drawn from the municipalities' population registers. All sampled individuals were contacted via postal mail, surveyed, and asked for their consent to be re-surveyed as panel members. Moreover, all sampled individuals who responded to the survey (from hereon referred to as "anchor persons" or APs) were asked to provide the names of all of their household members aged 18 and older (from hereon referred to as "household members" or HMs). The reported HMs were also contacted via postal mail, surveyed, and asked for consent to be re-surveyed. Due to this recruitment strategy, the SCP consists of individuals nested in their household contexts.

The initial recruitment survey is referred to from hereon as part one of wave one (W1P1). This is because due to the questionnaire space needed for panel consent questions and other recruitment features, the first panel survey wave was split into two parts. W1P1 was conducted from September 2021 to April 2022. The second part of wave 1 (W1P2) followed successively with those respondents who had completed W1P1 and provided panel consent from December 2021 to July 2022. Respondents were invited to W1P2 approximately three to six months after they had participated in W1P1. Fieldwork for the second wave (W2) of the SCP was conducted from September 2022 to January 2023. In W2, respondents were again invited in tranches with those who had participated early in W1P2 being the first to be invited to W2 and those who had participated late in W1P2 also being invited later during fieldwork. At each measurement time point, respondents received a 10€ cash incentive conditional on their participation together with a letter of appreciation. At W1P1, APs additionally received a 5€ unconditional cash incentive with their invitation letters to ensure that panel recruitment would be successful.

Overall, 43,819 people were invited to W1P1. Of those, 37,874 were APs drawn from the population registers and 5,945 were HMs reported by the APs. 17,027 individuals participated in W1P1 (13,053 APs and 3,974 HMs; 38.86% of all those invited). Of these, we excluded five from the analysis sample because they were younger and therefore did not fall within the defined age range (i.e., of legal age at the time they completed the first survey wave). 11,596 respondents (those who gave panel consent in W1P1 and in the meantime did not actively de-register, emigrate, die, or change address without letting us know) were invited to W2. At W2, new respondents could also enter the sample if they moved into a panel member's household or became 18 years old while living in a participating household. This is true for 274 people, who we exclude from our analyses, because they have no panel history. In total, 8,369 panel members participated in W2 (i.e., 72.17% of all invited).

6 Experimental Set-Up

In all survey waves, sample members were invited via postal mail and received up to two reminder letters (see Figure 1). In W2, a additional reminder email was sent to everyone who had previously provided their email address in the contact form, which was administered to all panel members at the end of the previous survey waves. Only 22% of all panel members had provided their email address, meaning that only a selective minority of panel members received this additional reminder. It was sent approximately a week after their invitation letter was posted. In both W1P1 and W1P2, a concurrent mixed mode design was applied. This means that the invitation letter and the second reminder contained both a link and QR code to the web version of the survey and a paper questionnaire alternative with a stamped mail-back envelope. For cost reasons, the first reminder letter only contained the link and QR code and not the paper questionnaire. However, the reminder letter encouraged sample members to fill out and mail back the paper questionnaire they had received with the first mailing if they preferred this offline option.

In W2, the majority of the sample was switched to a sequential push-to-web design while a random sub-sample remained in the concurrent mode design. This means that, in the sequential push-to-web group (i.e., the experimental group), respondents first received an invitation letter with the link and QR code to the web survey version only. It should be noted, however, that the invitation letter already mentioned that panel members who prefer to participate via pen-and-paper would be provided with a paper questionnaire with the next mailing approximately two weeks from the initial invitation. Both the first and second reminder letter then contained both the link and QR code and the paper questionnaire. Compared to the control group, which remained in the concurrent mode design respondents were used to from the two previous surveys (W1P1 and W1P2), the difference is not the number of mailings which contained the paper questionnaire but the timing: directly with the invitation versus only with the first reminder.

Regarding the sample composition, it should be noted that paper respondents differ from online respondents at all measurement timepoints (W1P1, W1P2, W2). Most notably, they are older (see Figure 2).

7 Methods

In the following, we describe the methods we use to analyze the experimental data along our hypotheses using R (R Core Team, 2024).

Hypotheses H1 and H2 focus on W2, where the design experiment was implemented. They are tested using logistic regression models as well as simple directed two-proportions χ^2-tests.

Our outcomes of interests for the logistic regressions are:

