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

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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 = 5734). 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. We also present self-reported reasons by panelists for not accepting the offer to switch modes that correspond to these findings. The results of this study can be used to develop effective push-to-web methods for longitudinal mixed-mode surveys.

Keywords

web survey, mixed-mode, panel survey, internet use, internet skills

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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 10 percent of Gallop panel members with internet access explicitly asked to send 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 of 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?

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.

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 cost 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 able 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.

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 and long-term mode switching:

> **H1:** The more frequently panelists use the internet, the more likely they are to switch to the web mode (a) in the short term and (b) in the long term.
> **H2:** The higher the variety of internet use, the more likely panelists are to switch to the web mode (a) in the short term and (b) 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:

> **H3:** The more web-enabled devices panelists of the mail mode use, the more likely they are to switch to the web mode (a) in the short term and (b) 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:

H4: The higher the level of internet skills of panelists, the more likely they are to switch to the web mode (a) in the short term and (b) 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. The higher the perceived risk in using the internet is for respondents, the higher the cost for switching the mode. Accordingly, we formulate the hypotheses:

H5: The lower the panelists perceive the risk of using the internet to be, the more likely they are to switch to the web mode (a) in the short term and (b) 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:

H6: The higher the panelists' affinity for technology, the more likely they are to switch to the web mode (a) in the short term and (b) in the long term.

Methods

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 5736 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

Table 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	(16)	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?"

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 1).

The survey waves of the GESIS Panel take place every 2 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 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 2 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.

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 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 10 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 3 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 ($\chi^2(61) = 2526.39$, $p <$ .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.

Table 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)
	…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	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)
Navigation	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)
	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)

(continued)

Table 2. (continued)

Dimension	Wording	Scale	Full sample (*n* = 1364) *M* (SD)	Short-term switchers (*n* = 380) *M* (SD)
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)
HH Income	How high is the average monthly 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 or 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

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 10 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. Estimates are averaged and the total variance over the repeated analyses is computed by Rubin's rules (Rubin, 1987).

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 average monthly net 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. Missing values in the demographic characteristics were imputed with data from the previous GESIS Panel wave where possible. The remaining missing values were again imputed using multivariate imputation by chained equations. 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.

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 simple 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 Tables 6–8 using the R package survey (Lumley, 2020). All statistical analyses were performed using R version 4.0.3 (R Core Team, 2019).

Results

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 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 Table 4 in the 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 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 retains a statistically significant association with short-term mode switching.

