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Web-Push Strategies for Probability-Based Mixed-Mode Panel Surveys

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Chapter 1

Introduction

1.1 Background and aims

Over the last decade, probability-based online panels have become an established tool for survey data collection in the social sciences (e.g., Blom et al., 2015; Callegaro et al., 2014; Das et al., 2018; Weiß et al., 2020). The term online panels generally refers to different study types that are distinguished by membership composition and selection procedure (Callegaro et al., 2015). In a narrower sense, probability-based online panels can be characterized by three survey design features (Callegaro et al., 2015; Weiß et al., 2020). First, a pool of panel members is selected on the basis of a random sampling mechanism in which each sample unit has a known and non-zero selection probability from a given sampling frame. Second, the data collection of the panel members is partly or fully conducted via web survey questionnaires, although the panel recruitment is typically done by one of, or a combination of, face-to-face, mail, or telephone interviews (Callegaro & Disogra, 2008; Schaurer, 2017). Third, the primary goal of online panels is to recruit a pool of members who can be invited to participate in surveys with unrelated topics in a timely and repeated manner (Callegaro et al., 2014). In this respect, online panels differ from traditional panel studies, whose main purpose is usually to measure intra-individual changes over time in a specific topic (Andreß et al., 2013).

Probability-based online panels are an attractive tool for surveying the general population because they combine the advantages of probability sampling with the benefits of web surveys. Probability-based sampling allows estimations of unbiased population parameters and calculations of the accuracy of these estimates to be made on the basis of strong theoretical assumptions (Kish, 1965). Research shows that such a sample design generally leads to more accurate estimates, especially regarding univariate statistics than surveys based on non-probability sampling techniques (see a review by Cornesse et al., 2020). Once a pool of panel members has been recruited, web surveys offer benefits for data collection in terms of speed and costs (Callegaro et al., 2015; Couper, 2008; Greenlaw & Brown-Welty, 2009). Web surveys also produce lower measurement error compared to interviewer-administered surveys due to a relatively small social desirability bias (Kreuter et al., 2008) and the absence of interviewer effects (West & Blom, 2016). Moreover, probability-based online panels as data infrastructures allow the implementation of different study designs, such as cross-sectional and longitudinal studies as well as experiments (Das et al., 2018). Since data are often collected several times a year, probability-based online panels additionally offer a rich set of variables for data analysis (Blom et al., 2015; Weiß et al., 2020).

Despite all these advantages, probability-based online panels face a challenge that threatens their ability to provide unbiased estimates of the general population: the inclusion of individuals without internet access. Even in countries with high internet penetration rates, a sizeable proportion of the population cannot participate in web surveys due to the lack of internet access (Internet World Stats, 2020). Several studies show that the offline population differs from internet users in relevant characteristics such as age, education, or income (Mohorko et al., 2013; Sterrett et al., 2017), which can result in biased population estimates from web surveys that do not include non-internet users. To deal with this problem, many probability-based online panels apply two main strategies for offering non-internet users an opportunity to become panel members (see a comparison by Cornesse & Schaurer, 2021). One inclusion strategy is to provide the offline population with equipment that allows individuals to take part in web surveys (e.g., the LISS Panel in the Netherlands, the Understanding America Study (UAS), the German Internet Panel, and ELIPSS in France). A second common inclusion strategy is to offer sample persons alternative survey modes, mostly using mail or telephone interviews in a mixed-mode design. Table 1.1 provides an overview of probability-based online panels that combine web surveys as the main mode with an additional offline mode (hereafter also referred to as mixed-mode panels).

TABLE 1.1: Characteristics of probability-based online panels using a mixed-mode design to include the offline population (adapted from Kaczmirek et al., 2019)

Country	Panel name (sponsor)	Sampling frame (recruitment method)	Survey modes to include offline population	Approx. number of panelists
Australia	Life in Australia™	DFRDD (CATI, standalone)	CATI, mail	3,000
Canada	Probit Panel	DFRDD (CATI, standalone)	CATI, mail	90,000
Germany	GESIS Panel	Population registry (F2F)	mail	5,000
Korea	Korean Academic Multimode Open Survey	Area probability (F2F, after completion of survey)	CATI, F2F	2,000
United Kingdom	NatCen Panel	A-BS (F2F, after completion of survey)	CATI	2,500
United States	AmeriSpeak	Area probability sample (F2F, with CATI follow-up)	CATI	49,000
United States	Gallup Panel	DFRDD and AB-S (mail and CATI)	CATI, mail	100,000
United States	SSRS Opinion Panel	DFRDD (CATI, part of omnibus survey)	CATI	10,000

Note: A-BS = address-based sample; F2F = face-to-face; CATI = computer-assisted telephone interviewing; DFRDD = dual-frame random digit dialling; RDD = random digit dialling

Information in this table was retrieved on April 23, 2021 from:Life in Australia™: `https://www.srcentre.com.au/our-research/life-in-australia-panel`; Probit Panel: `https://probit.ca/why-probit/our-methodology/`; GESIS Panel: `https://www.gesis.org/gesis-panel/documentation`; Korean Academic Multimode Open Survey: `http://cnukamos.com/eng/sub1/menu_1.php`; NatCen Panel: `https://www.natcen.ac.uk/our-expertise/methods-expertise/surveys/probability-panel/`; AmeriSpeak: `https://amerispeak.norc.org/about-amerispeak/Pages/Panel-Design.aspx`; Gallup Panel: `https://www.gallup.com/174158/gallup-panel-methodology.aspx`; SSRS Opinion Panel: `https://ssrs.com/opinion-panel/`

Compared to a single-mode panel design, the mixed-mode approach can include as panel members internet users who are unwilling to participate in panel studies online. Offering those individuals an alternative survey mode potentially improves data quality if panel members can be included who would not otherwise become participants (Cornesse & Schaurer, 2021). Indeed, some studies show that a substantial proportion of internet users do not participate in the web mode when this is offered in the recruitment of a mixed-mode panel and prefer alternative mode options (Pforr & Dannwolf, 2017; Rookey et al., 2008). However, cost considerations suggest that a mixed-mode design should collect more data via the less expensive survey mode. For this reason, and due to other advantages of online data collection, survey research has been developing strategies for mixed-mode surveys that aim to motivate respondents to participate in the cost-efficient web mode rather than in mail, telephone, or face-to-face mode options (see an overview by Dillman, 2017). Previous research shows that so-called web-push strategies improve web response in mixed-mode studies, for instance, by offering the web mode first, before providing a mode alternative to nonrespondents (Biemer et al., 2018; Bucks et al., 2020; Luijkx et al., 2020; Matthews et al., 2012; Mauz et al., 2018; McMaster et al., 2017; Patrick et al., 2018; Patrick et al., 2020) or by offering incentives (Biemer et al., 2018; Messer & Dillman, 2011). While several web-push studies have been tested in cross-sectional surveys, there is little research on whether web-push strategies are a valuable tool for mixed-mode panel studies.

This dissertation aims to fill this research gap by developing and exploring web-push strategies for probability-based mixed-mode panels. Investigating web-push strategies in panel studies faces different challenges than using such design features in cross-sectional studies. In fact, the characteristics of a panel study design offer some promising conditions for introducing an effective web-push intervention. For example, there is a high potential for cost savings if panel members can be persuaded to participate in the web mode, as the cost per mode accumulates over single waves (Patrick et al., 2019). Panel studies also allow the collection of extensive information and contact details from panel members, both of which open up more opportunities for implementing web-push strategies (Lynn, 2015; Lynn & Lugtig, 2017; Patrick et al., 2018). On the other hand, introducing web-push interventions in panel studies can affect data quality differently than using such strategies in cross-sectional studies, which particularly concerns nonresponse- and measurement issues (Bianchi et al., 2017; Jäckle et al., 2015).

The goal of this dissertation is to provide new evidence on both dimensions of web-push strategies for mixed-mode panels: investigating the effectiveness of strategies to push respondents to use the web mode and exploring consequences for survey costs and data quality. How a web-push intervention affects data quality and costs in surveys can be assessed using the total survey error framework. This framework addresses data quality from the error perspective of survey statistics and provides guidance on how survey design decisions can minimize errors within given constraints. The following section introduces the total survey error framework and describes error components that can be affected by implementing a web-push intervention in mixed-mode panels. In this context, I will discuss the research gaps and contributions this dissertation aims to fill. The chapter closes by providing an outline of each chapter.

1.2 Total survey error framework

An essential goal of a survey design is to produce high data quality by minimizing errors in survey statistics within budgetary constraints (Biemer, 2010; Groves & Lyberg, 2010). The total survey error framework describes various error components that may occur in the survey process and cause a difference between a survey estimate and the true value of the population parameter. Survey error components described by this framework can be categorized into two error dimensions: errors of observation and errors of nonobservation (Groves et al., 2013; Groves, 2004). Errors of observation reduce the accuracy of inferences from a coded response to a survey question to the underlying construct of interest. This error dimension includes the validity of measuring a construct with a given survey question, the measurement error that might arise in the process of responding to a survey question, and the processing error when editing the raw responses. Errors of nonobservation reduce the accuracy of inferences from the statistics of the respondents to the statistics of the population of interest. This error dimension includes coverage error when there is a mismatch between the sampling frame and the target population, sampling error from deliberately selecting a subset of elements from the frame, nonresponse error when invited sample members do not participate in the study, and adjustment error which can occur in postsurvey adjustments to improve the sample estimate.

All of these error sources also concern estimates based on panel data, but somewhat differently compared to data from cross-sectional studies (Lynn & Lugtig, 2017; Smith, 2011). In particular, nonresponse error and measurement error have unique characteristics when data are collected from the same sample element at multiple points in time. Nonresponse errors in panel studies arise as a combination of initial nonresponse in the panel recruitment, item and wave nonresponse, and panel attrition in the form of permanent dropout of panel members from the study. The consequences of nonresponse for panel studies are a loss of statistical power, the risk of biases in estimates, and the reduced ability to measure change (Lipps, 2009; Lugtig et al., 2014). The measurement of change in panel studies can also be inaccurate if data collection across waves is affected by different levels of measurement error. For example, biased estimates can result from panel conditioning, which occurs if respondents give different answers to survey questions because of learning effects from prior interviews (Struminskaya & Bosnjak, 2021) even though there is some evidence that panel conditioning can also lead to better data quality (Struminskaya, 2016; Uhrig, 2011).

The total survey error framework helps us to understand what kind of error components threaten the accuracy of survey statistics and how different design options might reduce error sources. However, most efforts to reduce survey errors by taking certain design decisions have costs implications, which typically act as a limiting factor. For this reason, the goal of a survey design can be described as finding a balance between error compositions that minimize the total survey error in estimates within given constraints of budget and other resources, also referred to as survey costs (Biemer & Lyberg, 2003; Groves, 2004). Survey costs are commonly divided into fixed and variable costs (Groves et al., 2013). While fixed costs relate to costs that arise regardless of the sample size, variable costs depend on the number of sample cases. For example, the implementation of the web mode in probability-based mixed-mode panels generally produces higher fixed costs for acquiring software and programming the questionnaire than the mail mode. But the mail mode has proportionally higher variable costs for printing, postage, or data entry. Thus, the total cost depends substantially on the number of contacts and responses, which in panel studies accumulates over single survey waves. Optimizing a survey design means taking cost implications into account and finding a set of design features that reduces errors cost-efficiently.

Optimizing the balance of survey costs and survey errors is the overall goal of web-push strategies implemented in probability-based mixed-mode panels. By encouraging participants to use the web mode rather than an offline alternative, these kinds of design features aim to reduce variable survey costs and take advantage of the other benefits of web surveys. However, the implementation of a web-push intervention can also affect survey errors of panel studies in various ways, particularly nonresponse and measurement error. Nonresponse error might occur in the panel recruitment if implementing a web-push strategy prevents sample persons from becoming panel members, for instance, by pushing them too harshly. In addition, a web-push strategy may introduce nonresponse error if members of an ongoing panel can be pushed to switch to the web mode but are more likely to drop out afterward, for example, because they realize they do not like participating this way. Measurement errors could arise if panel members give different answers to the same survey question after switching to the web mode due to different mode characteristics. Survey research has identified several mode characteristics that can cause a different level of measurement errors across survey modes and therefore compromise the comparability of data in mixed-mode surveys (for an overview, see Hox et al., 2017). Since time and mode effects can be confounded in panel studies, it is difficult to disentangle whether changes in responses over time reflect true changes or measurement errors due to mode switching (de Leeuw & Hox, 2011).

The implementation of web-push strategies will not improve the balance between survey costs and survey errors if a decrease in data quality outweighs potential cost reductions. Therefore, this dissertation investigates how to implement effective web-push strategies in mixed-mode panels and explores the impact on cost and particularly aspects of nonresponse errors. The following section describes research gaps in this context and how this present work contributes to filling these gaps.

1.3 Research gap and contribution

While several studies show that including non-internet users in an alternative survey mode reduces coverage bias of mixed-mode panels, there is little evidence on whether offering internet users an offline mode in the panel recruitment reduces nonresponse bias. The second chapter of this dissertation fills this research gap by investigating whether providing a mail mode option to internet users who are unwilling to participate online reduces nonresponse bias. This issue is important for establishing and refreshing mixed-mode panels, since internet users participating in an offline mode produce substantially higher survey costs. If these investments do not pay off in improved data quality, there might be specific web-push strategies or other design options that reduce survey errors more efficiently under given budget constraints. Chapter 2 contributes to this research issue to enable evidence-based design decisions about the mode assignment of respondents in the recruitment of mixed-mode panels.

Despite the high potential for cost savings in panel studies by web-push strategies, little is known about effective strategies for their implementation. This is particularly true for ongoing online panels extended to a mixed-mode design. To the best of my knowledge, no study has yet evaluated whether members of a mixed-mode panel are willing to switch from the mail to the web mode after they declined to participate online during the study recruitment. Chapter 3 describes an experiment that tests the effectiveness of three different web-push strategies for an ongoing mixed-mode panel. To evaluate these strategies from a total survey error perspective, the study provides new evidence on how the web-push affects panelists' willingness to switch modes, as well as the effects on panel attrition and survey costs.

As described above, a panel design allows the collection of a rich data set that can be used to understand and improve the effectiveness of web-push strategies implemented in panel studies after the recruitment. Still, research is lacking on the reasons that drive members of an ongoing panel to comply with the request to switch from an alternative mode to the web. Chapter 4 aims to fill this research gap by investigating how internet-related characteristics are linked to the willingness of panelists to switch from the mail mode to the web. By understanding whether these characteristics of individuals can explain their compliance to switch survey modes, the findings of this study contribute to developing effective web-push strategies for mixed-mode panel studies.

These three chapters make contributions to exploring the potential of web-push strategies for mixed-mode panels which allow survey researchers to make more informed design decisions. The next section provides an outline of each of the following chapters of this dissertation.

1.4 Outline of the dissertation

The analyses of this dissertation are based on data from the GESIS Panel. The GESIS Panel is a German probability-based mixed-mode panel operated by GESIS - Leibniz Institute for the Social Sciences (Bosnjak et al., 2018). Since the beginning of 2014, the GESIS Panel has been a fully operational panel infrastructure that is open to the research community from various fields of social sciences for the collection and use of data. The target population is German-speaking individuals aged 18 years and older and permanently residing in private households in Germany. The sampling strategy is based on a two-stage probability sampling procedure in which individuals are selected from population registers of randomly drawn municipalities. An initial sample was recruited in 2013 (restricted to individuals aged up to 70 years), and two refreshment cohorts were included in 2016 and 2018 (with no upper age restriction). The recruitment rate for the initial cohort is 31.6%, for the second cohort is 20.2%, and for the third cohort is 18.4% (detailed information about the GESIS Panel recruitment procedure can be found at Bosnjak et al. (2018), and for the three cohorts at Schaurer et al. (2014), Schaurer and Weyandt (2016), and Schaurer et al. (2020)).

The data collection of the GESIS Panel takes place every two months and is administered in two modes, namely in web-based surveys (web mode) and paper-and-pencil surveys sent via postal mail (mail mode). The modes are assigned in a multi-step recruitment procedure in which internet-using respondents are asked to take part in the surveys via the internet. While respondents who refuse to participate online are allowed to opt for the mail mode, non-internet users are automatically assigned to the mail mode.

This dissertation consists of three studies that explore different aspects of web-push strategies for mixed-mode panels. The chapters can be read independently from each other, while each includes a separate and, therefore, overlapping description of the GESIS Panel data. Chapter 2 focuses on the mode assignment in the recruitment of mixed-mode panels and explores whether offering internet users a mail mode option reduces nonresponse bias.[1] The research question is structured in three analysis steps. In the first step, I investigate whether internet users included in the mail mode differ from non-internet users assigned to the mail mode and internet users in the web mode. This analysis examines whether the recruitment of internet users in the mail mode brings in panel members with different characteristics. In a second step, I compare population estimates based on the full GESIS Panel data set with a reduced data set that excludes internet users in the mail mode. In addition, the estimates from both samples are compared to data from the German General Social Survey (ALLBUS) as a reference sample. This analysis allows the evaluation of potential

[1] This chapter is single-authored by David Bretschi and is currently under review.

nonresponse bias in the GESIS panel data by assuming that internet users were not included in the mail mode during the panel recruitment. In a third step, I reproduce two studies published with data from the GESIS Panel, again by comparing results of the full and the reduced sample without internet users being included in the mail mode. This method serves to investigate how the recruitment of internet users in the mail mode affects means and model estimates of multivariate analyses.

Chapter 3 provides a detailed description of a web-push experiment that was implemented in the GESIS Panel October/November wave in 2018.[2] All panel members of the mail mode were invited to complete the questionnaire for this survey wave online, and those respondents who accepted the invitation, were invited to switch to the web mode permanently. Panelists were randomly assigned to one of three experimental conditions to test two factors: 1) time of presenting the web-option (concurrent vs. sequential mixed-mode design) and 2) type of incentive (promised vs. prepaid incentive). I hypothesize that offering the web mode sequentially before providing panel members with a mail questionnaire is more effective in pushing respondents to the web mode than offering both mode options concurrently. The same effect is hypothesized for prepaid incentives, which I assume are more effective than promised incentives. The study in Chapter 3 examines how effective the three different web-push conditions are in motivating panelists in the mail mode to switch to the web mode in the current wave and for upcoming waves. Also, outcomes are compared in terms of panel attrition and survey costs after five consecutive waves.

Chapter 4 explores why some panel members are willing to switch from the mail to the web mode while others are not.[3] I hypothesize that internet-related characteristics are a central part of potential mechanisms that explain whether a panel member in the mail mode accepts the invitation to complete a survey online and switch to the web mode for upcoming waves when such an option is offered in an ongoing panel study. To test the hypotheses, I measured indicators of internet use,

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[2] The chapter is based on a joint paper with Ines Schaurer and Don A. Dillman. The paper has been published in the Journal of Survey Statistics and Methodology (Bretschi et al., 2021)

[3] This chapter is coauthored with Bernd Weiß and is currently under review.

internet skills, and attitudes toward the internet before implementing the web-push intervention in the GESIS Panel, which is described in Chapter 3. In addition, I explore why panel members declined to switch modes.

Chapter 5 provides conclusions to this dissertation by summarizing the key results and discussing potential directions for future research. Findings from this dissertation show that web-push strategies are a promising tool for probability-based mixed-mode panels. The results reveal that the implementation of web-push strategies in an ongoing mixed-mode panel has an impact on panelists' decision to switch modes, but that certain characteristics of participants drive their willingness to switch modes as well. However, it also becomes clear that there is a need for more research in order to comprehensively understand how to use these strategies most effectively and what the consequences are for different error components of panel surveys.

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Chapter 2

Does Including Internet Users in the Mail Mode Improve the Data Quality of a Probability-Based Mixed-Mode Panel?

Abstract

Previous research on probability-based online panels shows that providing the offline-population with an alternative survey mode reduces coverage bias. However, little is known about whether offering an offline mode to internet users who are unwilling to participate in panel surveys online pays off in lower nonresponse bias. This study uses data from the GESIS Panel, a probability-based web and mail panel, to investigate how including internet users in the mail mode affects nonresponse bias of population and model estimates. The results show that internet users included in the mail mode differ from non-internet users assigned to the mail mode and panelists responding in the web mode in demographic variables and internet usage after the recruitment. However, excluding internet users in the mail mode from the data set rarely introduces a higher bias in estimates of demographic characteristics compared to data from a reference sample. Further analyses examine how mean and model

estimates of two studies published with GESIS Panel data would have been affected by excluding internet users from the sample who are unwilling to provide survey data online. Here the findings show potential nonresponse bias in several estimates of means from the model variables. However, the model estimates of both studies are largely the same after removing those cases from the analyses. Therefore, authors' conclusions would likely have remained unchanged if internet users had not been included in the mail mode.

2.1 Introduction

In recent years, several probability-based online panels have been established in the social sciences (e.g., Blom et al., 2015; Callegaro et al., 2014; Das et al., 2018; Weiß et al., 2020). These panel studies repeatedly send out online questionnaires for collecting data from a pool of members recruited with probability-based sampling methods. This way, online panels aim to obtain unbiased population estimates based on cost-efficient, accurate and timely measurements from web surveys (Callegaro & Disogra, 2008; Couper, 2008; Greenlaw & Brown-Welty, 2009; Kreuter et al., 2008). However, as with all web surveys of the general population, the data quality of online panels is threatened by potential errors of nonobservation, such as coverage and nonresponse bias (Couper et al., 2007). Concerning sample means, both biases can be described as a product of two terms (Groves et al., 2013). A coverage bias relates to the proportion of the target population that cannot participate in an online panel due to a lack of internet access and the difference in variables of interest between individuals with and without internet access. A nonresponse bias occurs if eligible panel members refuse to participate and those refusals differ from participating panelists in target variables.

One strategy for online panels to deal with both biases is to implement a mixed-mode design where sampled persons are offered additional modes of responding (de Leeuw, 2005, 2018; Dillman et al., 2014). Studies show that including people without internet access in an alternative survey mode reduces coverage bias of population estimates (Bosnjak et al., 2018; Cornesse & Schaurer, 2021; Pforr & Dannwolf, 2017; Rookey et al., 2008). This is due to the fact that non-internet users differ from individuals using the internet in key characteristics such as demographics (Blom et al., 2017; Eckman, 2016), behavior (Zhang et al., 2009), attitudes (Robinson et al., 2002), and health (Schnell et al., 2017). However, little is known about whether offering an alternative mode to internet users who are unwilling to participate online reduces nonresponse bias. Allowing such internet users to complete mail, phone, or face-to-face interviews can increase the recruitment rate if these individuals would not otherwise become panel members. Additionally, it may reduce nonresponse bias if internet users unwilling to be surveyed online (hereafter also referred to as "unwilling onliners") differ from the remaining sample in the variables of interest. On the other hand, recruiting internet users in an offline survey mode can substantially increase survey costs because a lower proportion of panelists will participate in inexpensive web surveys. The mode of participation is particularly consequential for panel studies with frequent data collections, where the mode cost of each member accumulates across waves. Thus, an important question in establishing or refreshing online panels using a mixed-mode recruitment strategy is whether the investment of offering internet users the opportunity to participate in an offline survey mode pays off in terms of improved data quality.

This study uses data from the GESIS Panel, a German probability-based mixed-mode panel that combines web and mail surveys, to address the research question of whether recruiting internet users in the mail mode reduces nonresponse bias. Different nonresponse bias analyses assess the impact of including such unwilling onliners in the sample on population and model estimates. To investigate the overall question, this paper is organized into three specific research questions:

1. Do internet users recruited in the mail mode have different characteristics than non-internet users in the mail mode or internet users in the web mode?

2. How does the inclusion of internet users in the mail mode affect population estimates?

3. How does the inclusion of internet users in the mail mode affect estimates of multivariate models?

2.2 Previous research on nonresponse bias in probability-based online and mixed-mode panels

Compared to coverage bias, studies suggest that nonresponse bias is a less serious problem for probability-based online panels (Bosnjak et al., 2013; Couper et al., 2007). Coverage bias is a well-known risk for online panels since even in countries with internet penetration rates of over 90%, like Germany, there is a relevant proportion of the general population that do not have internet access (Internet World Stats, 2020). For this reason, probability-based online panels have developed two common strategies to include the offline population in the sample: implementing a mixed-mode design or providing equipment to individuals without internet access (Blom et al., 2015). Previous studies show that both recruitment strategies improve the accuracy of estimating demographic parameters such as age, gender, household size, and education (Blom et al., 2017; Bosnjak et al., 2018; Leenheer & Scherpenzeel, 2013; Revilla et al., 2015), or substantial variables such as political interest (Toepoel & Hendriks, 2016), the election outcome (Rookey et al., 2008), and other variables relevant for political science research (Pforr & Dannwolf, 2017).

However, after including the offline population as panel members, several studies still show deviations in estimates of population characteristics between probability-based online panels and benchmark data (Blom et al., 2017; Bosnjak et al., 2018; Struminskaya et al., 2014). These findings suggest an existing nonresponse bias that can arise at different levels of the panel process, such as in the typically used multi-step recruitment approach or at the wave or item level (Callegaro & Disogra, 2008; Hoogendoorn & Daalmans, 2009; Schaurer, 2017). After the panel recruitment phase, studies consistently indicate that nonresponse bias leads to an underrepresentation of persons with low education, one-person households, and non-citizenship (Cornesse & Schaurer, 2021; Leenheer & Scherpenzeel, 2013; Revilla et al., 2015).

Little is known yet about whether nonresponse bias of probability-based online panels is potentially driven by internet users who refuse to participate via the web mode. It is also unclear whether a mixed-mode approach can reduce such a bias by providing internet users an alternative mode of data collection. Several probability-based online panels extended to a mixed-mode design allow individuals with internet access to respond in the mail or telephone mode, such as the GESIS Panel in Germany (Bosnjak et al., 2018), the Life in Australia study in Australia (Kaczmirek et al., 2019), the NatCen panel in the U.K. (Jessop, 2017), or the Gallup panel (Rookey et al., 2008) and the AmeriSpeak panel (Dennis, 2019) both in the U.S. But few panels provide information on how many participants who use the internet privately do not participate via the web mode. For example, nearly 10% of the members who agreed to register for the Gallup panel explicitly asked to receive questionnaires by mail although they provided an email address (Rookey et al., 2008). The NatCen panel applies a sequential mixed-mode design, where panelists are first invited by multiple contacts to participate online before being asked by telephone if they had not yet responded after two weeks (Jessop, 2017). This web-first approach resulted in between two and five percent of individuals with internet access participating via the telephone mode. In the first cohort of the GESIS Panel, over 20% of the internet users declined to respond by the web mode and choose the mail mode instead (Bosnjak et al., 2018; Pforr & Dannwolf, 2017). A first indication of the effect from including internet users in the mail mode on sample accuracy is provided by Cornesse and Schaurer (2021). The study compared the sample accuracy of the full GESIS Panel sample from the first cohort with two versions of reduced data sets that 1) removed only non-internet users from the mail mode and 2) removed all members of the mail mode, including the unwilling onliners. The results suggest that including internet users in the mail mode reduces the bias aggregated across a set of demographic variables more than offering the mail mode to non-internet users only.

The current study extends the analysis of Cornesse and Schaurer (2021) by focusing on how offering unwilling onliners a mail mode option affects the nonresponse bias in estimates of population means and multivariate models. To this end, I will investigate the research questions of this study in three analysis steps and using data of the GESIS Panel, both of which are described in the next section.

2.3 Data and methods

2.3.1 Data

This study is based on data from the GESIS Panel, a German probability-based mixed-mode panel operated by GESIS - Leibniz Institute for the Social Sciences (GESIS, 2020). In December 2018, the panel consisted of 5,762 members from an initial cohort sampled in 2013 and two refreshment cohorts sampled in 2016 and 2018. The target population is German-speaking individuals aged 18 years and older (for the initial cohort between 18 and 70 years) that permanently reside in private households in Germany. The sampling strategy is based on a two-stage probability sampling procedure in which individuals are selected from population registers of randomly drawn municipalities. Panel members from 2016 and 2018 were recruited by applying a piggy-backing approach with the German General Social Survey (ALLBUS) as a vehicle for the recruitment. A piggy-backing approach can be used as a cost-efficient method to recruit panel members while they are being interviewed for a well-established survey. The ALLBUS is a cross-sectional face-to-face survey on attitudes, behavior, and social structure in Germany conducted every two years (Terwey, 2000). Detailed information about the GESIS Panel sampling and recruitment procedure can be found at Bosnjak et al. (2018), and for the three cohorts at Schaurer et al. (2014), Schaurer and Weyandt (2016), and Schaurer et al. (2020).

