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# How do people answer web surveys? The consequences of distractions, multitasking, and completion context

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**ABSTRACT**

Researchers have limited control over the completion context and response process in web surveys compared to interviewer-administered surveys. Respondents can answer questions from any location, at any time, and on various devices, often while multitasking. This variability may affect data quality. This study addresses the issue by examining the completion context and its associations with data quality using a Hungarian online survey. We used latent class analysis based on completion-related questions to identify five respondent profiles. Many respondents completed the survey under conditions often considered sub-optimal, such as on small screens, without privacy, or while multitasking. However, these factors showed little impact on conventional data quality indicators. The effects were limited to self-reported noise and concentration levels. We conclude that while sub-optimal conditions are common, their practical impact on data quality appears minimal. Nonetheless, monitoring completion behavior remains advisable in web surveys.

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Web survey; measurement error; data quality; multitasking; distractions

## 1. Introduction

As response rates of traditional interviewer-administered surveys are constantly dropping and their costs are increasing, self-administered modes such as web surveys are becoming increasingly popular (Olson et al., 2021). Whilst web surveys are attractive for various reasons, data quality in web surveys remains one of the major concerns (Couper, 2000b). One of the reasons behind this is that, as opposed to interviewer-administered modes, researchers have very limited control over the completion context of web surveys (Wenz, 2021). The context of completion (e.g. location, presence of others, distractions, and multitasking) is expected to influence the response process, yet often remains unknown to researchers.

The handful of prior research indeed shows that many online respondents engage in completion in sub-optimal settings (e.g. small device, night, low privacy, high

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multitasking) (Ansolabehere & Schaffner, 2015; De Bruijne & Oudejans, 2015; Höhne et al., 2020; Sendelbah et al., 2016; Wenz, 2021; Zwarun & Hall, 2014). Based on research in cognitive psychology (Krosnick, 1991; Sweller, 1988), in theory, respondents who respond in sub-optimal settings may be more prone to biases, potentially leading to lower response quality. Existing evidence, however, is scarce and mixed, and studies typically focus on a limited number of factors (see e.g. Antoun et al., 2017; De Bruijne & Oudejans, 2015; Höhne & Schlosser, 2018; Sendelbah et al., 2016). Even if researchers have little control over these factors, it is important to better understand the context of completion and respondents' multitasking and their impact on measurement, yet little focus has been placed on these questions. This question is not only methodological but also of broader relevance across the social sciences, as variation in completion context may influence substantive inferences in fields ranging from political behavior to sociological attitudes research.

To advance existing research, this study provides two contributions. Expanding upon earlier efforts by De Bruijne and Oudejans (2015) and Lynn and Kaminska (2013), we developed a theoretical framework that delineates the links among diverse facets of completion and the four stages of the response process as defined by Tourangeau et al. (2000). Additionally, we offer empirical evidence from survey data gathered in Hungary via an exhaustive set of questions on completion and paradata.

## 2. Theoretical background – towards an integrated framework of web survey completion

In this section, we review the literature to identify the various factors that may directly or indirectly influence measurement error in web surveys and summarize previous empirical findings for each factor. We use the frameworks provided by De Bruijne and Oudejans (2015) and Lynn and Kaminska (2013), and extend and generalize them to web surveys. The framework allows for the interpretation and measurement of the various components that may influence measurement error. Given the complex and multifaceted nature of conducting web surveys, we believe that it is necessary to establish a comprehensive framework to effectively address this complexity. We adopt a positivist ontology, treating features of the completion context as observable conditions that can systematically influence data quality, rather than an interpretive perspective that would view these contextual elements as integral parts of respondents' situated meaning-making (Alharahsheh & Pius, 2020).

Starting from the end of our framework (see Figure 1), we draw on Tourangeau et al. (2000) and consider the response process as a sequence of four basic cognitive steps (comprehension, retrieval, judgment, and reporting). We further apply the necessary conditions Lynn and Kaminska (2013) identified to perform these four steps. First, for respondents to retrieve adequate information, they must be able to see and read the questions properly. Another key condition for the retrieval phase is the respondent's ability to pay sufficient attention to the task. Attention can be defined as a cognitive process that involves focusing one's awareness in which attention and perception are concentrated on a specific stimulus while ignoring others (Kellogg, 2015). Following Lynn and Kaminska (2013), we disentangle attention from cognitive effort. The degree of cognitive effort determines whether someone can perform mental tasks with proficiency,

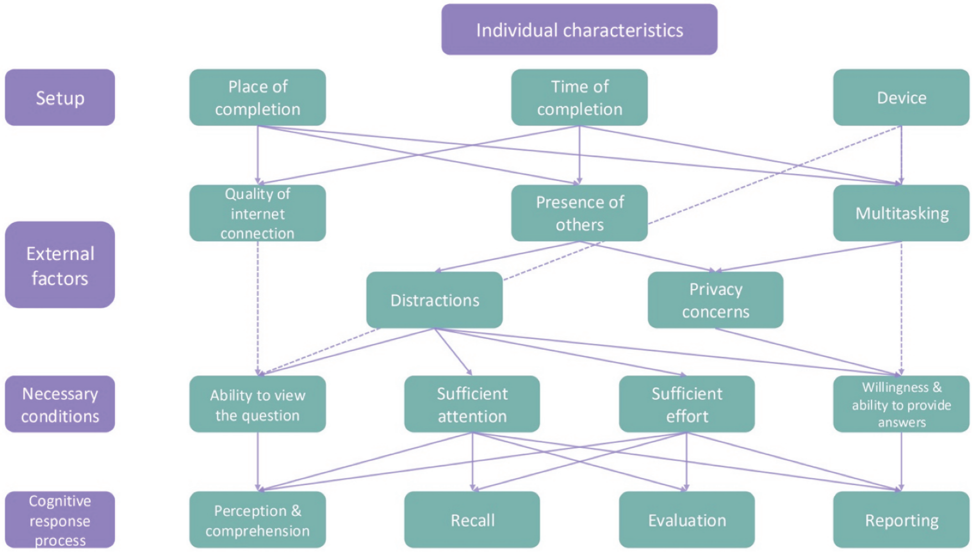


**Figure 1.** An integrated framework for understanding factors influencing measurement error in web surveys. *Note:* Extended framework of De Bruijne and Oudejans (2015) and Lynn and Kaminska (2013).

completing each step of the task and responding effectively (Cannell et al., 1981). Even if the respondent pays sufficient attention to the task, the cognitive effort may be low. Cognitive effort and attention are seen as necessary conditions for the retrieval, evaluation, and reporting phases. Finally, reporting also depends on the respondent's willingness and ability to communicate their answer. If the necessary conditions are not met, the respondent may rush or skip some steps in the response process by satisficing rather than optimizing (Krosnick, 1991).