Figure 1
Overview of the Experimental Setup

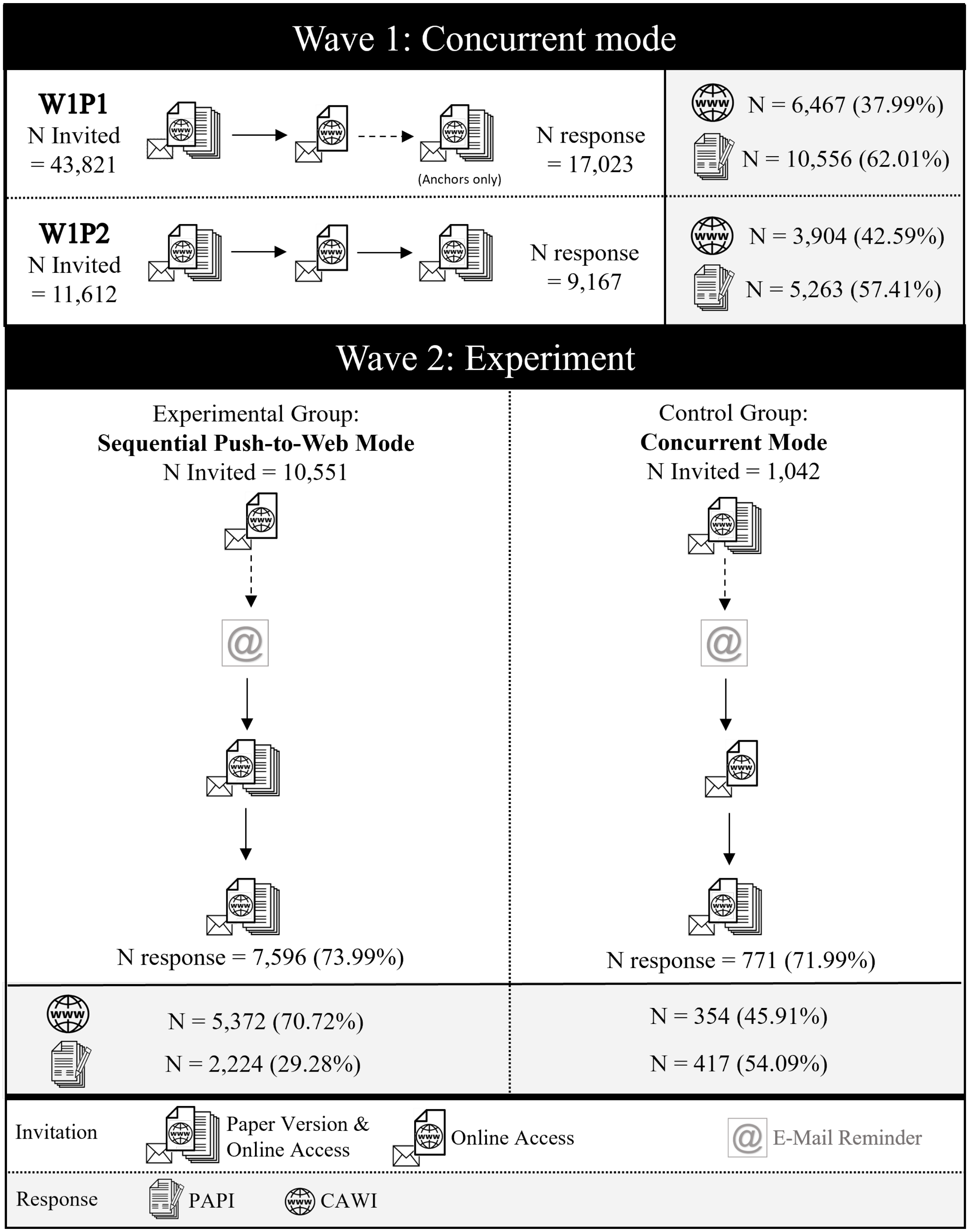
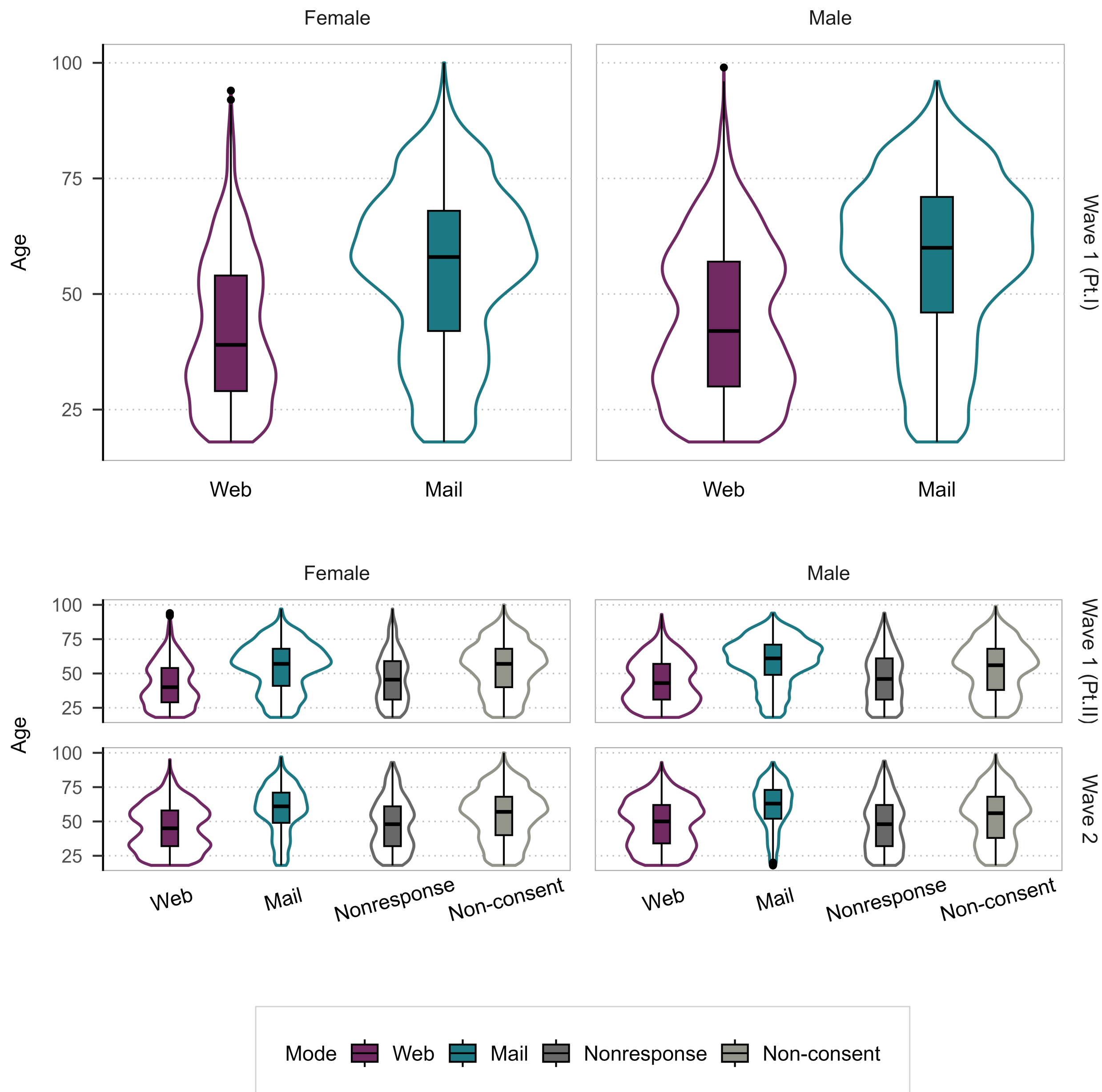


Figure 2

Distribution of Age and Gender Across Survey Waves and Modes Across the Three Measurement Timepoints Relevant for This Study (W1P1, W1P2, W2)



- H1: survey participation (respond vs. not respond at W2) conditional on panel consent at W1P1
- H2: survey mode (online vs. paper at W2) conditional on participation at W2

We test the following alternative hypotheses using directed two-proportions χ^2-tests:

- H1: $p(RespW2|SequentialDesign) < p(RespW2|ConcurrentDesign)$

  Conditional on panel consent at W1P1, the survey participation rate in the push-to-web design is significantly lower than in the concurrent design.

- H2: $p(WebW2|ConcurrentDesign) < p(WebW2|SequentialDesign)$ Conditional on participation at W2, online mode is significantly more common in the push-to-web than in the concurrent design.

We focus on the interpretation of the main effects of the experimental manipulation. Since the supplementary email reminder was not randomly allocated but disseminated to all participants who had provided an email address, we fit additional logistic regression models to account for its potential impact on survey participation (vs. nonresponse, H1) and online mode (vs. paper, H2) as our outcomes of interest in a sensitivity analysis. We include the experimental condition (remain in concurrent mode vs. switch to push-to-web) as the central predictor, and the email reminder as a control variable. Furthermore, we include an interaction term for the possible multiplicative impact of the design change from concurrent to push-to-web with the email reminder in our models. The results of the sensitivity analysis can be found in Table A1 in the Appendix A.1. In addition to these models, we also explore survey mode transition patterns across measurement timepoints descriptively using alluvial plots (Figure 3).

All three parts of hypothesis H3 focus on putting the results from the design experiment into the context of respondents' profile data collected during panel recruitment. However, due to the small number of measurement time points, longitudinal models (e.g., random effect models) are not applied. Instead, we fit logistic regression models with the following outcomes of interest:

- H3.1: online mode continuation (online participation at all measurement time points vs. paper at least once) conditional on participation in all survey waves.
- H3.2: mode switch (switch from paper in W1P2 to online in W2 vs. paper at both W1P2 and W2) conditional on participation in all survey waves)
- H3.3: switch to nonresponse (response to both W1P2 and W2 vs. response to W1P2 but not W2)

In all models for the H3 hypotheses we include the same set of predictors (for an overview see Table A2 in Appendix A.2). Direct measures of digital inequality that capture its key components digital access, use, and skills are unavailable in the data. Therefore, we use indicators which measure offline resources that, according to Helsper (2012)'s corresponding fields model, impact digital inequality. These are economic, cultural, social, and personal resources. In addition, we include proxy measures of digital access and use available either from the panel data or an external source. To represent economic resources, we include the logarithmized equivalized income (eurostat, 2025), employment status, and home ownership versus renting.