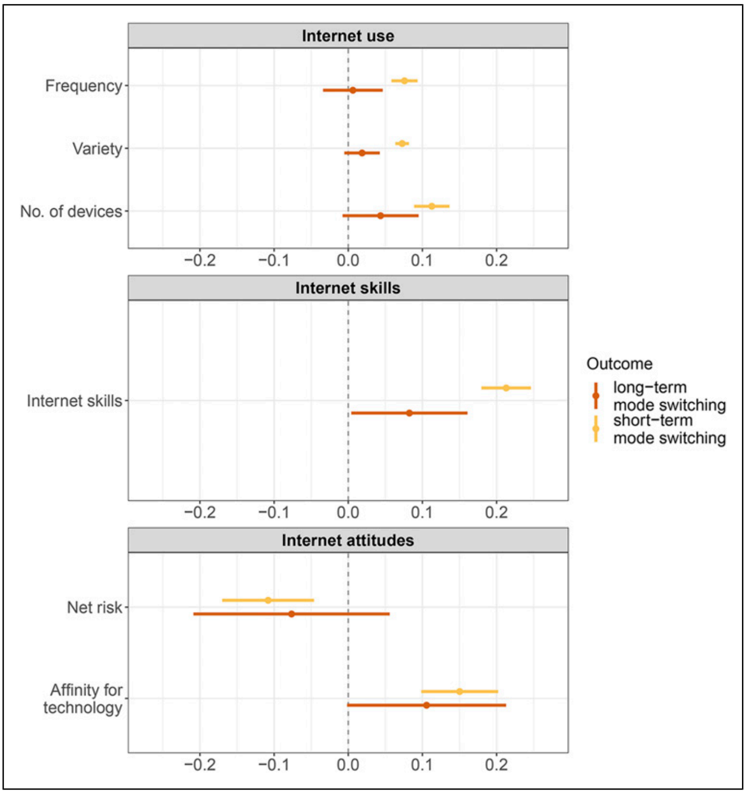

Figure 1. Average marginal effects and 95% confidence intervals from bivariate logistic regression models predicting short-term and long-term mode switching. Note: sample size short-term models: 1365; sample size long-term models: 380.

Table 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
Controls									
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									
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
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 2									
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		

Concerning the hypotheses about internet use, the model does not provide sufficient evidence to support hypothesis H1.a on an effect of frequency of internet use and hypothesis H3.a on the number of devices on mode switching in the multivariate setting. However, our findings are in line with hypothesis H2.a that panelists are more likely to switch to the web mode in a single wave if there is a greater variety of internet usage. With each additional activity individuals undertake online, the model estimates an increase in the average probability to switch to the web mode by five percentage points. These results could be affected by multicollinearity due to moderating 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 H4.a, 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. Model 1 of Table 3 suggests that a one standard deviation increase in internet skills is associated with an eight percentage points increase in the average probability of switching to the web mode in the short-term. Among the dimensions of attitudes, we did not find sufficient support for hypotheses H5.a and H6.a. According to our model, neither net risk nor affinity for technology significantly affects mode switching in a single wave.

As described in the hypotheses section, previous research suggests that the affinity for technology might influence whether individuals are willing to learn skills required to use services of the internet. It seems plausible that such an effect is also related to the risk people see in using the internet, making internet skills a potential mediator for the relationship between both variables of attitudes and short-term mode switching. Two mediation analyses were conducted to obtain preliminary evidence of whether such a mediating effect exists (see appendix for results). The first mediation model indicates a very small, but statistically significant indirect effect of internet skills for the path of affinity for technology to short-term mode switching. According to this result, individuals with higher affinity for technology are more likely to switch to the web mode in the short term, which is at least partly mediated by their higher internet skills. In the second mediation model, we also found a very small positive mediating effect of internet skills on the relationship between net risk and short-term mode switching. Assuming the model is correct, people who perceive higher risks in using the internet tend to have higher internet skills, which increases their willingness to switch to the web mode in the short term. However, sensitivity analyses for both models suggest that the mediation effects are not robust for unobserved confounders.

As shown in Table 3, none of the control variables included in Model 1 was significantly associated to short-term mode switching.

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 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 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 H1.b to H6.b 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