The likelihood of fulfilling these necessary conditions is influenced by various factors during completion (see Figure 1). We start with the basic decisions about completion (setup) and then move on to the factors that can have a more direct impact on the necessary conditions.

### 2.1. Setup

We refer to setup as the basic circumstances of completion consisting of three components: place, time, and the device used for completion. In contrast to interviewer-administered surveys, respondents to web surveys are free to decide where, when, and how they want to answer survey questions. Although we treat these decisions separately, place, time, and device are interconnected. For example, the decision on location can influence the choice of device and vice versa.

#### 2.1.1. The place of completion

As portable, network-connected devices (e.g. smartphones, tablets) are increasingly used for web surveys (Gummer et al., 2023), respondents can complete surveys in varied locations beyond the home, such as workplaces, schools, public places, or while travelling. Location matters because it can (1) influence multitasking (e.g. childcare at home or conversations at work; Stefkovics, 2022), (2) determine the presence of others (fewer familiar people at home vs. more strangers in public), (3) affect distractions, both environmental (e.g. traffic noise) and social, though evidence on which setting is most distracting is mixed (De Bruijne & Oudejans, 2015; Zwarun & Hall, 2011, 2014), and (4) impact internet connection quality. Antoun et al. (2017) even found that answering outside the home was linked to higher reports of binge drinking.

#### *2.1.2. The time of completion*

Web survey respondents can answer at any time during the survey period and do not need to complete it in a single session, offering greater flexibility than interviewer-administered surveys. However, little is known about whether respondents optimize completion time. Research on circadian rhythms shows that cognitive performance varies throughout the day, driven by sleepiness and alertness cycles, with older adults performing best in the morning and younger adults later in the day (May et al., 1993; Schmidt et al., 2007). Memory performance is generally poorer at night (Richards et al., 2020). Thus, survey timing may influence fatigue, attention, and motivation, both directly and by reducing multitasking and distractions. Despite its potential importance, the effect of completion timing on data quality remains largely overlooked.

#### *2.1.3. Device*

The device used for survey completion can influence the response process. Technological differences – such as screen size – affect how questions are displayed and how responses are submitted, potentially influencing willingness to answer (De Bruijne & Wijnant, 2014; Mavletova & Couper, 2013). Portable devices (e.g. smartphones, tablets) enable greater flexibility in location (Ansolabehere & Schaffner, 2015; Antoun et al., 2017) and may invite more multitasking, although findings are mixed. Smaller screens might reduce multitasking performance (Kim & Sundar, 2016), yet research shows no consistent differences in on-device multitasking between PCs and mobiles, and in some studies, PCs show higher rates (Höhne et al., 2020; Revilla & Couper, 2017). While smartphones are more susceptible to app notifications, PCs allow easier multitasking through multiple windows. Completion time is usually longer on mobile devices, particularly smartphones (Couper & Peterson, 2017), possibly reflecting increased distractions or multitasking.

### *2.2. Other external factors*

The next domain in our framework relates to the direct consequences of the setup that may affect task completion. These factors are more likely to directly affect the response process.

#### *2.2.1. Multitasking*

Respondents may multitask deliberately (e.g. listening to music, using the bathroom) or be forced to take on secondary activities (e.g. answering calls, childcare) while completing web surveys, and such behaviour appears common (Ansolabehere & Schaffner, 2015; De Bruijne & Oudejans, 2015; Höhne et al., 2020; Wenz, 2021). Salvucci and Taatgen (2011) distinguish between concurrent multitasking (simultaneous tasks) and sequential multitasking (task switching), while Zwarun and Hall (2014) differentiate media from non-media multitasking. According to cognitive capacity theories such as the Limited Capacity Model (Lang, 2000) and Threaded Cognition (Salvucci & Taatgen, 2011), the extent to which multitasking affects performance depends on the overlap in cognitive resources. For example, listening to music may have little impact, whereas checking emails draws on similar resources and can interfere with survey completion (Höhne & Schlosser, 2018; Wenz, 2021). Existing evidence on the negative effects of multitasking is mixed. Some studies report minor associations, such as an increased likelihood of selecting middle response categories during on-device task switching (Höhne et al., 2020), while others find no significant impact on response quality or item nonresponse (Antoun et al., 2017; Sendelbah et al., 2016). De Bruijne and Oudejans (2015) observed somewhat lower self-reported concentration among multitaskers, yet telephone survey research suggests similarly negligible effects (Aizpurua et al., 2018; Stefkovics, 2022). Overall, while multitasking is frequent, its impact on data quality remains uncertain and appears context-dependent.

#### *2.2.2. Presence of others*

The place of completion determines who and how many people are around the respondent, an aspect controllable in face-to-face surveys but not in web surveys. The presence of others can directly increase noise and distractions, reducing concentration (De Bruijne & Oudejans, 2015), and it also affects interview privacy – defined as the absence of third parties during the interview (Mneimneh et al., 2018). Privacy is critical for sensitive questions, as third-party presence may lead to response concealment or social desirability bias (Tourangeau & Yan, 2007). While interviewers can enforce privacy in face-to-face settings (Mneimneh et al., 2020), web surveys offer no such control. Evidence on web surveys is limited, but De Bruijne and Oudejans (2015) found that others were present in 38% of PC, 54% of mobile, and 62% of tablet completions in a Dutch panel survey.

#### *2.2.3. Quality of internet connection*

The place of completion or the device can determine the quality of the internet connection. A weak connection may negatively impact the ability to see the questions, the willingness and ability to provide answers, slowing down completion, prompting satisficing behaviour, and result in a poor survey experience in general.

#### *2.2.4. Distractions*

Respondents completing web surveys may face various distractions, which are closely linked to multitasking (Ansolabehere & Schaffner, 2015; Wenz, 2021). Distractions can stem from environmental sources (e.g. noise), media and non-media multitasking, or social presence (Zwarun & Hall, 2014). Because attention is finite, such interruptions can interfere with key cognitive processes in survey responding, including retrieval, evaluation, and communication (Lynn & Kaminska, 2013; Tourangeau et al., 2000). The extent of impact likely depends on the type of distraction: environmental noise may be easier to ignore than interruptions from close family members (Zwarun & Hall, 2014). Despite these theoretical concerns, empirical findings suggest minimal effects on data quality. Experimental studies found no significant impact of distractions such as loud conversations or music (Wenz, 2021), while device-switching distractions were associated with higher item nonresponse but not straightlining (Höhne & Schlosser, 2018; Sendelbah et al., 2016). Overall, distractions appear common, but their influence on survey quality remains small and context-dependent.