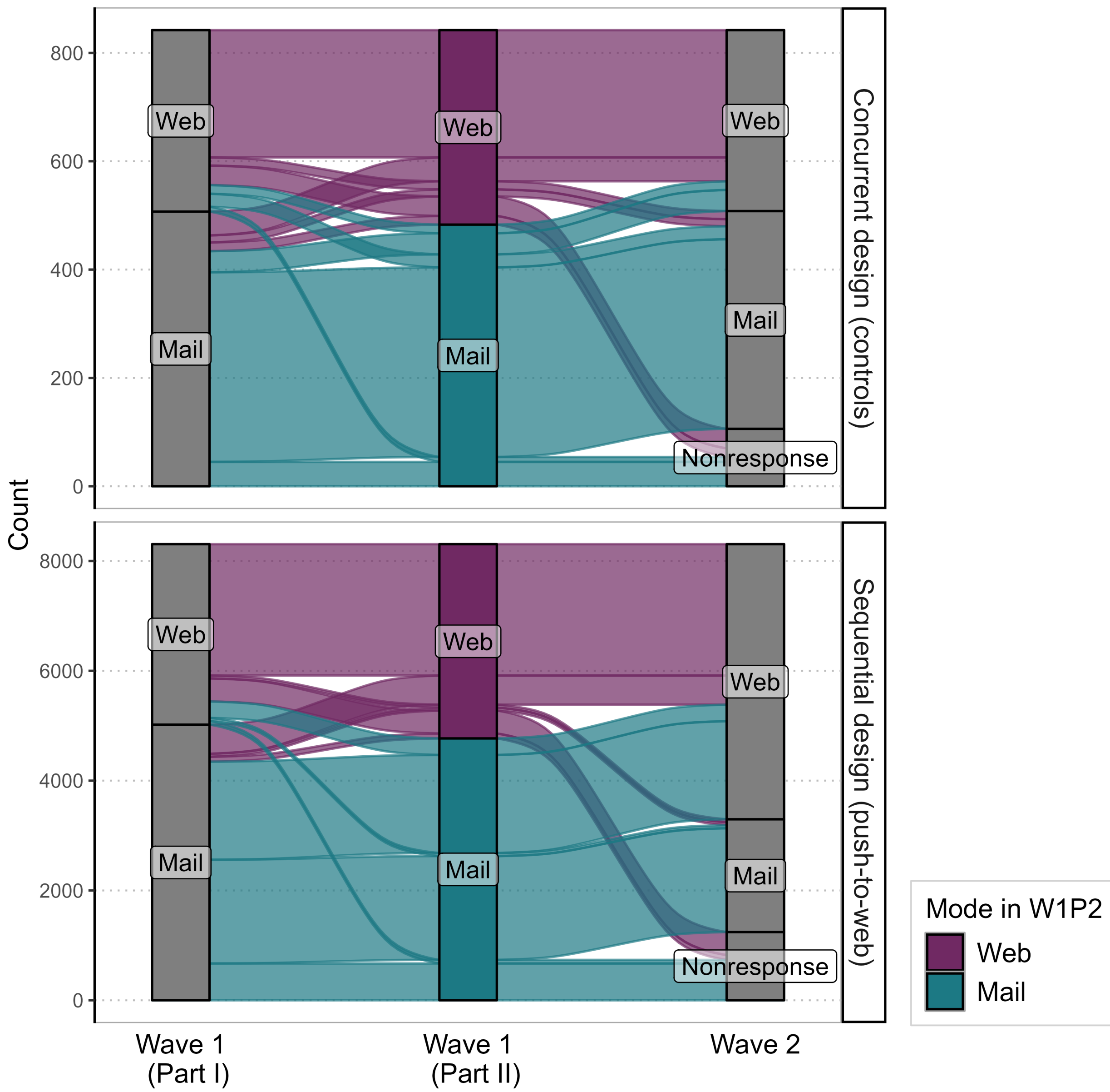
Cultural resources are operationalized using educational attainment and variables measuring generalized trust as well as trust in the government, science, and internet companies.

For social resources, we rely on network heterogeneity, the number of social contacts with family and friends, living situation (alone or in a shared household with other adults), and measures of social support availability expectations for personal matters, caregiving, and finances.

Personal resources are captured through the variables age, a quadratic age term to account for a non-

Figure 3

Survey Mode Transitions From W1P2 to W2 by Experimental Condition (n = 9,148)



linear association, and subjective health.

While direct measures of access are unavailable, the share of households in the area that can be provided with high-speed internet access serves as a key proxy for infrastructural access. We use microgeographic data based on official statistics for this purpose (infas360, 2021, based on Breitbandatlas, 2017). In addition, we include municipality size, since internet access in Germany is usually better in more urban than rural areas (Destatis, 2022). As a proxy for internet use, we include a variable on the use of email portals such as Yahoo or Gmail and social media platforms such as X or Facebook as a source of information (e.g., news consumption) as well as general active use of social media (i.e., (re-)posting own content) in our analyses.

We also control for gender, migration background, region (East/West Germany), the potential effect of the selectively sent e-mail reminder as well as the potential interaction of the reminder across experimental groups in our analyses.

All analysis samples only include participants who had consented to being panel members at W1P1, since only they had a chance to participate in multiple survey waves and were assigned to the push-to-web experiment at W2. We apply design weights in all our analyses to account for unequal selection probabilities as well as clustered standard errors to account for the nested data structure (individuals within households) in all analyses using the R survey package (Lumley, 2004).

Item nonresponse is present in various variables of the analysis datasets for H3.1, H3.2, and H3.3. In order to avert a substantial drop in the number of observations available for our analyses and to reduce potential nonresponse bias, we apply multiple imputation by chained equations (Rubin, 1987; Van Buuren et al., 2006) to complete the partially missing datasets. This procedure entails replacing each missing value through multiple imputed values that are plausible based on an imputation model. This yields multiple imputed datasets, which we can analyze separately and subsequently pool the different estimates through appropriate combining rules. Using the implementation of this procedure in the R packages mice (Van Buuren & Groothuis-Oudshoorn, 2011) and miceadds (Robitzsch & Grund, 2023), we generate 25 imputed datasets each for H3.1, H3.2, and H3.3. Our imputation models in particular employ classification trees (Doove et al., 2014) for imputing nominal and dichotomous variables and partial-least-squares predictive mean matching (Robitzsch et al., 2016) for ordinal and continuous variables. The imputation models use all analysis variables as predictors for the imputation. Imputation models for ordinal and continuous variables also include a selection of additional auxiliary predictor variables from the remaining survey data identified via lasso regression. In order to include the cases of respondents who self-identify as "diverse" in our analysis (ten people in the analysis of H3.1, four in H3.2, and twelve in H3.3), we also impute their binary gender values.