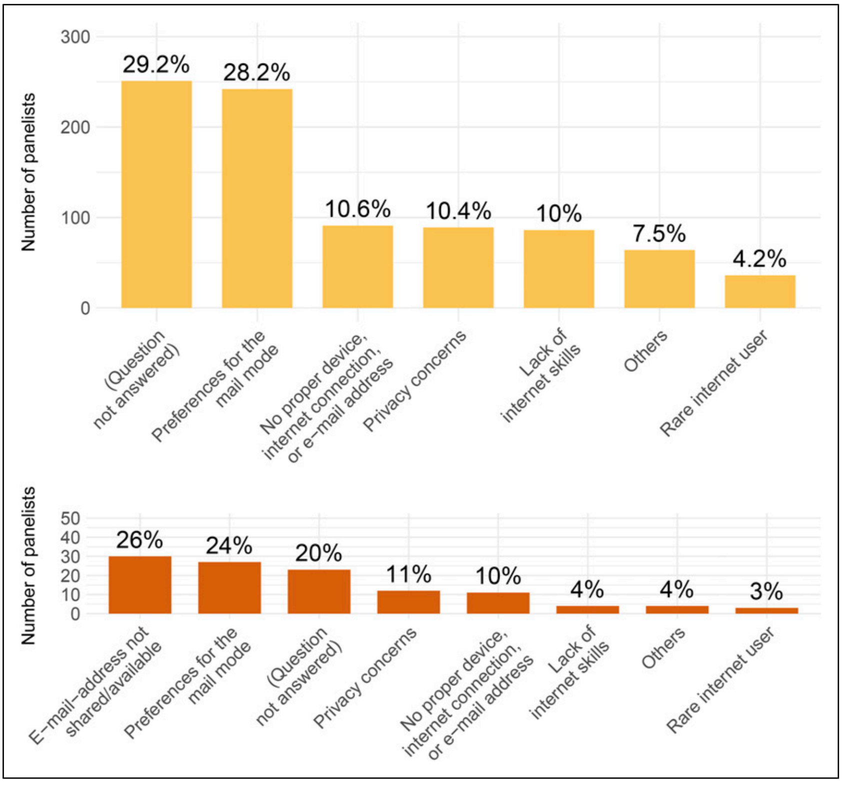

Figure 2. Panel members' self-reported reasons for not switching to the web mode in the short term (first graph) or in the long term (second graph). Note: The first bar chart represents coded answers from an open question. 895 panelists (internet−users only) who completed the mail questionnaire were asked why they did not switch to the web mode in the short term. 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."

if we fit data to the entire analysis data set. Results are shown in Model 3 of Table 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.

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. Figure 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 28% of the responses were coded as general preferences for the mail mode, for example, 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 ten percent 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 comprised around seven percent and were diverse. The responses referred, for example, to a lack of time or to being undecided. Around four percent of respondents explicitly said they did not complete the online questionnaire because they rarely used the internet.

The lower bar chart of Figure 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 around a quarter of the panelists as the reason why short-term mode switchers did not become long-term mode switchers. Nearly, the same proportion of answers was 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.

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 was 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 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 the risk individuals perceive in using the internet and for their 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 or if they have a higher affinity for the use of technology. On the other hand, the multivariate models did not reveal a significant effect of either characteristic. To gain a deeper understanding of these results, we ran two mediation models suggesting that the relationship between both attitudes toward the internet and short-term mode switching is mediated by internet skills. Although both models showed a small mediating effect of internet skills, the results should be interpreted with caution since causal interpretations of mediation analyses rely on strong assumptions. Sensitivity analyses proposed that these assumptions might be violated due to unobserved confounders. Nevertheless, we believe these findings are relevant and encourage further research on this topic.

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, which supports the relevance of the variables tested in this study. 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 unclear what characteristic of the mail and web mode produced these general preferences and whether they can be influenced by a combination of survey design features such as the order of offering survey modes, incentives, or a targeted communication strategy. Moreover, these findings raise the question to what extent pushing those individuals 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. Future studies should therefore not only investigate respondents' behavior in searching for effective web-push strategies, but also examine what long-term consequences may result for different survey error sources.

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 10 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. As one way, 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. In a further step, the findings of this study could be used to test and implement a targeting web-push strategy. In such a targeting strategy, subgroups of panel members receive a targeted treatment depending on pre-measured characteristics. For example, panelists with low internet skills could be provided with information on how easy it is to access the web survey while heavy users of mobile phones could receive a QR code with information highlighting cell phone friendliness. Overall, more research is needed to back such assumptions and to convert the findings into effective web-push strategies.

Appendix

Bivariate logistic regression models

Table 4. Average Marginal Effects (AME) With Standard Errors (s.e.) 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)	.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
Attitudes toward 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.