#### 2.2.5. Privacy concerns

As discussed earlier, the presence of others may raise privacy concerns and invite social desirability bias (SDB), which depends on the third party's relationship to the respondent and their prior knowledge (Aquilino, 1997; Tourangeau & Yan, 2007). Familiar bystanders may sometimes encourage honest reporting, whereas strangers typically have a negative effect (Mavletova & Couper, 2013). Privacy concerns can also arise regardless of bystander presence, such as when respondents fear workplace monitoring (Couper, 2000a). These concerns mainly affect the reporting phase of the response process by reducing willingness to disclose (Lynn & Kaminska, 2013). Evidence on the impact of social context is mixed. Mavletova and Couper (2013) found PC users trusted data confidentiality more than mobile users, but actual reporting levels did not differ. While mobile respondents were more often in public or with bystanders, this had no clear negative effect on sensitive disclosures; familiar bystanders even increased candor on some attitude items but reduced income reporting. Similarly, Antoun et al. (2017) found no consistent effects of bystander presence on disclosure.

#### 2.2.6. Individual differences

Respondent characteristics can shape survey completion context and moderate the effects of situational factors. Device choice, for example, is correlated with individual traits (Keusch & Yan, 2017; Lugtig et al., 2016), and visual ability may affect ease of viewing questions (De Bruijne & Wijnant, 2014). Age differences are notable: younger respondents report more frequent and varied multitasking (Carrier et al., 2009; Höhne et al., 2020), though Zwarun and Hall (2014) observed peak multitasking among middle-aged respondents. Education has also been linked to higher on-device task switching (Höhne et al., 2020), likely reflecting cognitive ability differences. While younger individuals tend to multitask more effectively (Carrier et al., 2009), susceptibility to distractions may vary by personality, motivation, and interest (Krosnick, 1991; Lynn & Kaminska, 2013). However, Wenz (2021) found no significant interactions between Big Five traits (Goldberg, 1992), need for cognition, or susceptibility to distraction and data quality indicators.

## 3. The current study

### 3.1. Aims

In our current study, we use an online survey conducted in Hungary to provide empirical insights into relationships between completion context and responses in web surveys. While the aim was not to formally test the theoretical framework, the study illustrates a practical approach to examining potential sources of measurement error in online data collection. The empirical analysis had two main focuses. First, we aimed to classify survey respondents using both self-report responses to a comprehensive set of questions and paradata. Classification can help identify typical groups of respondents, including those who participate in the survey from sub-optimal settings. We also provide a descriptive analysis of the groups. Second, we used several indicators of data quality to examine the relationship between latent class membership and data quality. Specifically, we wanted to determine whether response quality varied by the settings and secondary activities in which respondents completed the survey.

## 3.2. Data

### 3.2.1. Data collection and general context of the survey

Data collection for this study was conducted by a large Hungarian online public research company using its online access panel, which includes more than 100,000 registered users. The company routinely offers rewards to those who complete its surveys. A quota sampling approach was employed, setting specific quotas for gender, age, education, and geographical region. The online data collection ran from June 13 to 12 July 2022. In total, the survey involved 2,000 participants.

The questionnaire used for data collection consisted of two main parts. The first part addressed the survey's circumstances. It included questions about the concurrent activities, the situation in which the questionnaire was completed, the respondents' level of interest, their general state of mind, and their previous experience with different survey techniques. The second part of the questionnaire included non-methodological questions. Most of the questions were standard questions from the European Social Survey (ESS) relating to general attitudes towards refugees and their care, perceptions of the wave of refugees caused by the war in Ukraine, and the consequences of the coronavirus pandemic.

The items on completion context followed immediately after the introductory socio-demographic questions, so respondents did not yet know which specific topics would be included in the non-methodological section of the questionnaire. Therefore, they could not influence how they began answering the questions.

### 3.2.2. Questions for understanding completion context

The variables we used for the current analysis aimed to understand the context in which participants responded (see Appendix 7.1). A key area of interest was the type of device respondents used, categorized as either a large screen (desktop computer, laptop, or tablet) or a small screen (smartphone). The time of survey completion was also taken into account and divided into three periods: morning (6:00 a.m. to 12:00 p.m.), afternoon/evening (12:00 p.m. to 10:00 p.m.), and night (10:00 p.m. to 6:00 a.m.). The respondents' location at the time of survey completion was noted, with options including at home, at their place of work, or at any other location. Based on the number of people in the respondent's vicinity, we determined the level of privacy, which was recoded into three categories. No privacy refers to situations in which multiple people were in close proximity to the respondent, and some could easily have seen the device's screen while the respondent was completing the survey. Partial privacy was defined as situations in which several people were near the respondent, but none could see the screen. And finally, full privacy was applied to cases where the respondent was alone and could not be disturbed by anyone while completing the survey.

To understand multitasking patterns, participants were asked about their simultaneous activities while completing the survey. This included whether they listened to audio on their phones or other devices, and whether they watched videos on their devices or on other devices, such as a television. Communication behaviour was also recorded, i.e. whether respondents engaged in messaging, phone calls, or face-to-face conversations. Moreover, the survey sought to determine whether respondents were in motion or engaged in any work. The type of work was further divided into 'white-collar jobs', i.e. typical office work, and 'blue-collar jobs' or physical labour. Finally, it was also analysed whether the respondents were engaged in other activities, such as housework or childcare.

## 4. Methods

### 4.1. Classification of user types

We applied Latent Class Analysis (LCA) to identify distinct groups of respondents and uncover hidden patterns and heterogeneity within the sample. LCA of polytomous outcome variables is a statistical method used to identify unobservable (latent) subgroups within a population based on multiple observed categorical responses. LCA provides a probabilistic classification system in which observed polytomous outcomes (responses with more than two categories) are assumed to be influenced by an individual's membership in one of the latent classes. To find the most appropriate classification solution, we ran the model to obtain latent classes ranging from 3 to 7. We used Bayesian Information Criterion (BIC) to select the model that performed the best at capturing heterogeneity and explaining the data without unnecessarily increasing complexity. (See detailed statistics for the models in Appendix 7.2.)