To assess the H3 hypotheses, we fit logistic regression models for each respective hypothesis' outcome that initially include the complete set of predictors introduced above (a maximum model). On these maximum models, we employ two consecutive steps for the final model selection: As the first step we adopt a backwards stepwise AIC selection for which we use the MASS package (Venables & Ripley, 2002). Following Van Buuren (2018, Chapter 5.4), we apply the procedure separately on each of the 25 imputed datasets and include predictor variables if the algorithm selects them into at least 50% of the resulting 25 models.

The second step includes multivariate Wald-testing. Iteratively, we test the significance of each of the remaining predictors' relationship with the outcome. To that end, we fit a logistic regression model including a predictor and test it against a restricted model without the respective predictor. For this procedure, we utilize the D1 command from the mice package which uses the pooled models for the comparison. We remove variables in instances of insignificance (i.e., if $p > .05$). The results of both these selection steps are reported in Table A3 in Appendix A.4 for all H3 hypotheses.

Finally, we use the resulting set of predictors to fit the final model on the 25 imputed datasets. The estimates and standard errors are subsequently aggregated using Rubin's rules (see Rubin, 1987). To quantify the effect size, we calculate Nagelkerke pseudo-R2 values of the final model for each imputed dataset, and report its mean and dispersion.

8 Results

Table 1
Logistic Regression Table of Hypotheses 1 and 2

	H1: Wave 2 Response	H2: Wave 2 Web
(Intercept)	1.010 *** [0.848, 1.171]	-0.170 * [-0.338, -0.001]
Sequential Design	-0.090 [-0.259, 0.078]	1.041 *** [0.863, 1.219]
N	11,593	8,367
Nagelkerke R^2	0.0002	0.030

Note. Table displays logistic regression results of hypotheses 1 and 2. Coefficients are reported as logits. 95%-Confidence intervals shown in square brackets. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 1 shows the results for our first two hypotheses.

H1: Respondents will be more likely to respond to a survey if they remain in the concurrent mode design rather than being pushed to the web.

Contrary to H1, we find that panel participants are not more likely to respond if they remain in their accustomed design (concurrent) mode rather than being switched to a sequential push-to-web design (see left column of Table 1). The model-estimated probability to respond at W2 is 1.81% lower for respondents in the experimental group compared to the control group. The effect does not reach statistical significance ($p = .316$). This finding is confirmed in a directed χ^2-test ($\chi^2 = 1.79$, df = 1, $p = .091$, 95% CI $[-1, 0.004]$). As shown by Nagelkerke's R^2 (0.0002), the model including the experimental design as a predictor for W2 participation is very weak. This suggests that participation in W2 is very similar among people in the experimental groups. When adding the email reminder and interaction between email reminder and experimental design allocation to our model as a sensitivity analysis (see left column in Table A1 in Appendix A.1), the effect of the experimental design remains insignificant and changes direction.

H2: Respondents will be more likely to participate in a survey online rather than via paper mail-back questionnaire when they are pushed to the web rather than remaining in the concurrent mode design.

In line with H2, we find that panel participants are significantly more likely to participate online than on paper when being pushed to the web (see right column of Table 1). Based on the model, we predict a much higher probability to participate online for panel members in the experimental group than the control group (probability of online mode choice of 71% vs. 46%). This finding is confirmed in a directed χ^2-test ($\chi^2 = 198.26$, df $= 1$, $p < .001$, 95% CI $[0.22, 1]$) and also holds when controlling for the e-mail reminder (see right column in Table A1). When examining survey mode transitions across panel survey waves by experimental group visually, we find only a limited amount of switching from one mode to the other in the concurrent mode design from W1P1 via W1P2 to W2 (see upper panel of Figure 3). The pattern in the concurrent mode control group is mostly characterized by stability as well as a dominance of the paper mode over the web mode. In the experimental group, the pattern is different and characterized by a clear increase in web mode participation, especially from W1P1 to W2. In W2, web becomes the dominant mode. As can be seen in Figure A1 in Appendix Section A.3, in both the experimental and control group, it is older people who choose the paper mode (W2 median age paper: 59 years versus median age web 44 years in the concurrent mode group; median age paper: 63 years versus median age web 48 years in the sequential push-to-web mode group).

8.1 Overview (H3)

Using the analysis strategy described in Section 7, we find that some digital inequality indicators significantly explain the outcomes for H3.1 to H3.3. Key predictors present in at least 50% of imputed datasets after AIC reduction include:

- **Economic resources**: Employment status, income, and homeownership.
- **Cultural resources**: Education and generalized trust.
- **Social resources**: Network heterogeneity and expected caregiving support availability.
- **Personal resources**: Linear age term, quadratic age term, and subjective health.
- **Internet access**: High-speed internet coverage and municipality size.
- **Internet use**: Active social media use and using email portals for information.

All control variables (experimental design, email reminder, region, gender, migration background) are included in at least one final model. However, some indicators are excluded by the AIC-reduction since they did not contribute to improving any of the models (cultural resources: trust in government or Big Tech companies, social resources: frequency of social contacts, living in a household with other adults, expected support availability for personal or financial issues, internet use: using social media as a source of information).

8.1.1 H3.1: Participating online at all measurement timepoints

Regarding the correlation between digital inequality and participation by survey mode, we find partial support for the hypothesis that greater offline resources as well as internet access and use are associated with choosing the online survey mode over paper questionnaires (see model "Online Continuity" in the first column of Table 3). Our results are the following:

- **Economic resources**: Part-time workers are less likely to continuously participate online than full-time workers. Panel members with higher income and those in job training (e.g., university students) are more likely to do so. Homeownership does not remain in the model after the two-step variable selection process.
- **Cultural resources**: Panel members with medium to high education and higher trust in science are more likely to continuously participate online than panel members with low education and trust in science. Other trust indicators are not present in the final model.
- **Social resources**: Panel members with more heterogeneous networks are more likely to continuously participate online than those with more homogeneous networks. None of the other social resource indicators remain in the final model.
- **Personal resources**: We find a small quadratic age effect while the linear age term is not included in the AIC-reduced model. Descriptive visual inspection of the correlation suggests that younger panel members are more likely to continuously participate online than middle-aged or older panel members (see Figure A2 in Appendix A.5). Subjective health does not remain in the model.
- **Internet access**: Panel members who live in small towns (5,000 to under 20,000 inhabitants), cities (100,000 to under 500,000 inhabitants) or even large cities (500,000 and more inhabitants) are more likely to continuously participate online than panel members who live in the countryside. The effect is not statistically significant for medium-sized towns (20,000 to under 100,000 inhabitants) compared to the countryside (less than 5,000 inhabitants). The share of households in the area which can be supplied with high-speed internet access is not part of the AIC-reduced model.
- **Internet use**: Panel participants active on social media and those who use email portals as a source of information daily are more likely to continuously participate online than panel members who do not do so.
- **Controls**: Panel members who received the email reminder at W2 are less likely to continuously participate online than those who did not receive the email reminder. This seems counter-intuitive. It should be noted, however, that the email reminder was sent selectively to those panel members who had provided their email address in the address form during panel recruitment. Online respondents were less likely to provide their email address than paper respondents, which explains the effect. Only 5% of all email reminders were sent to people who had participated in W1P1 online versus 95% who had participated on paper (see Table 2). The reason for this stark difference were de-

sign issues with the online contact form, which could be resolved at W2. Residents of Eastern Germany, women, and panel members with migration background are more likely to participate than residents of Western Germany, men, and panel members without migration background.