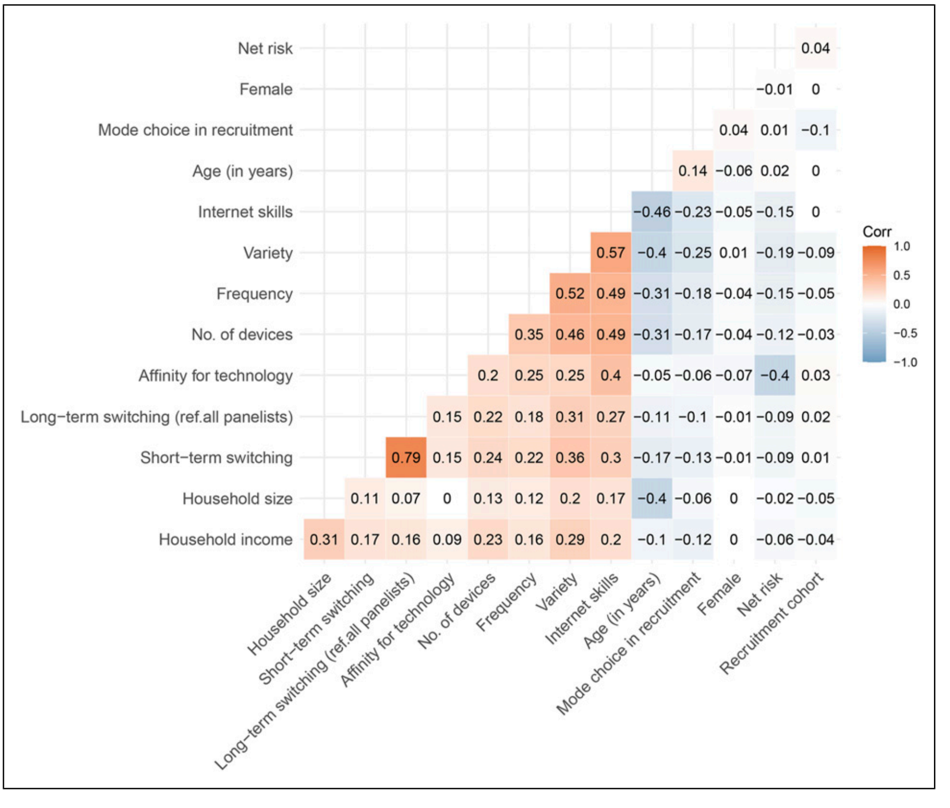

Figure 3. Correlation matrix of outcomes, explanatory and control variables (overall 10 imputed data sets).

Table 5. Logistic Regression Models With Different Combinations of the Internet Usage Dimensions: Coefficients 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		0.125*	0.018	0.14*		
		(0.063)	(0.067)	(0.063)		
Variety	0.304***		0.312***		0.315***	
	(0.043)		(0.043)		(0.042)	
No. of devices	0.129	0.228**				0.243**
	(0.089)	(0.085)				(0.084)
Internet skills	0.458**	0.678***	0.508**	0.793***	0.517**	0.755***
	(0.158)	(0.154)	(0.155)	(0.147)	(0.151)	(0.148)
Net risk	−0.045	−0.197	−0.051	−0.218	−0.052	−0.214
	(0.202)	(0.192)	(0.202)	(0.191)	(0.202)	(0.191)
Affinity for technology	0.124	0.15	0.118	0.146	0.122	0.183
	(0.179)	(0.176)	(0.179)	(0.175)	(0.178)	(0.175)
Controls						
Cohort 2016	−0.083	−0.135	−0.087	−0.143	−0.086	−0.13
	(0.174)	(0.169)	(0.174)	(0.169)	(0.173)	(0.169)
Cohort 2018	0.303·	0.166	0.302·	0.154	0.298·	0.129
	(0.162)	(0.158)	(0.162)	(0.157)	(0.162)	(0.157)
Ref. = Cohort 2013						
Age (in years)	0.303·	0.166	0.302·	0.154	0.298·	0.129
	(0.162)	(0.158)	(0.162)	(0.157)	(0.162)	(0.157)
Education: medium level	−0.111	−0.072	−0.102	−0.056	−0.101	−0.065
	(0.192)	(0.188)	(0.191)	(0.187)	(0.191)	(0.187)
Education: high level	0.216	0.299	0.233	0.337·	0.234	0.313
	(0.201)	(0.196)	(0.201)	(0.196)	(0.201)	(0.196)
Ref. = Education: low level						
Household income	0.064	0.097*	0.07	0.11**	0.07	0.098*
	(0.044)	(0.042)	(0.044)	(0.042)	(0.044)	(0.042)
Household size	0.086	0.091	0.082	0.085	0.082	0.087
	(0.074)	(0.073)	(0.074)	(0.073)	(0.073)	(0.072)
Female	0.058	0.082	0.051	0.067	0.05	0.077
	(0.14)	(0.137)	(0.14)	(0.137)	(0.14)	(0.137)
Ref. = Male						
Mode choice in recruitment	−0.327	−0.427·	−0.334	−0.45*	−0.335	−0.45*
	(0.224)	(0.217)	(0.224)	(0.216)	(0.224)	(0.216)
Exp. group 1	−0.292·	−0.272·	−0.272	−0.238	−0.273	−0.279·
	(0.167)	(0.163)	(0.166)	(0.162)	(0.166)	(0.163)
Exp. group 3	0.046	0.058	0.041	0.047	0.041	0.053
	(0.161)	(0.157)	(0.161)	(0.156)	(0.161)	(0.157)
Ref. = Exp. group 2						
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
Observations	1364	1364	1364	1364	1364	1364