### 4.2. Predicting data quality

To understand the relationship between circumstances and data quality, four widely used data quality measures were developed.

#### 4.2.1. Duration

The time taken to complete the survey was recorded by the CAWI software. Therefore, the total response time was calculated by taking the time between opening the first page of the questionnaire and clicking 'Submit' on the last page. Since respondents who abandoned the survey and other (infrequent) technical problems could result in extremely long completion times in the data, cases where the duration exceeded 90 minutes were removed. However, we did not set a lower limit, because we considered fast fillers an important (negative) signal for data quality. The mean duration was 26.27 minutes ($SD = 14.12$, $n = 1870$).

#### 4.2.2. Item-nonresponse

An indicator to measure item-nonresponse was also created by combining the number of (1) don't know, (2) refusal, or other (3) blank responses for each individual in the dataset. We selected 31 variables for which respondents could choose either option. In general, the level of item-nonresponse was rather low: 66.8% of the cases ($n = 1335$) had no missing values, 16.2% ($n = 323$) had only one, and the remaining 17.1% $n = 342$) had two or more items with missing values.

#### 4.2.3. Straightlining

To detect straightlining (when respondents gave identical answers in a battery of questions with the same response scale), patterns of responses to three topics with multiple items were analysed: (1) attitudes towards LGBT rights – 3 items, (2) interpersonal trust – 3 items, (3) trust in institutions – 7 items. For each of the three batteries of questions, we identified 11.3, 24.9, and 13.1% of straightlining in the data. Overall, 62.9% of respondents did not provide the same answer to any question; 27.4% straightlined on one battery; and 7.6% and 2.3% straightlined on two and all three batteries, respectively.

#### 4.2.4. Inconsistent responding

Finally, we created an additional indicator to measure potential inconsistencies in the data. To do this, we identified closely related items, and if someone gave very different answers, we suspected the responses were not well thought out. Data were available for three distinct topics: three items on interpersonal trust, two on political participation, and two on trust in political institutions. For all items, a 0–10 scale was used. We defined data as inconsistent if a combination of 0–1 vs. 9–10 values was found together within any of the three topics. In total, 4.3% ($n = 86$) showed at least one inconsistency in the data.

#### 4.2.5. Ambient sound disturbance and focus, concentration

We used two self-reported measures that asked respondents about the noise in their environment and their level of concentration. Although these measures are not direct indicators of data quality, they may indirectly signal a potential threat to optimal completion. Sound disturbance was measured by asking, '*On a scale of 0–10, how quiet or noisy do you feel your current environment is overall?*' Concentration was measured by asking, '*On a scale of 0–10, how much do you feel you can concentrate in your current environment*?'

## 5. Results

### 5.1. Classification of survey responders

Based on the LCA methodology outlined in the previous section, we identified five latent classes of user types based on the circumstances under which respondents completed the survey. The variables used for modelling, their class-specific distributions, and basic demographics are provided in the Appendix.

#### 5.1.1. Class 1: older at-home multitaskers on large-screen devices (n = 299, 14.9%)

Individuals in this group are primarily older and middle-aged adults with above-average levels of education. At the time of responding, they were frequently engaged in other activities. Most completed the survey at home using large-screen devices (73%), and three out of four simultaneously watched video content, most often television. (Based on the open-ended question about their parallel activities.) Many respondents were also interacting with others, either online or offline (71%), and performing additional tasks (74%), such as paying bills, working, or browsing the news. Despite the high level of multitasking, around 7 in 10 respondents reported full privacy, indicating that others were not interfering with their survey completion. Most surveys were completed in the morning (59%) or in the afternoon or evening (38%), with a slight overrepresentation of weekend completions (31%) and very few responses recorded at night (3%).

#### 5.1.2. Class 2: young mobile respondents with limited privacy (n = 336, 16.8%)

Respondents in this medium-sized group, primarily younger adults with a slight overrepresentation of women (61%), completed the survey almost exclusively on smartphones. They were more likely to respond in the afternoon or evening (51%) and at night (15%). Multitasking in this group was largely confined to smartphone-based activities, such as interacting with others via social media or messaging applications, or switching between the questionnaire and mobile games. Despite the relatively limited scope of parallel activities, respondents in this group were rarely alone. Most were surrounded by others (62%), and in a substantial share of cases (25%), others could see the respondent's screen. This indicates a markedly lower level of privacy compared to the other groups.

#### 5.1.3. Class 3: low-multitasking respondents at home (n = 823, 41.2%)

This is the largest latent class, comprising approximately 40% of the sample. While completing the survey, respondents in this group were predominantly at home (98%) and largely undisturbed by others (86%), indicating a high level of privacy and virtually no parallel communication with other people. Two-thirds of respondents used large-screen devices to complete the survey. The demographic composition of this group closely mirrors the overall sample, with no pronounced differences by gender, age, or education. Compared to the other classes, respondents in this group engaged in relatively little multitasking: 14% reported listening to audio content, and 25% reported watching something while answering the survey. Analysis of the open-ended responses indicates that, in most cases, this involved having the television on in the background.

#### 5.1.4. Class 4: extreme multitaskers combining work and other activities (N = 182, 9.1%)

Respondents in this small but distinctive class, characterized by an overrepresentation of individuals with only primary education (34%) and a moderate overrepresentation of women (59%), combined survey participation with an exceptionally high level of multitasking. They relied primarily, though not exclusively, on small-screen devices (66%) and frequently combined survey completion with media consumption, including audio (61%) and video (81%). Nearly all respondents engaged in communication with others during completion (96%), alongside a wide range of additional activities. Open-ended responses indicate that these activities included online shopping and banking, reading news, writing emails, and playing games.

A majority of respondents were also physically mobile while completing the survey (69%), which is likely related to the group's most distinctive characteristic: the very high prevalence of manual work during survey completion (83%). Despite this, most respondents completed the survey at home (71%), although a substantial minority did so at their workplace (13%) or in other locations (16%). These conditions resulted in a mixed privacy profile, with 55% reporting full privacy and 26% reporting partial privacy.

#### 5.1.5. Class 5: workplace survey respondents during working hours (n = 126, 6.3%)

Respondents in this small group combined survey participation with professional digital activities during working hours, predominantly in the morning (95%). Nearly all completed the survey at their workplace (99%), and a substantial share were engaged in white-collar work (51%). Survey completion appeared to take place alongside regular work tasks, as reflected in the predominant use of large-screen devices (65%), many of which were likely work computers. In addition to answering the survey, respondents frequently engaged in other activities, including face-to-face or digital communication, reading and writing emails, and completing work-related tasks. The multitasking patterns observed in this group suggest that survey participation was integrated into short pauses or transitions within the workday, rather than occurring as a stand-alone activity.

