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Explaining Response Errors of Self-Reported Frequency and Duration of TV Exposure Through Individual and Contextual Factors

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Abstract

Measures of TV exposure are crucial for many communication studies but possible flaws remain understudied. This study contributes to the discussion about the validity of survey measures of media use by assessing the extent to which people over- or underreport their viewing behavior by examining recency effects, and systematic variations in the accuracy of self-reports. Self-reported measures of TV exposure are directly compared with people-meter measures stemming from a single sample and the same time period. The findings reveal tendencies to overreport the frequency of watching and underreport the viewing duration. Response errors relate to sociodemographics and viewing-related characteristics.

Keywords

audience research, television exposure, self-reports, people meter

Survey designs remain a common approach to gain insight into media uses and effects, including areas such as political learning and opinion formation or cultivation effects (e.g., Delli Carpini, 2004; Druckman, 2005; Eveland, Hayes, Shah, & Kwak, 2005; Shrum, Lee, Burroughs, & Rindfleisch, 2011). For this reason, a large part of the evidence in these areas relies on self-reported measures of media use. However, reporting how often one uses or how much time one spends with a medium can be a challenging

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task for respondents who may be susceptible to errors. Watching television in particular is an increasingly time-consuming activity, with average viewing times of more than 3 hr per day in many Western countries (Robinson & Martin, 2010; Stichting KijkOnderzoek [SKO], 2012b; Eurodata TV Worldwide, 2012; Zubayr & Gerhard, 2012). Even in a new media environment, watching TV still is the most important leisure activity, accounting for a great deal of leisure time (U.S. Department of Labor, Bureau of Labor Statistics, 2015; Sociaal en Cultureel Planbureau, 2013). Important research questions relate to the uses and the effects of TV consumption while the possible flaws inherent in its measurement remain understudied.

Because of their crucial relevance for our understanding of the role of media as it relates to individuals and societies, self-reported measures of media use have become an object of critical discussion themselves (e.g., Romantan, Hornik, Price, Cappella, & Viswanath, 2008; Coromina & Saris, 2009; Potter & Chang, 1990). Thus far, however, validation studies drawing on observed measures to assess the possible biases of self-reporting are scarce. A comparison of self-reported media exposure and media-use diaries revealed general tendencies to overreport media use (Greenberg et al., 2005). A diary study among children indicated inaccuracies in self-reported TV viewing (van der Voort & Vooijs, 1990). More accurate knowledge about the nature and the scope of response errors of survey measures can be obtained by comparing self-reports to electronically recorded measures of media use (e.g., Ettema, 1985; Price & Zaller, 1993). Electronic data registration has the advantage of being independent from recall or estimation errors (Webster, Phalen, & Lichty, 2006). Studies comparing electronically recorded and self-reported measures have been conducted for the usage of specific TV genres (e.g., Prior, 2009a) or for other media types such as social media, video games, or mobile phones (e.g., Ettema, 1985; Goulet & Hampton, 2012; Kahn, Ratan, & Williams, 2014; Kobayashi & Boase, 2012). Comparing Nielsen and survey estimates, for instance, revealed tendencies to overreport exposure to television news (Prior, 2009a). The use of mobile phones has also been found to be overreported based on a comparison of log measures and self-reports (Kobayashi & Boase, 2012).

The validity of self-reports of general TV consumption in terms of their accuracy compared with electronically recorded data has not yet been assessed. The present study fills this gap with a unique research design that allows the direct comparison of self-reported TV exposure and people-meter data based on a single sample measured during the same time period. We conducted a secondary analysis of Dutch people-meter data on the individual level and the corresponding survey measures of TV use. We examined the level of convergence validity of survey and people-meter data, assessed recency effects, and detected to what extent respondents varied systematically in their response behavior.

Conceptualization of TV Exposure

Conceptualizations of media exposure differ in how they define exposure situations and in the type of media content that is considered. Situations of media exposure can vary from the mere opportunity to encounter a media message to an actual sensory perception of a message (McLeod & McDonald, 1985; Rossiter & Danaher, 1998). Most commonly, a minimum level of intentional behavior is presumed for exposure to take place without making assumptions about cognitive or affective processes of media reception. Paying attention to media content, message processing or recall, for example, has been considered as conceptually distinct from exposure (Chaffee & Schleuder, 1986; Napoli, 2010; Slater, 2004). On the content level, exposure may range from the content of a medium, such as television or newspapers or a particular outlet such as a TV program or an issue of a newspaper, to a very specific message, such as an advertising campaign. This study focuses on exposure to the medium of television. According to the Dutch Audience Foundation, television exposure is defined as being in a room where a TV set is turned on and attending to the screen (SKO, 2013). Drawing on active verbs such as viewing or watching, survey questions on TV exposure also imply a minimum level of attentiveness. Oftentimes, viewing situations are not clearly specified, leaving more room for interpretation by respondents (Gunter, 2000). Nonetheless, we assume that people-meter and survey measures build on an understanding of TV exposure as a behavioral concept—attending to some type of television screen—which, in turn, is a premise for subsequent modes of media reception as well as media effects. We discern two aspects of general viewing behavior that are frequently applied in survey research: the frequency and the duration of TV exposure (Althaus & Tewksbury, 2007; Bryant, Lucove, Evenson, & Marshall, 2007; Coromina & Saris, 2009).

The Nature of Response Errors of Self-Reported TV Exposure

The literature on survey methodology suggests four moments of possible response errors. Problems can occur during question comprehension, recalling, estimating, and reporting one's behavior (Schwarz, 2007). The oft-described nature of TV exposure as a low-involvement activity may be particularly challenging for self-reports (Comstock & Scharrer, 1999). Watching TV for relaxation, escapism, or simply to pass the time may hinder viewers from keeping track of and correctly recalling the time they spent in front of the screen. Because respondents find it difficult to give a correct answer, they might draw on flawed estimation heuristics (Burton & Blair, 1991; Prior, 2009b). The first aim of this study is to assess the magnitude of the deviation of self-reports from electronically recorded exposure measures. The degree of overlap between these two types of measures reflects their convergent validity.