The data collection of the GESIS Panel is administered in two modes, namely in web-based surveys (web mode) and paper-and-pencil surveys sent via postal mail

(mail mode). The mode assignment takes place in a multi-step recruitment procedure that encompasses an interviewer-administered recruitment interview and a self-administered profile survey. At the end of the recruitment interview, the web mode is presented to internet-using respondents as the default option for participation. This is done to increase the proportion of panel members who participate online. Respondents are classified as internet users if they indicate that they use the internet for private purposes at the time of the recruitment rarely, at least. If these internet users are not willing to participate in the web mode, they are allowed to opt for the mail mode. In the following, this mode group is called "internet users in the mail mode" or "unwilling onliners". Participants who do not use the internet at the time of panel recruitment are automatically assigned to the mail mode without having a choice. Individuals of this mode group are called "non-internet users in the mail mode", even though many of them reported using the internet after the recruitment. For the following analysis, affiliation to a mode group refers to the status of the recruitment, which is decisive for the group assignment. This status remains unchanged, regardless of whether respondents later use or do not use the internet or switched to web mode.[1] Among all internet users from the three GESIS Panel cohorts, 27.5% refused to participate in the web mode during the recruitment procedure and choose the mail mode instead. Thus, in relation to all panel members, 24.0% of participants were internet users in the mail mode right after the recruitment. This recruitment strategy of the GESIS Panel has consequences for survey costs since for each wave, the variable costs of panelists responding via the mail mode are around three times higher than a panel member responding via the web mode (Bretschi et al., 2021).

The survey waves of the GESIS Panel take place every second month, with each taking about 20 minutes. Every panel member, independently of participation mode, receives a survey invitation sent by mail, including a prepaid cash incentive of €5.

[1]Panel members of the GESIS Panel have not been offered to switch modes until the October/November wave 2018. As a result of a web-push intervention, 14.4% of all panelists of the mail mode agreed to permanently switch to the web mode in the upcoming waves (Bretschi et al., 2021).

Web mode panelists are sent an additional email invitation and those who have not answered the survey after one or two weeks receive up to two email reminders. Participants of the mail mode do not receive any reminders due to the cost of sending letters by post.

2.3.2 Methods

In accordance with the three research questions of this paper, I have structured the analysis in three steps. To address research question one, I explore whether internet users in the mail mode differ from non-internet users in the mail mode and internet users in the web mode. All mode groups are compared for differences in estimates of demographic characteristics, internet usage after the recruitment, and political interest. The demographic variables include age, gender, education, legal marital status, household size, and immigration background (defined in terms of German citizenship). The analysis is based on data from all panelists who were invited to the December/January wave 2018/2019 because the demographic characteristics were measured in this survey, and it is the first wave where all newly recruited panelists from the cohort 2018 are included. Table 2.1 shows the active panel members invited to the December/January wave 2018/2019 by mode groups and cohorts. Across all cohorts, 88.70% of the invited panelists fully or partially completed the survey. Missing values in the demographic characteristics were imputed with data from previous GESIS Panel waves where possible. Internet usage after the recruitment was measured in the October/November wave 2018 and political interest in the April/May wave 2019. Statistical differences between the mode groups are tested using two-sided t-tests for each category and adjusted for multiple comparisons using the Bonferroni-Holm correction method (Holm, 1979). The estimates and statistical tests take into account weighting factors which are required due to different inclusion probabilities of respondents from different cohorts (Kolb et al., 2020). To assess selection effects due to panel attrition, I present additional analyses of differences between mode groups for each recruitment cohort separately in the appendix.

TABLE 2.1: GESIS Panel members by mode groups and cohorts for panelists invited to the December/January 2018/2019 wave

	Cohort 2013		Cohort 2016		Cohort 2018		Total	
	%	(n)	%	(n)	%	(n)	%	(n)
Web Mode:	68.2	(1999)	65.9	(817)	66.1	(1043)	67.1	(3859)
Mail Mode:								
Internet users	20.5	(601)	22.4	(278)	22.3	(351)	21.4	(1230)
Non-internet users	11.4	(333)	11.7	(145)	11.6	(183)	11.5	(661)
Total:	100.0	(2933)	100.0	(1240)	100.0	(1577)	100.0	(5750)

Note: Mode groups and internet usage refer to the time of the panel recruitment. Non-internet users who were assigned to the mail mode during the recruitment retain this status regardless of whether they became internet users afterwards.

To answer research question two, I evaluate potential nonresponse bias by assuming that internet users were not offered the option of participating in the mail mode, that is, as if the GESIS Panel were composed only of panelists from the web mode and from non-internet users in the mail mode. For the same variables and data described above, I compare population estimates based on the full GESIS Panel data set with a reduced data set that excludes unwilling onliners. Additionally, estimations of both data sets are compared to estimates based on the full ALLBUS data from 2018 as a reference sample. The ALLBUS qualifies as benchmark data for two reasons. First, the ALLBUS is considered a high-quality survey that has been used as a reference sample before (Struminskaya et al., 2014, 2015). Second, the ALLBUS served as a vehicle for recruiting the GESIS Panel cohorts from 2016 and 2018. The recruitment interview for the GESIS Panel takes place at the end of the ALLBUS interview and is not announced to respondents beforehand. Therefore, ALLBUS estimates are not affected by the mode assignment and potential biases in the GESIS Panel data that could result from subsequent recruitment steps. All estimates are weighted using design weights to account for unequal selection probabilities. To assess statistical differences between the samples, I used two-sided weighted t-tests for each category, again using the Bonferroni-Holm correction method to adjust for multiple comparisons. The GESIS Panel cohort from 2013 was restricted to individuals aged up to 70 while the other cohorts did not employ this restriction. For this reason, I additionally present estimates for all three data sets with an age range between 18 and 70 in the appendix.

To address research question three, I use a different method to investigate how the inclusion of internet users in the mail mode affects means and model estimates of multivariate analyses. For this purpose, I have reproduced two studies published with data of the GESIS Panel with a full data set and a data set from which unwilling onliners are excluded in order to explore whether the conclusions from previous studies would change substantially. Again, comparing the results from both analyses allows an estimation of the counterfactual situation in which internet users were not recruited in the mail mode. The methods used for this third analysis step have been adopted from Eckman, who used this approach to investigate coverage bias using survey paradata (Eckmann, 2013) and including the offline population in the LISS panel (Eckman, 2016).

The two reproduced studies are Gherghina and Geissel (2019) and Heinisch and Wegscheider (2020), both from the field of political science, which is one of the most frequently used research areas for GESIS Panel data (`https://www.gesis.org/gesis-panel/gesis-panel-home/bibliography`). For the selection of the articles, I was guided by four criteria similar to those proposed by Eckman (2016).[2] Table 2.2 provides an overview of the two studies. While Heinisch and Wegscheider could provide the analysis code, this was not the case for the study of Gherghina and Geissel. For this reason, I used summary statistics to reproduce the analysis. I could not reproduce identically the exact numbers of two control variables (age and education) used by Gherghina and Geissel. In addition, five cases were removed from the analyses of Heinisch and Wegscheider and twelve cases from the analysis of Gherghina and Geissel due to missing values in the variable which defines the recruitment mode. In both reproduced studies, however, these minor discrepancies

[2] 1) The studies must be published in peer-reviewed journals; 2) The articles must include a table of summary statistics in addition to one or more regression models that assist in the reproduction; 3) The analysis of the study must focus on making an inference to a larger population, not to experimental conditions; 4) The articles' models must run in the software for statistical computing R.

do not substantially change the results based on the full GESIS Panel data set (for details see Table 2.11 to Table 2.13 in the appendix). I therefore assume that the research objective of comparing estimates between a full and reduced data set is not affected. Both studies use data only from the first cohort recruited in 2013, as no eligible studies could be found that additionally used data from the other two cohorts.

TABLE 2.2: Reproduced studies

Study	Journals	Citations in Google Scholar[a]
Heinisch, R., & Wegscheider, C. (2020). Disentangling how populism and radical host ideologies shape citizens' conceptions of democratic decision-making.	Politics and Governance	3
Gherghina, S., & Geissel, B. (2019). An alternative to representation: Explaining preferences for citizens as political decision-makers.	Political Studies Review	9

Note: [a]As of February 11, 2021.

Following Eckman (2016), I present means and model estimates for each of the two reproduced studies. The analysis begins with estimating the nonresponse bias and the absolute relative nonresponse bias in the population means for all independent and dependent variables used in the models of both studies. To assess nonresponse bias, I assume that population means are estimated based on the full GESIS Panel data set, defined as $\bar{y}_{pop}$. Means estimated using the reduced GESIS Panel data set without unwilling onliners is specified as $\bar{y}_r$. Nonresponse bias is then defined as the difference between the first and the second mean:

$$\text{bias}(\bar{Y}_r) = \bar{y}_r - \bar{y}_{pop} \tag{2.1}$$

I perform linear regression models for each variable that is included in the reproduced models to test whether the nonresponse bias estimated in Equation 1 is significantly different from zero. The dependent variable of these regression models is the variable of interest, and the sole independent variable is a binary indicator that flags cases of unwilling onliners. A significant coefficient indicates that the means between the cases of unwilling onliners and the cases of the remaining sample are different, and nonresponse bias in the mean is significant. However, since the model variables have different units, it is difficult to compare a bias across these items. For this reason, Eckman (2016) suggests as an additional analysis the estimation of the absolute relative bias, which in this context is:

$$\text{absolute relative bias}(\bar{Y}_r) = |\frac{\bar{y}_r - \bar{y}_{pop}}{\bar{y}_{pop}}| \tag{2.2}$$

There are no significance tests for the absolute relative bias because it is a ratio of two estimated quantities. A Hotelling test is used to explore whether the cases of unwilling onliners and the cases of the remaining sample differed in the means across all the model variables of each reproduced study.

In addition to assessing biases in the means, I present point estimates and confidence intervals of the reproduced regression models of both studies again based on GESIS Panel data with and without including the internet users in the mail mode. To assess the effect of removing cases from the analysis, an overlap measure is used that was developed by Karr et al. (2006). This overlap measure offers a quantitative indicator of the model agreement at the coefficient level. The measure calculates a range between 0% and 100% reflecting the match of the two confidence intervals. A high percentage expresses that the models based on the reduced and the full data set agree, and thus the model estimates are less affected by the removal of internet users in the mail mode.

Finally, I use logistic regression models to evaluate how well the models' independent variables can predict the indicator that identified unwilling onliners. This is due to the fact that nonresponse bias is less of a risk if a model includes variables that predict unwilling onliners. Therefore, the area under the receiver operating characteristic (ROC) curve can be used to show the models' ability to discriminate between cases of internet users in the mail mode and the combined cases of the other mode groups, where a higher percentage indicates better discrimination. All statistical analyses are performed using R version 4.0.3 (R Core Team, 2019).

2.4 Results

2.4.1 Do internet users recruited in the mail mode have different characteristics than non-internet users in the mail mode or internet users in the web mode?

Table 2.3 presents differences in characteristics between internet users recruited in the mail mode on the one hand and non-internet users assigned to the mail mode and panelists of the web mode on the other hand. The table includes all active panel members of the GESIS Panel who were invited to the December/January wave 2018/2019. The stars in the fourth and sixth columns indicate whether the characteristics of unwilling onliners differ significantly from panel members of each other mode group. The results show that unwilling onliners vary significantly from both other mode groups in many demographic characteristics such as age groups, education, individuals with a marital status single or widowed, as well as households with singles and three or more members. No significant differences between internet users in the mail mode and the other two mode groups only exist for the demographic characteristics of married/registered partners living apart or living together, two household members, and persons without German citizenship. Less surprisingly, substantial differences between the mode groups can be found for nearly all categories of internet usage measured in the October/November wave 2018. The table illustrates that nearly 33% of the non-internet users who were assigned to the mail mode during the panel recruitment indicated using the internet at this time rarely, at least. Concerning political interest, the results are quite similar across the three groups except for those whose interest is very strong. The outcomes are largely the same when variables are compared separately for the three GESIS Panel cohorts indicating a similar selection process for each recruitment (see appendix Table 2.6 to 2.8). The characteristics of panelists invited to the December/November wave do not appear to be substantially affected by a differential panel attrition.

As can be seen from Table 2.3, the values of the unwilling onliners fall somewhat between the values of the other two mode groups for many categories of the demographic characteristics and internet usage. Therefore, it is plausible to assume that although internet users in the mail mode are different in many characteristics from the remaining sample, their exclusion might have only a small effect on the estimation of population means and thus on a potential nonresponse bias of corresponding statistics. The next analysis step will evaluate this assumption by comparing point estimates of the same characteristics based on GESIS Panel data with and without the unwilling onliners and ALLBUS data.

TABLE 2.3: Comparison of weighted estimates of demographic characteristics, internet usage, and political interest between GESIS Panel mode groups

	Mail mode - internet users		Mail mode - non-internet users		Web mode	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.
Age groups						
age 30 and below	9.6	(7.6;11.5)	3.2***	(1.8;4.5)	**18.7*****	(17.2;20.3)
age 31-45	13.9	(12.0;15.9)	2.7***	(1.6;3.9)	**23.6*****	(22.2;24.9)
age 46-60	36.4	(33.6;39.2)	19.7***	(16.7;22.7)	**33.8**	(32.3;35.4)
age 60 and above	40.1	(37.1;43.0)	74.4***	(71.1;77.8)	**23.9*****	(22.4;25.3)
Gender						
female	56.9	(53.9;59.9)	53.9	(49.7;58.2)	**48.2*****	(46.5;49.9)
Education						
low	23.6	(21.0;26.2)	57.9***	(53.6;62.3)	**11.3*****	(10.2;12.4)
medium	39.4	(36.5;42.4)	28.0***	(24.1;31.9)	29.2***	(27.7;30.8)
high	37.0	(34.0;39.9)	14.1***	(11.0;17.2)	**59.4*****	(57.7;61.1)
Marital Status						
single	16.0	(13.7;18.2)	8.7***	(6.5;10.9)	**27.1*****	(25.5;28.7)
married/RP[a], living together	64.9	(62.0;67.9)	59.4	(55.0;63.7)	60.1	(58.4;61.8)
married/RP, living apart	2.4	(1.5;3.3)	2.5	(1.1;4.0)	1.9	(1.4;2.3)
divorced/RP, annulled	10.2	(8.3;12.0)	12.5	(9.8;15.3)	**7.5***	(6.6;8.3)
widowed/RP died	6.5	(4.8;8.2)	16.9***	(13.4;20.4)	**3.5****	(2.9;4.1)

(continued)

Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.
Household Size						
single household	36.3	(33.2;39.3)	56.8***	(52.2;61.4)	**17.5*****	(16.2;18.8)
two household members	39.5	(36.4;42.6)	34.4	(29.9;38.9)	**42.4**	(40.7;44.1)
three and more hh members	24.2	(21.5;26.9)	8.8***	(6.3;11.2)	**40.1*****	(38.3;41.8)
Citizenship						
no German citizenship	2.5	(1.6;3.4)	1.5	(0.6;2.4)	**3.1**	(2.5;3.6)
Private Internet usage						
daily	55.1	(52.1;58.1)	11.2***	(8.7;13.7)	**85.6*****	(84.4;86.7)
more than once a week	26.3	(23.6;28.9)	10.5***	(8.1;12.9)	12.3***	(11.2;13.4)
once a week	8.2	(6.5;9.8)	3.1***	(1.9;4.3)	**1.5*****	(1.1;1.9)
rare/once a month or less	5.8	(4.5;7.2)	8.4	(6.0;10.9)	**0.6*****	(0.3;0.8)
never	4.6	(3.4;5.8)	66.8***	(62.9;70.7)	**0.0*****	(0.0;0.1)
Political Interest						
very strong	5.3	(4.0;6.7)	9.0*	(6.3;11.7)	8.3**	(7.4;9.3)
strong	26.6	(23.8;29.3)	26.5	(22.3;30.6)	28.9	(27.3;30.4)
moderately	49.7	(46.6;52.7)	46.7	(42.3;51.1)	45.6	(43.9;47.3)
little	15.3	(13.2;17.5)	14.2	(11.4;17.1)	14.0	(12.8;15.2)
not at all	3.1	(2.1;4.1)	3.6	(2.2;5.0)	3.2	(2.5;3.8)

(continued)

Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; [a]RP = "Registered partnership"

Tests were adjusted for multiple comparisons using the Bonferroni-Holm correction method (Holm 1979).

Asterisks mark significant differences between internet users in the mail mode and the respective other mode groups.

Bold font marks differences between non-internet users in the mail mode and panelists of the web mode at the significance level of at least .05. Data are based on panelists invited to the December/Janurary wave 2018/2019.

2.4.2 How does the inclusion of internet users in the mail mode affect population estimates?

Table 2.4 provides estimates for all variables from the analysis above separately for a full GESIS Panel data set and a reduced data set without internet users in the mail mode. Significant differences between the two GESIS Panel data sets are marked by asterisks in the estimates of the full data set (fourth column). The comparison of the results shows significant differences only in a few demographic categories. Such differences were found for estimates of persons with high education and those living in households with a single member and three or more members. Additionally, both data sets differ significantly with respect to nearly every category of internet usage, but in none of the estimates of political interest.

To evaluate how a removal of unwilling onliners would affect a nonresponse bias in the GESIS Panel data, the categories with substantial differences between the data sets are compared to estimates of the ALLBUS, which serves as a reference sample. Significant differences between the reduced data set and the ALLBUS data are indicated by asterisks of the ALLBUS estimates and between the full data set and the ALLBUS data by a bold font of the ALLBUS estimates (both sixth column). Thus, ALLBUS estimates marked with asterisks and a bold font mean that the values differ significantly from both GESIS Panel data sets.

Regarding education, the results suggest that nonresponse bias is increased in estimates of the reduced data set. Removing unwilling onliners from the sample could lead to a further overrepresentation of individuals with a high level of education, which would exacerbate an already existing bias in online panels in favor of highly educated members. In contrast, both the estimates of single households and households with three or more members are closer to the results of the benchmark survey when based on the reduced rather than the full data set. In terms of internet usage, the exclusion of unwilling onliners shows a mixed picture. Daily internet users appear to be overrepresented in the reduced data set, but the estimates are more accurate in the other categories. However, this result should be interpreted with caution since internet usage was measured with different questions and response scales in both surveys and adjusted afterward. Moreover, the estimate of daily internet users based on the reduced data set is closer to the ALLBUS estimate when all samples are restricted to participants aged 70 and below due to the age restriction of the GESIS Panel cohort from 2013 (see appendix Table 2.9). In comparison to Table 2.4, the age-restricted samples also show slightly different results for estimating individuals with a low education level or households with three or more members, where in both cases a smaller bias can be found for the full GESIS Panel data set. For all the other categories, however, restricting the sample regarding age does not lead to substantially different estimates of the characteristics.

Overall, the removal of internet users in the mail mode from the analysis does not seem to affect many estimates of demographic variables or political interest but may increase an already existing bias regarding education. However, significant differences are to be expected in estimating private internet usage. Since analyses in the social sciences are typically more complex than estimating univariate population parameters, the next section assesses nonresponse bias in means and point estimates of multivariate models.

TABLE 2.4: Comparison of weighted estimates between a reduced GESIS Panel data set without unwilling onliners, a full GESIS Panel data set and a benchmark survey

	GESIS Panel (reduced data set)		GESIS Panel (full data set)		ALLBUS 2018	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.
Age groups						
Age 30 and below	16.3	(15.0;17.7)	14.9	(13.8;16.1)	15.7	(14.4;17.0)
Age 31-45	20.3	(19.2;21.5)	19.0	(18.0;20.0)	**22.2**	(20.7;23.6)
Age 46-60	31.7	(30.3;33.0)	32.6	(31.4;33.9)	**29.8**	(28.2;31.4)
Age 61 and above	31.7	(30.2;33.2)	33.4	(32.1;34.7)	32.3	(30.7;33.9)
Gender						
Female	49.1	(47.5;50.6)	50.7	(49.3;52.1)	48.9	(47.2;50.6)
Education						
Low	18.3	(17.0;19.6)	19.3	(18.2;20.5)	**26.5*****	(24.9;28.0)
Medium	29.1	(27.6;30.5)	31.1	(29.8;32.4)	31.9*	(30.3;33.5)
High	52.7	(51.1;54.3)	49.5**	(48.1;50.9)	**41.6*****	(39.9;43.3)
Marital Status						
Single	24.4	(22.9;25.8)	22.7	(21.5;24.0)	**26.1**	(24.6;27.6)
Married/RP[a], living together	60.0	(58.4;61.6)	61.0	(59.5;62.4)	56.2	(54.5;58.0)
Married/RP, living apart	2.0	(1.5;2.4)	2.1	(1.7;2.5)	1.9	(1.4;2.4)
Divorced/RP, annulled	8.2	(7.4;9.0)	8.6	(7.8;9.4)	9.3	(8.3;10.3)
Widowed/RP died	5.5	(4.7;6.3)	5.7	(5.0;6.4)	6.5	(5.6;7.3)

(continued)

Variable for comparison	GESIS Panel (reduced data set) Estimate	GESIS Panel (reduced data set) 95% Conf. Int.	GESIS Panel (full data set) Estimate	GESIS Panel (full data set) 95% Conf. Int.	ALLBUS 2018 Estimate	ALLBUS 2018 95% Conf. Int.
Household Size						
Single household	23.3	(21.9;24.7)	25.8**	(24.6;27.1)	**20.1****	(18.7;21.5)
Two household members	41.2	(39.6;42.9)	40.9	(39.5;42.3)	36.7	(35.0;38.4)
Three and more hh members	35.5	(33.9;37.1)	33.3*	(31.9;34.6)	**43.2*****	(41.5;44.9)
Citizenship						
No German citizenship	2.8	(2.3;3.3)	2.8	(2.3;3.2)	**6.6*****	(5.7;7.5)
Private Internet usage						
Daily	74.0	(72.6;75.4)	70.2***	(68.9;71.5)	70.4***	(68.8;72.0)
More than once a week	12.0	(11.1;13.0)	14.9***	(14.0;15.9)	**8.0*****	(7.1;9.0)
Once a week	1.8	(1.4;2.2)	3.1***	(2.6;3.5)	**2.0**	(1.5;2.5)
Rare/once a month or less	1.8	(1.3;2.2)	2.6*	(2.2;3.0)	**1.9**	(1.4;2.3)
Never	10.4	(9.3;11.4)	9.2	(8.3;10.1)	**17.7*****	(16.4;19.0)
Political Interest						
Very strong	8.4	(7.5;9.4)	7.8	(7.0;8.6)	**11.2*****	(10.1;12.3)
Strong	28.5	(27.1;30.0)	28.1	(26.8;29.4)	27.5	(25.9;29.0)
Moderately	45.8	(44.2;47.4)	46.5	(45.1;48.0)	45.7	(43.9;47.4)
Little	14.1	(12.9;15.2)	14.3	(13.3;15.3)	**12.4**	(11.2;13.5)
Not at all	3.2	(2.6;3.8)	3.2	(2.7;3.7)	3.3	(2.7;3.9)

(continued)

	GESIS Panel (reduced data set)		GESIS Panel (full data set)		ALLBUS 2018	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; [a]RP = "Registered partnership"

Tests were adjusted for multiple comparisons using the Bonferroni-Holm correction method (Holm 1979).

Asterisks mark significant differences between the reduced GESIS Panel data set and each of the other mode groups.

Bold font marks differences between the full GESIS Panel data set and ALLBUS at the significance level of at least .05.

GESIS Panel data sets are based on panelists invited to the December/Janurary wave 2018/2019.

2.4.3 How does the inclusion of internet users in the mail mode affect estimates of multivariate models?

The following section explores the impact of removing internet users in the mail mode from the sample on nonresponse bias in multivariate analyses. I start with a description of the hypotheses and results from each of two reproduced studies that were published using GESIS Panel data. Subsequently, I provide the results of nonresponse bias analysis in means of the model variables, followed by the presentation of figures of the reproduced models with and without internet users who participate in the mail mode.

Reproduction of Study 1 - Gherghina and Geissel (2019)

The article of Gherghina and Geissel (2019) investigates determinants of preferences for citizens as decision-makers. The authors argue that dissatisfaction with the institutions of representative democracy as well as political interest and active engagement in society are two main features that influence preferences for direct democratic decision-making. Three hypotheses are formulated regarding political dissatisfaction and two hypotheses concerning political engagement. To test these hypotheses, the study calculates odds ratios from two logistic regression models, one without and one with control variables. The dependent variable is the preference for citizens as decision-makers coded 1 if such preferences exist and 0 for alternative or inconsistent preferences. The model's independent variables include satisfaction with democracy, satisfaction with government performance, critique of parliament as the institution authorized to legislate, interest in politics, civic engagement, and consumption of political news, education, and age as controls.

Table 2.5 provides an overview of nonresponse bias in estimating means of variables used by the two reproduced studies. For Study 1, 66.7% or six of nine variables included in the full model with controls would show significant nonresponse bias in means if unwilling onliners were not included in the mail mode. A detailed list of variables from the two reproduced studies can be found in the Appendix in Table 2.10. For example, in Study 1, bias was found in estimates of the dependent variable and the control variables education and age. The range of the absolute relative bias is between just over 0% and over 4%, but for most variables below 1%. The result of a Hotelling test shows that means differ on the variables used in models. This test indicates that unwilling onliners and the combined cases of the other two mode groups have different characteristics on these variables.

TABLE 2.5: Comparison of means in analysis variables

Study	Model	% Cases of unwilling web-mode respondents	% Model variables with significant undercoverage bias (n)	Absolute relative bias (%) Min	Median	Max	Hotelling Test
1	Full	23.9	66.7 (6)	0.150	0.772	4.316	F(9, 3163) = 67.2*
2	Combined	18.9	64.3 (9)	0.065	1.248	7.161	F(14, 1787) = 91.3*

Figure 2.1 compares the odds ratios and confidence intervals of the two reproduced models from Study 1 estimated with the full and the reduced GESIS Panel data sets (full models are reported in Table 2.11 in the appendix). In both models, the estimates of the two data sets show odds ratios with similar values and largely consistent confidence intervals. Figure 2.3 presents an overlap measure of the confidence intervals which are included in the models for each study. The dotted line shows that all confidence intervals of Study 1 overlap by more than 90%, except two intervals which overlap around 80%. These results indicate that a removal of unwilling onliners from the data has a rather low impact on the estimates. However, in both models of Study 1, the odds ratios for satisfaction with democracy are no longer significant at the 5% level when the model is fitted with the reduced data set, which is also the case for age in Model 2. This is likely due to a loss of statistical power since 23.9% of the cases were removed from the full data set. Overall, the interpretation of results would likely be the same but may be uncertain for Hypothesis 1, which is tested with the variable satisfaction with democracy.