#### 5.1.6. Not classifiable, NAs (n = 234, 11.6%)

Of the 2,000 participants, 12.9% ($n = 258$) could not be classified into any of the five latent classes due to data gaps, so we treated them as a separate group.

#### 5.1.7. Associations with data quality

In the next step, we used both binary logistic regression models and multivariate linear regression models to closely examine the associations between completion context and data quality. The dependent variables in this analysis were the data quality indicators we developed: 'item nonresponse' (the instances in which respondents did not provide answers), 'straightlining' (a pattern of identical or similar responses across items), 'data inconsistency' (the discrepancies within respondents' answers), 'completion time' (the length of time it took to complete the survey), 'ambient sound disturbance' (relating to noise interruptions during the survey) and 'focus and concentration' (assessing respondents' attention). For the independent variables, we considered: (1) latent class membership, with Class 3 serving as the reference category, since respondents in the group had the most optimal external conditions for the survey; (2) gender, with males serving as the reference; (3) age group, with the 40–49 age group serving as the reference; (4) education level, with primary education as the reference; and (5) settlement type, with Budapest (capital) as the reference category.[1] The main results of the models, for each data quality dimension, are as follows.

(1) *Item-nonresponse*: Only two predictors demonstrated a significant association with item-nonresponse. Respondents in Class 4 had higher odds of skipping items or providing invalid responses compared to those in Class 3 (OR = 1.6, $p < .01$). The effect of gender is also found to be a significant predictor: women were somewhat more likely to skip valid responses (OR = 1.6, $p < .001$)
(2) *Straightlining*: Latent class membership had no direct impact on the probabilities of straightlining, but providing identical or similar responses across items seems

to be a rather age-related phenomenon. Younger adults (under 40) had a higher probability of straightlining (OR = 1.56-1.70, $p < .01$), while those aged 60 and older were less likely to do so. (OR = .65-.71, $p < .05$) Table 1 Table A1–A4 Additionally, the secondary level of education (compared to primary) is also associated with a higher chance of straightlining (OR = 1.57, $p < .001$).

(3) *Inconsistent responding*: Inconsistent data, where responses were difficult to reconcile, were more likely to occur in Class 4. (OR = 1.83, $p < .001$) Although this relationship is not statistically significant, it may be viewed as a weak and non-deterministic indication that multitasking, such as media consumption and work, is likely to negatively impact data quality. Similar to the previous model, the level of education also seems to matter to some extent: having secondary education is associated with higher odds of inconsistent data than primary education. (OR = 1.74, $p < 0.05$)

(4) *Completion time*: The duration of completing the survey is a quality indicator where very brief or/and very long completion times can be considered as proxies for poorer data quality (Loosveldt – Beullens 2013). Compared with the members of the potentially most relaxed circumstances in Class 3, respondents in the other four latent classes had significantly higher completion times. The differences ranged from 144 seconds (in Class 4) to 263 seconds (in Class 2). In other words, compared to Class 3, all other groups had average completion times 2–4 minutes longer. (See Figure 2 for the detailed distribution of completion times by latent classes.) Similar to straightlining, age seems to be the key factor here. Across the six age groups, the average completion time ranged from 22 minutes (18–29 years) to 34 minutes (above 70 years), and there appears to be a linear relationship between completion time and age. Although personal differences vary greatly, on average, a simple linear regression indicates that every extra year of age increases the average completion time by roughly 14 seconds. ($\beta_0 = 14.17$; $\beta_1 = .24$; $p < 0.001$) (See Figure 3)

(5) *Ambient sound disturbance*: Respondents were asked to subjectively evaluate the noisiness of the environment, with 0 representing complete silence and 10 indicating a very high level of background noise.[2] Similar to the previous model, being 'outside' of Class 3 signals a higher level of background noise, i.e. less optimal conditions. ($\beta_1$.=.54 – .95; $p < 0.01$) The results also suggest that those in the youngest age group (18 to 29 years) were faced with a significantly higher level of noise ($\beta_{1=.}46$; $p < .05$) And finally, living outside of large cities and towns seems to be a factor that could contribute to less disturbance from unwanted sources. ($\beta_{1=.}$-.35; $p < .05$)

(6) *Focus and concentration*: In the last model, we used a question on the ability to focus and concentrate when completing the survey. Again, a scale of 0 to 10 was used, with higher values indicating greater focus and concentration. Consistent with the results of the previous two models, membership in all non-reference-category latent classes (except Class 2, which is predominantly composed of younger people who use their phones) appears to be a significant predictor of a limited ability to focus and concentrate. ($\beta_1$.=−.78 – −.39; $p < 0.01$) A similar effect is shown in age for respondents under 40 ($\beta_1$.=−.75 – −.38; $p < 0.05$), and in education (respondents with secondary education) are experiencing the same pattern of effects. ($\beta_1$.=−.39;