Note: ***p < .001; **p < .01; *p < .05; ·p < .1; (Robust standard errors in brackets).

Sensitivity 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 3 and calculated the variance inflation factors (VIFs), as suggested, for example, 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 ($x^2 = 2.04$; $p = .154$) or both variables ($x^2 = 1.06$; $p = .345$) from the model 1 in Table 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 5).

Regression models based on weighted data

Table 6. Average Marginal Effects (AME) With Standard Errors (s.e.) 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)	.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 toward 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

Mediation analyses

To test whether attitudes toward technology and net risk affect short-term mode switching mediated by internet skills, we performed mediation analyses using the mediation framework proposed by Imai et al., 2010. The mediation analyses using a bootstrapping procedure with 1000 iterations were applied for each imputed data set and results were combined using the R mediation package (Tingley et al., 2014). We also ran sensitivity analyses for mediation effects to test whether there is evidence that the sequential ignorability assumption is violated. This is the case if unobserved variables influence the mediator and the outcome variable. The sensitivity analysis explores different values for rho (ρ) as a correlation between the residuals of the mediator and the

Table 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
Controls									
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									
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
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 2									
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		

outcome variable, allowing an assessment of how robust the mediation effect is to unobserved confounders.

The coefficient plot of Figure 4 shows a very small but statistically significant indirect mediation effect of internet skills for the path of affinity for technology to short-term mode switching (average indirect effect = 0.03, 95% CI of bootstrapped samples = 0.01, 0.05). Apart from this indirect effect, a significant total effect was detected by the analysis but not a direct effect (average direct effect = 0.03, 95% CI of bootstrapped samples = −0.03, 0.08; average total effect = 0.06, 95% CI of bootstrapped samples = 0.00, 0.11).

We tested the robustness of this result with a sensitivity analysis shown in Figure 5, which estimates the point at which the average indirect effect is approximately zero ($\rho = 0.05$, 95% CI = −0.01, 0.00, $R_M^{2*}R_Y^{2*}$ = 0.00, 0.00). This value suggests that the mediation effect is not robust for unobserved confounders.

Figure 6 presents a coefficient plot for a model testing the mediating effect of internet skills on the relationship between net risk and short-term mode switching. The model shows a very small indirect mediating effect of internet skills (average indirect effect = 0.03, 95% CI of