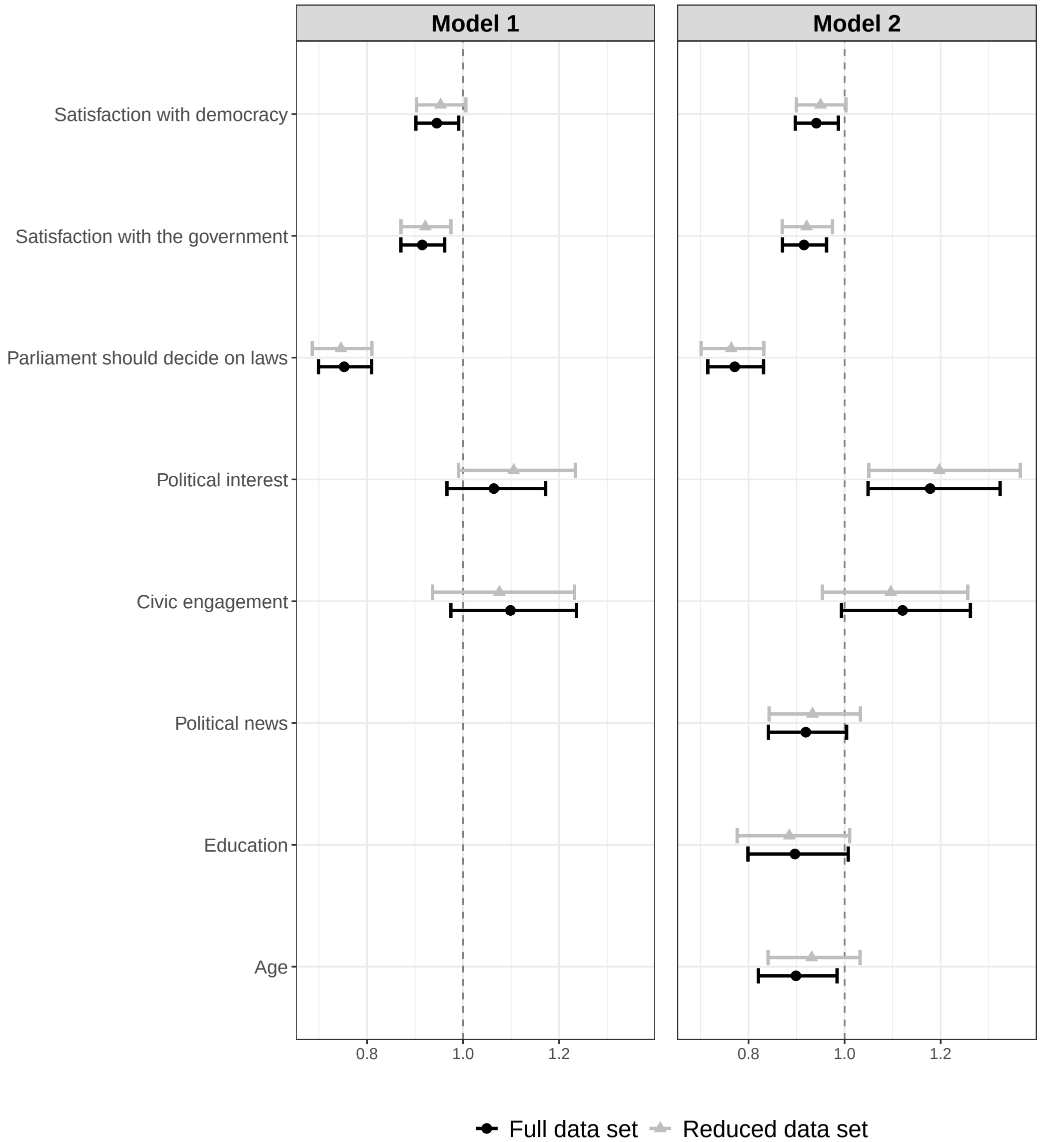

FIGURE 2.1: Comparison of odds ratios and 95% confidence intervals from logistic regression models: Full data set versus reduced data without internet users in the mail mode, Gherghina and Geissel (2019).

Reproduction of study 2 - Heinisch and Wegscheider (2020)

The second reproduced study by Heinisch and Wegscheider (2020) examines how populism and radical host ideologies shape citizens' conception of democratic decision-making. To investigate this issue, the study is based on data from Germany and Austria. As a German data set, GESIS Panel data are used to measure four conceptions of democratic decision-making: trusteeship democracy, anti-pluralism, deliberative proceduralism, and majoritarianism. The authors formulate hypotheses about how populist attitudes, radical right attitudes, and radical left attitudes are related to these four conceptions of democracy. The hypotheses are tested in four linear regression models, with the four conceptions of democracy as dependent variables. The main independent variables are attitudes toward populism and radical right and left host ideologies. Attitudes towards right host ideologies are captured by an indicator for right-wing authoritarianism and anti-immigration attitudes. Left host ideologies are measured by an indicator for the left-wing economy. All indicators are measured with one or more additive indices of different Likert items. The models also include several control variables.

The second row of Table 2.5 presents the results of nonresponse bias in means of the variables used by Study 2. Of all fourteen dependent and independent variables, 64.3% (9) would be affected by significant nonresponse bias in a sample that excluded internet users of the mail mode, which form 18.9% of the respondents. A bias would exist in two dependent variables (anti-pluralism and trusteeship democracy) as well as in independent variables (e.g., populist attitudes, right-wing authoritarianism) and demographic controls (gender, education, and age). The absolute relative bias ranges between just over 0% and 7%, which was found for education. However, for all variables except education, gender, and age, the absolute relative bias is less than 2%. A significant Hotelling test indicates that unwilling onliners and the remaining sample differ in the variables used in the models of Study 2.

Figure 2.2 shows coefficients and confidence intervals between the full and reduced GESIS Panel data sets for the regression models of the article (full models are reported in Table 2.12 and Table 2.13 in the appendix). Across all four models, the estimates are fairly close, and the confidence intervals are similar for most coefficients from the reproductions with both data sets. Figure 2.3 shows that all confidence intervals overlap more than 70% and for 37 of the 44 coefficients that we see in Figure 2.2, the overlap is greater than 80%. However, in both Model 1 and Model 2, one non-significant coefficient becomes significant at the 5% level after the removal of unwilling onliners (income and the left-right scale[2]). In Model 3, on the other hand, the left-right scale is not significant at the 5% level anymore when fitted with the reduced data. These deviations concern control variables, with coefficients and confidence intervals for the main independent variables being largely the same. Therefore, Heinisch and Wegscheider (2020) would likely come to the same conclusions regarding their hypotheses if their analysis were based on a GESIS Panel data set without unwilling onliners.

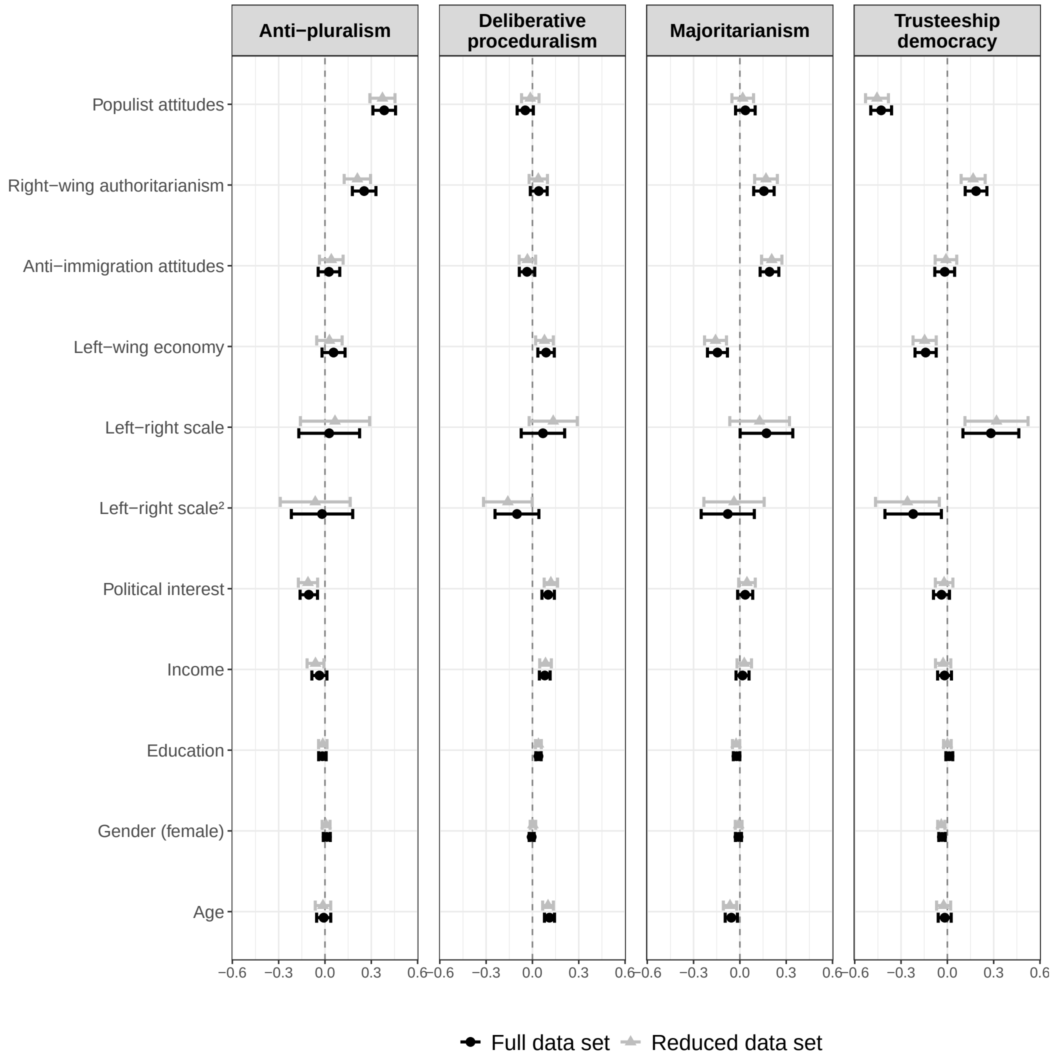

FIGURE 2.2: Comparison of coefficients and 95% confidence intervals from linear regression models: Full data set versus reduced data without internet users in the mail mode, Heinisch and Wegscheider (2020).

If the analysis models include independent variables that predict whether internet users participate in the mail mode, a potential bias in the model estimates will be reduced even if those panelists are removed from the data. The area under the ROC curve reveals how well the models' independent variables discriminate between unwilling onliners and the panelists of the remaining sample, where Hosmer and Lemeshow (2013, p. 177) consider values above 0.7 as a limit for acceptable discrimination. For the independent variables of the full model in Study 1, the area under the ROC curve is 0.60 and for the independent variables of the models in Study 2, it is 0.66. These rather low values indicate that nonresponse bias is not substantially reduced because the independent variables of the model correlate with the mode choice of unwilling onliners.

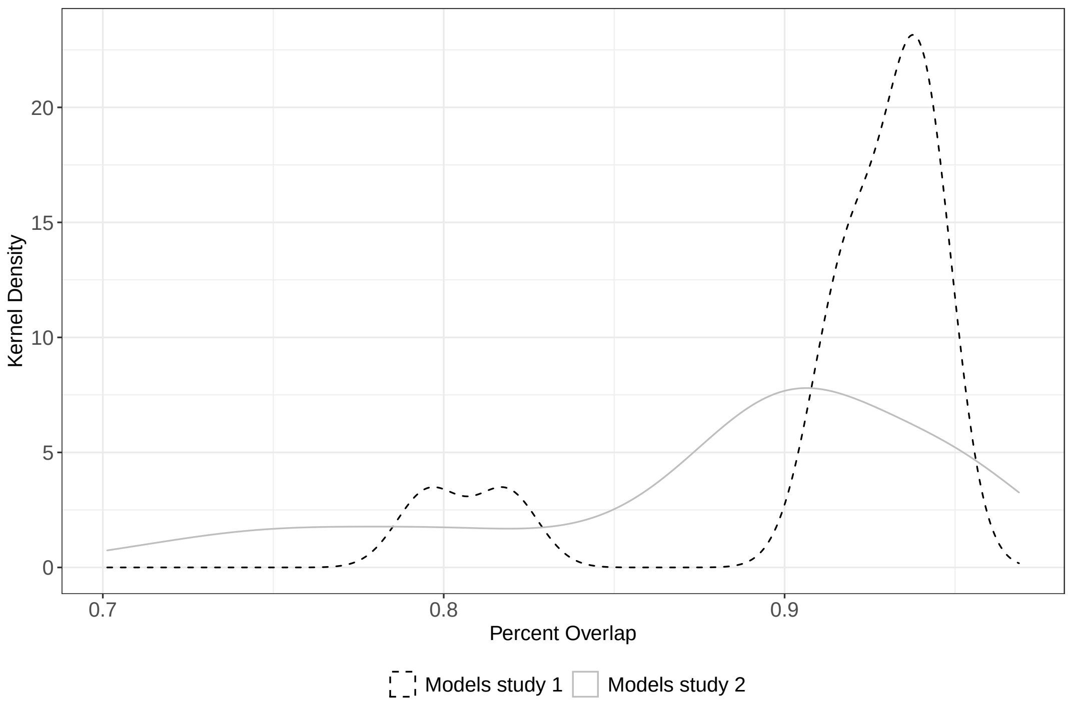

FIGURE 2.3: Density of the overlap of confidence intervals on model estimates, by study.

2.5 Summary and conclusions

This study explores how offering internet users who are unwilling to be surveyed online the option of responding in the mail mode affects nonresponse bias in a probability-based mixed-mode panel. Data from the German GESIS Panel have been used, in which 24.0% of all members became a mail mode participant after they refused to join the panel in the web mode. The results demonstrate that unwilling onliners are different in several demographic variables and private internet usage after the recruitment compared to panel members of the web mode or participants assigned to the mail mode because they were not internet users during the panel recruitment. However, the exclusion of unwilling onliners from the GESIS Panel sample hardly introduced a higher bias in estimates of demographic characteristics compared to the ALLBUS as a reference sample. An explanation for a rather small effect on mean estimates could be that the demographic characteristics of unwilling onliners fall between non-internet users in the mail mode and participants choosing the web mode. Nevertheless, a recruitment strategy that does not include unwilling onliners in the sample seems to have consequences for estimating education, as it extends an already existing overrepresentation of highly educated individuals. Further nonresponse bias analyses show how removing unwilling onliners from the analysis affects the mean and model estimates from two reproduced studies published with GESIS Panel data. The findings reveal that several means of variables used in the study models differ significantly between a full and a reduced GESIS Panel data set, indicating the presence of nonresponse bias. However, the models' point estimates and confidence intervals are largely the same after internet users in the mail mode are removed from the analysis. Accordingly, the authors from both reproduced studies would likely have come to the same conclusions if internet users had not been recruited in the mail mode.

From the total survey error perspective (e.g., Biemer & Lyberg, 2003; Groves et al., 2013), the question for online panels is whether offering internet users an option to participate in an alternative mode optimizes the balance between survey errors and survey cost. Beyond the increase in sample size, the overall results of this study give a first indication that the investment in recruiting Internet users in the mail mode may not pay off in substantially enhanced data quality of a probability-based web and mail panel. Based on these findings, a modification of the recruitment strategy potentially reduces survey costs with only a low impact on nonresponse bias. For example, expenses could be reduced by denying internet users the opportunity to participate via the mail mode or implementing a stricter push-to-web approach specifically targeted at the internet users reluctant to participate online to increase the proportion of web participants. The money saved in this way could then be invested in other design features to reduce survey errors more effectively within an available budget, such as sending reminder letters to panel members of the mail mode. Such mail reminders are currently not implemented in the GESIS Panel due to financial reasons.

However, this conclusion must be drawn with caution. Several factors may limit the ability to draw generalizations from the results of this study and should be considered before an online panel designs its recruitment strategy. First, the analysis comprises only a limited set of variables and reproduced studies. Both studies are from the field of political science, which is only one, albeit frequently used, area of research for which GESIS Panel data are used. A higher extent of nonresponse bias might be found for mean and model estimates in other areas of the social science where the variables of interest may be more strongly related to predictors of mode choice in the panel recruitment, such as media usage. This assumption is supported by significant differences in internet usage that was found between a full and a reduced data set. However, what Eckman (2016) found for coverage bias in the LISS panel seems also to be the case for nonresponse bias in the GESIS Panel: estimates of means are more affected by biases than estimates from multivariate models. Second, the results of this study are related to the specific recruitment strategy of the GESIS Panel. The proportion of internet users who do not participate in the web mode and its impact on nonresponse bias depends on the design and recruitment procedures of the online panels. Accordingly, denying internet users an alternative mode may have a different effect in panel studies from other countries and with different mixed-mode approaches. Third, data were analyzed from specific points in time with panel members of up to three cohorts responding in two different modes. Although no evidence was found in this study, Cornesse and Schaurer (2021) found decreasing sample accuracy in online panels and speculate that systematic attrition of certain population subgroups is responsible for this finding. Fourth, denying internet users the opportunity to participate in an alternative mode would most likely reduce the recruitment rate of panel studies. A smaller sample size goes along with a loss of statistical power and the potential for subsample analysis. Depending on research goals and the ability to recruit new members, online panels may have to rely on a strategy that maximizes the recruitment rate of participants.

In sum, the results of this study provide new insights for establishing or refreshing probability-based online panels using a mixed-mode design. A recruitment procedure that encourages a higher proportion of internet users to participate in the web mode will potentially reduce survey costs without risking a substantial increase of nonresponse bias. However, more research is needed to back this conclusion. For example, an experimental design to test different recruitment strategies for unwilling onliners would provide deeper evidence into how to balance survey errors and survey costs in the implementation of panel studies. In addition, further research could explore which selection process motivates internet users to refuse to participate in the web mode, or the extent to which potential nonresponse can or cannot be ignored or corrected by weighting or imputation techniques.

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Appendix

TABLE 2.6: Comparison of weighted estimates of demographic characteristics, internet usage, and political interest between GESIS Panel mode groups for members of the cohort from 2013

	Mail mode - internet users		Mail mode - non-internet users		Web mode	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.
Age groups						
Age 30 and below	8.3	(6.1;10.6)	4.3*	(2.0;6.5)	**13.2*****	(11.7;14.7)
Age 31-45	14.0	(11.2;16.8)	3.8***	(1.7;5.9)	**23.9*****	(22.0;25.8)
Age 46-60	40.4	(36.5;44.4)	28.0***	(23.1;32.9)	**38.7**	(36.6;40.9)
Age 61 and above	37.3	(33.4;41.2)	63.9***	(58.7;69.2)	**24.1*****	(22.2;26.0)
Gender						
Female	57.0	(53.0;61.1)	58.7	(53.3;64.2)	**49.0****	(46.7;51.2)
Education						
Low	26.5	(22.9;30.2)	56.0***	(50.5;61.6)	**12.3*****	(10.8;13.8)
Medium	38.0	(34.0;41.9)	30.6*	(25.6;35.6)	30.4**	(28.3;32.4)
High	35.5	(31.6;39.4)	13.3***	(9.5;17.2)	**57.3*****	(55.1;59.5)
Marital Status						
Single	15.2	(12.2;18.2)	11.8	(8.3;15.4)	**23.2*****	(21.3;25.1)
Married/RP[a], living together	65.3	(61.4;69.3)	59.3	(53.8;64.8)	63.2	(61.1;65.4)
Married/RP, living apart	3.0	(1.6;4.4)	2.8	(1.0;4.6)	2.1	(1.4;2.7)
Divorced/RP, annulled	10.2	(7.7;12.7)	13.4	(9.6;17.2)	**8.3**	(7.1;9.6)
Widowed/RP died	6.3	(4.3;8.3)	12.7**	(9.0;16.4)	**3.2****	(2.4;4.0)

(continued)

	Mail mode - internet users		Mail mode - non-internet users		Web mode	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.
Household Size						
Single household	37.3	(33.1;41.4)	61.1***	(55.4;66.9)	**17.5*****	(15.8;19.3)
Two household members	36.8	(32.7;41.0)	28.9*	(23.6;34.2)	**43.1***	(40.8;45.3)
Three and more hh members	25.9	(22.1;29.7)	10.0***	(6.4;13.6)	**39.4*****	(37.2;41.7)
Citizenship						
No German citizenship	3.5	(2.0;5.1)	1.6	(0.2;3.0)	3.1	(2.3;3.9)
Private Internet usage						
Daily	55.5	(51.4;59.6)	16.7***	(12.5;20.9)	**83.6*****	(82.0;85.3)
More than once a week	26.9	(23.2;30.6)	15.3***	(11.3;19.4)	13.8***	(12.3;15.3)
Once a week	7.9	(5.6;10.1)	4.0*	(1.9;6.0)	**1.8*****	(1.2;2.3)
Rare/once a month or less	5.1	(3.3;6.9)	8.2	(5.1;11.2)	**0.8*****	(0.4;1.2)
Never	4.6	(2.9;6.4)	55.8***	(50.3;61.3)	**0.1*****	(0.0;0.2)
Political Interest						
Very strong	3.9	(2.3;5.5)	5.7	(3.2;8.2)	6.9**	(5.8;8.1)
Strong	24.0	(20.5;27.6)	18.5	(14.2;22.8)	27.0	(25.0;29.0)
Moderately	50.3	(46.2;54.4)	52.3	(46.8;57.8)	46.4	(44.2;48.6)
Little	17.1	(14.0;20.2)	17.3	(13.2;21.5)	16.0	(14.3;17.6)
Not at all	4.7	(2.9;6.4)	6.2	(3.5;8.8)	3.7	(2.9;4.6)

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(continued)

	Mail mode - internet users		Mail mode - non-internet users		Web mode	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; [a]RP = "Registered partnership"

Tests were adjusted for multiple comparisons using the Bonferroni-Holm correction method (Holm 1979).

Asterisks mark significant differences between internet users in the mail mode and the respective other mode groups.

Bold font marks differences between non-internet users in the mail mode and panelists of the web mode at the significance level of at least .05. Data are based on panelists invited to the December/Janurary wave 2018/2019.

TABLE 2.7: Comparison of weighted estimates of demographic characteristics, internet usage, and political interest between GESIS Panel mode groups for members of the cohort from 2016

	Mail mode - internet users		Mail mode - non-internet users		Web mode	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.
Age groups						
Age 30 and below	9.7	(5.9;13.4)	4.0*	(1.0;7.0)	**18.6***	(15.5;21.7)
Age 31-45	11.1	(7.4;14.8)	1.4***	(0.0;3.0)	**20.7***	(17.9;23.5)
Age 46-60	33.1	(27.4;38.7)	10.6***	(6.1;15.2)	**33.5**	(30.2;36.8)
Age 61 and above	46.1	(39.8;52.5)	84.0***	(78.4;89.6)	**27.2***	(23.9;30.5)
Gender						
Female	53.8	(47.5;60.2)	45.5	(36.3;54.7)	45.8	(42.1;49.4)
Education						
Low	20.0	(15.0;25.1)	59.7***	(50.5;68.8)	**11.6****	(9.2;14.1)
Medium	40.5	(34.3;46.8)	24.3**	(16.4;32.1)	29.1**	(25.8;32.3)
High	39.4	(33.1;45.8)	16.1***	(9.3;22.8)	**59.3***	(55.7;62.9)
Marital Status						
Single	15.6	(10.8;20.4)	8.1*	(4.0;12.2)	**28.0***	(24.5;31.4)
Married/RP[a], living together	64.2	(57.9;70.5)	60.9	(52.0;69.9)	58.5	(54.8;62.1)
Married/RP, living apart	1.5	(0.2;2.9)	0.6	(0.0;1.8)	2.0	(0.8;3.1)
Divorced/RP, annulled	11.3	(7.4;15.3)	13.1	(7.2;18.9)	7.4	(5.6;9.2)
Widowed/RP died	7.4	(3.2;11.5)	17.3*	(10.0;24.6)	**4.2**	(2.7;5.7)

(continued)

	Mail mode - internet users		Mail mode - non-internet users		Web mode	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.
Household Size						
Single household	32.8	(26.3;39.2)	56.0***	(46.2;65.9)	**19.3*****	(16.3;22.3)
Two household members	44.6	(37.9;51.3)	41.1	(31.3;51.0)	43.7	(40.0;47.5)
Three and more hh members	22.6	(17.0;28.2)	2.8***	(0.1;5.6)	**37.0*****	(33.4;40.7)
Citizenship						
No German citizenship	1.0	(0.0;2.2)	0.6	(0.0;1.8)	**3.8****	(2.4;5.1)
Private Internet usage						
Daily	54.2	(47.9;60.6)	7.0***	(2.6;11.5)	**87.5*****	(85.1;90.0)
More than once a week	26.4	(20.8;32.1)	7.8***	(3.7;11.9)	10.5***	(8.3;12.8)
Once a week	8.5	(4.9;12.0)	1.8**	(0.0;3.9)	1.5***	(0.7;2.4)
Rare/once a month or less	5.2	(2.2;8.2)	4.6	(0.8;8.4)	0.4**	(0.0;0.8)
Never	5.7	(2.7;8.7)	78.7***	(71.7;85.7)	**0.0*****	(0.0;0.0)
Political Interest						
Very strong	7.3	(4.2;10.4)	12.7	(6.2;19.2)	10.3	(8.0;12.5)
Strong	31.2	(25.1;37.2)	28.8	(19.9;37.6)	30.2	(26.9;33.6)
Moderately	47.4	(41.0;53.7)	41.9	(32.9;51.0)	45.5	(41.9;49.2)
Little	12.9	(8.7;17.0)	14.4	(8.3;20.5)	11.8	(9.6;14.1)
Not at all	1.3	(0.0;2.6)	2.2	(0.0;4.4)	2.1	(1.1;3.1)

*

(continued)

	Mail mode - internet users		Mail mode - non-internet users		Web mode	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; [a]RP = "Registered partnership"

Tests were adjusted for multiple comparisons using the Bonferroni-Holm correction method (Holm 1979).

Asterisks mark significant differences between internet users in the mail mode and the respective other mode groups.

Bold font marks differences between non-internet users in the mail mode and panelists of the web mode at the significance level of at least .05. Data are based on panelists invited to the December/Janurary wave 2018/2019.

TABLE 2.8: Comparison of weighted estimates of demographic characteristics, internet usage, and political interest between GESIS Panel mode groups for members of the cohort from 2018

	Mail mode - internet users		Mail mode - non-internet users		Web mode	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.
Age groups						
Age 30 and below	11.7	(6.9;16.5)	1.1***	(0.0;3.2)	**28.3*****	(24.5;32.0)
Age 31-45	16.1	(12.3;19.9)	2.3***	(0.4;4.2)	**25.1*****	(22.4;27.7)
Age 46-60	32.2	(27.2;37.3)	15.7***	(10.9;20.6)	**25.7***	(23.0;28.4)
Age 61 and above	40.0	(34.2;45.7)	80.9***	(75.4;86.3)	**20.9*****	(18.2;23.7)
Gender						
Female	59.1	(53.3;64.8)	54.1	(45.8;62.3)	48.5**	(45.0;52.0)
Education						
Low	20.7	(15.4;26.0)	59.3***	(50.1;68.5)	**9.1*****	(6.9;11.3)
Medium	41.6	(35.4;47.8)	27.2*	(19.0;35.4)	27.1***	(23.9;30.3)
High	37.7	(31.6;43.9)	13.5***	(7.2;19.9)	**63.8*****	(60.3;67.3)
Marital Status						
Single	18.1	(13.2;23.0)	3.9***	(0.2;7.5)	**34.4*****	(30.5;38.3)
Married/RP, living together	64.9	(58.7;71.0)	58.0	(48.3;67.6)	55.0	(51.1;58.8)
Married/RP, living apart	2.2	(0.4;4.0)	4.0	(0.0;8.2)	1.3	(0.6;2.0)
Divorced/RP, annulled	8.8	(5.4;12.2)	10.6	(5.1;16.0)	5.7	(4.2;7.2)
Widowed/RP died	6.0	(2.4;9.6)	23.6***	(15.1;32.1)	**3.6**	(2.2;5.0)

(continued)

	Mail mode - internet users		Mail mode - non-internet users		Web mode	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.
Household Size						
Single household	37.6	(31.3;43.8)	50.8*	(41.3;60.4)	**16.2*****	(13.7;18.7)
Two household members	40.1	(33.9;46.3)	37.1	(27.7;46.6)	40.1	(36.4;43.7)
Three and more hh members	22.3	(17.1;27.5)	12.0**	(6.4;17.7)	**43.7*****	(39.9;47.5)
Citizenship						
No German citizenship	1.6	(0.2;3.0)	2.0	(0.0;4.0)	2.4	(1.4;3.5)
Private Internet usage						
Daily	55.1	(49.4;60.9)	7.0***	(3.0;11.0)	**87.4*****	(85.3;89.6)
More than once a week	25.2	(20.0;30.4)	6.1***	(2.3;9.9)	**11.1*****	(9.1;13.2)
Once a week	8.5	(5.2;11.7)	2.9**	(0.9;5.0)	1.1***	(0.4;1.8)
Rare/once a month or less	7.5	(4.7;10.2)	11.5	(6.0;17.0)	**0.3*****	(0.0;0.6)
Never	3.7	(1.8;5.6)	72.5***	(65.3;79.8)	**0.0*****	(0.0;0.0)
Political Interest						
Very strong	6.5	(3.5;9.4)	10.9	(4.7;17.1)	9.6	(7.4;11.9)
Strong	27.2	(21.2;33.2)	37.9	(28.3;47.5)	31.7	(28.2;35.1)
Moderately	50.6	(44.3;56.9)	41.7	(32.3;51.2)	43.9	(40.1;47.7)
Little	14.1	(9.9;18.2)	8.8	(4.2;13.5)	11.9	(9.2;14.7)
Not at all	1.6	(0.2;3.0)	0.6	(0.0;1.7)	2.9	(1.1;4.7)

*

(continued)

	Mail mode - internet users		Mail mode - non-internet users		Web mode	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; [a]RP = "Registered partnership"

Tests were adjusted for multiple comparisons using the Bonferroni-Holm correction method (Holm 1979).

Asterisks mark significant differences between internet users in the mail mode and the respective other mode groups.