Overall, the direction of all statistically significant results is in the direction expected in H3.1. With a Nagelkerke R^2 mean of 0.4129 over all imputations at marginal variability (SD = 0.0004), the model on H3.1 is relatively strong, suggesting that our digital inequality indicators explain continued online participation rather well.

Table 2
E-Mail Reminder by Survey Mode in W1P1

	Mode in W1P1		
	Web	Mail	**Total**
E-mail			
No	6,321 (44%)	7,942 (56%)	14,263 (100%)
Yes	146 (5.3%)	2,614 (95%)	2,760 (100%)
Total	6,467 (38%)	10,556 (62%)	17,023 (100%)

8.1.2 H3.2: Switching from paper to the online mode

Regarding the correlation of digital inequality with switching from paper to online, we again find partial support for our hypothesis that greater offline resources as well as internet access and use are associated with mode switching from paper at W1P2 to the web at W2 (model "Switch", see second model in Table 3):

- **Economic resources**: Panel respondents with higher income and homeowners are more likely to switch to the online mode than those with lower income and home renters. Employment status did not remain in the AIC-reduced model.
- **Cultural resources**: Panel members with medium and higher education are more likely to switch from paper to the web than those with low education. Trust indicators do not remain in the model.
- **Social resources**: None of the indicators remain in the AIC-reduced model.
- **Personal resources**: We find a similar weak quadratic but not linear age effect as in the results for H3.1 (see also Figure A2). In addition, panel members who report better subjective health are more likely to switch than those with poorer health.
- **Internet access**: Low high-speed internet coverage in the area is associated with reduced switching likelihood. Municipality size does not remain in the final model.
- **Internet use**: Daily active social media users and those using email portals as a source of information at least occasionally are more likely to switch online than panel members who do not do so.
- **Controls**: Being in the experimental group which was sequentially pushed to the web increases the likelihood of switching from paper to the web, as already established in H2. Panel members who re-

ceived the email reminder are more likely to switch from paper to the web, as already established in Table A1. Residents of Eastern Germany and women are less likely to switch from paper to the web. Migration background does not remain in the final model.

Overall, the direction of all statistically significant results is in the direction expected in H3.2. With a Nagelkerke R^2 mean of 0.2546 over all imputations at marginal variability (SD = 0.01), the model on H3.2 has moderate explanatory power, suggesting that our indicators explain switching to the online mode after recruitment to some extent.

8.1.3 H3.3: W2 Nonresponse

Regarding the correlation between digital inequality and nonresponse, we find limited support for the hypothesis that offline resources as well as internet access and use are associated with becoming nonrespondents at W2 (model "Nonresponse", see last model in Table 3). Very few of the resource indicators significantly contribute to explaining wave nonresponse:

- **Economic resources**: Renters are more likely to become nonrespondents than homeowners. Employment status and income are excluded from the final model.
- **Cultural resources**: Contrary to H3.3, panel respondents with higher generalized trust are more likely to become nonrespondents. In line with H3.3, panel respondents with higher trust in sciences are less likely to become nonrespondents. Education does not remain in the final model.
- **Social resources**: Contrary to H3.3, panel members who do not expect support for caregiving needs available to them are less likely to become nonrespondents compared to people who expect to have such support available to them if needed. Network heterogeneity does not remain in the final model.
- **Personal resources**: We find statistically significant coefficients for both the linear and the quadratic age term, indicating that both younger and middle aged panel members are less likely to become nonrespondents than older panel members (see also Figure A2). Since older people are more likely to become nonrespondents, we interpret this as support for H3.3. Panel members with poorer subjective health are more likely to become nonrespondents than people with good or very good subjective health.
- **Internet access**: None of the indicators remain in the AIC-reduced model.
- **Internet use**: Panel members who use email portals as a source of information at least occasionally are less likely to become nonrespondents than those who never do so. Social media use does not remain in the final model.
- **Controls**: Panel members with migration background are more likely to become nonrespondents. None of the other control variables remain in the final model.

Overall, the direction of the statistically significant effects is sometimes in the direction expected in H3.3

and sometimes opposed to it. Based on the Nagelkerke R^2 mean of 0.0224 at marginal variability (SD = 0.0005) over all imputations, the model for H3.3 is very weak, indicating that digital inequality indicators do not explain becoming nonrespondents at W2.

Table 3
Logistic Regression Results of Hypotheses 3

	Online Continuity		Switch		Nonresponse	
Indicator	**log(OR)**	**95% CI**	**log(OR)**	**95% CI**	**log(OR)**	**95% CI**
(Intercept)	-2.58***	-4.06, -1.10	-5.18**	-7.12, -3.25	-0.50	-1.12, 0.12
Control variables						
Experimental design (ref: Concurrent)						
Push-to-web			2.2***	1.8, 2.6		
Email Reminder (ref: No)						
Yes	-3.6***	-3.9, -3.2	0.36***	0.19, 0.52		
Gender (ref: Male)						
Female	-0.53***	-0.66, -0.39	-0.33***	-0.47, -0.19		
Migration (ref: No)						
Yes	0.24*	0.05, 0.44			0.22*	0.04, 0.40
EastWest (ref: West)						
East	-0.27***	-0.41, -0.12	-0.19*	-0.35, -0.03		
Economic resources						
Income (log)	0.20**	0.06, 0.34	0.37***	0.19, 0.56		
Employment (ref: Full-time)						
Part-time	-0.21*	-0.41, -0.01				
Retired	-0.21	-0.46, 0.05				
Marginally/none	0.01	-0.23, 0.26				
Uni/training	0.33*	0.06, 0.60				
Homeownership (ref: Ownership)						
Renting			-0.23*	-0.41, -0.05	0.17*	0.02, 0.32
Cultural resources						
Education (ref: None/low)						
Medium	0.54**	0.21, 0.88	0.36*	0.02, 0.70		
High	1.0***	0.64, 1.4	0.61**	0.22, 1.0		
Generalized trust					0.03*	0.00, 0.06
Trust science	0.05**	0.02, 0.09			-0.04*	-0.07, -0.01
Social resources						
NetworkHeterogeneity	0.02*	0.00, 0.04				
Support caregiving (ref: Yes)						
No					-0.24*	-0.45, -0.04
Personal resources						
Age					-0.04***	-0.06, -0.02
Age^2	-0.0004***	-0.00, -0.00	-0.0003***	-0.00, -0.00	0.00**	0.00, 0.00
SubjectiveHealth (ref: Good/very good)						
Moderate			-0.20*	-0.37, -0.03	0.07	-0.09, 0.23
Less good/bad			-0.24*	-0.46, -0.02	0.33**	0.13, 0.53
Internet access						
Internet availability (ref: Rather well)						
Rather poor			-0.29***	-0.46, -0.12		