**Table 1.** Effects of completion context and demography on data integrity indicators.

| | Model 1: Item-nonresponse (logit) | | | Model 2: Straightlining (logit) | | | Model 3: Inconsistent responding (logit) | | | Model 4: Fill time (OLS) | | | Model 5: Ambient sound disturbance (OLS) | | | Model 6: Focus and concentration (OLS) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Predictors* | *Odds Ratios* | *CI* | *p* | *Odds Ratios* | *CI* | *p* | *Odds Ratios* | *CI* | *p* | *Estimates* | *CI* | *p* | *Estimates* | *CI* | *p* | *Estimates* | *CI* | *p* |
| (Intercept) | 0.38 | 0.27–0.54 | **<0.001** | 0.65 | 0.46–0.91 | **0.013** | 0.04 | 0.02–0.08 | **<0.001** | 23.04 | 20.86–25.21 | **<0.001** | 3.36 | 2.96–3.76 | **<0.001** | 8.15 | 7.79–8.52 | **<0.001** |
| **LATENT CLASS MEMBERSHIP (ref: Class 3)** | | | | | | | | | | | | | | | | | | |
| Class 1 | 1.11 | 0.82–1.50 | 0.487 | 1.05 | 0.78–1.41 | 0.737 | 0.94 | 0.45–1.86 | 0.874 | 3.22 | 1.36–5.08 | **0.001** | 0.70 | 0.36–1.04 | **<0.001** | −0.39 | −0.70 – −0.08 | **0.014** |
| Class 2 | 1.08 | 0.80–1.44 | 0.625 | 0.89 | 0.67–1.18 | 0.421 | 1.28 | 0.66–2.41 | 0.453 | 4.38 | 2.53–6.23 | **<0.001** | 0.54 | 0.20–0.88 | **0.002** | −0.27 | −0.57 – 0.04 | 0.089 |
| Class 4 | 1.60 | 1.13–2.27 | **0.008** | 0.72 | 0.50–1.04 | 0.080 | 1.83 | 0.90–3.55 | 0.082 | 2.40 | 0.14–4.66 | **0.037** | 0.95 | 0.54–1.37 | **<0.001** | −0.78 | −1.16 – −0.41 | **<0.001** |
| Class 5 | 0.77 | 0.48–1.19 | 0.251 | 0.99 | 0.65–1.48 | 0.944 | 0.72 | 0.17–2.11 | 0.601 | 2.88 | 0.23–5.53 | **0.033** | 0.88 | 0.39–1.36 | **<0.001** | −0.67 | −1.11 – −0.23 | **0.003** |
| Not classifiable | 1.34 | 0.97–1.85 | 0.076 | 0.96 | 0.70–1.33 | 0.822 | 0.76 | 0.30–1.67 | 0.523 | 0.91 | −1.17 – 2.98 | 0.391 | 1.17 | 0.79–1.55 | **<0.001** | −0.54 | −0.88 – −0.19 | **0.002** |
| **GENDER (ref: male)** | | | | | | | | | | | | | | | | | | |
| female | 1.60 | 1.30–1.96 | **<0.001** | 0.95 | 0.78–1.16 | 0.628 | 0.87 | 0.55–1.38 | 0.554 | 0.10 | −1.17 – 1.37 | 0.874 | −0.43 | −0.66 – −0.20 | **<0.001** | 0.32 | 0.11–0.53 | **0.003** |
| **AGE GROUP (ref: 40–49)** | | | | | | | | | | | | | | | | | | |
| 18–29 | 1.33 | 0.94–1.88 | 0.108 | 1.70 | 1.21–2.39 | **0.002** | 1.68 | 0.80–3.54 | 0.170 | −3.35 | −5.62 – −1.09 | **0.004** | 0.46 | 0.04–0.87 | **0.031** | −0.75 | −1.13 – −0.37 | **<0.001** |
| 30–39 | 0.97 | 0.69–1.36 | 0.860 | 1.56 | 1.12–2.16 | **0.008** | 0.66 | 0.26–1.55 | 0.351 | −2.96 | −5.11 – −0.81 | **0.007** | 0.11 | −0.29 – 0.50 | 0.601 | −0.38 | −0.74 – −0.02 | **0.038** |
| 50–59 | 0.74 | 0.54–1.02 | 0.064 | 0.95 | 0.70–1.29 | 0.746 | 0.63 | 0.28–1.39 | 0.259 | 0.57 | −1.40 – 2.54 | 0.569 | −0.03 | −0.40 – 0.33 | 0.857 | −0.07 | −0.40 – 0.25 | 0.655 |
| 60–69 | 0.80 | 0.58–1.10 | 0.169 | 0.71 | 0.52–0.98 | **0.038** | 1.23 | 0.61–2.55 | 0.563 | 4.45 | 2.44–6.45 | **<0.001** | −0.16 | −0.53 – 0.21 | 0.392 | 0.15 | −0.18 – 0.49 | 0.370 |
| 70+ | 0.94 | 0.66–1.33 | 0.723 | 0.65 | 0.45–0.93 | **0.019** | 1.35 | 0.61–2.96 | 0.456 | 9.69 | 7.48–11.91 | **<0.001** | −0.27 | −0.68 – 0.14 | 0.196 | 0.22 | −0.15 – 0.59 | 0.236 |
| **EDUCATION (ref: primary)** | | | | | | | | | | | | | | | | | | |
| secondary | 0.98 | 0.76–1.26 | 0.872 | 1.57 | 1.24–2.00 | **<0.001** | 1.74 | 1.02–2.98 | **0.042** | −0.13 | −1.70 – 1.44 | 0.873 | 0.22 | −0.07 – 0.51 | 0.138 | −0.39 | −0.65 – −0.12 | **0.004** |
| tertiary | 1.08 | 0.86–1.37 | 0.510 | 0.86 | 0.68–1.09 | 0.222 | 0.95 | 0.53–1.68 | 0.859 | −0.83 | −2.30 – 0.64 | 0.267 | −0.08 | −0.35 – 0.19 | 0.557 | 0.14 | −0.10 – 0.38 | 0.258 |
| **TYPE OF SETTLEMENT (ref: Budapest/capital)** | | | | | | | | | | | | | | | | | | |
| cities and towns | 0.97 | 0.75–1.26 | 0.801 | 0.86 | 0.67–1.11 | 0.259 | 1.06 | 0.59–2.01 | 0.851 | 0.39 | −1.23 – 2.00 | 0.640 | −0.14 | −0.43 – 0.16 | 0.367 | 0.13 | −0.14 – 0.40 | 0.332 |
| villages | 0.92 | 0.68–1.25 | 0.594 | 0.90 | 0.67–1.21 | 0.477 | 1.02 | 0.51–2.09 | 0.947 | 0.15 | −1.74 – 2.03 | 0.879 | −0.35 | −0.70 – −0.00 | **0.047** | 0.33 | 0.01–0.64 | **0.041** |
| **Observations** | **1870** | | | **1870** | | | **1870** | | | **1870** | | | **1870** | | | **1870** | | |
| $R^2$ *Tjur* | *0.028* | | | *0.039* | | | *0.011* | | | *0.094 / 0.087* | | | *0.046 / 0.038* | | | *0.046 / 0.038* | | |

Cases with completion time exceeding 90 minutes (n = 130) were removed before the regression analyses; analytic N = 1,870.

