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ORIGINAL ARTICLE

Using a two-part mixed-effects model for understanding daily, individual-level media behavior

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Abstract
This study supports a strategic analytics proposal, namely that there is conceptual and practical utility in applying a two-part mixed-effects model for understanding individual differences in daily media use. Individual-level daily diary measures of media use typically contain information about a person's likeliness to use media, extent of usage, and variation in use across days that, taken together, can provide data for evaluating media behavior that is otherwise masked by using aggregate measures. The statistical framework developed and demonstrated here focuses on these three metrics. The approach, applied to daily diary measures of television use in a large, representative U.S. sample, yields results that add value when weighing media strategies centered on the twin tactics of reach and frequency. The implications for the proposed analytic strategy are discussed.

Keywords Media · TV · Mixed-effects models · Diary data · Repeated measures · Frequency versus reach

Introduction

Media use is inherently continuous and varies both within and between individuals. How media use is measured and the data analyzed are therefore critical to fully understanding media behaviors. Commonly, media behavior studies fail to mention or discuss the zeros that result for respondents who report no media use. Thus, for a given study, it may not be clear if the sample is comprised of only those who engaged in the media behavior, if the data for subjects who did not engage in the behavior were excluded from the analysis, or if zeros were included in the analysis without being attended to. In any case, zeros are a natural result and can provide important information about media behavior. Along with the occurrence of zeros, media use can be highly variable within individuals, such as individuals varying in their own use from day to day, as well as between individuals, such as individuals varying in their average use across a week. Taken together, it is clear that media use data need to be collected in an effective manner to capture its many facets.

Media use data share features with time use measures reported in other domains of research. That is, time use measures often include a spike of zeros that represents the subset of respondents who did not engage in the target behavior or were not engaged in the behavior at the time of measurement. For those who used, the amount of time spent naturally varies between individuals. As a result, a visual display of time spent can spike at zero and include a tail extending to the right representing users of increasing time spent. Data with this pattern of zeros combined with positive and continuous values are called semi-continuous data. Statistical models—specifically, two-part models—have been developed to address these particular features of semi-continuous data (Duan et al. 1983; Olsen and Schafer 2001). Although these models are gaining popularity in many fields of research, including the social and biological sciences, as a means for understanding semi-continuous data, there is scant evidence of their use in media research. For repeated-measures data in particular in which the same subjects are measured repeatedly over multiple occasions, a two-part model can be effective in addressing semi-continuous data, capturing the within- and between-individual variation typical of media behavior data.

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The purpose of this study is to develop and demonstrate the application of a two-part mixed-effects model for semi-continuous daily diary data for testing within-person predictors (time-varying variables, such as daily media interest and access) and between-person predictors (time-invariant variables, such as gender and age) of media use. Here, the media use behaviors of interest are (1) the average daily likelihood that an individual engages with a specific medium, (2) an individual's daily average time spent with the medium conditional on any positive amount of time spent, and (3) an individual's variation from day to day in time spent engaged with the medium. In demonstrating how a two-part mixed-effects model can be applied to daily media use data, this study facilitates the exploration and consideration of the individual-level behaviors often overlooked or concealed when summary measures are instead collected. Indeed, summary data, such as individual reports of typical or average use, can give rise to counter-intuitive implications in media planning for frequency and reach.

Methodological considerations

Three methodological considerations underlie the choices made here in applying the model to relevant data: use of diary data, use of a single medium, and choice in metrics to be predicted.

Diary data

A data collection method suited to this context is diary data. Diary studies, based on a type of data collection that targets individual-level behaviors, not only provide population-level information that can be used to describe different segments of the population, but, importantly, can also be used to reveal variation in media use within individuals, giving opportunities to understand why individuals differ in this variation.

Diary methods can be preferable to data collection using retrospective surveys, in part by reducing recall errors occasioned, for example, by lapse in memory or recency bias. Diary methods more frequently capture measures of interest, such as by asking respondents to provide summaries of their behaviors at the end of each day with the process repeated across a series of days. Conversely, retrospective reports rely on a recall of past events over a relatively long period of time, such as asking individuals to report on their behavior for the past week, and thus are more susceptible to self-edits and efforts to generate coherence or an overriding rationalization. Although both methods yield self-report measures, diary recordings yield reports that typically cover shorter periods of time (for example, repeated behavioral summaries for each 24-h period across a week) and are measured closer to the event of interest. When capturing real-time measures of behaviors (for example, ecological momentary assessments) are not possible, daily diary methods are arguably the next best option, as they offer a relatively convenient and reliable method of data collection.

Single medium

Focusing an analysis on a single medium provides a simple context to understand the framework used and its ability to provide insight. In line with Beal et al. (2018), the present study focuses on TV and analyzes individual-level, rather than group-level, behaviors.