Continued on next page

Table 3 continued from previous page

	Online Continuity		Switch		Nonresponse	
Indicator	**log(OR)**	**95% CI**	**log(OR)**	**95% CI**	**log(OR)**	**95% CI**
Municipality size (ref: Rural)						
Small towns	0.35**	0.14, 0.56				
Medium-sized towns	0.07	-0.15, 0.29				
Cities	0.38**	0.14, 0.61				
Large cities	0.29*	0.06, 0.52				
Internet use						
Social media use (ref: Never)						
Occasionally	0.24**	0.06, 0.42	0.16	-0.03, 0.36		
Daily	0.26**	0.08, 0.44	0.35***	0.15, 0.56		
Email portals information (ref: Never)						
Occasionally	0.10	-0.05, 0.24	0.48***	0.31, 0.66	-0.21**	-0.36, -0.06
Daily	0.35***	0.15, 0.54	0.54***	0.32, 0.77	-0.37***	-0.58, -0.16
Nagelkerke R^2: M (SD)	0.4129 (0.0004)		0.2546 (0.001)		0.0224 (0.0005)	
Observations	7,799		4,462		9,167	

OR = Odds Ratio, CI = Confidence Interval

* p<0.05; ** p<0.01, ***p<0.001

9 Conclusion

Our study aimed to address the following question: Which consequences does switching a mixed-mode panel survey from a concurrent to a sequential push-to-web design have? To answer this question, we conducted an experiment with random allocation in a probability-based panel survey recruited via a concurrent mode design. In the experiment, a control group was kept in the concurrent mode design panel members were used to from the recruitment. An experimental group was switched to a sequential push-to-web mixed-mode design where people were invited to an online survey and only the reminder letters contained paper mail-back questionnaires as an offline participation alternative.

Results showed that our worry about increased nonresponse in the experimental group as compared to the control group (H1) was unwarranted. There was no backlash to the design change. As expected and desired, however, the share of respondents who chose the online rather than offline mode was much larger in the experimental than control group (H2). The sequential design really did push respondents to the web. This is particularly striking as the push to the web was very soft, because panel members in the experimental group were already informed in the survey wave invitation letter that they would have the possibility of participating on paper if they waited for the first reminder letter. In line with our expectation, respondents who chose the online mode continuously (H3.1) or switched from offline to online (H3.2) or from participating in the panel recruitment to being nonrespondents (H3.3) at W2 differ on a number of offline resource as well as internet access and use indicators related to the concept of digital inequality. This includes economic resource indicators (income, employment status, homeownership), cultural resources (education, generalized trust, trust in science), social resources (network heterogeneity, expected availability of support for caregiving needs), and personal resources (age, subjective health) as well as some proxy data on internet access (share of households in the area that can be supplied with high-speed internet access as measured using micro-geographic area data, municipality size) and use (social media use, using email portals as a source of information). These findings suggest that not offering the paper mail-back mode anymore may selectively disadvantage people with lower socio-digital status and increase bias in the data for such subgroups. It should be noted, however, that while the explanatory power of our model on choosing the online mode at all three measurement time points was rather good ($R^2 = 0.41$), it was only moderate for our model on switching from paper questionnaires during the recruitment to the web at W2 ($R^2 = 0.25$) and low for the model on switching from participation in the panel recruitment to nonresponse at W2 ($R^2 = 0.02$). This suggests that factors other than digital inequality impact mode choice, mode switching, and nonresponse. Based on our findings, we recommend switching a mixed-mode panel study from concurrent to sequential mode after recruitment, but not to let go of the paper mode altogether.

A limitation of the present study is that the SCP questionnaires do not directly measure digital inequality. For example, rather than an indicator of the share of households that can be supplied with high-speed internet access in the area where the respondents live it would be desirable to ascertain whether the respondents themselves actually have access to high-speed internet connections at home. It would also be important to ask respondents how much and for which purposes they use the internet, on which devices, and how they rate their digital skill levels. Moreover, additional attitudinal measures related to internet use (e.g., relating to data protection concerns) as well as personality traits (e.g., Big Five) may help improve models such as ours. For future research on the impact of switching modes, we, therefore, recommend that panel studies with mixed-mode designs include suitable predictors in their questionnaires. These may also be useful to monitor and correct for attrition bias or mode effects across the panel in relation to digital inequality.

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A Appendix

A.1 Logistic Regression Results H1 and H2 with Control for E-Mail

Table A1

Logistic Regression Table of Hypotheses 1 and 2

	H1: Wave 2 Response	H2: Wave 2 Web
(Intercept)	0.872 *** [0.690, 1.055]	0.138 [-0.062, 0.338]
Sequential Design	0.021 [-0.169, 0.212]	0.813 *** [0.602, 1.024]
E-Mail Reminder	0.582 ** [0.183, 0.981]	-1.130 *** [-1.533, -0.727]
E-Mail Reminder : Sequential Design	-0.467 * [-0.884, -0.051]	0.804 *** [0.380, 1.229]
N	11,593	8,367
Nagelkerke R^2	0.002	0.042

Note. Table displays logistic regression results of hypotheses 1 and 2 with e-mail reminder as control variable. Coefficients are reported as logits. 95%-Confidence intervals shown in square brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A.2 Outcome and predictor variable overview

Table A2
List of All Variables Used for Hypotheses Testing

Indicator	Levels	Explanations	Hypotheses
		Dependent Variables	
Response W2	0: Nonresponse 1: Web or Mail	Response in W2	H1 (Outcome)
WebW2	0: Mail 1: Web	Web in W2	H2 (Outcome)
Online continuity	0: Mail in W1P1, W1P2, and W2 1: Web in W1P1, W1P2, and W2	Online continuation	H3.1 (Outcome)
Switch W2	0: Mail in both W1P2 and W2 1: Mail in W1P2 and Web in W2	Switch from Mail in W1P2 to Web in W2	H3.2 (Outcome)
Nonresponse W2	0: Response in both W1P2 and W2 1: Response in W1P2 and nonresponse in W2	Unit Nonresponse in W2	H3.3 (Outcome)
		Independent Variables	
Control Variables			
Experimental design	Sequential — Concurrent design	Experimental group assignment	H1, H2, all H3
Email	Yes — No	Additional e-mail invitation to respondents who voluntarily had indicated their e-mail address	H1, H2, all H3
Gender	Male — Female	Non-binary cases were imputed	all H3
Migration	No — Yes	Migration history (no German citizenship or immigrant parents)	all H3
Region	West — East	Residence in East (former GDR or Berlin) or West Germany	all H3
Economic resources			
Income	(continuous)	Logarithmized equivalized net income	all H3