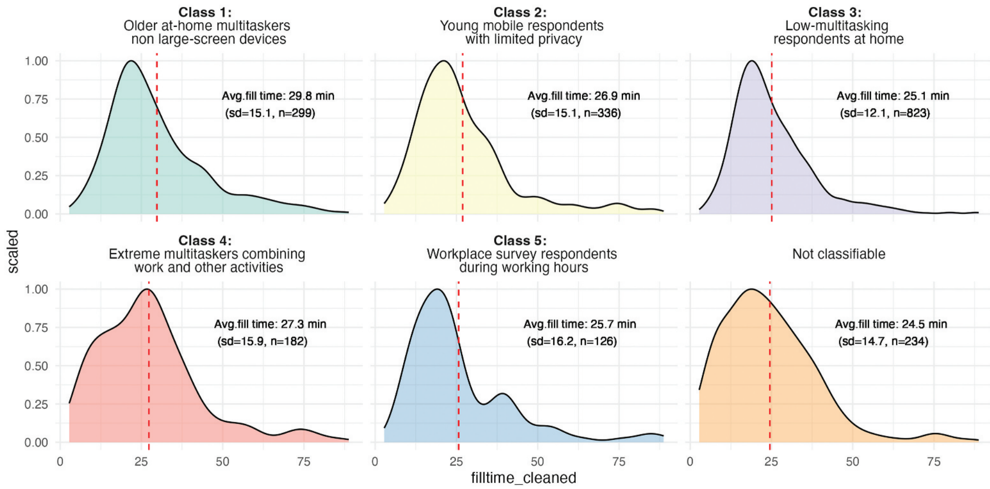


**Figure 2.** Duration of completing the survey by latent classes.

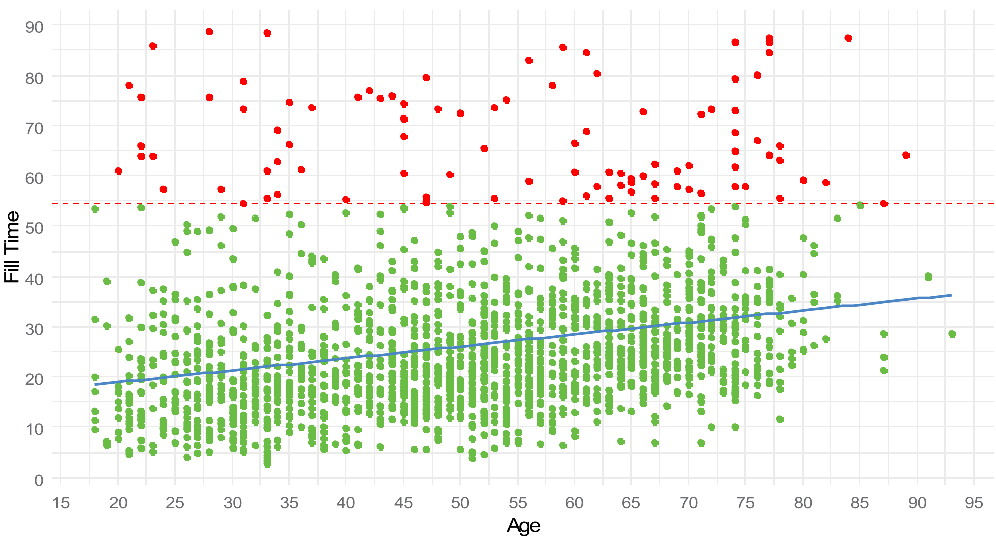


**Figure 3.** Duration of filling out the survey by age.

$p < 0.005$) As a final point, the relationship observed in the previous model is also present here: rural life (in general) is more conducive to focused attention. ($\beta_1$.=.33; $p < 0.05$)

## 6. Discussion

With the advent of online surveys, researchers have lost control over the context of response completion and the response process. Participants in online surveys can respond from any location, at any time, using various devices, and often multitask while completing the survey. The circumstances under which participants respond to surveys can affect data quality. This study contributed to this area of research in two ways. Building on prior attempts (De Bruijne & Oudejans, 2015; Lynn & Kaminska, 2013), we developed a theoretical framework, a conceptual starting point for future work, which outlines associations between various aspects of completion and the four steps of the response process (Tourangeau et al., 2000) and their necessary conditions. Second, we provided empirical evidence sourced from responses to an extensive set of questions about completion, collected through an online survey conducted in Hungary.

Our results confirm previous findings (Ansolabehere & Schaffner, 2015; De Bruijne & Oudejans, 2015; Höhne et al., 2020; Sendelbah et al., 2016; Wenz, 2021; Zwarun & Hall, 2014) by showing that online survey respondents complete surveys from a variety of settings and many of them engage in multitasking. Our latent class analysis showed that a number of respondents completed the survey from settings that, at least theoretically, can be labelled as non-optimal (e.g. small device, night, low privacy, high multitasking). If we consider Class 3 to be theoretically optimal, around 60% of the sample completed the survey under suboptimal circumstances. Patterns of completion context decisions systematically differ between certain groups of respondents. Age and gender were the two relatively important factors that influenced how individuals completed the survey.

Nonetheless, one may argue that individual preferences differ, and the 'optimal' can vary from person to person. Our findings regarding the negative consequences of completion context are mixed. We found that all groups that differed from the 'optimal' reference group reported lower concentration and higher distraction. This aligns with the findings of De Bruijne and Oudejans (2015). Moreover, the survey duration was also longer in some cases. Nevertheless, when considering 'harder' data quality indicators such as item-nonresponse or straightlining, we found no statistically significant association with completion context. Lower levels of concentration, distractions, and the speed of completion did not necessarily harm performance during the response process. A possible explanation is that participants who choose sub-optimal settings are those who handle distractions better or have higher multitasking performance. Another reason may be that our sample comprised individuals who routinely participate in surveys, indicating familiarity with this cognitive task and established proficiency in navigating and interpreting survey questionnaires.

Our findings suggest important directions for future research. First, despite the lack of clear negative consequences of completion context, these factors can potentially affect the response process in other surveys or countries. Thus, we encourage researchers to include measures of completion context in their surveys and use them for controlling purposes or to detect potentially harmful respondent behaviour. An analogous case is when researchers control for interviewer characteristics in interviewer-administered surveys. Although highly skilled interviewers are unlikely to harm measurement, it is still reasonable to routinely control for potential interviewer effects. Second, measuring completion context can help to understand satisficing behaviour. The design of this study did not allow us to tease out the individual effects of the various factors outlined in our framework, but future research could examine the individual causal chain more deeply, for example, by using experimental methods. Third, measuring completion traits can also be valuable for optimizing survey requests. Future research may experiment with tailoring survey requests to panel members' prior completion patterns.

This study is not without limitations. Our measurement related to completion context was based mostly on self-reports (device type, time of completion, and duration were the exceptions). Given that self-reports are known to be prone to various cognitive biases (Dunning et al., 2004), it is possible that some respondents under- or overreported their activities, misreported the presence of others, etc. Future research should tackle this by using paradata such as web-tracking data (see Höhne et al. (2020) and Höhne and Schlosser (2018)). Another issue is generalizability. We used data collected from a single country's non-probability-based online panel. It remains a question of the extent to which our findings generalize to the general Hungarian population or to other cultures. Lastly, because we rely on observational data, causality cannot be established, underscoring the need for future experimental research to test specific pathways within the theoretical model.