Researchers are often interested in average viewing behavior as opposed to exposure on specific days. This is why the congruency of self-reports with behavior over a longer versus a shorter reference period is crucial. Although self-reports are assumed to reflect long-term behavior, the most recent viewing experiences might bias respondents' estimates, resulting in a so-called recency effect (e.g., Haugtvedt & Wegener, 1994). Previous studies showed that self-reports on media use were influenced by the reference period presented in survey questions (Chang & Krosnick, 2003; Price, 1993). Price (1993), for instance, found lower reports of news media use for more the recent time period "in the past week" compared with the longer time periods "in a typical week." Our first research question and hypothesis address the convergent validity and recency effects of self-reported exposure measures.

RQ1: What is the magnitude of response errors of self-reported *frequency* (RQ1a) and *duration* (RQ1b) of TV exposure relative to equivalent people-meter measures?
H1: Response errors of self-reported *frequency* (H1a) and *duration* (H2b) of TV exposure are smaller for a more recent time period compared with a longer time frame.

Systematic Bias in Response Behavior

The validity of measures and any conclusions about TV use and effects are limited as soon as biases of self-reports systematically differ between subgroups of a sample (Prior, 2009a; Southwell et al., 2010). We discern three types of viewer characteristics that can potentially be linked to differences in response errors: sociodemographics, contextual factors of TV viewing, and viewing-related factors.

Sociodemographic Factors

General differences in response behavior between sociodemographic groups have been related to social desirability (Holbrook, Green, & Krosnick, 2003). While overreporting has been detected for behavior widely accepted as a civic duty, such as voting or news consumption (Katosh & Traugott, 1981; Prior, 2009a), undesirable behavior, such as gaming or smoking, has been found to be underestimated by surveys (Moskowitz, 2004; Kahn et al., 2014). Self-identification of members of higher social classes, for instance, based on their level of education or income, may foster a greater awareness of the negative image of heavy viewing (Putnam, 1995, 2000). Early research on audience behavior has identified discrepancies, especially for better educated members, between their oftentimes negative attitudes toward watching TV and their actual viewing behavior (Bower, 1973; Steiner, 1963). Similarly, validation studies on self-reports of other types of media use point to an impact of self-identification. Television news exposure has been found to be more strongly overreported by respondents with higher incomes (Prior, 2009a), while higher education levels were associated with underreporting the number of hours spent video gaming (Kahn et al., 2014). In sum, social desirability in particular may cause respondents of a higher social status to underreport their TV exposure.

H2: Education is positively associated with underreporting *frequency* (H2a) and *duration* (H2b) of TV exposure.
H3: Income is positively associated with underreporting *frequency* (H3a) and *duration* (H3b) of TV exposure.

In addition to individual differences that might be explained by social desirability, other individual factors could relate to systematic differences in response errors.

Younger people as well as men have been found to be more likely to overreport television news exposure (Prior, 2009a). In addition, other media-use behavior might be influential. Increasing levels of media multitasking could be expected to facilitate underreporting of the use of a single medium (Wang, Irwin, Cooper, & Srivastava, 2015). People who use a greater diversity of media may be more susceptible to underreporting their TV exposure. The following hypotheses address these possible relationships:

H4: Age is negatively related to the magnitude of response errors in self-reported *frequency* (H4a) and *duration* (H4b) of TV exposure.
H5: Men are more prone to response errors in self-reported *frequency* (H5a) and *duration* (H5b) of TV exposure compared with women.
H6: Higher levels of general media use are positively related to underreporting self-reported *frequency* (H6a) and *duration* (H6b) of TV exposure.

Viewing Motivations and Behavior

Attitudes toward a reported activity may challenge the validity of self-reports. The theory of cognitive dissonance (Festinger, 1957) or balance theory (Heider, 1946) offer explanations for these relationships (see Kahn et al., 2014). Both theories describe tendencies to strive for consistency or balance of cognitive elements. In the case of self-reported media exposure, the crucial cognitive elements are perceptions of one's media-use behavior and attitudes toward this behavior. Previous research showed that overreporting the use of mobile phones related to levels of social activity (Kobayashi & Boase, 2012). Self-reports of using an agricultural information system were biased by the interest in this specific information (Ettema, 1985). Finally, the degree of underreporting video gaming decreased with higher levels of perceived enjoyment of gaming (Kahn et al., 2014). Accordingly, viewers who have strong viewing preferences and greatly enjoy watching TV may strive for consistency between their strong viewing interest and their actual exposure. Strong viewing interests may consequently facilitate overreporting while lower interests may coincide with underreporting of exposure.

Inaccurate reports of viewing behavior might also occur completely unintentionally due to flawed estimation. Watching TV is a part of daily routines and is thus often conducted habitually. Media habits are considered as automatic behaviors that are triggered by key stimuli (Koch, 2010; LaRose, 2010). The less conscious people are about their choices to switch on the TV or to continue to watch, the more difficult it might be to correctly remember past viewing behavior. Habitual behavior should not, however, be equated with the mere frequency of a behavior (Aarts, Verplanken, & Knippenberg, 1998; Verplanken, 2006). Frequent repetition is a precondition to develop mental structures of habits and actual habitual behavior. The mere frequency or amount of watching TV may also influence self-reports; however, as it has been suggested that in general, the recall of frequent behavior may be less accurate (Menon, 1993; Schwarz & Oyserman, 2001). Heavy viewers might find it more difficult to estimate the time they usually spend watching TV on a given day compared with, for instance, someone who only watches a TV series for 45 min every day. In sum, recalling and estimating may depend on one's overall viewing motivations and behavior. The latter includes the amount of time spent watching as well as the stability of viewing habits, that is, the extent to which the viewing time and programs watched are consistent over time.