Bold font marks differences between non-internet users in the mail mode and panelists of the web mode at the significance level of at least .05. Data are based on panelists invited to the December/Janurary wave 2018/2019.

TABLE 2.9: Comparison of weighted estimates between a reduced GESIS Panel data set without unwilling onliners, a full GESIS Panel data set and a benchmark survey restricted to participants aged 70 and below

	GESIS Panel (reduced data set)		GESIS Panel (full data set)		ALLBUS 2018	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.
Age groups						
Age 30 and below	17.0	(15.5;18.5)	15.3	(14.0;16.5)	**18.5**	(17.1;20.0)
Age 31-45	24.2	(22.8;25.5)	22.7	(21.5;23.9)	**26.2**	(24.5;27.8)
Age 46-60	37.6	(36.1;39.2)	38.9	(37.5;40.3)	**35.1**	(33.3;36.9)
Age 61 and above	21.2	(19.9;22.5)	23.2	(22.0;24.4)	**20.1**	(18.6;21.6)
Gender						
Female	50.3	(48.7;52.0)	52.1	(50.7;53.6)	**49.1**	(47.2;51.0)
Education						
Low	14.2	(13.0;15.3)	15.9*	(14.8;17.0)	**21.1*****	(19.6;22.7)
Medium	29.8	(28.3;31.3)	32.0	(30.6;33.4)	33.8**	(32.0;35.6)
High	56.0	(54.4;57.7)	52.1***	(50.6;53.6)	**45.1*****	(43.2;47.0)
Marital Status						
Single	27.8	(26.2;29.4)	25.8*	(24.4;27.2)	**30.4***	(28.6;32.1)
Married/RP[a], living together	58.9	(57.2;60.6)	59.9	(58.4;61.4)	55.2	(53.3;57.1)
Married/RP, living apart	1.8	(1.4;2.2)	2.0	(1.6;2.4)	2.0	(1.5;2.6)
Divorced/RP, annulled	8.4	(7.5;9.3)	8.9	(8.1;9.7)	9.7	(8.6;10.8)
Widowed/RP died	3.1	(2.5;3.6)	3.4	(2.9;3.9)	2.6	(2.0;3.3)

(continued)

Variable for comparison	GESIS Panel (reduced data set) Estimate	GESIS Panel (reduced data set) 95% Conf. Int.	GESIS Panel (full data set) Estimate	GESIS Panel (full data set) 95% Conf. Int.	ALLBUS 2018 Estimate	ALLBUS 2018 95% Conf. Int.
Household Size						
Single household	20.9	(19.6;22.3)	23.5**	(22.2;24.7)	**18.0****	(16.6;19.5)
Two household members	38.7	(37.0;40.3)	38.6	(37.2;40.1)	43.1	(41.2;45.0)
Three and more hh members	40.4	(38.7;42.2)	37.9*	(36.4;39.4)	**38.9*****	(37.0;40.7)
Citizenship						
No German citizenship	3.0	(2.5;3.6)	2.9	(2.4;3.4)	**7.4*****	(6.4;8.4)
Private Internet usage						
Daily	79.9	(78.6;81.1)	75.5***	(74.3;76.8)	**78.0**	(76.5;79.6)
More than once a week	11.7	(10.7;12.7)	14.4***	(13.4;15.4)	**8.1*****	(7.1;9.1)
Once a week	1.7	(1.3;2.1)	2.8**	(2.3;3.3)	2.1	(1.6;2.7)
Rare/once a month or less	1.5	(1.1;1.9)	2.3*	(1.9;2.7)	1.7	(1.2;2.1)
Never	5.3	(4.6;6.0)	5.0	(4.4;5.6)	**10.1*****	(9.0;11.2)
Political Interest						
Very strong	7.8	(6.8;8.7)	7.2	(6.4;8.0)	**10.3*****	(9.2;11.5)
Strong	26.4	(25.0;27.9)	25.7	(24.4;27.0)	27.2	(25.6;28.9)
Moderately	46.6	(44.9;48.3)	47.6	(46.1;49.1)	46.6	(44.7;48.5)
Little	15.6	(14.3;16.8)	15.9	(14.8;17.0)	**12.4*****	(11.1;13.6)
Not at all	3.6	(2.9;4.3)	3.6	(3.0;4.2)	3.4	(2.7;4.1)

*

(continued)

	GESIS Panel (reduced data set)		GESIS Panel (full data set)		ALLBUS 2018	
Variable for comparison	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.	Estimate	95% Conf. Int.

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; [a]RP = "Registered partnership"

Tests were adjusted for multiple comparisons using the Bonferroni-Holm correction method (Holm 1979).

Asterisks mark significant differences between the reduced GESIS Panel data set and the respective other mode groups.

Bold font marks differences between the full GESIS Panel data set and ALLBUS at the significance level of at least .05.

GESIS Panel data sets are based on panelists invited to the December/Janurary wave 2018/2019.

TABLE 2.10: Nonresponse bias in means of variables used by the two reproduced studies when internet users in the mail mode are excluded from the estimations

Study 1 Gherghina and Geissel (2019)	Study 2 Heinisch and Wegscheider (2020)
Preference for citizens as decision-makers**	**Trusteeship democracy***
Satisfaction with democracy*	**Anti-pluralism*****
Satisfaction with the government	Deliberative proceduralism
Parliament should decide on laws**	Majoritarianism
Political interest*	**Populist attitudes****
Civic engagement	**Right-wing authoritarianism*****
Political news	**Anti-immigration attitudes***
Education***	Left-wing economy
Age***	Left-right scale
	Political interest**
	Income
	Education***
	Gender (female)**
	Age***

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

TABLE 2.11: Comparision of odds ratios and standard errors (in brackets) from linear regression models: original, and reproduced with the full and reduced GESIS Panel data sets, Gherghina and Geissel (2019)

	Model 1			Model 2		
	original	repr. full data	repr. reduced data	original	repr. full data	reduced data
Satisfaction with democracy	0.95^{**}	0.95^{*}	0.95	0.94^{**}	0.94^{*}	0.95
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Satisfaction with the government	0.92^{***}	0.92^{***}	0.92^{**}	0.91^{***}	0.92^{***}	0.92^{**}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Parliament should decide on laws	0.75^{***}	0.75^{***}	0.75^{***}	0.77^{***}	0.77^{***}	0.76^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Political interest	1.07	1.06	1.11	1.18^{***}	1.18^{**}	1.20^{**}
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)
Civic engagement	1.10	1.10	1.08	1.12^{*}	1.12	1.10
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)
Political news				0.92^{*}	0.92	0.93
				(0.05)	(0.05)	(0.05)
Education				0.94	0.90	0.88
				(0.06)	(0.06)	(0.07)
Age				0.88^{***}	0.90^{*}	0.93
				(0.05)	(0.05)	(0.05)
Observations	3248	3239	2539	3192	3180	2499

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

DV = “Preference for citizens as decision-makers”

TABLE 2.12: Comparision of coefficients and standard errors (in brackets) from linear regression models: original, and reproduced with the full and reduced GESIS Panel data sets (anti-pluralism and deliberative proceduralism), Heinisch and Wegscheider (2020)

	Anti-pluralism			Deliberative proceduralism		
	original	repr. full data	repr. reduced data	original	full data set	reduced data set
Populist attitudes	0.39***	0.38***	0.37***	−0.05	−0.05	−0.01
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Right-wing authoritarianism	0.26***	0.25***	0.21***	0.04	0.04	0.04
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Anti-immigration attitudes	0.02	0.03	0.04	−0.03	−0.04	−0.03
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Left-wing economy	0.05	0.06	0.03	0.09**	0.09**	0.08**
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Left-right scale	0.02	0.03	0.06	0.08	0.07	0.13
	(0.10)	(0.10)	(0.11)	(0.07)	(0.07)	(0.08)
Left-right scale^2	−0.02	−0.02	−0.06	−0.11	−0.10	−0.16*
	(0.10)	(0.10)	(0.12)	(0.07)	(0.07)	(0.08)
Political interest	−0.10***	−0.10***	−0.11***	0.10***	0.10***	0.12***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Income	−0.04	−0.04	−0.06*	0.08***	0.08***	0.08***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Education	−0.02	−0.02	−0.01	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Gender (female)	0.01	0.01	0.01	−0.00	−0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	−0.01	−0.01	−0.01	0.11***	0.11***	0.10***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Observations	1807	1802	1462	1807	1802	1462

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

TABLE 2.13: Comparision of coefficients and standard errors (in brackets) from linear regression models: original, and reproduced with the full and reduced GESIS Panel data sets (majoritarianism and trusteeship democracy), Heinisch and Wegscheider (2020)

	Majoritarianism			Trusteeship democracy		
	original	repr. full data	repr. reduced data	original	full data set	reduced data set
Populist attitudes	0.04	0.04	0.02	-0.43^{***}	-0.43^{***}	-0.46^{***}
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Right-wing authoritarianism	0.16^{***}	0.16^{***}	0.17^{***}	0.19^{***}	0.19^{***}	0.17^{***}
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Anti-immigration attitudes	0.19^{***}	0.19^{***}	0.21^{***}	-0.02	-0.02	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Left-wing economy	-0.15^{***}	-0.15^{***}	-0.16^{***}	-0.14^{***}	-0.14^{***}	-0.15^{***}
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Left-right scale	0.17	0.17^{*}	0.13	0.28^{**}	0.28^{**}	0.32^{**}
	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)	(0.10)
Left-right scale^2	-0.08	-0.07	-0.04	-0.22^{*}	-0.22^{*}	-0.26^{*}
	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)	(0.11)
Political interest	0.03	0.04	0.05	-0.04	-0.04	-0.02
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Income	0.02	0.02	0.03	-0.02	-0.02	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Education	-0.02^{*}	-0.02^{*}	-0.02^{*}	0.01	0.01	0.0001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Gender (female)	-0.01	-0.01	-0.01	-0.03^{**}	-0.03^{**}	-0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	-0.06^{**}	-0.06^{**}	-0.06^{**}	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	1807	1802	1462	1807	1802	1462

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

Chapter 3

An Experimental Comparison of Three Strategies for Converting Mail Respondents in a Probability-Based Mixed-Mode Panel to Internet Respondents

Abstract

In recent years, web-push strategies have been developed in cross-sectional mixed-mode surveys to improve response rates and reduce the costs of data collection. However, pushing respondents into the more cost-efficient web mode has rarely been examined in the context of panel surveys. This study evaluates how a web-push intervention affects the willingness of panel members to switch survey modes from mail to web. We tested three web-push strategies in a German probability-based mixed-mode panel by randomly assigning 1,895 panelists of the mail mode to one of three conditions: (1) the web option was offered to panelists concurrently with the paper questionnaire including a promised €10 incentive for completing the survey on the web, (2) the web option was presented sequentially two weeks before sending

the paper questionnaire and respondents were also promised an incentive of €10, or (3) same sequential web-first approach as for condition 2, but with a prepaid €10 incentive instead of a promised incentive. The study found that a sequential presentation of the web option significantly increases the web response in a single survey but may not motivate more panelists to switch to the web mode permanently. Contrary to our expectation, offering prepaid incentives neither improves the web response nor the proportion of mode switchers. Overall, all three web-push strategies show the potential to effectively reduce survey costs without causing differences in panel attrition after five consecutive waves. Condition 2, the sequential web-first design combined with a promised incentive was most effective in pushing respondents to switch to the web mode and in reducing costs.

3.1 Introduction

With the spread of web surveys, several probability-based online panel infrastructures have been established in the social sciences (Blom et al., 2015; Bosnjak et al., 2016; Callegaro et al., 2014; Das et al., 2018; Weiß et al., 2020). Online panels use web-based questionnaires as a fast and cost-efficient method for academic researchers to collect survey data on a variety of topics. In contrast to volunteer opt-in panels, probability-based online panels pre-recruit a pool of members based on probability sampling methods that allow unbiased inference about the general population (Callegaro & Disogra, 2008). In this context, online panels must deal with individuals who lack internet access to reduce possible errors of non-observation (Couper et al., 2007).

One strategy to include the non-internet population was to implement a mixed-mode design that combined the web mode with one or more alternative survey modes (de Leeuw, 2005, 2018; Dillman et al., 2014). Such a mixed-mode design has the potential to increase response rates and reduce nonresponse errors by offering an alternative mode option to internet users. In this way, you can recruit people who are willing to participate in a panel study but are reluctant to use the web mode.

However, convincing more respondents to participate over the internet reduces costs by obtaining fewer responses by the more expensive mail, telephone, or face-to-face modes of responding. In recent years, survey researchers have developed strategies for cross-sectional studies to push more respondents to participate in the web mode rather than in a more expensive alternative (Dillman, 2017). Less attention has been paid to pushing panel members to the web mode in an ongoing mixed-mode panel where participants were unwilling or unable to respond via the internet during panel recruitment.

This paper aims at filling this gap by investigating whether and how panel members who originally chose the mail mode for responding can be switched to web. We tested three different web-push strategies that combine the order of presenting the web mode and the use of incentives. The experiment was implemented in a German probability-based mixed-mode panel to evaluate how web-push conditions affect (1) the web completion in a single wave, and (2) respondents' willingness to permanently switch to the web mode for the upcoming surveys. In addition, we analyze the differences between the conditions in terms of (3) panel attrition, and (4) the survey costs after five consecutive waves.

3.2 Background

3.2.1 Literature on sequential mode requests and the use of incentives in web-push surveys

Over the past decade, a growing number of mixed-mode surveys has been using methods to increase response by the web mode (Dillman, 2017). Such web-push surveys usually send study invitations by postal mail to ask for response via the internet rather than by alternative mode options. As we discuss in the following section, web-push surveys have mainly been tested in a cross-sectional setting to increase the proportion of web response, although this was not directly associated with improving overall response rates.

Several studies of mixed-mode surveys have demonstrated that web response rates depend on the order in which the web option is offered to respondents. A meta-analysis by Medway and Fulton (2012) compared results of mail-only surveys with a mixed-mode design that offers respondents a web option along with a mail questionnaire in the initial survey request (concurrent design). The study showed that the concurrent design achieved slightly lower response rates than offering the mail-only option, but the majority of individuals (84%) responded by paper instead of web (16%). This result was consistent with evidence from other studies in which mail surveys with a concurrent web option achieved only modest response by the web mode (Holmberg et al., 2010; Matthews et al., 2012; Tancreto et al., 2012). In contrast, web response rates increased substantially in a mixed-mode design were respondents are initially asked to participate in a web survey before a mode alternative was offered to non-respondents at a later stage in the implementation process (sequential web-first design). Dillman (2017) summarized the results of ten experimental tests of such sequential web-first studies that demonstrated an average web participation of 60%, even if the mean response rate was lower than for the mail-only comparisons. Subsequent studies confirmed the positive effect of a sequential web-first design on the proportion of web respondents in surveys on varying topics and with different samples (Biemer et al., 2018; Bucks et al., 2020; Matthews et al., 2012; Mauz et al., 2018; McMaster et al., 2017; Patrick et al., 2018).

Incentives are another design feature that was tested in cross-sectional mixed-mode studies to enhance web response. Messer and Dillman (2011) found that a $5 prepaid incentive offered in a sequential web-first design increased the usage of the web mode by around 18 percentage points (13% vs. 31%) compared to a no incentive group. A study conducted by Biemer et al. (2018) tested how two promised incentive treatments ($10 vs. $20) affect response rates and the choice of survey modes in a mixed-mode survey. Their experimental design combined both incentive treatments with a concurrent vs. a sequential approach of web and mail modes. The results showed that offering respondents a higher incentive increases web usage in the sequential web-first design, but not if both modes were offered concurrently. The paper introduced a second incentive along with a concurrent design that promised respondents an additional $10 incentive for web completion. This new protocol not only improved response rates but also motivated respondents to choose the web mode at nearly the same level as used for the sequential web-first design for both incentive treatments.

While most of the web-push studies have been implemented in cross-sectional surveys, there is comparatively less evidence on how web-push methods work in an ongoing longitudinal study. Introducing a web-push intervention in a running panel faces somewhat different challenges and priorities, compared to a cross-sectional survey (Bianchi et al., 2017; Jäckle et al., 2015). On the one hand, it can be assumed that the situation of panel members differs from that of sample members invited to a single survey in terms of trust, experience, and habits. For instance, members of a panel might develop response habits, which means they use repeated patterns of behavior when answering surveys to reduce efforts of participation (Lemay, 2009; Lugtig, 2014). Such response habits can affect individuals' perceptions and awareness of the invitation material and their behavior when participating in a single panel wave. On the other hand, panel studies are usually subject to panel attrition. The loss of respondents over time is a major concern since many research questions require multiple measurements of the same sample unit, and dropouts cannot simply be replaced by new participants. In that regard, panelists could perceive a web-push intervention as intrusive and annoying, particularly if they feel pushed too harshly. Lemay (2009) and Lugtig (2014) call such an unpleasant experience a "shock", which they see as one reason for panel attrition.

In contrast to cross-sectional surveys, panel studies might also provide some favorable conditions for a web-push intervention. It is reasonable that panel members have already established a certain level of trust and commitment to the panel infrastructure. For instance, respondents with an initial skepticism towards the web mode could now trust that their data will be treated with sufficient care by the survey sponsor. Additionally, many online panels offer their members a monetary incentive with each survey (Blom et al., 2015), which is why panelists may have a high degree of confidence that incentives offered in a web-push intervention will actually be received.

To test the effect of a sequential mixed-mode design in a longitudinal study, Jäckle et al. (2015) implemented a web option and face-to-face follow-up interviews in the fifth wave of the Understanding Society Innovation Panel. The study found that 35% of all households responded by the web mode, obtaining slightly lower overall response rates for the mixed-mode approach than for the face-to-face group. Jäckle et al. (2015) showed that the web response rate by households increases with offering higher prepaid cash incentives as well as with an additional promised incentive for an early web completion (see Carpenter and Burton (2018) for further tests). In addition to this study, further web-push strategies have been tested as follow-up surveys to longitudinal studies. The findings of this research confirm that the survey design can improve the web response rate. For example, responses via the web were enhanced by a targeted sequential web-first design where respondents were offered different web-push protocols depending on their likelihood of responding by web (Freedman et al., 2018) or using an email augmentation approach (see Millar & Dillman, 2011) where respondents receive supportive emails as an additional contact mode (Patrick et al., 2018).

Overall, previous research suggests that a sequential web-first design and the use of monetary incentives effectively increases web response in cross-sectional mixed-mode studies, but not necessarily overall response rates. In contrast, there is less evidence for the response effect of web-push methods in longitudinal surveys. To the best of our knowledge, it has not been evaluated whether respondents of a panel study are willing to switch from the mail mode to the web after they declined to participate using the web mode in the study recruitment. This paper tests different web-push conditions for a running mixed-mode panel, developed based on theoretical assumptions described in the next section.

3.2.2 Theoretical background and hypotheses

According to the theory of social exchange, respondents are more willing to comply with a survey request if they expect and trust that the benefits of participating will exceed the perceived costs involved (Dillman et al., 2014). To increase the willingness to respond, this framework suggests that survey participation should be as convenient and effortless as possible. Sample members who receive a postal invitation to complete a survey via the web instead of paper are confronted with transition costs. Transition costs occur because respondents have to switch the medium from paper to a web-enabled device on which access data need to be entered. In a sequential mixed-mode design, respondents must make these efforts if they intend to participate since no alternative mode is immediately available. In a concurrent web/mail design, however, a mail questionnaire offers an eye-catching and immediately accessible response option. It is, therefore, attractive even for respondents with a high web affinity. Holmberg et al. (2008) found indications for this mechanism among respondents who expressed preferences to participate via the internet. Following this assumption, we expect that a sequential web-first design increases web response in a panel context as well, since initially offering the web mode alone interrupts potential response habits of panel members and draws attention to the web option.

H1: *Offering only the web mode in the initial contact results in a higher proportion of panelists completing the survey using the web mode than offering the web and mail modes concurrently.*

With regard to incentives, social exchange theory suggests that offering prepaid incentives with the survey invitation is an effective way to increase response rates by drawing attention to the request, establishing trust in the intention of the study, and by triggering a sense of reciprocity (Dillman et al., 2014). There is clear evidence that prepaid incentives are more effective in increasing response rates than promised ones, which is especially well-documented for mail surveys (Church, 1993; Edwards et al., 2002; Mercer et al., 2015; Singer & Ye, 2013). Research from web-push studies also showed that prepaid incentives are an effective method to improve web response rates in cross-sectional surveys (Messer & Dillman, 2011). We believe that incentives in general could be effective for web-push of panelists who have previously answered surveys in the mail mode, as they have to abandon their familiar procedure of participating by mail and face the challenge of trying a new mode. From the perspective of the social exchange theory, the difference in terms of response rates between both types of incentives may be smaller in an ongoing panel than in cross-sectional studies, because recipients of promised incentives may have greater trust that the incentive will be sent to them. However, we still expect that prepaid monetary incentives are more effective in increasing web response than promised incentives by triggering a sense of reciprocity and attracting attention to the web option.

H2: *Offering a prepaid incentive for responding in the web mode results in a higher proportion of panelists completing the survey using the web mode than offering a promised incentive.*

The ultimate goal of implementing a web-push strategy in an ongoing panel is to motivate panelists to switch the mode from mail to web permanently. The web-push strategies tested in this study assume that panel members will be more willing to switch to the web mode for future waves after they have agreed to use it once. Following this assumption, we expect that the treatment which performs best to push respondents to use the web mode in a single wave, will finally result in a higher proportion of panelists who give their consent to switch to the web mode for upcoming surveys.

H3: *Offering only the web mode in the initial contact results in a higher proportion of panelists permanently switching to the web mode than offering the web and mail mode concurrently.*

H4: *Offering a prepaid incentive for responding in the web mode results in a higher proportion of panelists permanently switching to the web mode than offering a promised incentive.*

This paper includes further analyses to evaluate the effectiveness and efficiency of different web-push strategies from a long-term perspective. As mentioned above, a possible consequence of a web-push intervention could be that participants leave the panel afterwards. The web-push strategies tested in this study may differ in their impact on panel attrition. An effective treatment could, for example, nudge more panelists to switch modes who in turn have a rather low propensity to participate in web surveys. Consequently, those panelists may be more likely to attrite after subsequent waves, thus contradicting the short-term effectiveness of the treatment. To test these assumptions, we investigate whether panel attrition varies between different web-push strategies and the mode of response for five consecutive waves after the intervention.

A main goal of pushing panel members from mail to web is to improve the cost-efficiency of surveys. Compared to a cross-sectional survey, a successful web-push in a panel study has an even greater potential for cost savings, as the expenses for the single surveys cumulate over waves. Since the web-push strategies of this study are connected to different financial investments and may differ in the number of mode switchers and panel attrition, we compare survey costs between the conditions for the web-push intervention and the five waves that follow.

3.3 Methods

3.3.1 Data

This study is based on data from the GESIS Panel, a German probability-based mixed-mode panel operated by GESIS - Leibniz Institute for the Social Sciences (Bosnjak et al., 2018). Since the beginning of 2014, the GESIS Panel has been a fully operational panel infrastructure open for data collection to the academic research community. In October 2018, the panel consisted of 5,734 members from an initial cohort sampled in 2013, and two refreshment cohorts sampled in 2016, and 2018. The target population is German-speaking individuals aged 18 years and older (for the initial cohort between

18 and 70 years) permanently residing in private households in Germany. All panelists are recruited from random samples drawn from the municipal population registers. The recruitment rate for the initial cohort is 31.6%, for the second cohort is 20.2%, and for the third cohort is 18.4% (correspond to the AAPOR response rate 5). Detailed information about the GESIS Panel sampling and recruitment procedure can be found at Bosnjak et al. (2018), and for the three cohorts at Schaurer et al. (2014), Schaurer and Weyandt (2016), and Schaurer et al. (2020).

The data collection of the GESIS Panel is administered in two modes, namely in web-based surveys (web mode) and paper-and-pencil surveys sent via postal mail (mail mode). The mode assignment takes place in a multi-step recruitment procedure that encompasses a face-to-face recruitment interview and a first self-administered profile survey. At the end of the recruitment interview, internet-using respondents were presented the web mode as the default option for participation. However, if respondents were not willing to participate in web surveys, they could opt for the mail mode. Participants who did not use the internet at the time of panel recruitment were automatically assigned to the mail mode. After the recruitment procedure, participants have not actively been offered an option to switch survey modes.

The survey waves of the GESIS Panel take place every two months, each taking about 20 minutes. Every panel member, independently of participation mode, receives a survey invitation sent by mail, including a prepaid cash incentive of €5. Web mode panelists are additionally invited by email and receive a maximum of two email reminders as long as they have not answered the survey. Participants of the mail mode do not receive a regular reminder due to the costs of sending letters by post.

This study was conducted by implementing a web-push experiment in the GESIS Panel October/November survey 2018 (Bretschi et al., 2018; GESIS, 2020). For this wave, Table 3.1 provides an overview of the modes of participation and internet usage among panelists of the mail mode by the recruitment cohorts. In total, 33% of all panelists were invited to the mail mode in October 2018, with 73.1% stating that they use the internet for private purposes.

TABLE 3.1: Modes of participation (and internet usage among mail mode panelists) by recruitment cohort in the October/November 2018 survey

	Cohort 2013		Cohort 2016		Cohort 2018		Total	
	%	(n)	%	(n)	%	(n)	%	(n)
Web Mode:	68.0	(2035)	65.3	(826)	66.2	(978)	67.0	(3839)
Mail Mode:	32.0	(957)	34.7	(438)	33.8	(500)	33.0	(1895)
Internet users:	74.9	(695)	71.7	(301)	71.0	(333)	73.1	(1329)
Non-internet users:	25.1	(233)	28.3	(119)	29.0	(136)	26.9	(488)
Total:	100.0	(2992)	100.0	(1264)	100.0	(1478)	100.0	(5734)

Note:
Internet usage are measured in the August-/September survey 2018. Missing values were imputed where possible by data of previous GESIS Panel waves. Existing deviations are the result of remaining item nonresponse. Question in the August/September survey 2018: "Do you use the internet at least occasionally for private purposes, whether through computers, laptops, tablets or smartphones at home, at work or anywhere else?".

3.3.2 Experimental design

We tested our hypotheses by developing an incompletely crossed experimental design with two factors: 1) time of presenting the web-option (concurrent vs. sequential mixed-mode design) and 2) type of incentive (promised vs. prepaid incentive). Our design included three conditions rather than a fully crossed experimental design with four conditions, as an a priori power analysis suggested that statistical power would not be sufficient to reliably detect an effect that we had expected for the web-push treatments. Furthermore, the web option was offered to all participants of the mail mode, although around 27% of those panelists reported that they do not use the internet for private purposes. This approach was chosen to avoid reducing the sample size by erroneously excluding internet users, as the accuracy and timeliness of data on internet use was unclear. All 1,895 active panel members of the mail mode were randomly assigned to one of three experimental conditions (Table 3.2).

In condition 1, the web option was offered to respondents concurrently with the mail questionnaire at the regular start of the wave. All respondents received the usual invitation documents, which included an invitation letter, a mail questionnaire, a return envelope, and €5 regular incentive. The invitation letter informed respondents

TABLE 3.2: Experimental treatments by condition

Condition (n)	Week -2 Early Invitation	Week 0 Regular Invitation	Week +2 Reminder
1) concurrent/promised (631)		• ✉ login credentials + €10 promised • mail questionnaire • €5 regular incentive • return envelope	• ✉ login credentials + €10 promised
2) sequential/promised (631)	• ✉ login credentials + €10 promised	• ✉ login credentials + €10 promised • mail questionnaire • €5 regular incentive • return envelope	
3) sequential/prepaid (633)	• ✉ login credentials + €10 prepaid	• ✉ login credentials • mail questionnaire • €5 regular incentive • return envelope	

Note:
Field period of condition 1: 19 Oct. 2018 - 11 Dec 2018
Field period of conditions 2 and 3: 05 Oct. 2018 - 11 Dec 2018

of the opportunity to complete the survey via the web, including access information in the form of a survey URL and personal login credentials. Access data were also printed on the cover page of the mail questionnaire, as there are indications that some respondents tend to focus on the questionnaire while ignoring other materials in a mailing (Tancreto et al., 2012). Two weeks after the start of the October/November wave, respondents who had not yet completed the survey online received a reminder letter with login information to the web mode but without a mail questionnaire. This reminder ensures that respondents were contacted twice in each condition. All members of condition 1 were promised a €10 incentive for completing the survey on the web.