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Variable Name	Levels	Explanations	Hypotheses
Employment	Full time Part-time Retired Marginally/none Uni/training	- Full-time employed - Part-time employed - (Early) Retirement - Short-time work, mini-job, maternity/parental leave, registered unemployed, voluntary service, homemaker - Apprenticeship, in further education, retraining rehabilitation, or else	all H3
Homeownership	Ownership — Renting	Living in home ownership or (sub)renting	all H3
Cultural resources			
Educational attainment	None, low, ongoing Medium High	Level of formal education: - currently in school, primary, or lower secondary education - upper secondary, post-secondary non-tertiary short-cycle tertiary education, Bachelors or equivalent level - Masters or Doctoral or equivalent level	all H3
Generalized trust	continuous	Generalized trust: *Generally speaking: would you say that most people can be trusted, or that you can't be too careful in dealing with people?* with 11-level Likert scale ((0) - You can't be too careful; (10) - Most people can be trusted)	all H3
Trust government	continuous	Institutional trust ((0)- No trust at all, (10) - Complete trust): *How much do you personally trust each of the organizations or institutions. How about ...* *... the Federal Government?*	all H3
Trust internet companies	continuous	*... large internet companies (e.g. Google, Facebook, Twitter)?*	all H3
Trust science	continuous	*... the sciences?*	all H3
Social resources			

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Variable Name	**Levels**	**Explanations**	**Hypotheses**
Network heterogeneity	continuous	Sociodemographic heterogeneity in respondent's social networks. Item battery wording: *"Next, your circle of acquaintances. We define acquaintances as people whose names you know and with whom you would have a brief conversation if you met them on the street or while shopping. How many of your acquaintances..."*, followed by 17 items (*"...live in a big city?", "...live in the countryside?", "...come from East Germany?", "...come from West Germany?", "...have German citizenship?", "...have immigrated to Germany?", "...are devout Muslims?", "...are devout Christians?", "...have a university degree?", "...do not have an educational qualification?", have verylittle money (e.g. live on Hartz IV/basic benefits, work at minimum wage)", "...have plenty of money (e.g. are millionaires, own several houses)?", "...are politically left-wing?", "...are politically right-wing?", "...sympathize with Die Grünen?", "...sympathize with Alternative für Deutschland (AfD)?", "...are homosexual?"*) Response options: (1) None, (2) Very few of them, (3) Several of them, (4) Many of them, (5) Most of them, (6) All of them, (7) Don't know. Over all these items, we treated "Don't know" as missing and summed up all substantial responses resulting in a continuous variable with higher levels representing more heterogeneous networks	all H3
Social contacts	Rarely/never Occasionally Often/daily	Aggregation of two items on social contact frequency taken from a battery on leisure time activities: *Please indicate how often you take part in each activity: Visiting or being visited by* (a)*neighbors, friends, or acquaintances*, (b) *family members or relatives* Response options (1) Every day, (2) At least once per week, (3) At least once per month, (4) Rarely, (5) Never) were re-coded and summed up with higher values representing a higher frequency in social contacts. Final categories correspond to 0-3, 4-5, and 6-8 points.	all H3

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Variable Name	Levels	Explanations	Hypotheses
Living situation	Alone Joint +1 Joint +more	Sharing own household with other adults	all H3
		Expected social support in:	
Support personal	Yes — No	- personal matters	all H3
Support financial	Yes — No	- financial and legal problems	all H3
Support caregiving	Yes — No	- care in case of dependency on care	all H3
Personal resources			
Age	continuous	Age	all H3
Age^2	continuous	Age	all H3
Subjective health	Good/very good Satisfying Less good/bad	General state of health (self-assessment, condensed 5-level Likert scale)	all H3
Internet availability			
Internet	Rather well — Rather poor	Private broadband availability; all technologies up to 1000 Mbit/s, available to >=10% of households vs. available to <10% of households	all H3
Municipality size	Rural Small towns Medium-sized towns Cities Large Cities	Political commune size (number of inhabitants): < 5000 (GKPOL 1 and 2) 5,000 - 20,000 (GKPOL 3) 20,000 - 100,000 (GKPOL 4 and 5) 100,000 - 500,000 (GKPOL 6) > 500,000 (GKPOL 7)	all H3
Internet use			
Social media use Social media information Email portals information	Occasionally Never Daily	Usage frequency of: - e-mail portals as source of information - social media as source of information - online social networks in leisure time Original categories were (1) Every day, (2) At least once per week, (3) At least once per month, (4) Rarely, (5) Never. Aggregated levels (2)-(4) for category "Occasionally".	all H3
Control Variables			

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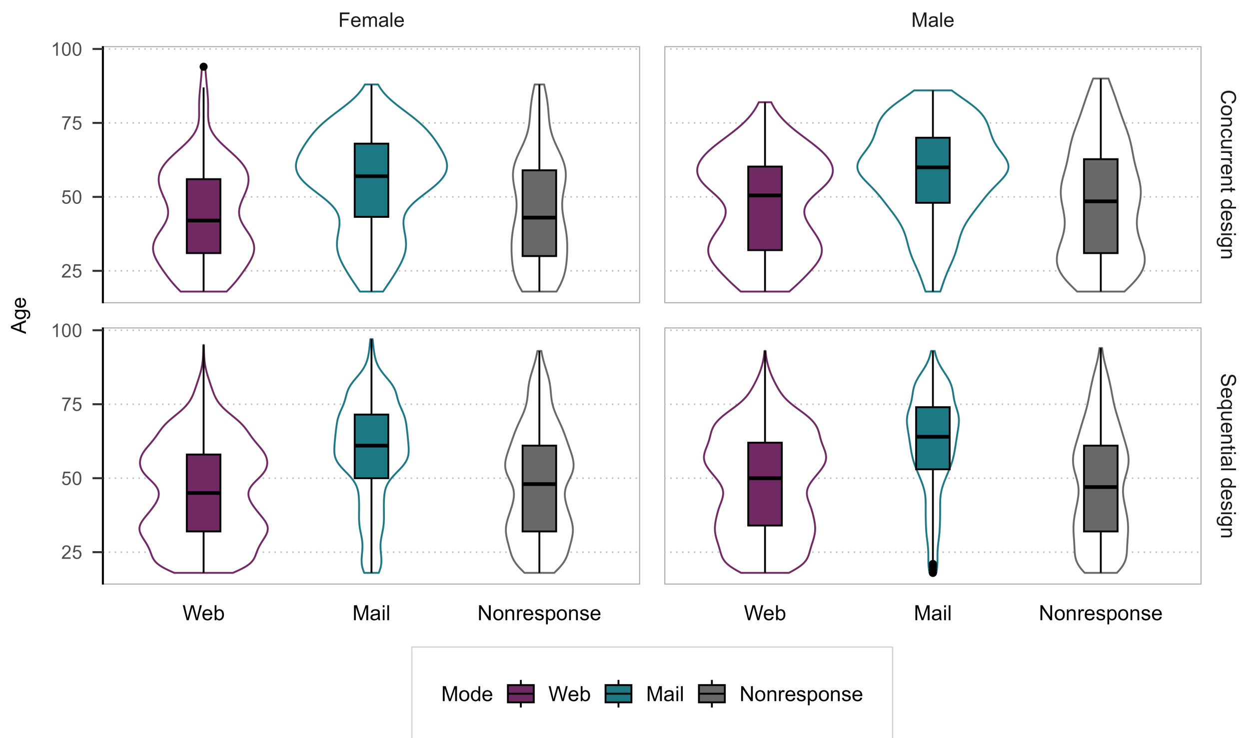
Table A2 continued from previous page