H7: Response errors of self-reported *frequency* (H7a) and *duration* (H7b) of TV exposure relate positively to the respondent's interest in TV viewing.
H8: Response errors of self-reported *frequency* (H8a) and *duration* (H8b) of TV exposure relate positively to the respondent's strength of viewing habits.
H9: Response errors of self-reported *frequency* (H9a) and *duration* (H9b) of TV exposure relate positively to the overall amount of viewing.

Viewing Context

According to the structural approach to media use, contextual factors have a strong impact on viewing behavior (Cooper, 1996; Webster & Phalen, 1997). The viewing environment has been assumed to particularly shape unintentional viewing behavior (Wonneberger, Schoenbach, & van Meurs, 2011). To a certain extent, watching TV generally or a specific program might happen due to contextual circumstances such as being in the room with other household members who have turned on the TV. The number of TV sets or the availability of digital or analog TV in a household also influence the viewing habits that are developed. Because these types of contextual factors, which comprise the characteristics of home viewing situations, influence viewing behavior in a subtle, unobtrusive way, they might also affect perceptions of one's viewing behavior. With more household members, for instance, co-viewing or joining viewing situations less intentionally becomes more likely. Thus, bigger households might facilitate the underreporting of viewing behavior. Greater inaccuracies in reporting exposure to television news, for example, have been found for respondents living in a household with children (Prior, 2009a). In addition, the presence of viewing opportunities in the form of TV sets, digital TV, or recording devices might create the impression that TV is available at any time. This increased availability with a greater space-time independence of TV exposure may reinforce a sense of increased actual viewing behavior. The following hypotheses address the influence of the household viewing context on the accuracy of self-reports:

H10: Household size is positively related to underreporting *frequency* (H10a) and *duration* (H10b) of TV exposure.
H11: The number of TV sets in a household is positively related to overreporting *frequency* (H11a) and *duration* (H11b) of TV exposure.
H12: The presence of digital TV is positively related to overreporting *frequency* (H12a) and *duration* (H12b) of TV exposure.
H13: The presence of TV recording devices is positively related to overreporting *frequency* (H13a) and *duration* (H13b) of TV exposure.

Method

Data from the national television audience research in the Netherlands offered electronically recorded and self-reported viewing measures from a single sample. The data were provided by SKO, a joint venture of public broadcasting (NPO), sale houses of public and commercial broadcasters (SPOT), advertisers (BVA), and media agencies (PMA). SKO commissions Intomart GfK to provide television audience measurement data collected from a national audience panel based on people-meters. The panel ($N = 2,800$, aged ≥3) is representative of all persons in private households in the Netherlands (15.8 million).

People-meters are connected to every TV set, TV player and recorder, and set-top box in all participating households. All household members are asked to log on to the meter system with a separate remote control every time they watch TV. The meters electronically register all the viewing behavior of all persons logged on. Data are collected on a second-by-second basis and include time-shifted viewing that takes place within 7 days of the original broadcast. Intomart GfK conducts a face to face recruitment survey and an annual survey among all panel members that covers sociodemographics, household characteristics, individual interests and preferences as well as television and other media-use behavior (SKO, 2013).

People-Meter Versus Self-Reports

This study assumes that people-meter measures can serve as an adequate benchmark for self-reported measures of TV exposure. Most importantly, information gathered by the meter system is not prone to response errors that typically occur in survey research because these data are not based on recall, estimation, and reporting of past behavior. People-meter measures also have their limitations, however, and they have been critiqued repeatedly in public and academic debates (e.g., Ettema & Whitney, 1994; Napoli, 2005). First of all, the accuracy of the measures depends on the willingness of the participants to register correctly every time they watch TV. A second concern regard the sample quality and its consequences for the representativeness of the population, especially of minority groups (Milavsky, 1992; Napoli, 2003). For the 2011 Dutch television panel, coincidental checks conducted by telephone yielded an accuracy of logging behavior of 95% at the individual level. The accuracy did not differ due to household size or duration of panel membership. In addition, no significant differences in the accuracy of logging behavior related to individual characteristics such as age, gender, or household position could be found. Ethnic minorities represent an independent quota per region and monthly controls assure the cells are filled in.

With the introduction of new online viewing devices, criticism has been raised regarding the scope of people-meter measures. Thirty-six percent of Dutch people above the age of 13 occasionally watched TV on desktop computers, laptops, tablets, or smart phones in 2012; however, only a small share of this viewing behavior was devoted to live streaming (SKO, 2012a). In short, varying forms of online viewing should be taken into account for a comparison of people-meter measures and self-reports. However, traditional offline viewing still was the main viewing mode in the Netherlands in 2011.

Data Selection

For our analysis, we contrasted self-reported viewing behavior with people-meter measures obtained in the same week of the survey fieldwork and in a circumjacent period of 11 weeks. For this purpose, a subsample of respondents who successfully participated in the survey during the period from March 21 to June 5 in 2011 was selected. Because self-reports of respondents younger than 13 were provided by their parents, panel members aged 13 and older were included. In this way, a total of 1,735 respondents from 922 households were selected. During the 3 months of the sample period, levels of television exposure were relatively normal, in contrast to low levels during the summer and peaks during the winter holidays. In addition, no exceptional events, such as international soccer championships, took place. A comparison of sociodemographics and TV- and media-related variables between the total sample and the subsample did not reveal substantial deviations (see the appendix).

Measures

The two exposure measures used for the analyses were the number of viewing days per week and the average viewing duration per day. The original measures from the meter system were transformed to allow a direct comparison to equivalent self-reports based on the same metric. In doing so, differences between both types of measures were unrelated to the fact that meter measures are based on more differentiated scales compared with self-reports.