Members of condition 2 were offered the web option sequentially two weeks before sending them the mail questionnaire with the regular start of the October/November wave. The early invitation letter informed respondents about the option to take the survey via the web. The letter also signaled to panelists unwilling or unable to participate in the web mode that the mail questionnaire would arrive with the regular invitation. All respondents in condition 2 received the usual invitation documents after two weeks, in which the web option and login information were presented on the invitation letter and the first page of the questionnaire. We also promised respondents of condition 2 a €10 incentive for completing the survey on the web.

In condition 3, respondents were offered the web option in the same sequential order and with the same procedure as in condition 2. But instead of promising respondents a €10 incentive after completing the questionnaire on the internet, all participants of condition 3 received an unconditional €10 incentive with the early invitation letter.

The content and visual presentation of all invitation letters were designed according to the principles of the social exchange theory (Dillman et al., 2014). English translations of the invitation letters as well as the distribution of demographic characteristics by the experimental conditions (Table 3.6) can be found in the appendix.

3.3.3 Analysis plan

This study is interested in how the web-push conditions affect four main outcomes: (1) web completion and (2) the willingness to switch to the web mode in a single wave, (3) panel attrition and (4) survey costs after five waves following the intervention. The hypotheses relate to the results of web completion and the willingness to web mode switching in a single wave. This analysis plan outlines all outcomes and how hypotheses were tested.

Analysis of web completion and web mode switching

The web-push treatments of this study were designed to trigger the willingness of panel members to respond the October/November survey in the web mode, but with the ultimate goal to maximize the proportion of long-term web mode switchers. To evaluate the overall effectiveness of the treatments, we investigated the proportion of panel members who 1) completed the survey online, and 2) who agreed to switch to the web mode in relation to all panelists invited to the experiment. By referring to all panel members, these two outcomes combine the effect of up to three selection steps which can be affected differently by the web-push treatments. In the first step, panelists must decide to participate in the survey. In the second step, those who participate must agree to complete the questionnaire online. Finally, those who responded online must accept switching to the web mode for upcoming waves. We introduce three completion rates for these selection steps, which we then cumulate in final response rates to test our hypotheses (oriented on Callegaro & Disogra, 2008).

At step one, a completion rate (COMR) is measured as the proportion of panelists who fully or partially completed the October/November survey 2018 in the mail or web mode over all eligible panel members invited to the web-push experiment.

$$\text{Completion Rate (COMR)} = \frac{\mathrm{I_{Web}} + \mathrm{I_{Mail}} + \mathrm{P_{Web}} + \mathrm{P_{Mail}}}{\mathrm{I_{Web}} + \mathrm{I_{Mail}} + \mathrm{P_{Web}} + \mathrm{P_{Mail}} + \mathrm{R} + \mathrm{NC} + \mathrm{O}} \tag{3.1}$$

where $\mathrm{I_{Web}}$ are Interviews in the web mode, $\mathrm{I_{Mail}}$ are Interview in the mail mode, $\mathrm{P_{Web}}$ are partial Interviews in the web mode, $\mathrm{P_{Mail}}$ are partial Interviews in the mail mode, R are cases actively refusing, NC are noncontacts, and O are other cases. A partially completed survey comprises between 50% and 80% of answered questions.

At step two, the Web Completion Rate (WCOMR) is calculated as the proportion of panel members who fully or partially completed the survey online over all panelists of the experiment who fully or partially completed the survey by mail or web.

$$\text{Web Completion Rate (WCOMR)} = \frac{\mathrm{I_{Web}} + \mathrm{P_{Web}}}{\mathrm{I_{Web}} + \mathrm{I_{Mail}} + \mathrm{P_{Web}} + \mathrm{P_{Mail}}} \tag{3.2}$$

Panelists are counted as web mode participants even if they additionally returned a mail questionnaire (n = 31). If respondents entered the web survey but broke off and sent back a partially or fully completed mail questionnaire, they were considered as mail mode respondents (n = 12).

At step three, the Web Switch Rate (WSR) is defined as the proportion of panelists who switched to the web mode over all panelists who fully or partially completed the questionnaire online.

$$\text{Web Switch Rate (WSR)} = \frac{\text{WS}}{\text{I}_{\text{Web}} + \text{P}_{\text{Web}}} \tag{3.3}$$

where WS are valid cases who agreed to switch to the web mode in subsequent waves. At the end of the online questionnaire, respondents were asked whether they agreed to switch to the web mode for upcoming waves. Panel members who had agreed were requested to provide a valid email address to send them additional invitations in future waves. Participants stayed in the mail mode if they refused to share an email address or if an email address was unavailable.

By cumulating these single completion rates, we evaluate the overall effect of the treatments on all panelists who were invited to the study. Accordingly, our hypotheses were tested in two consecutive steps. In the first step, we examined how the conditions affect the Cumulative Web Completion Rate (CUM-WCOMR), which multiplies the completion rate with the web completion rate.

$$\text{Cumulative Web Completion Rate (CUM-WCOMR)} = \text{COMR x WCOMR} \tag{3.4}$$

The CUM-WCOMR is the proportion of those respondents who fully or partially completed the survey via the web mode over all eligible panel members invited to the experimental conditions. We tested Hypothesis 1 that offering the web mode first in a mode sequence is more effective than providing mail and web together by comparing the CUM-WCOMR between condition 1 and condition 2, where both conditions were offered with a promised incentive. To evaluate Hypothesis 2 and test if a prepaid incentive pushes more participants to the web than a promised incentive, we compared the CUM-WCOMR between condition 2 and condition 3; both conditions provided the web mode to panelists sequentially.

In a second step, we investigated how the web-push strategies influenced the Cumulative Web Switch Rate (CUM-WSR) which is the product of the three single outcome rates of this intervention.

$$\text{Cumulative Web Switch Rate (CUM-WSR)} = \text{COMR x WCOMR x WSR} \tag{3.5}$$

The CUM-WSR is the proportion of those panelists who switched to the web mode in relation to all panel members who were part of the experimental conditions. We tested Hypothesis 3, which expects a higher mode switch in the sequential web-first approach, by comparing the CUM-WSR between condition 1 and condition 2. Hypothesis 4, which claims that a prepaid incentive is superior to a promised incentive, was examined by comparing the CUM-WSR between condition 2 and condition 3.

The sequential approach of this experiment extended the field period for panel members of the conditions 2 and 3 by two weeks. To test Hypotheses 1 and 3 for a same survey period, we also compared the CUM-WCOMR and the CUM-WSR of condition 2 after 54 days with the final outcomes of condition 1. In addition to the hypothesis tests, we performed two logistic regression analyses to investigate whether the recruitment cohorts and internet usage are related to cumulative web completion and mode switching.

Analysis of panel attrition

To investigate how the web-push strategies affect whether participants remain members of the panel, we compared the differences in the panel attrition rate after five consecutive waves following the October/November survey 2018. The panel attrition rate was measured as the percentage of panelists who were considered as eligible panel members to the October/November survey 2019, after participating in the experiment of the October/November survey 2018.

$$\text{Panel Attrition Rate}_{\text{Oct/Nov19}} = \frac{\text{Participants@Oct/Nov Survey 2018} - \text{Panelists@Oct/Nov Survey 2019}}{\text{Participants@Oct/Nov Survey 2018}} \tag{3.6}$$

In addition, separate attrition rates were calculated for panelists who switched to the web mode and panel members who remained in the mail mode. To allow a comparison of the two groups, we excluded panelists from the analysis who did not respond to the October/November survey 2018. This exclusion was necessary due to the definition of panel attrition in the GESIS Panel, according to which panelists can request to be removed from the panel or be automatically removed if they did not respond to three consecutive waves (see appendix for details). To test whether the web-push strategies and the mode of response differ on panel attrition, we fitted a logistic regression model where dropouts of panelists (1 = attrition; 0 = eligible panelist) was regressed on the experimental conditions and on web mode switchers vs. those who remain in the mail mode.

Analysis of survey costs

Survey costs were analyzed by comparing the relative cumulative cost of each condition for six consecutive waves, including the October/November survey 2018. These cumulative costs were related to the status quo, which was defined as a hypothetical mail-only group. The panel attrition rate of the mail-only group was estimated based on data from four GESIS Panel waves before the start of the experiment (February/March 2018 - August/September 2018). The cost calculation for each condition combines all variable costs for the web-push treatments and the regular fieldwork of the GESIS Panel. Investments for the web-push treatments include the extra incentives, material, printing, postage, and service for sending the invitation and reminder letters. Regular fieldwork cost involves the €5 incentives, material, printing, postage, and service to send the invitation letters and the mail questionnaires. The return of mail questionnaires produced additional fieldwork costs for postage and coding of the data. We excluded fixed costs for staff and infrastructure (e.g., wages, IT, survey design) because we expect that the expenses are equal over the conditions.

All analyses for this study were done in R version 4.0.2 (R Core Team, 2019). To test hypotheses, we used a two-proportion z-test. Statistical significance was set at the five percent level ($p < .05$). All hypothesis tests were adjusted for multiple comparisons using the Bonferroni-Holm correction method (Holm, 1979).

3.4 Results

3.4.1 Web completion and web mode switching

Table 3.3 provides an overview of the outcomes of the experiment in the October/November survey 2018. On average, 88.5% of all panel members who were invited to the experiment participated in the survey by mail or web (COMR). This value is similar to the completion rate of panelists invited to the mail mode in the prior August/September survey 2018 (89.2%). Over all participants, 23.4% completed the questionnaire online (WCOMR) and 69.5% of the web respondents finally switched to the web mode (WSR). If we look at the experimental conditions, we did not find statistically significant differences in the COMR and WSR. However, two conditions differ significantly in the WCOMR, where the sequential web-first approach of condition 2 outperformed the concurrent presentation of the modes in condition 1 (26.2% *vs*. 20.5%, p = .026).

TABLE 3.3: Experimental conditions and outcome rates of the web-push intervention in the October/November 2018 survey

Outcome	1) concurrent/ promised		2) sequential/ promised		3) sequential/ prepaid		Total	
	%	(n)	%	(n)	%	(n)	%	(n)
Sample size	100.0	(631)	100.0	(631)	100.0	(633)	100.0	(1895)
Completion Rate (COMR)	88.1	(556)	87.2	(550)	90.4	(572)	88.5	(1678)
Web Completion Rate (WCOMR)[a]	[2]20.5	(114)	[1]26.2	(144)	23.4	(134)	23.4	(392)
Web Switch Rate (WSR)	70.2	(80)	72.2	(104)	66.4	(89)	69.5	(273)
CUM-WCOMR (COMR x WCOMR)[b]	[2]18.1	(114)	[1]22.8	(144)	21.2	(134)	20.7	(392)
CUM-WSR (COMR x WCOMR x WSR)	[*1]12.7	(80)	[*2]16.5	(104)	14.1	(89)	14.4	(273)

Note:

[a] Superscripts 1, 2 indicate a significant difference in outcome rates at the $p \leq .05$ level compared with the corresponding condition. Two-sided z-tests for differences in proportions were used.

[b] One-tailed z-tests for differences in proportions. Tests were adjusted for multiple comparisons using the Bonferroni-Holm correction method (Holm 1979). [*]indicate $p \leq .05$ for tests before correction for multiple testing.

Hypotheses 1 and 2 were tested by comparing the CUM-WCOMR that evaluate the proportion of web completion in relation to all panelists who were invited to the experiment. On average, the CUM-WCOMR was 20.7%. Figure 3.1 illustrates how the CUM-WCOMR varied by date and experimental condition. Consistent with Hypothesis 1, we found that condition 2 reached a significantly higher cumulative web completion rate than condition 1 (22.8% *vs*. 18.1%, $z = 2.09$, $p = .036$). The CUM-WCOMR of condition 2 remained substantially higher if we take into account that the field period was 14 days longer than in condition 1 due to the early opportunity to participate in the web mode. When comparing the first 54 days of the field period in each condition, there was still a significant difference in the web completion (22.6% *vs*. 18%, $z = 2.03$, $p = .043$). However, we found no evidence to confirm our second Hypothesis. The prepaid incentives strategy of condition 3 did not result in a higher CUM-WCOMR than the promised incentive strategy of condition 2 (21.2% *vs*. 22.8%, $z = 0.71$, $p = .761$).

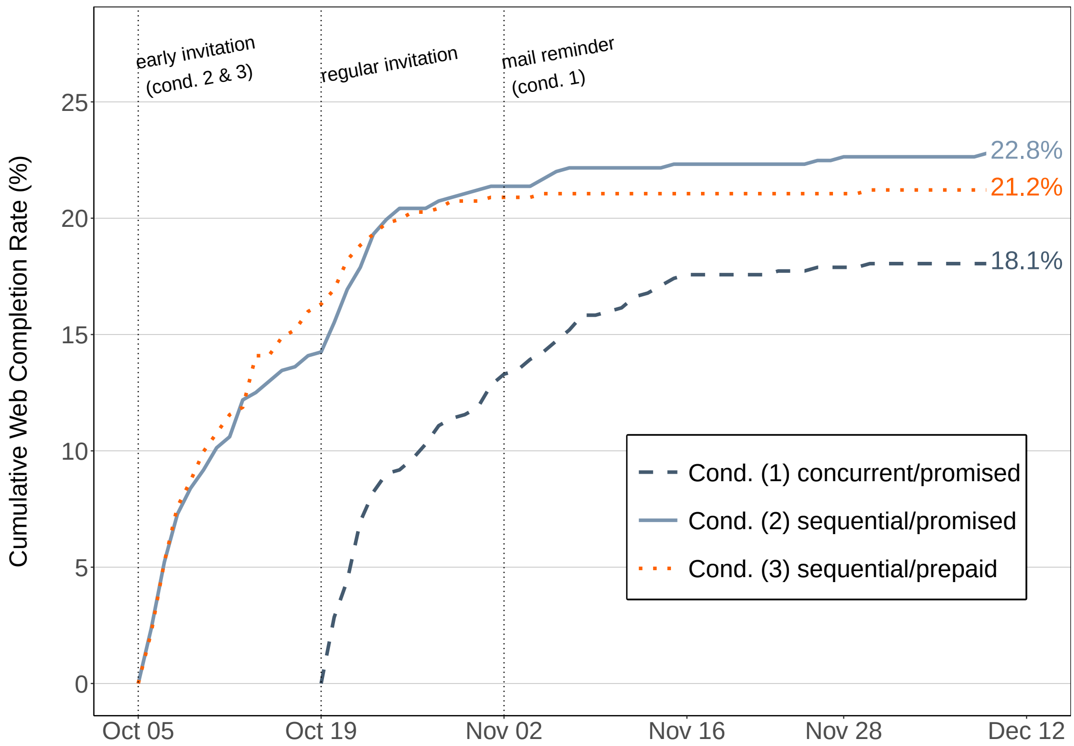

FIGURE 3.1: Cumulative web completion rate by date and experimental condition.

To test Hypotheses 3 and 4, we evaluate the proportion of mode switchers over all invited panelists by comparing the CUM-WSR. Across all conditions, 14.4% of the panel members switched permanently to the web mode. Consistent with the CUM-WCOMR, the sequential web-first approach of condition 2 achieved a higher CUM-WSR than the concurrent approach of condition 1 (16.5% *vs*. 12.7%, z = 1.91, p = .056), although this difference did not reach the predefined level of statistical significance. Nearly the same result was found when comparing the first 54 days of field period of both conditions to control for the longer field period in condition 2 (16.3% *vs*. 12.7%, z = 1.85, p = .064). As reported with the CUM-WCOMR, no significant differences were detected between the incentive strategies regarding the CUM-WSR. The prepaid incentive of condition 3 did not result in a higher proportion of mode switchers than the promised incentives of condition 2 (14.1% *vs*. 16.5 %, z = 1.20, p = .884). These results taken together provide no evidence to support Hypothesis 4 that offering prepaid incentives motivates more panel members to switch from mail to web permanently.

Since the recruitment cohorts and internet usage are potentially related to the outcomes, we run additional tests to examine whether these variables are associated to cumulative web completion and mode switching (see Table 3.7 in the appendix). Once controlling for the experimental conditions, the results of two logistic regression analyses indicate that the time of panel membership, measured by the recruitment cohorts, is not related to the outcomes. Less surprising is the finding that internet usage is highly predictive of whether panelists will complete the survey online and permanently switch to the web mode.

The analysis also provides support for the robustness of findings from the hypothesis tests above. Panelists from condition 1 are significantly less likely to complete the survey online than members of the reference condition 2 after adjusting for the covariates.

3.4.2 Panel attrition

In the long run, the effectiveness of a web-push strategy depends on whether participants are willing to remain members of the panel after the web-push intervention. Panel attrition matters for panelists who switched to the web mode and those who continued to participate in the mail mode. Table 3.4 presents the number of dropouts and the attrition rates of panel members after five consecutive waves following the October/November survey 2018. Due to the definition of panel attrition in the GESIS Panel, the analysis only includes panelists who participated in the October/November survey. Two cases were removed due to misclassification and because one mode switcher asked to switch back to the mail mode.

TABLE 3.4: Dropouts and panel attrition rates for panelists who completed the October/November survey after five consecutive waves (August/September 2019 survey)

Cohorts	1) concurrent/ promised		2) sequential/ promised		3) sequential/ prepaid		Total	
	%	(*n*)	%	(*n*)	%	(*n*)	%	(*n*)
Sample size	100.0	(558)	100.0	(553)	100.0	(576)	100.0	(1687)
Overall attrition rate	5.6	(31)	6.1	(34)	5.6	(32)	5.7	(97)
Among mail mode:	6.1	(29)	6.9	(31)	5.7	(28)	6.2	(88)
Among web mode:	2.5	(2)	2.9	(3)	4.5	(4)	3.3	(9)

Overall, the table illustrates that all three conditions show similar attrition rates of around six percent. Regarding the mode of response, switchers to the web mode for all conditions dropped out at a lower rate (3.3%) than the panelists who continued in the mail mode (6.2%). We performed a logistic regression model to test whether the attrition differs significantly between the experimental conditions and the mode of response. Figure 3.2 provides coefficients with 95% confidence intervals for the outcome panel attrition after the August/September survey 2019. The results show that neither the concurrent approach of condition 1, nor the prepaid approach of condition 3 differs significantly from the sequential/promised strategy of condition 2. We also found no sufficient evidence that mode switchers and panelists who

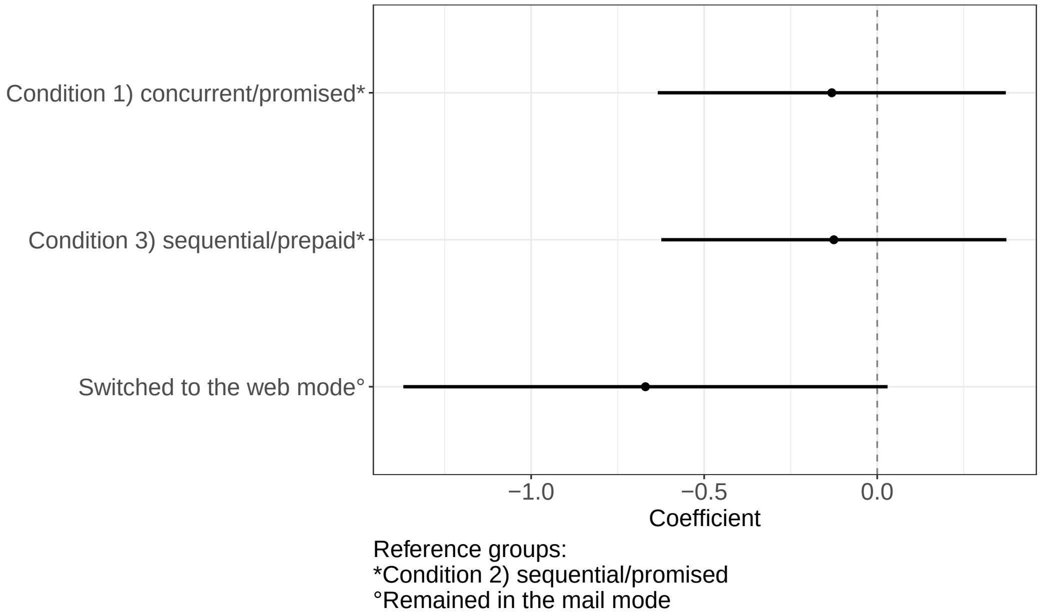

FIGURE 3.2: Panel attrition after five waves following the October/November 2018 survey: 95% confidence intervals for coefficients of experimental conditions and mode of response.

continued to respond in the mail mode have a significantly different likelihood to drop out from the panel. Even when the subgroups are small and results should be interpreted with caution, the findings do not show any indication that the web-push conditions differently affect panel attrition after five waves. Moreover, the data suggest that switchers to the web mode are at least no more likely to attrite from the panel than panelists who continued in the mail mode.

3.4.3 Survey costs

To evaluate the cost-efficiency of the web-push intervention, we compared cumulative costs of each condition for six waves, including the October/November survey (Table 3.5). Cumulative costs are presented in relation to a hypothetical "mail-only" group of panel members who did not receive a web-push treatment, which allows us to assess costs compared to the status quo.

Across all web-push conditions, the intervention reduced survey costs after the sixth wave by an average of -6.3% in relation to the estimated costs of a mail-only

TABLE 3.5: Cumulative survey costs of the web-push conditions in relation to a hypothetical status quo (mail-only) for six waves

Condition	Wave					
	Oct/Nov	Dec/Jan	Feb/Mar	Apr/May	Jun/Jul	Aug/Sep
	%	%	%	%	%	%
Status quo: mail-only	-	-	-	-	-	-
1) concurrent/promised	7.4	−1.4	−4.1	−5.5	−6.7	−7.8
2) sequential/promised	8.7	−2.5	−5.7	−7.7	−9.4	−10.7
3) sequential/prepaid	52.6	21.4	11.0	5.8	2.3	−0.4
Average of conditions	22.9	5.9	0.4	−2.4	−4.6	−6.3

Note:
Costs are presented in relation to a hypothetical mail-only condition with a gross sample size of 632 panelists, a completion rate of 88.4%, and an attrition rate of 1.6% for each wave. The completion rate and the attrition rate are estimated based on response rates of panelists of the mail mode from four previous waves of the GESIS Panel (February/March 2018 survey - August/September 2018 survey).

group. Table 3.5 illustrates that the conditions have different potentials for cost reductions. The web-push performance of condition 2 is associated with the highest relative cost-savings, followed by condition 1. Both strategies with promised incentives achieved savings for cumulative costs in the first wave after the web-push. Condition 3 was cost-efficient in relation to a hypothetical mail-only group after six waves, even if the cumulative mode switch rate was two percentage points higher than for condition 1. This outcome can mainly be attributed to the high investment costs resulting from the prepaid web-push incentive strategy. Compared to the promised incentive conditions, the monetary incentive costs for condition 3 alone were four to five times higher, but without leading to a substantially higher proportion of mode switchers. However, the cost differences between the web-push conditions are also due to slight, but not significant, variations in the completion and attrition rates. Overall, the trend in Table 3.5 shows that all three web-push strategies increase their cost-efficiency in the long term. While for condition 1 and condition 2 the investment costs amortize in the first wave after the web-push, condition 3 requires more than five waves for that to occur.

3.5 Summary and conclusions

The purpose of this study was to investigate whether and how members of a running mixed-mode panel can be motivated to switch the survey mode from mail to web. Drawing on past research, we tested three different web-push strategies in an experimental design to evaluate how the order of presenting the web mode and the use of incentives affect web completion and the willingness of panelists to permanently switch to the web mode. Additionally, we examined the impact of the web-push conditions on panel attrition and survey costs after five waves following the intervention. Subjects of the experiment were participants of a probability-based mixed-mode panel who had no internet access at the time of the panel recruitment or refused to participate in the web mode during the recruitment interview.

Overall, all three web-push conditions were successful in motivating participants to complete the web mode immediately (20.7%) and to convince panelists to switch to the web mode in the long-term (14.4%). By introducing the web-option first, we achieved a higher cumulative web completion rate than by presenting the web and mail option together. This result provides additional evidence to findings from cross-sectional studies that offering the web mode first in a sequence improves web response also under the conditions of a running panel. The size of the effect for the sequential approach may even be a conservative estimation since panelists of these conditions were informed in the initial letter that a paper questionnaire would soon be available. Nevertheless, we assume that respondents are more willing to accept transition costs of the web mode if a mail questionnaire is not immediately available as a salient and low-cost alternative.

It is not clear whether the sequential web-first approach also positively affects the ultimate mode switch of panel members. The effect failed to reach significance although the cumulative mode switch rate was nearly four percentage points higher than in the comparable concurrent/promised condition. The findings suggest that it might be effective to motivate as many panelists as possible to test the web mode in a single wave, as a higher proportion may agree to switch the mode for future waves. However, the results also show that some panelists are willing to complete a web questionnaire once, but otherwise prefer the mail mode. We still lack knowledge of the process that drives respondents to choose a survey mode in mixed-mode panels. Replications of this study, preferably with more statistical power, would be helpful to learn more about this process and retest the Hypothesis that a sequential web-first approach increases the proportion of mode switchers.

One unanticipated result was that the well-documented superior effect of prepaid incentives over promised incentives on response rates in general and by the web mode, was not found in this experiment. Providing prepaid incentives achieved a slightly, but not significantly lower cumulative web completion and mode switch rate than offering promised incentives if both treatments are accompanied by a sequential web-first design. We assumed that prepaid incentives would be more effective by triggering a sense of reciprocity and drawing attention to the web option. However, panelists may feel that they are already making a contribution by participating in the survey. In addition, the prior delivery of incentives with the first contact may encourage trust that promised incentives will be received.

A concern with pushing panel members from mail to web is the attrition of participants after changing the mode or because they were confronted with a web-push intervention. After five consecutive waves, our study found no indications that any of the tested web-push strategies affect panel attrition differently. Conspicuously, mode switchers showed a lower attrition rate than those panel members who remained in the mail mode. However, the differences are not significant, perhaps due to the small sample size. If this effect can be replicated, there may be several explanations. For example, a selection effect might motivate panel members to switch modes with higher propensity to remain in panel studies. Panel members may also feel committed to stay in the survey due to the decision of mode switching itself. One specific reason for this finding could also be that the switchers to the web mode received the two email reminders in the GESIS Panel, while those who remain in the mail mode did not obtain such an additional stimulus. Further research with a larger sample size and a mail-only control group is needed to learn more about this phenomenon.

As intended, all web-push strategies reduced the cumulative survey costs in the long run. The conditions using promised incentives saved costs from the first wave after the intervention compared to the status quo without web-push. Both strategies can contribute to considerable cost reductions due to their comparatively low investment costs. In contrast, it took much longer until the prepaid strategy pays-off, as the investments for incentives were around four to five times higher than for the promised incentive conditions. However, since the cost differences between participants in both modes are considerable, even the prepaid/sequential condition was cost-efficient after five consecutive waves.

A limitation of this study is that we did not test a fully crossed experimental design, mainly due to a lack of statistical power. Thus, there is no information about the web-push effect of a concurrent design combined with an additional prepaid incentive for responding via the web mode. We did not have strong assumptions of an interaction effect between the two factors, but it would still be interesting to test whether an interaction effect exists. A lack of statistical power was also the main reason why no mail-only control group was tested in this study. Such a mail-only condition is important for evaluating how a web-push intervention affects data quality indicators such as panel attrition and measurement effects. It would also improve the reliability of the cost analysis, as we would no longer have to estimate the cost of a hypothetical "mail-only" group. We recommend investigating the impact of web-push interventions on data quality in future studies by implementing a mail-only control condition. As a further point, this experiment was designed for a probability-based mail-web panel. It would be interesting to see if the effects of the web-push conditions can be found in panels with another setup as well.

In sum, our study was able to show how panel members of the mail mode can be motivated to switch to the web after most of them refused to use the web mode during the panel recruitment. While a sequential web-first approach seems to be an effective method, promised web-push incentives are an efficient approach for reducing survey costs. Consequently, the combination of both treatments proved to be the most successful web-push strategy of our design. This study did not examine whether mode effects exist within the responses of mode switchers that affect the measurement of longitudinal data. From a total survey error perspective, mode effects can counteract the positive effect of a web-push on survey costs by increasing survey errors. Although measurement effects between the self-administered web and mail mode may be small (Klausch et al., 2013), future research should investigate this issue.