Table 8. Logistic Regression Models With Different Combinations of the Internet Usage Dimensions: Coefficients 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		0.134*	0.03	0.152*		
		(0.066)	(0.068)	(0.064)		
Variety	0.31***		0.319***		0.324***	
	(0.043)		(0.043)		(0.042)	
No. of devices	0.158·	0.26**				0.276**
	(0.092)	(0.089)				(0.089)
Internet skills	0.548**	0.781***	0.608***	0.917***	0.623***	0.865***
	(0.159)	(0.153)	(0.158)	(0.147)	(0.153)	(0.147)
Net risk	−0.034	−0.17	−0.04	−0.194	−0.042	−0.187
	(0.208)	(0.196)	(0.209)	(0.196)	(0.209)	(0.196)
Affinity for technology	0.121	0.15	0.106	0.137	0.114	0.192
	(0.184)	(0.181)	(0.184)	(0.18)	(0.183)	(0.18)
Controls						
Cohort 2016	−0.173	−0.224	−0.181	−0.236	−0.178	−0.215
	(0.178)	(0.175)	(0.178)	(0.175)	(0.178)	(0.174)
Cohort 2018	0.363*	0.212	0.364*	0.198	0.36*	0.18
	(0.172)	(0.167)	(0.173)	(0.166)	(0.172)	(0.166)
Ref. = Cohort 2013						
Age (in years)	0.363*	0.212	0.364*	0.198	0.36*	0.18
	(0.172)	(0.167)	(0.173)	(0.166)	(0.172)	(0.166)
Education: medium level	−0.136	−0.096	−0.123	−0.074	−0.121	−0.086
	(0.2)	(0.195)	(0.2)	(0.195)	(0.2)	(0.195)
Education: high level	0.138	0.214	0.159	0.259	0.161	0.234
	(0.205)	(0.201)	(0.204)	(0.198)	(0.204)	(0.2)
Ref. = Education: low level						
Household income	0.073	0.107*	0.08·	0.12**	0.08·	0.107*
	(0.046)	(0.045)	(0.046)	(0.044)	(0.046)	(0.045)
Household size	0.102	0.11	0.097	0.103	0.096	0.106
	(0.075)	(0.073)	(0.075)	(0.073)	(0.075)	(0.073)
Female	0.01	0.041	−0.001	0.021	−0.003	0.037
	(0.144)	(0.141)	(0.143)	(0.141)	(0.144)	(0.141)
Ref. = Male						
Mode choice in recruitment	−0.228	−0.316	−0.234	−0.339	−0.234	−0.333
	(0.23)	(0.22)	(0.231)	(0.222)	(0.232)	(0.22)
Exp. group 1	−0.245	−0.223	−0.218	−0.181	−0.22	−0.232
	(0.167)	(0.164)	(0.167)	(0.163)	(0.167)	(0.163)
Exp. group 3	0.053	0.064	0.046	0.049	0.046	0.061
	(0.17)	(0.166)	(0.169)	(0.165)	(0.169)	(0.167)
Ref. = Exp. group 2						
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
Observations	1364	1364	1364	1364	1364	1364

Note: ***p < .001; **p < .01; *p < .05; ·p < .1; (Robust standard errors in brackets).

bootstrapped samples = 0.01, 0.05). As with affinity for technology, the model reveals no direct effect for this path, though this time has no total effect either (average direct effect = −0.01, 95% CI of bootstrapped samples = −0.07, 0.05; average total effect = 0.00, 95% CI of bootstrapped samples = −0.06, 0.06).

The sensitivity analysis shown in Figure 7 also posits that unobserved variables might confound the mediating effect (ρ = 0.05, 95% CI = 0.00, 0.00, $R_M^{2*}R_Y^{2*}$ = 0.00, 0.00).

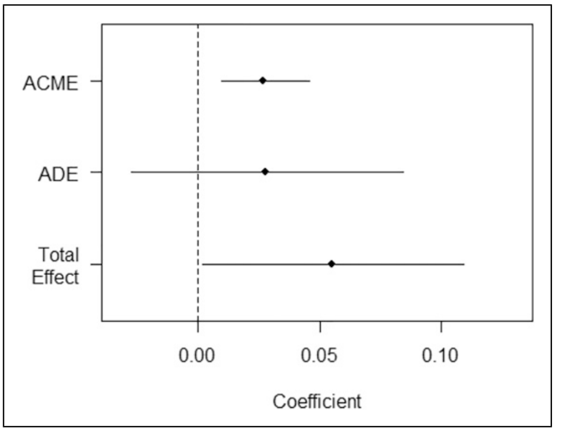

Figure 4. Coefficients and 95% confidence intervals for the average causal mediation effect (ACME), average direct effect (ADE), and total effect from a mediation analysis testing the path affinity for technology ⇒ internet skills ⇒ short-term mode switching. The graph was produced with the *R* mediation package (Tingley et al., 2014).