Self-Reported Viewing Behavior

Two survey questions gauged self-reported viewing behavior. First, respondents were asked how many days per week on average they watched TV. Response options for the *viewing days per week* ranged from 0 to 7 days. Second, respondents were asked how much time they spent watching on average on the days they watched TV. Before distributing the data, the survey company transformed the reported viewing duration per day to the average number of hours spent watching TV per week by multiplying the viewing duration per day by the number of days watched per week. This recoded measure ranged from 0 to 96 hr coded in 1-hr steps. To prevent confounding the self-reported viewing duration and viewing days, we deconstructed the delivered measure. Dividing by the number of viewing days per week yielded the self-reported measure of the average *viewing duration per viewing day.*

People-Meter Measures

For every day of our sample period, we retrieved the exact duration of viewing in minutes. We calculated the average number of *days per week* a person had watched TV during the 11 weeks of the sample period. This average was rounded so that values were equivalent to the response options of the self-reports ranging from 0 to 7 days per week. We calculated the average duration of TV watching per week during the entire research period. To derive consistent measures, the same categorization of hours watched per week used for the self-reported measures was applied. Based on both categorized measures of viewing days and duration per week, the average *viewing duration per viewing day* was calculated. In addition to the overall measures, the number of days per week and the hours spent watching per viewing day were computed for the week during which a participant was surveyed.

Response Errors

The differences between the equivalent self-reports and the people-meter measures indicated the magnitude of response errors for individual viewers. The *response error of viewing days* was calculated by subtracting the recorded viewing days per week from the self-reported days per week. Likewise, the recorded viewing duration per day in hours was subtracted from the self-reported duration to obtain the *response error of viewing duration*. Negative response errors indicated underreporting whereas positive values indicated overreporting of viewing behavior. Response errors were calculated for the entire sample period as well as for the individual week of survey participation.

Individual and Contextual Characteristics

Education comprised six categories that complied with the Dutch educational system. *Income* was gauged on a 10-point scale consisting of 10 equally distributed income groups. The self-reported use of *newspaper, radio*, and *Internet*—each measured on a scale from 1 to 3—comprised other forms of media use. Furthermore, respondents were asked whether they were *viewing TV online*.

The following measures reflected general viewing motivations and behavior. Panel members were asked to indicate their interest in nine different TV genres on a 3-point scale. A composite score was built from these items indicating the general *viewing interest*. A measure of *habit strength* was composed using the standard deviation of the number of days watched in each of the 11 weeks subtracted from seven—the maximum number of equal viewing days per week. More stable viewing behavior would thus result in stronger habits. Finally, the average time respondents spent watching TV per day during the entire sample period reflected their overall *amount of viewing*.

A first contextual factor on the household level was *household size*, defined by the number of persons living in the household. Further information from the household level provided by the survey was the number of *TV sets* per household, the availability of *TV recorders* and *digital TV*.

Results

Convergent Validity and Recency Effects

The first aim of this study was to assess the level of overlap between self-reported and observed measures. The average number of viewing days per week derived by

Table 1. Bivariate Correlations Between Self-Reported and People-Meter Measures (N = 1,735).

	Self-reports		People-meter measures			
			Overall		Survey week	
	Viewing days	Viewing duration	Viewing days	Viewing duration	Viewing days	Viewing duration
Self-reports						
Viewing days	1	.253	.465	.277	.417	.255
Viewing duration		1	.357	.582	.297	.551
People-meter–Overall						
Viewing days			1	.483	.780	.503
Viewing duration				1	.395	.875
People-meter–Survey week						
Viewing days					1	.494
Viewing duration						1

Note. All correlations are significant on the level of $p < .001$.

the people-meter was smaller for the entire sample period (M = 5.28; SD = 1.73) as well as for the survey week (M = 5.55; SD = 1.99) compared with the self-reports (M = 6.48; SD = 1.29). In contrast, a greater average viewing duration per day was observed for the overall period (M = 3.44; SD = 2.03) and the survey week (M = 3.34; SD = 2.26) than was reported by respondents (M = 2.92; SD = 1.81). These comparisons thus indicate tendencies to overreport viewing days but underreport viewing duration. Repeated measures ANOVA revealed that the differences between self-reported and observed measures were significant on the individual level for both viewing days, overall: $F(1, 1734) = 964.34, p < .001, \eta_p^2 = .357$; survey week: $F(1, 1734) = 434.20, p < .001, \eta_p^2 = .200$, and viewing duration, overall: $F(1, 1734) = 150.28, p < .001, \eta_p^2 = .080$; survey week: $F(1, 1734) = 82.09, p < .001, \eta_p^2 = .045$. High correlations between the different types of measures would express convergent validity; however, correlations were found to be on moderate levels of approximately .4 to .5 for viewing days and approximately .6 for viewing duration (Table 1).

The average response error of the number of viewing days per week was significantly smaller for the survey week (M = 0.93; SD = 1.87) than for the longer period of 11 weeks (M = 1.20; SD = 1.61), $t(1,734) = -8.69$; $p < .001$; $d_z = 0.209$. In addition, the absolute value of the average response error of the viewing duration per day was significantly smaller for the survey week (M = −0.43; SD = 1.97) than for the overall period (M = −0.51; SD = 1.77), $t(1,734) = -3.49$; $p < .001$; $d_z = 0.084$. Figure 1 provides a more detailed picture of how viewing days per week were overreported and viewing hours per day were underreported relative to the overall period as well as the survey week. For the longer time frame, approximately 31%