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Appendix

Definition of panel attrition in the GESIS Panel

Following DiSogra and Callegaro (2016), the GESIS Panel distinguishes between voluntarily and involuntarily panel attrition (Bretschi et al., 2018). Voluntary attrition is a result of panel members contacting the GESIS Panel and requesting to be removed from the panel. Involuntary attrition occurs when panel members are excluded from the panel because they do not respond to three consecutive waves or cannot be reached for three consecutive waves. According to this rule, involuntary attrition of mode switchers in the web mode can occur only in the case if they did not participate in any of the following three surveys, including the April/May survey 2019. On the other hand, panelists who remained in the mail mode could be excluded in each wave after the October/November survey (if they had neither participated in the October/November survey nor in the surveys before), which would overestimate the attrition rate of those respondents who remained in the mail.

Additional tables

TABLE 3.6: Distribution of demographic characteristics by experimental conditions

	1) concurrent/ promised		2) sequential/ promised		3) sequential/ prepaid	
	%	(*n*)	%	(*n*)	%	(*n*)
Female	56.1	(346)	57.8	(351)	54.8	(340)
No german citizenship	6.1	(35)	2.8	(16)	5.2	(30)
Having Children	75.2	(395)	76.5	(391)	75.9	(403)
Living in a partnership	76.6	(395)	77.0	(389)	77.0	(406)
Age 29 and below	3.9	(24)	2.6	(16)	5.5	(34)
Age 30 - 39	6.7	(41)	6.5	(39)	5.3	(33)
Age 40 - 49	13.2	(81)	14.2	(86)	8.9	(55)
Age 50 - 59	24.8	(152)	20.7	(125)	26.3	(163)
Age 60 - 69	29.9	(183)	31.8	(192)	30.4	(188)
Age 70 and above	21.5	(132)	24.2	(146)	23.6	(146)
Highest school degree: low	31.6	(179)	32.3	(185)	36.3	(208)
Highest school degree: medium	42.4	(240)	35.5	(203)	37.5	(215)
Highest school degree: high	26.0	(147)	32.2	(184)	26.2	(150)
Household size: 1 person	43.4	(227)	42.0	(218)	47.7	(254)
Household size: 2 persons	38.0	(199)	38.9	(202)	33.5	(178)
Household size: 3 persons	8.2	(43)	38.9	(202)	33.5	(178)
Household size: 4 persons and more	10.3	(54)	11.0	(57)	9.8	(52)
Private internet use	71.1	(433)	75.2	(454)	73.2	(442)
Recruitment cohort: 2013	53.7	(339)	48.8	(308)	49.0	(310)
Recruitment cohort: 2016	20.6	(130)	24.2	(153)	24.5	(155)
Recruitment cohort: 2018	25.7	(162)	26.9	(170)	26.5	(168)
Nr. of wave participation: 0 - 6	25.7	(162)	27.1	(171)	27.0	(171)
Nr. of wave participation: 7 - 12	8.2	(52)	11.7	(74)	9.6	(61)
Nr. of wave participation: 13 - 18	12.7	(80)	12.8	(81)	15.0	(95)
Nr. of wave participation: 19 - 25	5.2	(33)	5.7	(36)	6.3	(40)
Nr. of wave participation: 26 - 31	48.2	(304)	42.6	(269)	42.0	(266)

Note:

Demographic variables were measured in the GESIS Panel December/January survey 2018/2019, except for the variables on internet usage, recruitment cohorts, and number of waves. We used data from the December/January survey after the web-push intervention because this data had less missing values, and we considered the demographic characteristics as stable over the short period of time. Missing values were imputed where possible by data of other GESIS Panel waves. Existing deviations are the result of remaining item nonresponse.

TABLE 3.7: Logistic regression models predicting web completion and mode switching (coefficients, 95% confidence intervals in parentheses)

	Model 1 Web completion	Model 2 Web mode switching
Experimental conditions (ref. condition 2)		
Condition 1) concurrent/promised	−0.328	−0.304
	(-0.619; -0.036)	(-0.633; 0.024)
Condition 3) sequential/prepaid	−0.121	−0.223
	(-0.403; 0.161)	(-0.544; 0.099)
Recruitment cohorts (ref. cohort 2013)		
Cohort 2016	−0.121	−0.046
	(-0.423; 0.180)	(-0.388; 0.297)
Cohort 2018	0.041	0.114
	(-0.242; 0.325)	(-0.206; 0.434)
Internet users (ref. non-internet users)	2.710	2.797
	(2.124; 3.295)	(2.038; 3.555)
Intercept	−3.514	−4.076
	(-4.122; -2.906)	(-4.857; -3.295)
Observations	1817	1817

Note:

Dependent variables are coded 1 for web completion/web switching, 0 for all panelists invited to the experiment who did not respond online/switch to the web mode. Cases with missing data were removed from the analysis.

Letters of invitation

Below are the letters of invitation for the GESIS Panel October/November survey of the three experimental conditions. The letters are English translations of the original German versions. The original invitation letters in German as well as all questionnaires and data of the GESIS panel are available at www.gesis.org/gesis-panel/.

Condition 1: concurrent approach/promised incentive

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Mannheim, 18. October 2018

Invitation to the October-/November-Survey with the option to participate online

Dear Mr. Doe,

Thank you very much for participating in the GESIS GesellschaftsMonitor. You have helped us a lot by completing the paper questionnaires for this scientific study - we really appreciate that!

Today we would like to offer you the opportunity to complete the October/November survey on the Internet. All you need to do is:

Go to this Internet-address: **www.gesis-gesellschaftsmonitor.de/online**

Enter this password: **Br3WFE2**

For submitting your answers **online**, we will be pleased to send you a one-time **10 euro** as an additional thank-you. You will receive the 10 euro by postal mail after the end of the October/November survey. We are offering you this opportunity to participate because more and more people prefer to use the Internet. By answering the questions online, you help us to get faster results and reduce our survey costs.

If you cannot or do not want to answer the questions via the Internet, you may of course complete the paper questionnaire as before. The most important thing for us is that you continue to participate in the GESIS GesellschaftsMonitor. No matter how you answer the survey, we are very grateful for your support. As a thank-you for your participation, we have enclosed **5 euro** as usual in this letter.

If you have any questions, please contact Ms. Hoffmann by telephone at 0621–1246–564 or by e-mail at info@gesis-gesellschaftsmonitor.de. We look forward to your participation and will gladly answer your questions.

With kind regards

<<Signature>>

Dr. Bernd Weiß and the entire project team

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Mannheim, 2. November 2018

Online Participation in the GESIS GesellschaftsMonitor

Dear Mr. Doe,

A few days ago, we sent you an invitation to the October-November survey. If you have already completed the questionnaire, we would like to thank you for your participation.

If you have not yet completed the survey, you are welcome to send us the completed paper questionnaire or simply try participating online this time. All you need to do is:

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No matter how you respond, we hope you enjoy filling in the survey.

If you have any questions, please contact Ms. Hoffmann by telephone at 0621–1246–564 or by e-mail at info@gesis-gesellschaftsmonitor.de. We look forward to your participation and will gladly answer your questions.

With kind regards

<<Signature>>

Dr. Bernd Weiß and the entire project team

Condition 2: sequential web-first approach/promised incentive

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Mannheim, 4. October 2018

Online Participation in the GESIS GesellschaftsMonitor

Dear Mr. Doe,

Thank you very much for participating in the GESIS GesellschaftsMonitor. You have helped us a lot by completing the paper questionnaires for this scientific study - we really appreciate that!

Today we would like to offer you the opportunity to complete the October/November survey on the Internet a few days before its regular start. All you need to do is:

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Regardless of whether you respond by the Internet or not, you will receive a paper questionnaire in a few days and, as usual, **5 euro** as a thank you for your support. If you cannot or do not want to answer the questions online, you may fill out the paper questionnaire as before. What is most important for us is that you continue to participate in the GESIS GesellschaftsMonitor. No matter which way you answer the survey, we are very grateful for your support.

If you have any questions, please contact Ms. Hoffmann by telephone at 0621–1246–564 or by e-mail at info@gesis-gesellschaftsmonitor.de. We look forward to your participation and will gladly answer your questions.

With kind regards

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Mannheim, 18. October 2018

Invitation to the October-/November-Survey with the option to participate online

Dear Mr. Doe,

A few days ago, we sent you a letter to offer you the opportunity to complete the October/November survey on the Internet. If you are one of those respondents who have already answered our questions online, we would like to thank you for your participation. Please do not return the enclosed paper questionnaire in this case.

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No matter how you respond, we hope you enjoy filling in the survey. As a thank-you for your participation, we have enclosed **5 euro** as usual in this letter.

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With kind regards

<<Signature>>

Dr. Bernd Weiß and the entire project team

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Condition 3: sequential web-first approach/prepaid incentive

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Mannheim, 4. October 2018

Online Participation in the GESIS GesellschaftsMonitor

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Enter this password: **Br3WFE2**

As a token of appreciation for your efforts, we would like to thank you with an additional **10 euros**, which are attached to this letter. We are offering you this opportunity to participate because more and more people prefer to use the Internet. By answering the questions online, you help us to get faster results and reduce our survey costs.

Regardless of whether you respond by the Internet or not, you will receive a paper questionnaire in a few days and, as usual, **5 euro** as a thank you for your support. If you cannot or do not want to answer the questions online, you may fill out the paper questionnaire as before. What is most important for us is that you continue to participate in the GESIS GesellschaftsMonitor. No matter which way you answer the survey, we are very grateful for your support.

If you have any questions, please contact Ms. Hoffmann by telephone at 0621–1246–564 or by e-mail at info@gesis-gesellschaftsmonitor.de. We look forward to your participation and will gladly answer your questions.

With kind regards

<<Signature>>

Dr. Bernd Weiß and the entire project team

GesellschaftsMonitor gesis

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Mannheim, 18. October 2018

Invitation to the October-/November-Survey with the option to participate online

Dear Mr. Doe,

A few days ago, we sent you a letter to offer you the opportunity to complete the October/November survey on the Internet. If you are one of those respondents who have already answered our questions online, we would like to thank you for your participation. Please do not return the enclosed paper questionnaire in this case.

If you have not yet completed the survey, you are welcome to send us the completed paper questionnaire or simply try participating online this time. All you need to do is:

Go to this Internet-address: **www.gesis-gesellschaftsmonitor.de/online**

Enter this password: **Br3WFE2**

No matter how you respond, we hope you enjoy filling in the survey. As a thank-you for your participation, we have enclosed **5 euro** as usual in this letter.

If you have any questions, please contact Ms. Hoffmann by telephone at 0621–1246–564 or by e-mail at info@gesis-gesellschaftsmonitor.de. We look forward to your participation and will gladly answer your questions.

With kind regards

<<Signature>>

Dr. Bernd Weiß and the entire project team

Chapter 4

How Do Internet-related Characteristics Affect Whether Members of a German Mixed-Mode Panel Switch from the Mail to the Web Mode?

Abstract

In recent years, several longitudinal studies have transitioned from an interviewer-administered to a mixed-mode design, using the internet as one of the modes of data collection. However, a substantial proportion of panelists are reluctant to participate in web surveys when offered a choice in an ongoing mixed-mode panel. We still know little about the characteristics of panel members that drive them to comply with the request to complete surveys via the internet. This study aims to fill this gap by investigating how internet-related characteristics are linked to the willingness of panelists to switch from the mail mode to the web. We use data from multiple waves of the GESIS Panel, a probability-based mixed-mode panel in Germany (N=5,734). A web-push intervention motivated 28% of 1364 panelists of the mail mode to complete

the survey online in a single wave and 70% of these 380 short-term switchers to switch to the web mode permanently. We measured indicators of internet use, internet skills, and attitudes toward the internet as potential mechanisms of this short-term and long-term mode switching in the two waves before the intervention. Our results suggest that internet use and internet skills affect respondents' willingness to switch modes in a single wave. For these short-term switchers, however, none of the internet-related characteristics could explain mode switching in the long term. The findings of this study can be used to develop effective push-to-web methods for longitudinal mixed-mode surveys.

4.1 Introduction

In recent years, several longitudinal studies have made a transition from an interviewer-administered to a mixed-mode design, introducing web-based surveys as one mode of data collection (Olson et al., 2020). Using web surveys is attractive for study designers, as the internet enables the collection of high-quality data fast and cost-efficiently (Couper, 2008; Greenlaw & Brown-Welty, 2009; Kreuter et al., 2008). Particularly for panel studies, web surveys provide additional benefits such as using e-mail addresses as a low-cost method for recontacting the members (Bianchi et al., 2017).

A panel study offering the web mode in a mixed-mode design can become more cost-efficient if a large number of respondents participate via the internet where costs of collecting data are low. For this reason, survey researchers have developed web-push strategies mainly for cross-sectional mixed-mode surveys to motivate more respondents to participate online rather than responding via face-to-face, telephone, or mail interviews (for an overview, see Dillman, 2017). Nevertheless, some panel studies report that a substantial proportion of members with internet access refused to participate in the web mode or preferred to use alternative mode options. For instance, over 20% of the internet users declined to respond by the web mode in the initial recruitment of the GESIS Panel (Pforr & Dannwolf, 2017), and around ten percent of Gallop panel members with internet access explicitly asked to be sent the questionnaires by mail (Rookey et al., 2008). A substantial proportion of internet users also declined to respond online after the web mode had been introduced as the first mode option in ongoing panel studies, instead choosing an alternative mode (Fitzgerald et al., 2019; Jäckle et al., 2015). Since internet penetration rates are still increasing in most countries, internet-using respondents who are reluctant to participate in web surveys may become more relevant for survey research as a reflection of a new digital divide (Herzing & Blom, 2018). This is also true for ongoing panel studies in which panel members are asked to switch to the web mode. So far, however, we are not aware of any detailed investigation on what characteristics of the panelists affect their willingness to switch modes. Learning more about the characteristics that drive panelists to switch survey modes can help design effective web-push methods to increase online participation.

This study aims to fill this research gap by investigating mode switching in an ongoing mixed-mode panel. We are particularly interested in how internet-related characteristics affect the willingness of panelists to switch from the mail mode to the web. The data comes from a web-push intervention in a German probability-based mixed-mode panel, in which panel members in the mail mode could choose to complete the questionnaire of a single wave via the internet (short-term mode switching). At the end of the web survey, those short-term switchers were asked if they were willing to switch to the web mode for upcoming waves (long-term mode switching). We measured potential determinants of mode switching in the two waves before the web-push intervention to answer the following research questions:

1 How do internet-related characteristics affect the willingness of panel members in the mail mode to switch to the web mode in the short term?

2 How do internet-related characteristics affect the willingness of short-term switchers to switch to the web mode in the long term?

4.1.1 Previous research

So far, little attention has been paid to the reasons that drive members of an ongoing panel to comply with the request to switch from an alternative mode to the web. Previous research on mode switching in longitudinal studies has focused on demographic characteristics, mostly without differentiating internet users from people who do not use the internet. Allum et al. (2018) reported that switchers to the web mode in the face-to-face UK Innovation Panel are more likely to be male, older, more highly educated, and in the professional or intermediate occupational classes. Fitzgerald et al. (2019) found that panelists of the Australian Longitudinal Study on Women's Health are more likely to switch from mail to web mode if they live in major cities, are more highly educated, are employed, do not smoke and do not drink alcohol. The findings regarding the level of education are consistent with results from cross-sectional mixed-mode studies about respondents who choose to participate via the web mode instead of a face-to-face Interview (Lynn, 2020).

Other studies investigated which characteristics predict whether respondents will participate in web surveys. Olson et al. (2012) showed that respondents are more likely to participate in a web survey when they had expressed preferences for that mode in a previous telephone interview. Preferences for the web mode could, in turn, be predicted by access to and familiarity with the internet, by a high level of education, and by being employed (Smyth et al., 2014). Couper et al. (2007) explored how the willingness of panel members to participate in a web survey correlated with demographic variables in the US Health and Retirement Study. Among internet users, younger individuals, white persons, and people with higher levels of education were significantly more willing to respond via the web. A subsample of those internet users was later actually invited to participate in a web survey. For this subsample of individuals, education and race remained significant predictors of participation. Once the internet use was controlled, Couper et al. (2007) showed that demographic characteristics could hardly predict whether respondents would be willing to participate in web surveys. Instead, the authors assumed that experience with the internet might better explain respondents' behavior.

We follow the assumption that demographic characteristics do not sufficiently reflect the underlying mechanism that motivates panelists to switch survey modes or not. To better understand which characteristics affect the respondents' decision to switch modes, we will focus on theoretically derived variables of internet-related characteristics that are described in the next section.

4.1.2 Theoretical framework

The behavior of respondents in social surveys can be explained by rational-choice-based theories such as the benefit-cost theory (Schnell, 1997; Singer, 2011). The benefit-cost theory postulates that individuals decide on the basis of a subjective calculus for the course of action from which they expect that the benefits of doing so will outweigh the costs. We follow this assumption as a general principle for identifying and testing cost implications of respondents' decisions to switch survey modes. For the sake of simplicity, we focus on costs implications, although individuals may and will consider several benefits by weighting their decision to switch survey modes. Accordingly, we assume that the lower they perceive the costs of switching to be, the more likely panel members of an alternative mode will be to switch to the web mode. Costs of web mode switching may include, for example, the efforts to find a device and get access to the online questionnaire, uncertainty, concerns about the consequences of sharing personal information on the internet, or opportunity costs when abandoning a known procedure of participating in an offline mode. Since the internet is the vehicle for web surveys, we expect that these cost implications are related to how individuals use the internet in their daily life and how they feel about it.

Previous research has shown that internet use, internet skills, and attitudes toward the internet are connected to whether people participate in online panels (Herzing & Blom, 2018) or use different online activities, such as political or health participation

(Lutz et al., 2014). We suggest that these characteristics also determine how panelists perceive the costs of mode switching. In the following section, hypotheses will be elaborated about how internet use, skills, and attitudes affect panelists' willingness to switch modes in a single survey, and for those short-term switchers, to switch to the web mode in the long term. Although both decisions may be influenced by different situational factors, we assume that the internet-related characteristics have a similar impact on both outcomes of mode switching. Thus, we argue that from a theoretical point of view, the expected costs of long-term mode switching remain the same as for short-term mode switching. Accordingly, our hypotheses have the same structure for both outcomes.

4.1.3 Hypotheses

Internet use

Dutton and Shepherd (2006) describe the internet as an experience technology. By gaining experience with the internet, users find it easier to engage in online services, for instance, by getting people more involved in e-commerce (Blank & Dutton, 2012). We assume that panelists' use of the internet also affects how they evaluate the costs of mode switching in panel surveys. However, internet use is a diverse phenomenon that can be divided into different dimensions. A basic differentiation is made between internet use in terms of frequency of use and the variety of several online activities (Blank & Groselj, 2014; Scheerder et al., 2017). Frequency of use can be specified as a measure of how often people use the internet in their day-to-day life. Variety of internet use can be defined as the number of different types of activities that individuals undertake online such as information seeking, commerce, or entertainment. Regarding both characteristics, the hypotheses are based on the assumption that the costs of mode switching decrease with a higher frequency and variety of internet use. In line with this assumption, we hypothesize for the outcomes short-term mode switching (ST) and long-term mode switching (LT):

ST-1: *The more frequently panelists use the internet, the more likely they are to switch to the web mode in the short term.*

ST-2: *The higher the variety of internet use, the more likely panelists are to switch to the web mode in the short term.*

LT-1: *The more frequently short-term switchers use the internet, the more likely they are to switch to the web mode in the long term.*

LT-2: *The higher the variety of internet use, the more likely short-term switchers are to switch to the web mode in the long term.*

As a third dimension of internet usage, we consider the number of web-enabled devices respondents use to participate in web surveys (Antoun, 2015). We expect that the costs of participation increase if respondents have fewer devices that they can use to go online. The underlying mechanism could be that the fewer devices are used, the higher is the barrier to accessing a web survey. In line with this assumption, we hypothesize:

ST-3: *The more web-enabled devices panelists of the mail mode use, the more likely they are to switch to the web mode in the short term.*

LT-3: *The more web-enabled devices short-term switchers use, the more likely they are to switch to the web mode in the long term.*

Internet skills

Research on the digital divide has long focused on internet skills to identify people who have access to the internet but cannot effectively use it, which is called second-level digital divide (Hargittai, 2002; van Deursen & van Dijk, 2010). Respondents need to have a basic level of internet skills in order to participate in web surveys for which invitations are sent by postal mail. That is, to open a browser, find the correct URL, enter login credentials, and navigate through the online questionnaire. Such basic skills particularly require the ability to operate and navigate the internet, which is related to what van Deursen et al. (2011) describe as medium-related internet skills in contrast to content-related skills. Accordingly, we expect that with higher internet skills the costs of switching will decrease. In line with this assumption, we hypothesize:

ST-4 *The higher the level of internet skills of panelists, the more likely they are to switch to the web mode in the short term.*

LT-4 *The higher the level of internet skills of short-term switchers, the more likely they are to switch to the web mode in the long term.*

Attitudes toward the internet and technology

Studies show that people's attitudes toward the internet and technology are related to their willingness to use web-based services (Han et al., 2012; Nonnecke et al., 2006). For example, Blank and Dutton (2012) argue that general trust is an important aspect in the calculus of individuals about whether to use opportunities of the internet insofar as that trust reduces the costs of transactions. Their study identifies "net risk" as one component of trust toward the internet, which describes how people see risk in using online activities. We assume that respondents' attitudes toward net risk are an issue of costs in their decision to switch to the web mode. Costs for mode switching may rise, the higher the perceived risk in using the internet is for respondents. Accordingly, we formulate the hypotheses:

ST-5: *The lower panelists perceive the risk of using the internet to be, the more likely they are to switch to the web mode in the short term.*

LT-5: *The lower short-term switchers perceive the risk of using the internet to be, the more likely they are to switch to the web mode in the long term.*

Blank and Dutton (2012) also find that attitudes toward technology have a large impact on perceptions of risk but are also related to online activities such as e-commerce. As the authors presume, people with negative attitudes are less willing to overcome the hurdles in dealing with the services of the internet and learn the necessary skills. Following this rationale, we view the affinity for technology as another potential characteristic of respondents that is related to the perceived costs of switching to the web mode. Thus, we derive the following hypotheses:

ST-6: *The higher panelists' affinity for technology, the more likely they are to switch to the web mode in the short term.*

LT-6: *The higher short-term switchers' affinity for technology, the more likely they are to switch to the web mode in the long term.*

4.2 Methods

4.2.1 Data

The GESIS Panel

This study is based on data from the GESIS Panel, a German probability-based mixed-mode panel operated by GESIS - Leibniz Institute for the Social Sciences (GESIS, 2019). Since the beginning of 2014, the GESIS Panel has been a fully operational panel infrastructure open for data collection to the academic research community. In October 2018, the panel consisted of 5,736 members from an initial cohort sampled in 2013 and two refreshment cohorts sampled in 2016 and 2018. The target population is German-speaking individuals aged 18 years and older (for the initial cohort between 18 and 70 years) who reside permanently in private households in Germany. All panelists are recruited from random samples drawn from the municipal population registers. The recruitment rate for the initial cohort is 31.6%, for the second cohort is 20.2%, and for the third cohort is 18.4%. Detailed information about the GESIS Panel sampling and recruitment procedure can be found at Bosnjak et al. (2018), and for the three cohorts at Schaurer et al. (2014), Schaurer and Weyandt (2016), and Schaurer et al. (2020).

The data collection of the GESIS Panel is administered in two modes, namely in web-based surveys (web mode) and paper-and-pencil surveys sent via postal mail (mail mode). The mode assignment took place in a multi-step recruitment procedure that encompasses an interviewer-administered recruitment interview and a first self-administered profile survey. At the end of the recruitment interview, the web mode was presented to internet-using respondents as the default option for participation. However, if respondents were not willing to participate in web surveys, they were allowed to opt for the mail mode. Participants who did not use the internet at the time of panel recruitment were automatically assigned to the mail mode. Panel members have not actively been offered the possibility of switching survey modes after the recruitment procedure. As a result, 33% of all panelists were invited to the mail mode in October 2018 (see Table 4.1).

TABLE 4.1: Modes of invitation (and internet usage among mail mode panelists) by recruitment cohort in the October/November wave 2018

	Cohort 2013		Cohort 2016		Cohort 2018		Total	
	%	(*n*)	%	(*n*)	%	(*n*)	%	(*n*)
Web Mode:	68.0	(2035)	65.3	(826)	66.2	(978)	67.0	(3839)
Mail Mode:	32.0	(957)	34.7	(438)	33.8	(500)	33.0	(1895)
Internet users:	73.8	(706)	70.1	(307)	70.2	(351)	72.0	(1364)
Non-internet users:	24.6	(235)	27.4	(120)	28.8	(144)	26.3	(499)
Missing Information:	1.7	(235)	2.5	(11)	1.0	(5)	1.7	(32)
Total:	100.0	(2992)	100.0	(1264)	100.0	(1478)	100.0	(5734)

Note: Internet usage was measured in the August/September wave 2018. Missing values were imputed using data from other GESIS Panel waves where possible, including data from the October/November wave 2018 as the last step. Question in the August/September wave 2018: "Do you use the Internet at least occasionally for private purposes, whether through computers, laptops, tablets or smartphones at home, at work or anywhere else?".

The survey waves of the GESIS Panel take place every two month, each taking about 20 minutes. Every panel member, independently of their participation mode, receives a survey invitation sent by mail, which includes a prepaid cash incentive of €5. Panelists of the web mode are sent an additional e-mail invitation, and two e-mail reminders are sent to those who have not answered the survey. Participants of the mail mode do not receive a regular reminder due to the cost of sending letters by post.

Web-push intervention in the October/November wave 2018

In the October/November wave 2018, a web-push intervention was implemented in the GESIS Panel, offering all panelists of the mail mode the opportunity to complete the survey via the internet. Table 4.1 provides an overview of the modes of invitation and internet usage among panelists of the mail mode by the recruitment cohorts for all respondents who were invited to this wave. As part of the web-push intervention, three experimental treatments were tested to examine which strategy most effectively persuaded panelists of the mail mode to become respondents of the web mode (for details, see Bretschi et al., 2021). All 1895 panelists of the mail mode were randomly assigned to one of three conditions: (1) the web option was offered to panelists concurrently with the paper questionnaire, including a promised €10 incentive for completing the survey on the web, (2) the web option was presented sequentially two weeks before sending the paper questionnaire, and respondents were also promised an incentive of €10, or (3) the same sequential web-first approach as for condition 2, but with a prepaid €10 incentive instead of a promised incentive. Those respondents who completed the survey online were asked at the end of the online questionnaire, whether they were willing to switch to the web mode for the upcoming waves. Panel members who had agreed to switch modes permanently received invitations for the web mode in future GESIS Panel waves. Overall, 20.7% of the participants who had been invited to the experiment completed the survey online immediately as a short-term switch, and 14.4% of all panelists in the mail mode were willing to switch to the web in the long term.

For this study, we were only interested in panelists who reported using the internet for private purposes at least occasionally, as only this group of participants was considered to have a realistic choice for switching modes. Out of the 1895 panelists of the mail mode who were invited in the October/November wave, 72.0%

indicated that they use the internet for private purposes. In sum, our analysis sample thus consists of 1364 panel members.

4.2.2 Measures

Outcome variables

As mentioned above, this study's research questions refer to the two dichotomous outcomes short-term and long-term mode switching. Short-term mode switching was defined as panel members of the mail mode who fully or partially completed the survey via the web mode in the October/November wave 2018. While a fully completed questionnaire consists of 80% and more answered survey questions, a partially completed survey comprises between 50% and 80% answered questions in the wave questionnaire. The completion rate of the analysis sample was 90.8%. Those 9.2% panelists who did not complete the survey by mail or web were included in the analysis as non-switchers (n = 125), since the request to switch modes may have influenced their decision not to participate. Overall, 380 (27.9%) out of 1364 panelists switched to the web mode in the single October/November wave 2018 ("short-term switchers").

Once respondents had completed the survey online in the October/November wave 2018, they were asked whether they agreed to respond permanently via the web mode for a long-term mode switch. Panel members who agreed to switch the survey mode were requested to provide a valid e-mail address for receiving additional invitations for upcoming waves. Participants stayed in the mail mode if they refused to share an e-mail address or if an e-mail address was unavailable. Overall, 266 (70.0%) out of 380 panelists agreed to switch to the web mode permanently ("long-term switchers").

Explanatory variables

Table 4.2 provides an overview of how the explanatory variables of this study were operationalized. The frequency of internet use was measured as an ordinal variable about how frequently respondents are online. The variety of internet use was quantified by an additive index of ten types of online activities. The number of devices was measured with an index of up to four devices that respondents had used in the last three months before the wave.