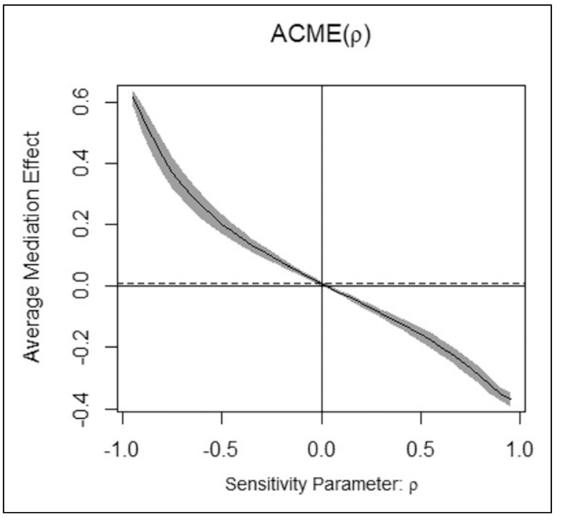

Figure 5. Graph of sensitivity for the mediation analysis testing the path affinity for technology ⇒ internet skills ⇒ short-term mode switching. The graph was produced with the *R* mediation package (Tingley et al., 2014).

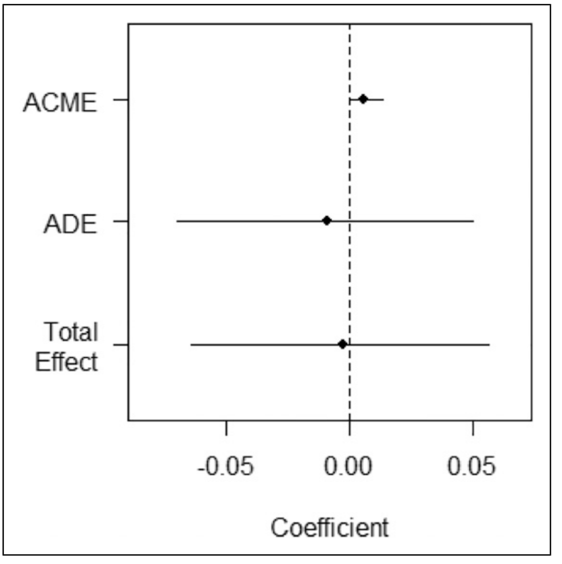

Figure 6. Coefficients and 95% confidence intervals for the average causal mediation effect (ACME), average direct effect (ADE), and total effect from a mediation analysis testing the path net risk ⇒ internet skills ⇒ short-term mode switching. The graph was produced with the *R* mediation package (Tingley et al., 2014).

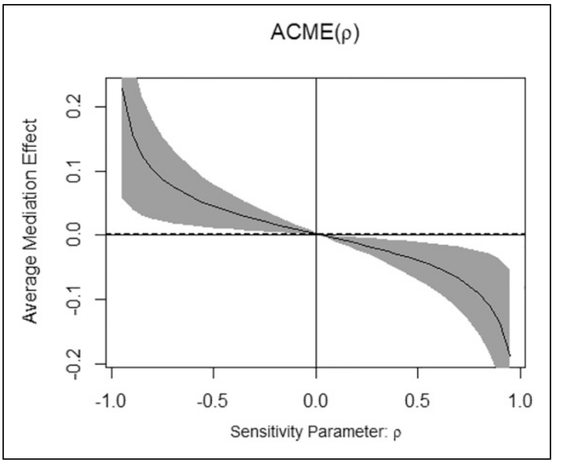

Figure 7. Graph of sensitivity for the mediation analysis testing the path net risk ⇒ internet skills ⇒ short-term mode switching. The graph was produced with the *R* mediation package (Tingley et al., 2014).

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Note

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.

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