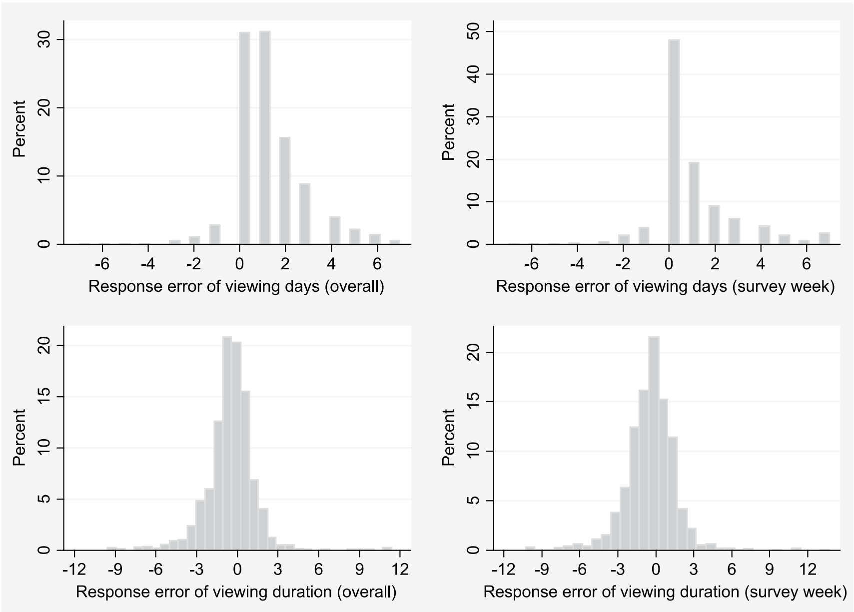

Figure 1. Distributions of response errors of viewing days per week and viewing duration in hours per day for overall sample period and survey week (*N* = 1,735).

of the respondents gave the correct account of their average viewing days; that is, the response error was zero because self-reports and people-meter scores were equal. Another 31% reported watching 1 day more than was observed, followed by 16% overreporting 2 days. For the survey week as the reference period, in contrast, 48% correctly reported the viewing days, followed by 19% overreporting 1 day and 9% overreporting 2 days. Regarding viewing duration, approximately 6% gave the correct account of the time spent watching relative to the overall period, while 36% underreported the viewing duration with up to 1 hr per day. Another 15% underreported the viewing time between 1 to 2 hr. For the survey week, only 4% correctly reported the viewing duration, followed by 30% underreporting up to 1 hr and 16% underreporting between 1 and 2 hr.

In sum, regarding RQ1, mean differences and moderate correlations indicated a low convergent validity between self-reported and observed measures of TV exposure. Tendencies to overreport viewing days and underreport viewing duration were found. **H1a** and **H1b** concerning recency effects could be confirmed. The magnitude of the response errors of the self-reported frequency and duration of TV exposure relative to the observed measures was smaller for the more recent time period compared with a longer time frame; however, the recency effect was more pronounced for the viewing frequency than for the viewing duration.

Table 2. Multilevel Models of Response Errors.

	Response error of viewing days		Response error of viewing duration	
	β	*SE*	β	*SE*
Intercept	1.13***	0.08	−0.61***	0.09
Level 1 fixed effects (viewer)				
Sociodemographics and media use				
Age	−0.01***	0.00	0.01***	0.00
Gender (male)	0.08	0.07	0.07	0.07
Education	−0.08***	0.02	−0.08***	0.02
Income respondent	−0.04	0.02	−0.07**	0.03
Newspaper	−0.01	0.04	−0.06	0.05
Radio	−0.01	0.04	0.06	0.04
Internet	0.00	0.05	0.05	0.05
TV viewing online	−0.01	0.07	−0.01	0.08
Viewing motivation and behavior				
Viewing interest	0.01	0.01	0.07***	0.01
Habit strength	−0.55***	0.05	0.38***	0.05
Viewing amount	−0.27***	0.02	−0.56***	0.02
Level 2 fixed effects (household)				
Household size	−0.06	0.03	−0.12**	0.04
TV sets	0.06	0.04	0.11*	0.05
TV recorder	−0.15	0.08	−0.05	0.09
Digital TV	0.11	0.08	0.11	0.09
Random parameters				
Variance at household level	0.30***	0.06	0.53***	0.09
Variance at viewer level	1.51***	0.07	1.59***	0.08
Compared with model without predictors				
Variance explained at household level		0.549		0.493
Variance explained at viewer level		0.209		0.243
Likelihood ratio test (*df* = 15)		568.22***		634.81***

Note. n_{viewer} = 1,735; $n_{\text{household}}$ = 922. Predictors are grand mean centered except for the dummy variables gender, TV viewing online, TV recorder, and digital TV.
*p < .05. **p < .01. ***p < .001.

Explaining Response Errors

The next aim of this study was to assess differences in the accuracy of self-reports. Because of the hierarchical structure of the data with respondents nested in households, multilevel models on the two measures of response errors were estimated to determine structural differences in response accuracy (Table 2). All predictors except for the dummy variables gender, viewing TV online, TV recorder, and digital TV were grand mean centered to obtain more meaningful coefficients and intercepts. To further enhance interpretation,