To examine internet skills, we adapted items from the Internet Skills Scale (ISS) developed by van Deursen et al. (2016). The ISS is a validated instrument consisting of five types of internet skills: operational, information navigation, social, creative, and mobile. We assumed that participating in web surveys requires a basic level of internet skills, and so we focused on the dimensions operational, information navigation, and mobile skills. The dimensions operational and information navigation skills were measured with five items and the dimension mobile skills with three items. We ran a second-order confirmatory factor analysis (CFA) of the three dimensions as first-order factors with maximum likelihood estimation using the R package lavaan (Rosseel et al., 2019). Indices of fit were calculated for the measurement model. According to the guidelines by Hooper et al. (2008), the results showed an acceptable fit ($\chi^2(61)$ = 2,526.39, p <.001, Comparative Fit Index = 0.97; Tucker-Lewis Index = 0.97; RMSEA = .052, SRMR = .028). Based on the CFA model, a second-order factor score was estimated as an indicator of internet skills and included in our analyses.

To investigate attitudes toward the internet, items were adapted from the Oxford Internet Survey (OxIS). We used translations of four items identified by Blank and Dutton (2012) as indicators of net risk. Additionally, we adapted three items of the OxIS, which we propose to use for measuring affinity for technology. A CFA was calculated to test and identify factors for net risk and affinity for technology. One item ("It is easy to assess quality of products one can buy on the Internet") did not load strongly on the factor net risk and was removed from the model. After modification, the model showed an acceptable model fit ($\chi^2(8.00) = 24.23$, $p < .002$, Comparative Fit Index = 0.98; Tucker-Lewis Index = 0.96; RMSEA = .039, SRMR = .025). Based on this model, factor scores were calculated as indicators for net risk and affinity for technology.

All explanatory variables were collected in the two previous waves before panelists were offered the possibility of switching modes, so some data are missing due to unit and item nonresponse. Additionally, specific items were not collected for some of the panel members who were recruited in 2018.[1] To deal with the problem of missing values, we imputed ten times with 20 iterations by multivariate imputation by chained equations using the R package mice (van Buuren & Groothuis-Oudshoorn, 2011). The imputation model predicted missing data with a set of selected variables from the complete-data model and basic demographic variables.

[1] According to the GESIS Panel recruitment procedure, newly recruited panelists were included in the regular panel waves in six tranches from the April/May wave 2018 to the December/January wave 2018/2019. Panelists who were integrated late missed one or both waves before the October/November wave 2018. To reduce this problem, we included explanatory variables in the profile survey in which panelists participated before receiving an invitation to the regular surveys. However, this was not possible for items of the internet skills scale and the items for attitudes toward technology. Overall, 11.4% of values from the explanatory variables are missing, with up to 19% of missing values for specific variables.

TABLE 4.2: Constructs, dimensions and operationalization of the explanatory and control variables

Dimension	Wording	Scale	Full sample (n = 1364) M (SD)	Short-term switchers (n = 380) M (SD)
INTERNET USE				
Frequency	**How often do you use the internet?**	**5-point**	**2.92 (1.26)**	**3.36 (1.14)**
Variety	**Index of variety of internet use**	**11-point**	**5.43 (2.23)**	**6.73 (1.90)**
	Have you ever used the internet: to read news	yes/no	0.87 (0.34)	0.95 (0.22)
	... to find out more about a topic		0.94 (0.23)	0.99 (0.11)
	... to shop		0.72 (0.45)	0.88 (0.33)
	... to transfer money		0.49 (0.50)	0.70 (0.46)
	... to read or send e-mails		0.87 (0.33)	0.97 (0.16)
	... to book a holiday		0.55 (0.50)	0.72 (0.45)
	... to take care of matters from authorities		0.30 (0.46)	0.46 (0.50)
	... to organize yourself		0.21 (0.41)	0.34 (0.47)
	... to read or share something on social networks		0.34 (0.47)	0.43 (0.50)
	... to participate in a betting or a sweepstake		0.15 (0.15)	0.28 (0.28)
No. of devices	**Index of number of web-enabled devices**	**5-point**	**2.04 (0.92)**	**2.39 (0.92)**
	What devices have you used: Desktop computer/PC	yes/no	0.40 (0.49)	0.49 (0.50)

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Table 4.2 Continued from previous page

Dimension	Wording	Scale	Full sample M (SD)	Short-term switchers M (SD)
	... Laptop		0.55 (0.50)	0.59 (0.49)
	... Tablet		0.37 (0.48)	0.50 (0.50)
	... Smartphone		0.72 (0.45)	0.81 (0.39)
INTERNET SKILLS				
Global skills	**Factor scores of global skills**	**continuous**	**0.01 (0.65)**	**0.33 (0.58)**
Operational	I know how to open downloaded files	5-point	3.92 (1.18)	4.29 (0.94)
	I know how to download/save a photo I found online		3.68 (1.31)	3.68 (1.31)
	I know how to use shortcut keys		3.25 (1.39)	3.77 (1.26)
	I know how to open a new tab in my browser		3.32 (1.47)	3.92 (1.31)
	I know how to bookmark a website		2.94 (1.49)	3.51 (1.47)
	I know how to open a new tab in my browser		2.54 (1.18)	2.34 (1.14)
Information navigation	I find it hard to decide what the best keywords are to use for online searches	5-point	2.33 (1.10)	2.01 (0.97)
	I find it hard to find a website I visited before		2.34 (1.11)	2.07 (1.02)
	I get tired when looking for information online		2.59 (1.21)	2.28 (1.13)
	Sometimes I end up on websites without knowing how I got there		3.15 (1.08)	2.95 (1.06)
	I find the way in which many websites are designed confusing		3.37 (1.48)	3.93 (1.33)
Mobile	I know how to install apps on a mobile device	5-point	3.37 (1.46)	3.92 (1.32)

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Table 4.2 Continued from previous page

Dimension	Wording	Scale	Full sample $M\ (SD)$	Short-term switchers $M\ (SD)$
	I know how to download apps to my mobile device		3.09 (1.40)	3.49 (1.35)
	I know how to keep track of the costs of mobile app use		3.30 (1.47)	3.81 (1.34)
ATTITUDES TOWARD THE INTERNET				
Net risk	**Factor scores**	**continuous**	**0.00 (0.36)**	**-0.06 (0.34)**
	When paying on the internet, you should be concerned about the security of your credit card information	5-point	3.95 (0.96)	3.85 (0.89)
	The internet is a threat to personal privacy.		3.34 (0.97)	3.17 (0.96)
	It is too easy to find other people's contact information on the internet.		3.69 (0.86)	3.69 (0.79)
	It is easy to assess the quality of products you can buy on the internet.		2.80 (0.98)	2.86 (0.93)
Affinity for technology	**Factor scores**	**continuous**	**0.00 (0.43)**	**0.11 (0.41)**
	It is exciting to try out newly invented technologies or devices.	5-point	3.30 (0.94)	3.55 (0.92)
	It is important for me that my technical devices at home, such as mobile phones, televisions, or computers are state of the art.		2.93 (0.97)	2.99 (0.93)
	The internet simplifies communication between people		3.63 (0.93)	3.80 (0.86)
CONTROLS				
Age	When were you born?	in years	56.06 (13.48)	52.34 (14.01)
Education	What is your highest general degree of education?	low/medium/high	2.09 (0.76)	2.29 (0.76)

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Table 4.2 Continued from previous page

Dimension	Wording	Scale	Full sample M (SD)	Short-term switchers M (SD)
HH Income	How high is the average net income of your household	10-point	4.93 (1.89)	5.45 (1.84)
HH Size	How many people, you included, regularly live in your household?	5-point	2.31 (1.04)	2.50 (1.08)
Gender	Are you male of female?	male/female	0.58 (0.49)	0.57 (0.49)
Internet users when recruited	How often do you use the internet?	6-point	0.16 (0.37)	0.09 (0.28)

Note: M = Mean; SD = Standard Deviation

Controls

A selected set of control variables was used in our analyses to reduce potential confounding bias in the estimations. We mainly controlled for variables for which previous studies had found associations with mode switching and internet-related characteristics. Literature suggests that age and education are associated with internet use (Blank & Dutton, 2012) and internet skills (Scheerder et al., 2017; van Deursen et al., 2011; van Deursen & van Dijk, 2010). We thus include educational attainment (no degree or lower secondary school, secondary school, general qualification for technical college and university entrance), age, and gender in our models. Additionally, we included variables for household size (measured as five categories from 1 to 5 and more household members) and household income (measured as ten categories from under 900 Euros to 10,000 Euros and more). In contrast to the explanatory variables, these control variables were measured in the December/January wave 2018/2019. We used data from the December/January wave after the web-push intervention because this data had fewer missing values, and we assumed the demographic characteristics to be stable over the short period. As a further control variable, each multivariate model was adjusted for the experimental randomization to control for the different treatments of the web-push intervention. We also included a dummy variable in our models on whether panelists were internet users during the recruitment and refused to participate in the web mode or were assigned to the mail mode due to a lack of internet access at the time of recruitment.

4.2.3 Analysis plan

Research question 1, about short-term switching, was addressed by fitting logistic regression models to the data. First, we ran a series of bivariate logistic models for each explanatory variable and with short-term switching as the outcome. Panelists remaining in the mail mode were coded 0, and those switching to the web mode were coded 1. The bivariate analyses allow detecting statistical associations, which are important for studies that aim at predicting mode switching. For example, such information can be used to implement a targeting web-push design where subgroups of panel members were treated with a different contact strategy depending on predefined characteristics (Freedman et al., 2018; Lynn, 2015, 2016). All hypotheses were subsequently tested using a multiple logistic regression model adjusted for all explanatory and control variables. To answer research question 2, we regress long-term mode switching on the explanatory variables again in a series of bivariate and multivariate analyses. For the analysis and hypotheses tests of long-term mode switching, we included only those panelists who are considered short-term mode switchers. However, we also present results of a multiple logistic regression model where long-term mode switching was fitted to data from all panelists of the analysis sample.

We also analyzed the answers to two open questions, asking the panelists why they refused to switch to the web mode in the short term, and in the case of short-term switchers, why they declined a switch in the long term. All responses were coded by the main author and a research assistant independently. Discrepancies were decided by the main author.

If not specified otherwise, the significance level for hypotheses testing was set at the five percent level ($p < .05$) with two-tailed testing. Despite the complex survey design of the GESIS Panel, we present regression models based on unweighted data since we did not find substantial differences to models based on weighted data. Winship and Radbill (1994) argue that the unweighted models are more efficient and estimated standard errors will be correct if the estimates of regression analysis based on weighted and unweighted data are substantially similar. Results of weighted models can be found in the appendix using the R package survey (Lumley, 2020). All statistical analyses were performed using R version 4.0.3 (R Core Team, 2019).

4.3 Results

4.3.1 Findings with regard to short-term mode switching

Bivariate findings

We begin our analysis by examining the bivariate association between the explanatory variables and the outcome short-term mode switching. Figure 4.1 provides an overview of average marginal effects with 95% confidence intervals from a series of logistic regression models for both outcomes of mode switching (see appendix for detailed results). Concerning short-term mode switchers, the figure shows that all dimensions of internet use are positively and significantly related to panelists' willingness to use the web mode in a single wave, which is also true for internet skills. Additionally, we found statistically significant associations in the expected direction regarding attitudes toward net risks and the affinity for technology.

Multivariate findings

To test our hypotheses, we fitted a multiple logistic regression model for the outcome short-term mode switching, now including all explanatory variables and adjusting for a set of control variables. The results are presented in the first model of Table 4.3. In contrast to the bivariate analyses, most explanatory variables of the multivariate model no longer show a statistically significant relation to respondents' willingness to make a short-term switch. We found that only variety of internet use and internet skills retain a statistically significant association with short-term mode switching.

Concerning the hypotheses about internet use, the model does not provide sufficient evidence to support hypothesis ST-1 on an effect of frequency of internet use and hypothesis ST-3 on the number of devices on mode switching in the multivariate setting. However, our findings are in line with hypothesis ST-2 that panelists are more likely to switch to the web mode in a single wave if there is a greater variety of internet usage. These results could be affected by multicollinearity due to moderating

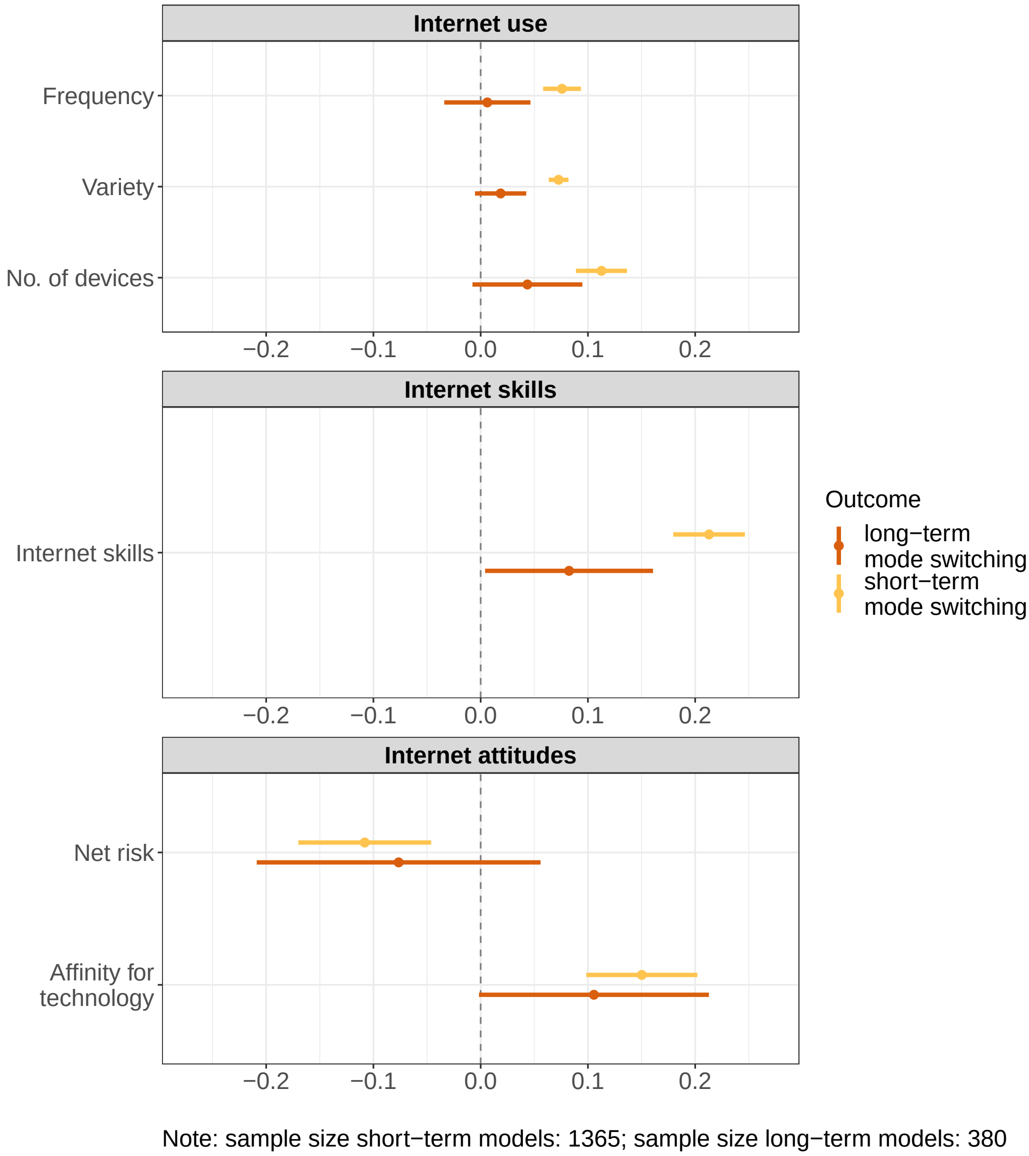

FIGURE 4.1: Average marginal effects and 95% confidence intervals from bivariate logistic regression models predicting short-term and long-term mode switching.

and mediating effects between the different dimensions of internet use. Even if people may differ in all three dimensions, the variety of use and the number of devices can be related to each other and to the amount of internet use. For instance, individuals may use the internet more frequently if they access the internet with more devices and use the internet for more different types of online activities. To get a better understanding of how the dimensions frequency of use, variety of use and number of devices affect the outcome short-term mode switching, we checked multicollinearity and performed sensitivity tests (see appendix for results). Sensitivity analyses show that each of the three dimensions of internet use is significantly associated with short-term mode switching if the other two dimensions are excluded from the multivariate model. Although these findings indicate that the three dimensions share variance, the results of the Variance Inflation Factor are below the suggested thresholds of 10 and did not exceed the value of 2.

Regarding hypothesis ST-4, our analysis supports the assumption that respondents with higher internet skills are significantly more likely to switch to the web mode in a single wave. Among the dimensions of attitudes, we did not find sufficient support for Hypotheses ST-5 and ST-6. According to our model, neither net risk nor affinity for technology significantly affects mode switching in a single wave. As shown in Table 4.3, none of the control variables included in Model 1 was significantly associated to short-term mode switching.

4.3.2 Findings with regard to long-term mode switching

Bivariate findings

To address research question 2, bivariate analyses were performed again to investigate whether internet use, internet skills, and internet attitudes are related to the willingness for long-term mode switching. The analyses now include the reduced sample size of all panelists who used the web mode in the single survey. Figure 4.1 clarifies that the size of the coefficients tends to be smaller in the models for long-term mode switching compared to the short-term models, but basically shows the same expected direction. However, only internet skills are still positively associated with mode switching on the five percent level of significance.

Multivariate findings

The multivariate Model 2 of Table 4.3 reveals that none of the explanatory variables are significantly associated with the decision for long-term mode switching on a 95% confidence level. According to these results, we did not find sufficient evidence that the decision to make a long-term switch depends on any tested internet characteristics once panelists used the web mode in the single survey. Consequently, Hypotheses LT-1 to LT-6 cannot be supported. Again, the results show no significant relation between any of the control variables and long-term mode switching.

Since Model 2 was fitted to the short-term mode switchers only, we performed an additional model to investigate whether the characteristics of interest can explain long-term mode switching if we fit data to the entire analysis data set. Results are shown in Model 3 of Table 4.3. As with Model 1, variety of internet use and internet skills are significantly related to the outcome. The analysis indicates that both variables explain mode switching not only in the short term but also in the long term when the entire sample is considered.

TABLE 4.3: Average marginal effects (AME) with standard errors (s.e.) and p-values (p) from multiple logistic regression models predicting likelihood of willingness to switch to the web mode in the short term (Model 1), in the long term among short-term switchers (Model 2), and in the long term among all panelists (Model 3)

	Model 1			Model 2			Model 3		
	AME	(s.e.)	p	AME	(s.e.)	p	AME	(s.e.)	p
Internet characteristics									
Frequency	0.00	(0.02)	.920	−0.02	(0.05)	.726	0.00	(0.02)	.858
Variety	0.05	(0.02)	.009	0.01	(0.05)	.797	0.04	(0.02)	.026
No. of devices	0.02	(0.02)	.358	0.02	(0.05)	.682	0.02	(0.02)	.330
Internet skills	0.08	(0.03)	.016	0.11	(0.07)	.156	0.08	(0.03)	.005
Net risk	−0.01	(0.04)	.846	−0.01	(0.08)	.871	−0.01	(0.03)	.791
Affinity for technology	0.02	(0.03)	.563	0.03	(0.08)	.709	0.02	(0.03)	.482
Recruitment cohorts									
Cohort 2016	−0.01	(0.03)	.685	0.06	(0.07)	.417	0.01	(0.03)	.827
Cohort 2018	0.05	(0.03)	.116	0.04	(0.07)	.553	0.06	(0.03)	.065
Ref. = Cohort 2013									
Recruitment cohorts									
Age (in years)	0.00	(0.02)	.942	0.01	(0.04)	.892	0.00	(0.02)	.878
Education: medium level	−0.02	(0.04)	.612	−0.04	(0.08)	.620	−0.02	(0.03)	.457
Education: high level	0.04	(0.04)	.321	0.05	(0.08)	.560	0.03	(0.03)	.333

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Table 4.3 Continued from previous page

TABLE 4.3: Average marginal effects (AME) with standard errors (s.e.) and p-values (p) from multiple logistic regression models predicting likelihood of willingness to switch to the web mode in the short term (Model 1), in the long term among short-term switchers (Model 2), and in the long term among all panelists (Model 3) *(continued)*

	Model 1			Model 2			Model 3		
	AME	(s.e.)	p	AME	(s.e.)	p	AME	(s.e.)	p
Ref. = Education: low level									
Household income	0.01	(0.02)	.577	0.01	(0.05)	.866	0.01	(0.02)	.587
Household size	0.01	(0.02)	.507	−0.01	(0.05)	.797	0.01	(0.02)	.782
Female	0.01	(0.03)	.738	0.01	(0.07)	.893	0.01	(0.03)	.707
Ref. = Male									
Non-internet users when recruited	−0.05	(0.04)	.178	0.00	(0.09)	.986	−0.03	(0.04)	.354
Ref. = Internet users when recruited									
Exp. group 1	−0.05	(0.03)	.144	−0.01	(0.07)	.841	−0.04	(0.03)	.188
Exp. group 3	0.01	(0.03)	.813	−0.05	(0.07)	.470	−0.01	(0.03)	.714
Ref. = Exp. group 3									
Mcfadden's adjusted R^2	0.13			-0.03			0.12		
Mcfadden's R^2	0.15			0.05			0.14		
Observations	1364			380			1364		

4.3.3 Self-reported reasons for not switching to the web mode

The previous analysis showed that internet-related characteristics are helpful in explaining short-term mode switching, but the characteristics are less suitable for explaining a permanent mode switch among short-term mode switchers. These findings suggest that there may be additional variables that affect panel members' decisions to switch modes. To get a better understanding of respondents' motivation, the panelists who refused to switch modes in the short term or the long term were asked why they had made such a decision. Graph 4.2 summarizes the coded results of two open questions.

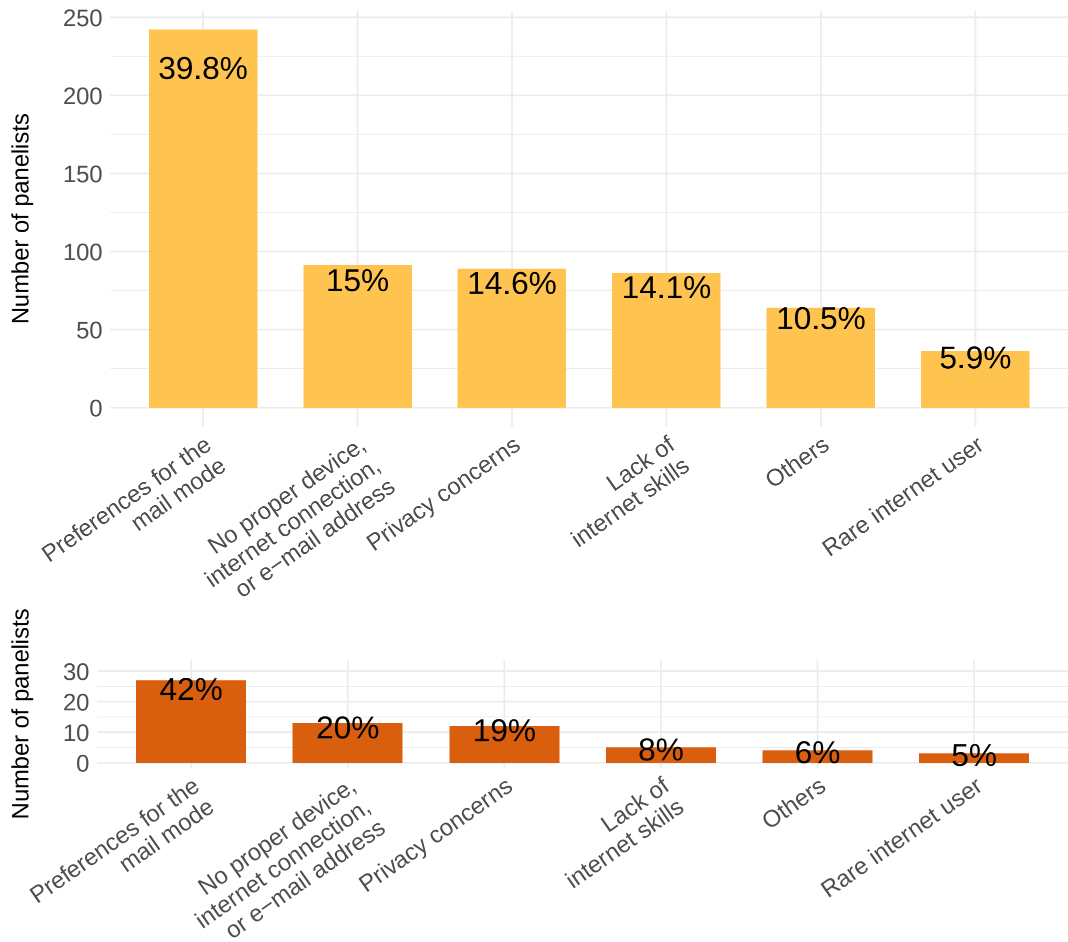
The upper bar chart represents the reported reasons from a question that 859 panel members who completed the paper-and-pencil questionnaire were asked about why they did not switch to the web mode in the short term. About 40% of the responses were coded as general preferences for the mail mode, e.g., because panelists feel paper forms are easy to fill in, are clearer, or because they use electronic devices too often in their everyday lives. Approximately 15% of the answers were assigned to categories according to which panelists did not have the proper equipment, had concerns regarding the internet,or lacked internet skills required to participate in web surveys. The latter category also includes respondents who tried to respond via the internet but failed to do so. The remaining reasons mentioned were diverse and referred, for example, to a lack of time or to being undecided. Around six percent of respondents explicitly said they did not complete the online questionnaire because they rarely used the internet.

The lower bar chart of graph 4.2 shows the coded responses from a second open question that 84 short-term mode switchers were asked after they had declined to switch to the web mode in the long term. The chart also includes data from 30 short-term switchers who agreed to switch to the web mode in the long term but were unwilling or unable to provide the GESIS Panel with a valid e-mail-address. A valid e-mail-address was required for participation in the web mode for further waves, and panelists were asked to remain in the mail mode if no e-mail-address was provided. An unavailable e-mail-address was identified by one-third of the panelists as the reason why short-term mode switchers did not become long-term mode switchers. Nearly the same proportion of answers were coded as preferences for the mail mode when participants were asked about reasons for not switching to the web mode. Mail mode preferences were justified by the fact that paper-and-pencil questionnaires are a better reminder to participate or that respondents would like to spend less time in front of a computer. A smaller proportion of responses were coded as a lack of proper equipment, existing privacy concerns, or insufficient internet skills. Again, the remaining responses could not be assigned to a common category and a small number of respondents described themselves as using the internet only rarely.

4.4 Summary and conclusions

This paper investigated mechanisms of mode switching in an ongoing mixed-mode panel. The study was designed to determine whether different dimensions of internet use, internet skills, and attitudes toward the internet affect the willingness of panel members to switch from the mail mode to the web mode in the short term and the long term. We used data from a web-push intervention in a German probability-based mixed-mode panel study, the GESIS Panel, where indicators of internet-related characteristics were measured in the two previous waves before panelists received an option to switch modes.

Regarding short-term mode switching, we found evidence in bivariate analyses that frequency of internet use, variety of online activities, and the number of devices were positively associated with the willingness to participate in web surveys. However, when fitting a model with indicators for all presumed determinants and control variables, only the variety of internet use showed a statistically significant effect. We speculate that the three dimensions of internet use moderate and mediate their effect on short-term mode switching between them. As a consequence, the effect size of



Note:
The first bar chart represents coded answers from an open question. 859 panelists (internet−users only) who completed the mail questionnaire were asked why they did not switch to the web mode in the short term.
Not shown: 252 cases of item nonresponse (29.3%)

The second bar chart displays the coded answers from an open question 84 short−term switchers were asked regarding why they refused to do a long−term switch.
30 short−term switchers agreed to a long−term mode switch but were not willing or able to share an e−mail−address that was required to permanently switch modes.
These cases are represented in the bar 'E−mail−address not shared/available'.
Not shown: 24 cases of item nonresponse (20.2%)

FIGURE 4.2: Panel members' self-reported reasons for not switching to the web mode in the short term (first graph) or in the long term (second graph).

the three dimensions might be underestimated in our model due to an overcontrol bias (Elwert & Winship, 2014). As there has been little research in this area, we are less interested in estimating each dimension's total effect in a first step, but rather in understanding which dimension is meaningful. However, further research is needed to understand the relationship between the different dimensions of internet use and respondents' behavior. As a result of this study, we recommend that future studies should take into account the variety of individuals' online activities in order to better understand and predict the participation of respondents in web surveys. Overall, the study results support the claim that internet use is a complex and multidimensional phenomenon (Blank & Groselj, 2014; Scheerder et al., 2017).