Variable Name	**Levels**	**Explanations**	**Hypotheses**
Gender	Male — Female	Non-binary cases were imputed	all H3
Migration history	No — Yes	Migration history (self or parent)	all H3
Region	West — East	Residence in East (former GDR or Berlin) or West Germany	all H3
Experimental design	Sequential — Concurrent design	Experimental group assignment	H1, H2, all H3
E-Mail	Yes — No	Additional e-mail invitation to respondents who had voluntarily indicated their e-mail address	H1, H2, all H3

A.3 Demography of Web and Paper Users per Experimental Group Across Waves

Figure A1

Distribution of Age and Gender per Experimental Group in W2 (n = 11,552)



A.4 Two-Step Variables Selection Process

Table A3

Variables Selection by Stepwise AIC Reduction and Wald Testing

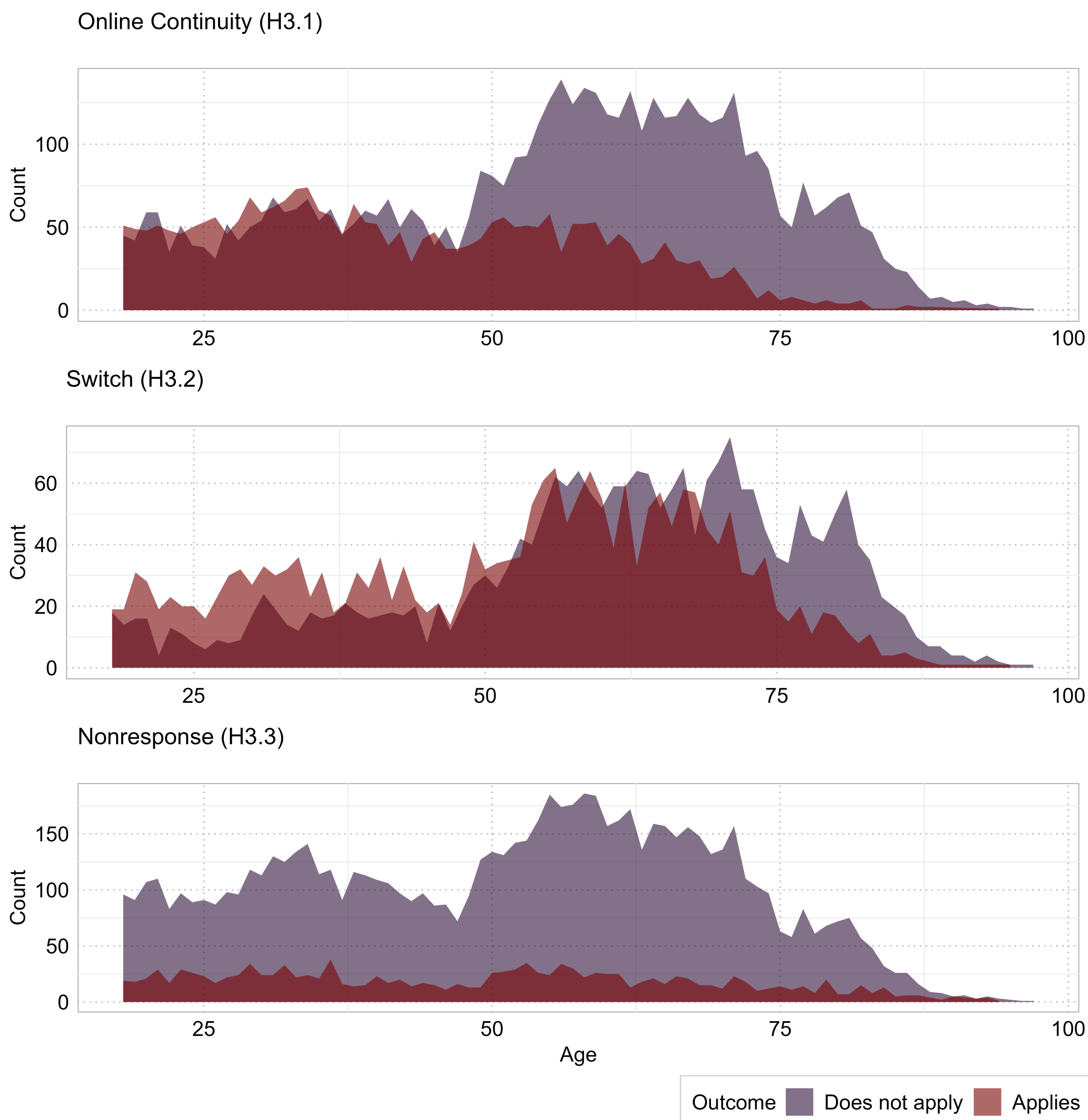
Predictor	H3.1 (OnlineCont)		H3.2 (Switch)		H3.3 (Nonresp)	
	A	B	A	B	A	B
Control variables						
Experimental Design	0	/	25	<.001(+)	25	.071 (-)
Email	25	<.001 (+)	25	<.001 (+)	0	/
Exp. Design:Email (Interaction)	0	/	0	/	0	/
Gender	25	<.001 (+)	25	<.001 (+)	0	/
Migration history	25	.024 (+)	0	/	25	.013 (+)
Region	25	<.001 (+)	25	.016 (+)	0	/
Economic resources						
Income	25	.010 (+)	25	<.001 (+)	12	/
Employment	25	.010 (+)	0	/	25	.063 (-)
Homeownership	25	.095 (-)	25	.010 (+)	23	.034 (+)
Cultural resources						
Educational attainment	25	<.001 (+)	25	.011 (+)	12	/
Generalized trust	0	/	0	/	25	.016 (+)
Trust government	25	.125 (-)	0	/	25	.127 (-)
Trust internet companies	25	.088 (-)	1	/	0	/
Trust science	25	.002 (+)	25	.060 (-)	25	.025 (+)
Social resources						
Network heterogeneity	25	.012 (+)	0	/	0	/
Social contacts	25	.073 (-)	0	/	25	.059 (-)
Living situation	0	/	25	.061 (-)	0	/
Support personal	17	.113 (-)	25	.185 (-)	19	.275 (-)
Support financial	1	/	0	/	0	/
Support caregiving	0	/	0	/	25	.042 (+)
Personal resources						
Age	0	/	0	/	25	<.001 (+)
Age^2	25	<.001 (+)	25	<.001 (+)	25	<.001 (+)
Subjective health	0	/	25	.037 (+)	25	.006 (+)
Internet availability						
Internet access	0	/	25	.001 (+)	10	/
Municipality size	25	<.001 (+)	0	/	3	/
Internet use						
Social media use	25	.007 (+)	25	.002 (+)	0	/
Social media information	0	/	0	/	0	/
Email portals information	25	.005 (+)	25	<.001 (+)	25	<.001 (+)

Note. A Number of models a predictor was selected in during AIC stepwise selection step 1, B p-value of reduction step 2 Wald-test and inclusion into final selection of predictors: (+) included, (-) not included, / already excluded in step 1.

A.5 Age in H3

Figure A2

Bivariate Association of Age with Outcomes of Hypotheses 3



Note. Darker parts show overlap of the distributions of age by outcome.