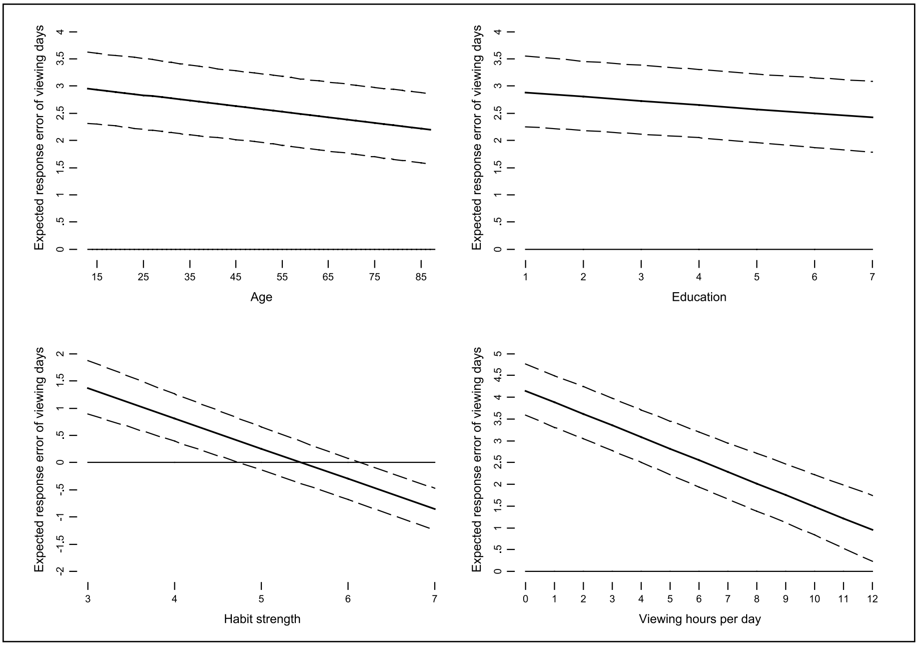

Figure 2. Expected values of response errors of viewing days per week (and 95% CI).
Note. Expected values of significant fixed effects and 95% CIs based on the multilevel model on response error of viewing days. The expected values were calculated based on a simulated sample (n = 1,000) of the coefficients with all other predictor variables set to their mean. CI = confidence interval.

statistical simulation was used to calculate the expected values and the 95% confidence intervals of the response errors for the entire range of scores of each significant predictor variable (King, Tomz, & Wittenberg, 2000). For this step, the models were estimated using the original scales of the predictor variables. To calculate expected values for specific scores of one predictor, all other predictors were set to their mean. Figures 2 and 3 depict the expected values and confidence intervals derived by the simulation. The figures enhance the interpretation of the regression coefficients by displaying for which values of a predictor the overreporting or underreporting of TV exposure can be expected.

Relative to the empty model with a random intercept and no predictors, the model of the response error of viewing days could explain 55% of the variance at the household level and 21% of the variance at the viewer level. Similarly, the model of the response error of viewing duration could explain 49% of the variance at the household level and 24% of the variance at the viewer level.

Individual Characteristics

The models revealed a number of differences in response accuracy due to sociodemographic characteristics. Education was found to be negatively related to response errors of

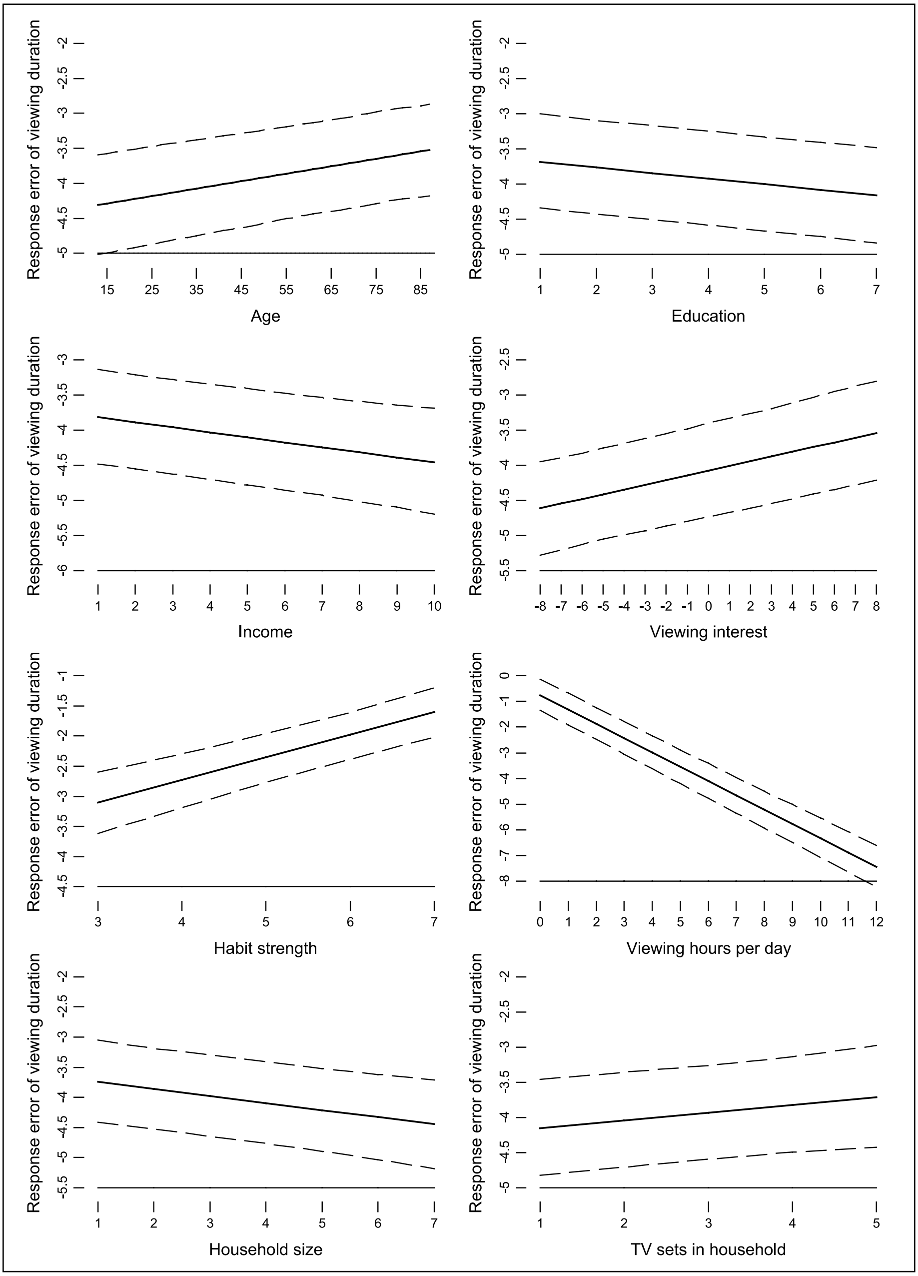

Figure 3. Expected response errors of viewing duration in hours per day (and 95% CI).
Note. Expected values of significant fixed effects and 95% CIs based on the multilevel model on response error of viewing duration. The expected values were calculated based on a simulated sample (n = 1,000) of the coefficients with all other predictor variables set to their mean. CI = confidence interval.