A major finding of this study was that basic internet skills are an important mechanism of short-term switching to the web mode. Internet skills help to explain mode switching in addition to internet use. This result is in line with previous research, which showed that even basic internet skills are not determined by the frequency of internet use (van Deursen et al., 2011; van Deursen & van Diepen, 2013). Our findings support the assumption that internet skills are an independent mechanism for explaining mode switching, whereas the dimensions of internet use cannot serve as a valid indicator for skills. We are not aware of any study which has systematically examined this relationship. Internet skills could become a more important characteristic in explaining respondents' behavior in web surveys when internet access and use are spreading even further into our daily lives. For instance, it would be interesting to learn more on how internet skills are related to phenomena of interest in survey research such as data quality, use of devices, or panel attrition.

Our findings are inconclusive for attitudes toward the internet. Bivariate analyses showed an expected association, by which panelists are more likely to switch to the web mode in a single wave if they see lower risks in using online activities and if they have a higher affinity for the use of technology. However, the multivariate models did not reveal a significant effect of either characteristic. So there is still a lack of evidence that these attitudes affect respondents' willingness to switch to the web mode.

Panel members who completed the survey online in the single wave were asked to switch to the web mode for upcoming waves. For those short-term mode switchers, we investigated how internet use, internet skills, and internet attitudes are related to their decision to make a long-term mode switch. Only internet skills showed a significant association in the bivariate analysis, and no explanatory variable was found significant in the multivariate model on the five percent level. However, considering the reduced statistical power as a result of the smaller sample size, it is noteworthy that the affinity for technology showed a significant bivariate relationship in the expected direction on the ten percent level. This is also true for internet skills in the multivariate model. While internet use and internet skills seem to help explain the decision process of short-term mode switching, insufficient evidence was found that this also applies to a long-term perspective.

We assumed that internet-related characteristics affect both short-term and long-term mode switching since the expected costs are considered to be basically the same in both decisions. Due to the two-step selection procedure, however, short-term switchers tend to be more similar in characteristics associated with the decision of a short-term mode switch. As a consequence, those variables may lose explanatory power to explain the variance of long-term mode switching. Moreover, the smaller sample size of the short-term switchers reduces the statistical power for detecting an effect on long-term switching. We could show that variety of internet use and internet skills significantly affect long-term mode switching when considering the full sample of panelists who were offered to switch modes from the beginning. However, our findings indicate that other variables than internet-related characteristics seem to affect panelists' decision to make a long-term mode switch once they have used the web mode in a single wave.

To explore which additional factors might impact panelists' decisions, respondents who declined to switch modes were asked for reasons. The reasons mentioned by panel members were coded in categories that correspond to internet-related characteristics such as usage of the internet, insufficient skills, or concerns about their data when it is shared over the internet. However, many panel members refer to general preferences for the mail mode as the main reason for not switching modes in the short term or in the long term. It is also noticeable that the order and proportion of categories are quite similar for short-term and long-term mode switchers. Although this information provides an explorative insight into the motivation of the panelists who refused a single or permanent switch to the web mode, it is questionable to what extent self-reported reasons of respondents' behavior correspond with the true causes of their decision. As Schnell (2019) argues, respondents may not know the true reasons for their actions or may not be willing to report them honestly.

A limitation of this study is that the internet-related characteristics are measured by self-reporting. Although we have used a validated scale to measure internet skills, self-reporting by respondents in surveys may have lower internal validity than performance tests and may be affected by socially desirable responding (Hargittai & Shafer, 2006; Litt, 2013). Moreover, how people use or think about the internet and different online applications may change rather quickly due to the development of digitalization. This development may affect our adaptation of the components for net risk, which were used ten years ago by Blank and Dutton (2012). Future research should not only focus on confirming the finding of this study but also investigate whether mechanisms for mode switching change over time. We would also like to point out that this study focuses on panel members with specific characteristics, such as participants of the mail mode who used the internet for private purposes and refused to participate in web surveys during the panel recruitment or who did not use the internet at this time. Although we believe that these individuals are particularly interesting for survey research, it is unclear to what extent the results of this study apply to other survey settings.

As a growing number of longitudinal studies introduce web surveys as a data collection mode, the question arises on how to convince panel members to participate via the internet effectively. Understanding the mechanisms of mode switching may help to design web-push methods for ongoing panel surveys. A conclusion of this study could concern the communication strategy of web-push interventions. Since internet skills seem to matter, it may be more important to convince respondents that participating in web surveys is easy, rather than reducing potential concerns about sharing personal information online. More research is needed to back such assumptions and to convert the findings into effective web-push strategies.

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Appendix

Bivariate logistic regression models

TABLE 4.4: Average marginal effects (AME) with standard errors (s.e.) and p-values (p) from bivariate logistic regression models predicting likelihood of willingness to switch to the web mode in the short and the long-term

	Short-term mode switching			Long-term mode switching		
	AME	(s.e.)	p	AME	(s.e.)	p
Internet use						
Frequency	0.08	(0.01)	.000	0.01	(0.02)	.762
Variety	0.07	(0.00)	.000	0.02	(0.01)	.127
No. of devices	0.11	(0.01)	.000	0.04	(0.03)	.095
Internet skills						
Internet skills	0.21	(0.02)	.000	0.08	(0.04)	.039
Attitiudes towards the internet						
Net risk	−0.11	(0.03)	.001	−0.08	(0.07)	.258
Affinity for technology	0.15	(0.03)	.000	0.11	(0.05)	.053

Note: Each row represents a single model.

Sensivity analyses

To examine whether the results of the multivariate model for short-term mode switching are affected by multicollinearity, we present a correlation matrix in Figure 4.3 and calculated the variance inflation factors (VIFs), as suggested, e.g., by Hair et al. (2013). The mean values of the Generalized VIFs over the multiple imputed data sets were for each variable well below the suggested thresholds of 10 and did not exceed the value of 2, indicating a moderate share of variance of the explanatory variables with the outcome.

We also examined how the model fit is affected by removing single dimensions of internet use from a multiple logistic regression model with the outcome short-term mode switching. A series of likelihood-ratio tests were used for a set of nested models with different combinations of internet use, internet skills, and internet attitudes. The results show that the model fit does not significantly decrease when removing frequency of internet use (x^2 = -0.05; p = > .999) or the number of devices (x^2 =

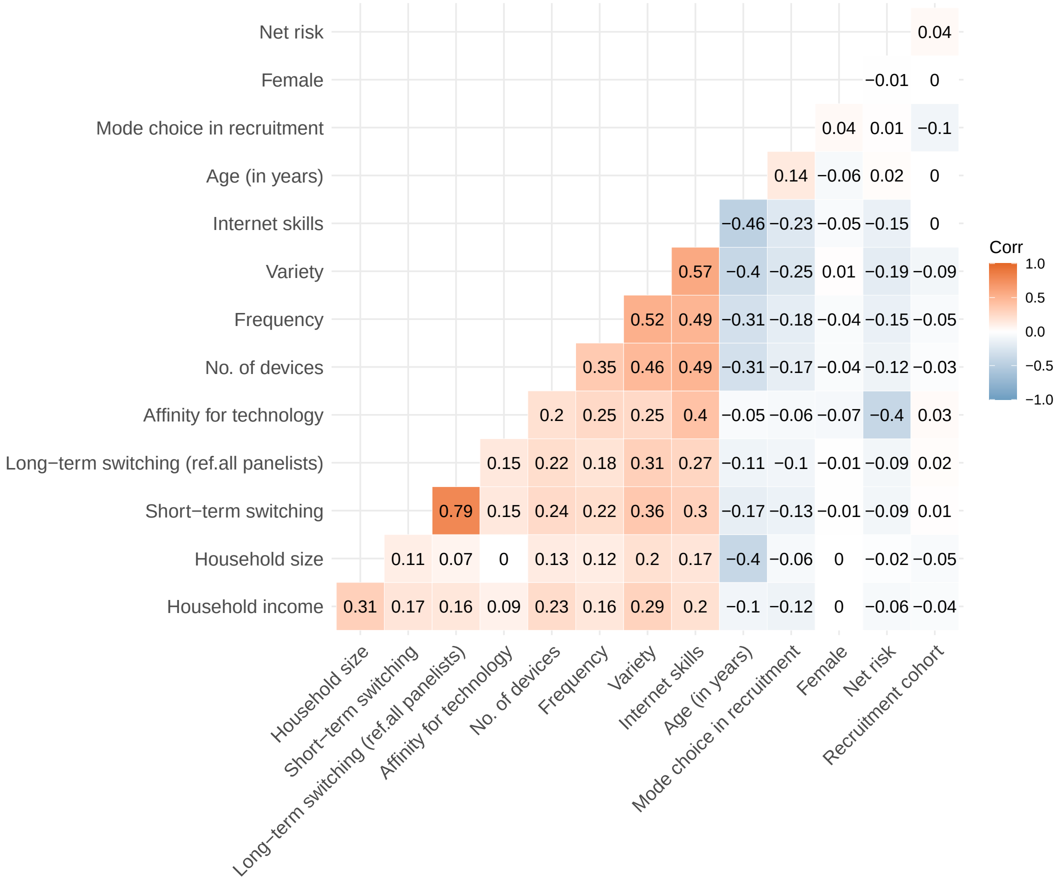

FIGURE 4.3: Correlation matrix of outcomes, explanatory and control variables (over all ten imputed data sets).

2.04; $p = .154$) or both variables ($x^2 = 1.06$; $p = .345$) from the model 1 in Table 4.3 as long as variety of use is included. However, each dimension of internet use indicates a positive and significant association to short-term mode switching if the other dimensions are excluded from the multivariate model (see Table 4.5).

TABLE 4.5: Logistic regression models with different combinations of the internet usage dimensions: average marginal effects with standard errors predicting likelihood of willingness to switch to the web mode in the short term

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Internet Characteristics						
Frequency		0.02	0.00	0.02		
		(0.022)	(0.021)	(0.021)		
Variety	0.05^{**}		0.052^{**}		0.052^{**}	
	(0.019)		(0.019)		(0.018)	
No. of devices	0.021	$0.039^{\cdot}$				$0.042^{\cdot}$
	(0.023)	(0.023)				(0.023)
Internet skills	0.076^{*}	0.118^{***}	0.085^{**}	0.138^{***}	0.086^{**}	0.131^{***}
	(0.031)	(0.031)	(0.03)	(0.03)	(0.03)	(0.03)
Net risk	−0.007	−0.034	−0.008	−0.038	−0.009	−0.037
	(0.038)	(0.038)	(0.038)	(0.038)	(0.037)	(0.038)
Affinity for technology	0.021	0.026	0.02	0.025	0.02	0.032
	(0.034)	(0.035)	(0.034)	(0.035)	(0.034)	(0.035)
Recruitment Cohorts						
Cohort 2016	−0.013	−0.023	−0.014	−0.024	−0.014	−0.022

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Table 4.5 Continued from previous page

TABLE 4.5: Logistic regression models with different combinations of the internet usage dimensions: average marginal effects with standard errors predicting likelihood of willingness to switch to the web mode in the short term *(continued)*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(0.033)	(0.034)	(0.033)	(0.034)	(0.033)	(0.034)
Cohort 2018	0.052	0.029	0.052	0.027	0.051	0.023
	(0.033)	(0.034)	(0.033)	(0.034)	(0.033)	(0.033)
Controls						
Age (in years)	0.001	0.000	0.001	0.000	0.001	0.000
	(0.018)	(0.019)	(0.017)	(0.018)	(0.017)	(0.018)
Education: medium level	−0.018	−0.012	−0.017	−0.01	−0.017	−0.011
	(0.035)	(0.036)	(0.035)	(0.036)	(0.035)	(0.036)
Education: high level	0.037	0.054	0.04	0.061	0.04	0.057
	(0.038)	(0.038)	(0.037)	(0.038)	(0.037)	(0.038)
Household income	0.011	0.017	0.012	0.019	0.012	0.017
	(0.019)	(0.02)	(0.019)	(0.019)	(0.018)	(0.02)
Household size	0.014	0.016	0.014	0.015	0.014	0.015
	(0.021)	(0.022)	(0.021)	(0.022)	(0.021)	(0.022)
Gender	0.01	0.014	0.009	0.012	0.008	0.013
	(0.029)	(0.03)	(0.029)	(0.03)	(0.029)	(0.03)

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TABLE 4.5: Logistic regression models with different combinations of the internet usage dimensions: average marginal effects with standard errors predicting likelihood of willingness to switch to the web mode in the short term *(continued)*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Mode choice in recruitment	-0.052	$-0.07^{\cdot}$	-0.054	$-0.074^{\cdot}$	-0.054	$-0.074^{\cdot}$
	(0.039)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Exp. group 1	-0.048	-0.046	-0.044	-0.041	-0.045	-0.047
	(0.032)	(0.033)	(0.032)	(0.033)	(0.032)	(0.033)
Exp. group 3	0.008	0.01	0.007	0.008	0.007	0.01
	(0.033)	(0.034)	(0.033)	(0.033)	(0.032)	(0.034)
Mcfadden's adjusted R^2	0.13	0.10	0.13	0.09	0.13	0.10
Mcfadden's R^2	0.15	0.12	0.15	0.11	0.15	0.12
Obs	1364	1364	1364	1364	1364	1364

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; $^{\cdot}p < .1$; (Robust standard errors in brackets)

Regression models based on weighted data

TABLE 4.6: Average marginal effects (AME) with standard errors (s.e.) and p-values (p) from bivariate logistic regression models predicting likelihood of willingness to switch to the web mode in the short and the long-term using survey weights

	Short-term mode switching			Long-term mode switching		
	AME	(s.e.)	p	AME	(s.e.)	p
Internet use						
Frequency	0.08	(0.01)	.000	0.01	(0.02)	.719
Variety	0.07	(0.00)	.000	0.02	(0.01)	.129
No. of devices	0.12	(0.01)	.000	0.05	(0.03)	.062
Internet skills						
Internet skills	0.22	(0.02)	.000	0.09	(0.04)	.031
Attitudes towards the internet						
Net risk	−0.10	(0.03)	.001	−0.12	(0.07)	.108
Affinity for technology	0.16	(0.03)	.000	0.12	(0.06)	.039

Note: Each row represents a single model.

TABLE 4.7: Average marginal effects (AME) with standard errors (s.e.) and p-values (*p*) from multiple logistic regression models predicting likelihood of willingness to switch to the web mode in the short term (Model 1), in the long term among short-term switchers (Model 2), and in the long term among all panelists (Model 3) using survey weights

	Model 1			Model 2			Model 3		
	AME	(s.e.)	*p*	AME	(s.e.)	*p*	AME	(s.e.)	*p*
Internet Characteristics									
Frequency	0.00	(0.02)	.852	−0.02	(0.05)	.682	0.00	(0.02)	.883
Variety	0.05	(0.02)	.006	0.01	(0.05)	.832	0.04	(0.02)	.029
No. of devices	0.03	(0.02)	.260	0.02	(0.06)	.659	0.02	(0.02)	.260
Internet skills	0.09	(0.03)	.004	0.11	(0.08)	.175	0.09	(0.03)	.001
Net risk	−0.01	(0.04)	.890	−0.06	(0.09)	.488	−0.02	(0.03)	.589
Affinity for technology	0.02	(0.03)	.589	0.03	(0.08)	.709	0.02	(0.03)	.510
Recruitment Cohorts									
Cohort 2016	−0.03	(0.03)	.400	0.06	(0.07)	.413	0.00	(0.03)	.904
Cohort 2018	0.06	(0.03)	.068	0.03	(0.07)	.725	0.06	(0.03)	.058
Ref. = Cohort 2013									
Recruitment Cohorts									
Age (in years)	0.00	(0.02)	.909	0.01	(0.05)	.904	0.00	(0.02)	.867
Education: medium level	−0.02	(0.04)	.539	−0.03	(0.09)	.762	−0.02	(0.03)	.485
Education: high level	0.02	(0.04)	.538	0.07	(0.08)	.433	0.03	(0.04)	.423

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Table 4.7 Continued from previous page

TABLE 4.7: Average marginal effects (AME) with standard errors (s.e.) and p-values (p) from multiple logistic regression models based on weighted data predicting likelihood of willingness to switch to the web mode in the short term (Model 1), in the long term among short-term switchers (Model 2), and in the long term among all panelists (Model 3) using survey weights *(continued)*

	Model 1			Model 2			Model 3		
	AME	(s.e.)	p	AME	(s.e.)	p	AME	(s.e.)	p
Ref. = Education: low level									
Household income	0.01	(0.02)	.512	0.00	(0.05)	.920	0.01	(0.02)	.586
Household size	0.02	(0.02)	.425	−0.01	(0.05)	.873	0.01	(0.02)	.668
Female	0.00	(0.03)	.952	−0.01	(0.07)	.824	0.00	(0.03)	.930
Ref. = Male									
Non-internet users when recruited	−0.04	(0.04)	.357	−0.01	(0.1)	.897	−0.02	(0.04)	.503
Ref. = Internet users when recruited									
Exp. group 1	−0.04	(0.03)	.218	−0.02	(0.07)	.837	−0.03	(0.03)	.262
Exp. group 3	0.01	(0.03)	.790	−0.05	(0.07)	.507	−0.01	(0.03)	.787
Ref. = Exp. group 3									
Mcfadden's adjusted R^2	0.15			0.01			0.15		
Mcfadden's R^2	0.16			0.06			0.16		
Observations	1364			380			1364		

TABLE 4.8: Logistic regression models with different combinations of the internet usage dimensions: average marginal effects with standard errors predicting likelihood of willingness to switch to the web mode in the short term using survey weights

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Internet Characteristics						
Frequency		0.02	0.00	0.03		
		(0.021)	(0.02)	(0.02)		
Variety	0.05**		0.052**		0.053**	
	(0.018)		(0.018)		(0.017)	
No. of devices	0.026	0.044·				0.047*
	(0.022)	(0.023)				(0.023)
Internet skills	0.089**	0.132***	0.099**	0.157***	0.101***	0.147***
	(0.03)	(0.03)	(0.03)	(0.029)	(0.029)	(0.029)
Net risk	−0.006	−0.029	−0.006	−0.033	−0.007	−0.032
	(0.038)	(0.037)	(0.038)	(0.037)	(0.037)	(0.037)
Affinity for technology	0.02	0.025	0.017	0.023	0.019	0.033
	(0.034)	(0.035)	(0.034)	(0.035)	(0.034)	(0.035)
Recruitment Cohorts						

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Table 4.8 Continued from previous page

TABLE 4.8: Logistic regression models with different combinations of the internet usage dimensions: average marginal effects with standard errors predicting likelihood of willingness to switch to the web mode in the short term using survey weights *(continued)*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Cohort 2016	−0.027	−0.036	−0.028	−0.039	−0.028	−0.035
	(0.032)	(0.033)	(0.032)	(0.033)	(0.032)	(0.033)
Cohort 2018	0.061$^{\cdot}$	0.037	0.062$^{\cdot}$	0.035	0.061$^{\cdot}$	0.032
	(0.034)	(0.034)	(0.034)	(0.034)	(0.033)	(0.034)
Controls						
Age (in years)	0.002	0.001	0.002	0.001	0.002	0.001
	(0.017)	(0.018)	(0.017)	(0.017)	(0.016)	(0.017)
Education: medium level	−0.022	−0.016	−0.02	−0.012	−0.019	−0.014
	(0.035)	(0.036)	(0.035)	(0.036)	(0.035)	(0.036)
Education: high level	0.023	0.038	0.027	0.046	0.027	0.041
	(0.037)	(0.038)	(0.037)	(0.038)	(0.037)	(0.038)
Household income	0.012	0.018	0.013	0.021	0.013	0.018
	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.019)
Household size	0.017	0.019	0.016	0.018	0.016	0.018
	(0.021)	(0.021)	(0.02)	(0.021)	(0.02)	(0.021)

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Table 4.8 Continued from previous page

TABLE 4.8: Logistic regression models with different combinations of the internet usage dimensions: average marginal effects with standard errors predicting likelihood of willingness to switch to the web mode in the short term using survey weights *(continued)*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	0.002	0.007	0.000	0.004	0.000	0.006
	(0.029)	(0.029)	(0.028)	(0.029)	(0.028)	(0.029)
Mode choice in recruitment	−0.036	−0.052	−0.037	−0.056	−0.037	−0.055
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Exp. group 1	−0.039	−0.037	−0.035	−0.03	−0.035	−0.039
	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)
Exp. group 3	0.009	0.011	0.008	0.008	0.008	0.011
	(0.033)	(0.034)	(0.033)	(0.033)	(0.033)	(0.034)
Mcfadden's adjusted R^2	0.151	0.118	0.149	0.112	0.15	0.116
Mcfadden's R^2	0.161	0.128	0.159	0.122	0.159	0.125
Obs	1364	1364	1364	1364	1364	1364

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; $^{\cdot}p < .1$; (Robust standard errors in brackets)

Chapter 5

Conclusions

With declining response rates and rising costs for interviewer-administered surveys, the internet has become a predominant mode of data collection (Couper, 2017). As part of this development, a rising number of probability-based panels using the internet as the sole or main mode has been established in several countries worldwide (Kaczmirek et al., 2019). Such probability-based online and mixed-mode panels provide an opportunity to collect high-quality data in a cost-efficient and timely manner. Although mixed-mode panels offer an alternative mode to panelists, and thus can reduce coverage and nonresponse errors, surveyors are typically interested in having as many panelists as possible participate via the least expensive web mode. By pushing panel members to use the web mode rather than a more expensive mode alternative, mixed-mode panels potentially improve the balance of survey errors and survey costs.

The goal of this dissertation was to explore and further develop web-push strategies for probability-based mixed-mode panels. In three separate studies, I investigated how the inclusion strategy of internet users in the mail mode affects data quality in the recruitment of a mixed-mode panel, tested strategies to push panel members from the mail mode to the web, and explored why some panel members are willing to switch to the web mode while others are not. In the following, I briefly summarize the findings of each study, present conclusions and limitations, and suggest further research. I close this chapter by discussing the direction of future research of web-push strategies for mixed-mode panel studies.

In the first study described in Chapter 2, I focused on the recruitment procedure of mixed-mode panels to investigate whether offering internet users a mail mode option affects nonresponse bias. This question is important for survey research, since internet users responding in the mail mode produce substantially more survey costs than their counterparts using the web mode. I tested this research issue in three analysis steps. The first step suggests that the group of internet users included in the mail mode differs from non-internet users in the mail mode and panelists in the web mode in several characteristics. However, by excluding this group from the analysis in a second step, I found nonresponse bias in only a few estimates compared to the benchmark survey. A third analysis step provided evidence that estimates of the means in variables used by two reproduced studies differ significantly between the full and the reduced data set that did not include the internet users in the mail mode. In contrast, estimates of multivariate analyses were only slightly affected if internet users were not included in the mail mode, and the original authors would probably have come to the same substantive conclusions based on the reduced data set. Even if offering a mail mode option to internet users is likely to increase recruitment rates of a mixed-mode panel, this study provides preliminary evidence that the higher investment may not pay off. From a total survey error perspective, survey designers should weigh up whether other design options are available which would more efficiently reduce survey errors within a given budget. For example, special incentives or different wording of the mode choice question could encourage more reluctant internet users to participate online without risking a substantial loss of data quality. It might also be more cost-efficient to offer an alternative survey mode only to non-internet users and instead draw a larger sample to compensate for higher dropouts of onliners unwilling to participate through the internet. However, these conclusions should be drawn with caution, since the study focused on a limited set of variables and reproduced studies based on the specific recruitment procedure of the GESIS Panel. Therefore, more research is needed to examine the robustness of these findings, preferably by testing different panel recruitment and web-push strategies in an experimental setting.

The second study, presented in Chapter 3, addressed whether and how members of an ongoing mixed-mode panel can be pushed to switch the survey mode from mail to the web. I experimentally tested how the order of presenting the web mode and offering an incentive affect four main outcomes: participants' willingness to use the web mode in the short- and long-term, panel attrition, and survey costs. The results show that a sequential web-first condition convinced significantly more panel members to complete the questionnaire online in a single wave than offering the web and mail mode concurrently but may not motivate more panelists to switch to the web mode permanently. Contrary to my expectation, offering prepaid incentives neither improved the web response nor the proportion of mode switchers compared to promised incentives. In sum, 14.4% of all panelists in the mail mode were willing to use the web mode in future waves, and all three web-push strategies tested were able to effectively reduce survey costs without causing differences in panel attrition after five consecutive waves. These findings provide new evidence that a web-push intervention in an ongoing panel study is an effective design option for persuading mail respondents to switch to the web mode. In particular, sequentially offering the web mode combined with a promised incentive shows potential as a cost-efficient web-push strategy. Due to a lack of statistical power, this study did not test a control condition in which panel members did not receive an invitation to use the web mode. This treatment would allow the evaluation of how a web-push intervention affects data quality indicators, such as panel attrition and measurement mode effects. The implementation of a control condition in future experimental settings is necessary to fully assess the impact of web-push strategies on different survey error components.

The third study, presented in Chapter 4, follows up on the web-push study from Chapter 3 by addressing the question of why panel members are willing or unwilling to switch from the mail to the web mode when offered the opportunity. I was particularly interested in whether internet-related characteristics can explain respondents' decisions by measuring indicators of internet use, internet skills, and attitudes toward the internet before a web-push intervention was implemented. The results of this study suggest that internet use and internet skills affect respondents' willingness to switch modes in a single wave. For these short-term switchers, however, none of the internet-related characteristics could explain mode switching in the long term. Overall, this study indicates that internet use and skills are more important in predicting and explaining mode switching than attitudes, such as perceived internet-related risks. Further research is needed to back up these findings, particularly because the study has limitations in terms of operationalizing internet-related characteristics, which are measured via self-reports. Nevertheless, these findings may help to develop more effective web-push strategies for mixed-mode panels, for instance, by applying a targeted web-push design. This type of targeted design could offer different treatment to subsamples of panel members, depending on predefined characteristics and their propensity to switch to the web mode. For example, panel members who rarely use the internet, or have low internet skills, could be provided with different instructions or arguments than panelists who have concerns about personal information being shared via a web survey.

The overall findings of this dissertation show that web-push strategies are a promising tool for probability-based mixed-mode panels. However, the use of such strategies in panel studies is still relatively new in survey methodology, and more research is needed to learn how to use this design feature effectively and unleash its full potential. In this regard, the current work provides conclusions and suggestions on how web-push strategies can be further developed and refined. I see two important directions of research that can be drawn from these findings. First, the web-push intervention described in this dissertation demonstrates that design decisions matter. The implementation of a strategy can influence the participants' decision regarding the mode in which they complete the survey questions. It is, therefore, worthwhile researching more effective strategies to convince respondents to use the web mode.

Here, panel studies offer excellent conditions for the implementation of targeting web-push designs. For example, machine learning techniques are able to estimate panelists' propensities to switch modes after a web-push intervention based on the rich data set of mixed-mode panels. Such a trained model could then be used to predict switching propensities of panel members from a newly recruited sample. In a targeting design, panelists with a low propensity could receive different treatment, such as a higher web-push incentive, than respondents with a high propensity to improve the cost-efficiency of the web-push intervention. Second, the respondents' decision does not depend on the web-push strategy alone. Some individuals do not have a real option for participating in web surveys because they do not have internet access or an internet-enabled device. Without offering this group of people an alternative to the web mode, there is a risk of lower data quality due to biased estimates for the general population. However, even in households with internet access, individuals might not be able or willing to participate in web surveys. This may be because these individuals lack certain skills necessary to complete a web survey, do not feel comfortable sharing private details via the internet, or just have preferences for other modes if they are offered. It is questionable to what extent pushing these people to the web mode will benefit data quality and cost reduction in the long run. The most effective web-push strategy could backfire by increasing other sources of survey errors, such as higher panel attrition or measurement error. Therefore, a second important research direction is to investigate all relevant consequences for survey quality resulting from the use of these strategies. While the research of this dissertation provides first evidence on the effects of web-push interventions on nonresponse error, further research on the impact on measurement error is particularly desirable. An experimental design implementing a control group with no switching option could investigate whether switching to the web mode causes mode measurement effects within and between panel members. Such mode effects would affect the ability to measure change and thus counteract the benefits of a web-push intervention for mixed-mode panels. Overall, both research directions are needed to assess the potential of web-push strategies to produce the lowest total survey error within given constraints of budget and other resources.

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