Our study has contributed theoretical and empirical insights into survey completion and respondent behaviour in online surveys. We hope that our findings will serve as a catalyst for further research in this overlooked area of survey methodology. Given the widespread use of web surveys across the social sciences, an improved understanding of completion context is also substantively relevant for researchers studying political attitudes, social behaviour, and a wide range of other domains.

## Notes

1. Settlement type was measured using three categories: 1: village, 2: cities and towns, 3: Capital (Budapest).
2. "On a scale of 0–10, how quiet or noisy do you feel your current environment is at the moment overall?"

## Author contributions

CRediT: **Bence Ságvári:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Visualization, Writing – original draft, Writing – review & editing; **Ádám Stefkovics:** Conceptualization, Writing – original draft, Writing – review & editing.

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# Appendix

**Table A1.** Variables used for the latent class analysis (LCA).

| Variable name | Description | Categories |
|---|---|---|
| screen_size | Type of device used for answering | 1: large screen,<br>2: small_screen |
| daypart2 | Part of day when completing the survey | 1: morning (6 h-12 h),<br>2: afternoon/evening (12 h-22 h),<br>3: night (22 h-06 h) |
| mt_audio | Listening to audio on the phone or from other sources | 1: yes, 0:no |
| mt_video | Watching video on the device or from other sources (e.g. TV) | 1: yes, 0:no |
| mt_communication | Communicating with others via messaging, phone or in person | 1: yes, 0:no |
| mt_move | Moving while completing the survey | 1: yes, 0:no |
| mt_work1 | Working while completing the survey ('white collar') | 1: yes, 0:no |
| mt_work2 | Working while completing the survey ('blue collar'/physical) | 1: yes, 0:no |
| mt_other | Other activities (incl. childcare) | 1: yes, 0:no |
| location | Location when responding to the survey | 1: home, 2: work, 3: other |
| privacy | Degree of privacy measured by the presence of others and their ability to see the respondent's screen. | 1: no privacy<br>2: partial privacy<br>3: full privacy |

**Table A2.** LCA Model indicators for 3 to 7 latent class models.

| model | log-likelihood | resid. df | BIC | aBIC | cAIC | likelihood-ratio | Entropy |
|---|---|---|---|---|---|---|---|
| Model 3 | −11,983.86 | 1,719.00 | 24,319.11 | 24,169.79 | 24,366.11 | 3,028.94 | 0.772 |
| Model 4 | −11,875.01 | 1,703.00 | 24,221.04 | 24,020.89 | 24,284.04 | 2,811.25 | 0.693 |
| **Model 5** | **-11814.20** | **1,687.00** | **24,219.03** | **23,968.06** | **24,298.03** | **2,689.62** | **0.665** |
| Model 6 | −11,759.62 | 1,671.00 | 24,229.50 | 23,927.69 | 24,324.50 | 2,580.47 | 0.647 |
| Model 7 | −11,722.62 | 1,655.00 | 24,275.12 | 23,922.48 | 24,386.12 | 2,506.47 | 0.626 |

**Table A3.** Basic latent class characteristics.

| Factor | Category | Latent Class 1 Older at-home multitaskers on large-screen devices | 2 Young mobile respondents with limited privacy | 3 Low-multitasking respondents at home | 4 Extreme multitaskers combining work and other activities | 5 Workplace survey respondents during working hours |
|---|---|---|---|---|---|---|
| Screen size | large screen | 73 | 7 | 67 | 34 | 65 |
| | small screen | 27 | 93 | 33 | 66 | 35 |
| Location | home | 100 | 76 | 98 | 71 | 0 |
| | work | 0 | 2 | 2 | 13 | 99 |
| | other | 0 | 22 | 0 | 16 | 1 |
| Time during the day | morning | 59 | 34 | 41 | 52 | 95 |
| | afternoon/ evening | 38 | 51 | 49 | 38 | 5 |
| | night | 3 | 15 | 9 | 10 | 0 |
| Day of the week | Weekday | 69 | 82 | 75 | 82 | 98 |
| | Weekend | 31 | 18 | 25 | 18 | 2 |
| Multitasking | audio | 39 | 9 | 14 | 61 | 34 |
| | video | 71 | 33 | 25 | 81 | 5 |
| | communication | 71 | 32 | 1 | 96 | 39 |
| | moving | 2 | 3 | 0 | 69 | 3 |
| | working (white collar | 45 | 0 | 5 | 29 | 51 |
| | working (blue collar) | 37 | 7 | 6 | 83 | 8 |
| | other | 74 | 33 | 21 | 90 | 25 |
| Level of privacy | no privacy | 9 | 25 | 4 | 19 | 14 |
| | partial privacy | 20 | 62 | 10 | 26 | 37 |
| | full privacy | 71 | 13 | 86 | 55 | 49 |
| | *Frequency (per cent)* | *15* | *17* | *41* | *9* | *6* |

**Table A4.** Latent class demography.

| | Category | Latent Class 1 Older at-home multitaskers on large-screen devices | 2 Young mobile respondents with limited privacy | 3 Low-multitasking respondents at home | 4 Extreme multitaskers combining work and other activities | 5 Workplace survey respondents during working hours |
|---|---|---|---|---|---|---|
| Gender | male | 55 | 39 | 54 | 41 | 45 |
| | female | 46 | 61 | 46 | 59 | 55 |
| Age | 18–29 | 6 | 24 | 9 | 11 | 16 |
| | 30–39 | 9 | 22 | 11 | 18 | 18 |
| | 40–49 | 14 | 21 | 18 | 19 | 25 |
| | 50–59 | 17 | 18 | 23 | 16 | 26 |
| | 60–69 | 23 | 13 | 24 | 17 | 14 |
| | 70+ | 30 | 2 | 16 | 19 | 1 |
| Education | Primary | 20 | 32 | 24 | 34 | 9 |
| | Secondary | 40 | 45 | 41 | 42 | 49 |
| | Tertiary | 41 | 24 | 35 | 24 | 42 |
| Settlement type | Budapest | 22 | 15 | 23 | 15 | 20 |
| | Cities and towns | 57 | 50 | 55 | 53 | 59 |
| | Villages | 21 | 35 | 22 | 32 | 21 |