viewing days ($\beta = -.08$, $p < .001$) and duration ($\beta = -.08$, $p < .01$). Figure 2 reveals that this negative relationship is not associated with underreporting viewing days. Less educated viewers overreported more strongly compared with more highly educated viewers. **H2a** was therefore not confirmed. Figure 3 shows that levels of underreporting viewing duration gradually increased with higher education levels, confirming **H2b**. Income did not relate significantly to response errors of viewing days ($\beta = -.04$, *ns*). **H3a** was therefore rejected. Response errors of viewing duration were negatively related to income ($\beta = -.07$, $p < .01$). According to Figure 3, underreporting of viewing duration increased with income, confirming **H3b**. Age was negatively related to response errors of viewing days ($\beta = -.01$, $p < .001$) and positively related to response errors of viewing duration ($\beta = .01$, $p < .001$), confirming both **H4a** and **H4b**. More specifically, younger viewers overreported their viewing frequency simultaneously underreporting their viewing duration more strongly than older ones (Figure 2 and 3). Gender and other forms of media use were not related to both types of response errors. Thus, **H5a** and **H5b** and **H6a** and **H6b** were not confirmed. In addition, self-reported online viewing, which was included to control for other viewing modes not captured by the meter system, was not significantly related to errors of reporting viewing days or duration.

Viewing Motivations and Behavior

The impact of motivational and behavioral aspects of TV viewing was examined. Viewing interest showed no significant relationship with response errors of viewing days ($\beta = .01$, *ns*); however, interest was positively related to response errors of viewing duration ($\beta = .07$, $p < .001$). Consequently, H7a was not confirmed while H7b could be confirmed. Habit strength related negatively to response errors of viewing days ($\beta = -.55$, $p < .001$)—confirming H8a—but positively to response errors of viewing duration ($\beta = .38$, $p < .001$)—not confirming H8b. Both types of response errors showed negative relationships with the amount of viewing with $\beta = -.27$, $p < .001$ for viewing days and $\beta = -.56$, $p < .001$ for viewing duration. Thus, H9a and H9b were also confirmed. Again, Figures 2 and 3 offer further insight into the nature of these relationships. The more interested viewers were in different program genres, the more accurately they reported the time they spent watching TV, while less interested viewers were prone to underreporting their viewing duration. The more stable viewers were in their viewing habits according to the meter, the more accurately they reported viewing days as well as viewing duration. Less habitual viewers overreported their viewing days more often but also showed a stronger tendency to underreport the time spent watching. Viewers who were observed to spend less time in front of the screen overreported both their viewing days and duration. Those who spent more time watching TV, in contrast, were more prone to underreport the frequency and the amount of TV exposure.

Viewing Context

Overall, factors shaping the context of watching TV at the household level appeared to be less influential than was expected. No effects of household-level variables on the accuracy of reporting viewing days were found. Therewith, **H10a, H11a, H12a**, and **H13a** were not confirmed. Household size was negatively related to response errors of viewing duration ($\beta = -.12$, $p < .01$). According to Figure 3, people in larger households underreported their viewing duration more strongly than viewers in smaller households, confirming **H10b**. The number of TV sets in a household, in contrast, related positively to response errors of viewing duration ($\beta = .11$, $p < .05$). With just a few TV sets available, viewers overreported their viewing duration, while an increasing number of TV sets was related to a more accurate account of the time spent watching (Figure 3). **H11b** was not confirmed as more TV sets were not associated with overreporting viewing duration. The presence of digital TV or TV recording devices did not significantly relate to response errors of the viewing duration. Thus, **H12b** and **H13b** were also not confirmed.

Conclusion

By comparing self-reports and people-meter measures of TV exposure, this study revealed detailed characteristics of response errors to survey questions on TV viewing behavior. There was a clear tendency to overreport the days of watching TV in 1 week while viewing duration was more frequently underreported. More strongly flawed answers might be explained by the higher cognitive demand of duration as opposed to frequency questions. To some extent, response errors can be explained by recency effects. Self-reports matched viewing behavior during the week of survey participation more closely than the average viewing behavior during the 11 weeks of the study. We found that response errors systematically related to age, education, and income. On a contextual level, household size and the number of TV sets available were generally found to influence the accuracy self-reported viewing duration.

Generally, the different directions of response errors for viewing days and duration may point to different manners of approaching the related survey questions. The tendency to overreport viewing days seems to confirm previous findings on news exposure showing that frequency measures were not affected by social desirability (Prior, 2009b). The underreporting of viewing duration by those with higher education and income, however, may be indicative of the socially desirable response behavior that has been found by earlier studies on TV exposure (Bower, 1973; Steiner, 1963). Thus, duration measures might be more prone to social desirability than frequency measures.

Our findings show that the same variables, specifically age and habit strength, predicted underreporting of viewing days and overreporting of viewing duration for the same groups of respondents. In addition, less educated individuals overreported viewing days but were more correct in reporting viewing duration. In contrast, more highly educated individuals responded more correctly regarding their viewing frequency but underreported their viewing duration. Thus, a composite score of viewing frequency and duration may countervail positive and negative response errors to some extent.

Most troubling, however, may be the strong negative relationship between the overall amount of TV exposure with both types of response errors. The more time viewers actually spent watching, the more they underreported their exposure. Light viewers, in contrast, were found to overreport their viewing behavior—especially in terms of days watched per week—more often. Such response inaccuracies that are related to the behavior itself can be considered as a particular challenge for the validity of exposure measures. This type of response bias is responsible for a reduced variation of self-reports that may effectively diminish any empirical findings regarding media use and effects. The tendency, especially of heavy viewers, to underreport the time spent watching reflects the difficulty of recalling highly frequent behavior (Schwarz & Oyserman, 2001). This does not apply, however, to the relationships found for habit strength. Those with the most stable viewing patterns were in fact the most accurate in reporting viewing days and duration. These findings confirm that habit and frequency are distinct behavioral aspects (Verplanken, 2006). Plausibly, viewers with fixed viewing routines may be highly aware of their viewing schedules, whereas those who simply spend a great deal of time watching without sticking to stable routines may have greater difficulties correctly recalling and estimating the exact amount of exposure.

In addition to viewing behavior, viewing motivations also present an important source of response errors. Viewers with a strong interest in watching TV were less biased in reporting viewing duration, whereas the less interested viewers showed a tendency to underreport their time spent watching, thus balancing between their behavioral perceptions and attitudes (Kahn et al., 2014). While true viewing behavior can hardly be controlled for in survey research, the possibly confounding attitude toward watching TV can be taken into account to correct for corresponding biases. It should be noted, however, that the measures of genre interests available for this study could hardly serve as proxy for viewing motivations.

Discussion

An important assumption of this study was that people-meter measures accurately represent the number of days viewers watched TV per week and the time they spent watching per week because they are not prone to cognitive problems associated with self-reported measures. Arguably, meter data are not free from criticism as no measurement is a perfect representation of its empirical phenomenon. The measures strongly depend on panel members' willingness to participate and correctly log on and off each time they watch TV. In the Netherlands, only viewing situations in which viewers are aware of watching and actively attend to the screen are gauged by the system. This excludes unintended watching or only listening to the TV while being in the same room, which would be included, for instance, by passive meter systems. By relying on recall of exposure situations, however, self-reports also mainly address conscious viewing situations and thus implicitly build on the same conceptualization of TV exposure as the Dutch people-meter measures, which enhances the comparability of both types of measures. Because panel members were expected to log on and log off each time they start and stop watching TV, however, their active engagement with the people-meter system may increase awareness of their viewing behavior and thus lead to even lower response errors.

A further potential drawback of people-meters is the exclusion of online viewing or watching with other devises such as mobile phones. Self-reports of online viewing were included in our analysis, although they revealed no influences on response errors. For the Netherlands, offline reception remains by far the most relevant mode of watching TV (SKO, 2012a). In viewing environments with higher shares of online viewing, a comparison between people-meter and self-reported measures of TV exposure could be less valid. In addition, other media use did not interfere with individuals' perceptions of TV exposure. However, these and the results for online viewing were based on self-reported behavior. More accurate media-use measures via diary methods or portable meters, for instance, could reveal that the time spent watching or listening to different sources and particularly forms of media multitasking might indeed influence accurate reporting of exposure to a single medium.

Because this study was a secondary analysis, further limitations apply, particularly to the survey measures of TV exposure. Although the frequency question closely matched often-used survey measures of media exposure by asking for the number of days in a typical week (Althaus & Tewksbury, 2007; Ridout, Shah, Goldstein, & Franz, 2004), no minimum time frame for a viewing day was specified, leaving ample room for interpretation by respondents (Gunter, 2000). The people-meter system, in contrast, applies a clear threshold of 15 s. In addition, the minimal level of attentiveness that respondents consider as necessary to watch TV may vary from the instruction of when to log on to the meter system. Such issues present important limitations to the validity of comparing registered and self-reported measures. In addition, instead of the average viewing duration per viewing day reported by the respondents, the survey company provided the average number of hours spent watching TV per week. In order not to confound our frequency and duration measures, we reconstructed the viewing duration per day. Although it was not measured directly, the constructed duration measure thus closely matched frequently used survey measures (e.g., Bryant et al., 2007; Greenberg et al., 2005).

Overall, our findings indicate that systematic variations in response errors constitute a threat to the validity of exposure measures and conclusions drawn on the basis of these measures. Therefore, it is important to know which factors are particularly influential and to at least consider controlling for these. While some factors found in this study, such as viewing interests and habits, are specific to television exposure, it can be argued that self-reports of other forms of media use may also be affected by individual, contextual, and media-use factors, making the framework of this study more widely applicable. Because age, education, and income have also been found to be related to response accuracy in news exposure and video gaming (Kahn et al., 2014; Prior, 2009a), the effects of sociodemographic factors may be generalizable to other forms of media use as well. In particular, effects of media use and motivations should be considered as influencing the validity of self-reports of media exposure. Such behavior-inherent response errors may cause lower levels of variance in self-reported exposure, which may, for instance, considerably reduce the statistical power of self-reported measures to explain media use or effects of media consumption. More research is necessary to identify the processes responsible for the tendency of respondents to converge to average viewing behavior instead of reporting actual, more extreme behavior. While this study focused on problems and possible origins of inaccurate survey measures, further developing and testing survey measures by introducing contextual or population cues (Potts & Seger, 2013; Prior, 2009b), for instance, would be the next logical step toward improving self-reports of media use.

Appendix

Table A1. Distribution of Individual Characteristics in the Total Sample and the Subsample of the Dutch Audience Research Panel.

	Total sample 13+		Subsample 13+	
Individual characteristics	*M*	*SD*	*M*	*SD*
Gender (male)	1.52	0.50	1.52	0.50
Age	45.67	17.86	46.01	17.94
Household size	2.74	1.37	2.76	1.40
Education	5.43	1.61	5.43	1.61
Income	24.33	39.85	22.97	38.90
TV sets in household	1.83	1.00	1.86	1.00
TV recorder in household	0.62	0.49	0.62	0.49
Digital TV in household	0.71	0.45	0.70	0.46
TV viewing, days per week	6.52	1.24	6.48	1.29
TV viewing, hours per week	20.81	15.29	19.49	13.06
TV viewing online	0.46	0.85	0.45	0.83
Internet use	1.83	0.75	1.81	0.74
Radio use	2.00	0.82	2.01	0.82
Newspaper reading	1.97	0.80	1.99	0.80

Note. The total sample includes 2,368 panel members of 13 years and older who comprised the Dutch audience panel in Week 27, 2011. The subsample includes all 1,735 respondents of 13 years and older who were surveyed between Week 12 and Week 22, 2011.

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