Notably, the relationship between media choice and consumer behavior continues as an important topic of academic and practitioner interest. Some research focuses on choice behavior for a single medium (for example, Beal et al. 2018), whereas other studies consider choice from a multiplexing perspective (for example, Kazakova et al. 2016; Lin et al. 2013) that refers to the increasing tendency of consumers to engage with different media in a series of "small, incomplete chunks" across the whole media spectrum—from print to the Internet within relatively short periods of time. Although the idea of multiplexing is relevant, consumers cannot engage in all possible media options simultaneously, and not all consumers engage in multiplexing behavior. In fact, Lin et al. (2013) note that in their sample of over 1700 consumers '…nearly one out of five consumers in the sample are multiplexors.' (p. 315); in other words, a little more than 80% of individuals in their sample were not multiplexors. Findings from Lin et al. (2013) suggest that understanding individual media choice behavior is important given the media options consumers have at hand. Although there are many media options for consumers, work by Beal et al. (2018) suggests that TV is still an important single medium to study, stating '…television has proved itself a consummate entertainer that has almost universal access and robust view levels' (p. 463). In fact, AdAge's (2017) Marketing Fact Pack (AdAge 2017) reports that 2016 U.S. measured-media spending for TV reached $78.9 billion.

Choice of metrics

The framework developed to characterize daily media use at the individual level employs three key metrics. The first relates to an individual's daily likelihood to use a given medium. Understanding the likeliness of using a given medium is important in today's highly fragmented media environment. If an individual's daily probability of use can be predicted, then one might be able to predict the best time and vehicle for an advertising placement. The second metric relates to the amount of daily time consumers spend with a medium and its importance lies in its implications for reach and frequency. That is, if time spent with a medium increases, then a viewer's opportunities to be exposed to a given message (frequency) increases as well. For consumers who spend less time with media, the media planning might focus on reach, as these individuals are not as likely to spend enough time with media to be exposed to the same message multiple times. The third metric concerns the stability of a consumer's daily time spent using a given medium across multiple days. Stability informs the evaluation of the comparative potential for frequency and reach tactics. Greater stability may arguably set the stage for frequency strategies, as it translates to a greater likeliness of the opportunity to be exposed to a given message more often. Conversely, lower stability may make reach goals more attractive, as their less-predictable behavior suggests they are less likely to see a given ad multiple times within a specified period (Fig. 1).

It is important to note that the relationship among the key metrics depends on factors that influence an individual's engagement with media. These factors and their impact on daily media use can have within-person or between-person effects. Within-person effects relate to aspects of an individual that can change from one day to the next. For TV use, factors might include programming interests or ease of access that may vary daily for the individual. Between-person effects involve aspects of the person that do not vary across days, such as gender.

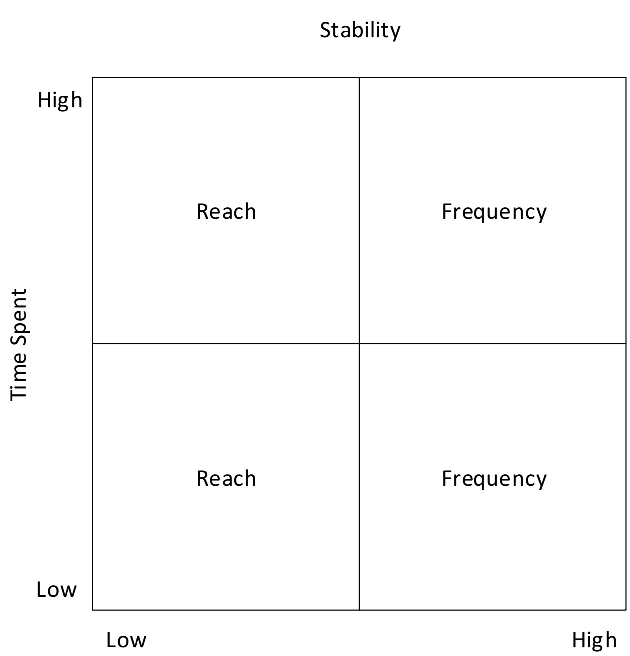


Fig. 1 Conceptual reach/frequency decision matrix

Two-part and two-part mixed-effects models

The use of two-part and two-part mixed-effects models have seemingly not been employed in media research. Two particular issues need attention to provide an understanding of the approach reported here: a general explanation of the rationale underlying use of these models and an outline of specific methodological challenges presented by the data, namely missing data and the occurrence of zeros.

Rationale

Two-part models were developed for semi-continuous data from non-complex samples (for example, simple random samples) (Duan et al. 1983). The models allow for distinct predictors of whether or not an individual engaged in a behavior, and in cases where engagement existed, the level of engagement conditional on any positive level. As noted, these models have been successfully applied in various fields of study, such as studies of medical expenditures. Fitting a two-part model requires the creation of two new variables from the original semi-continuous response. Typically, researchers create a binary variable to denote whether or not an individual engaged in the behavior. A continuous variable is then created to represent the extent of engagement conditional on any positive level of engagement; a score is omitted if no engagement occurred. The analysis of the two variables is conducted independently. For instance, the binary response can be analyzed using logistic regression to study predictors of the likeliness of engagement. A linear regression model, such as one that assumes a lognormal distribution for a positively skewed response, can be applied to the conditional continuous response to study predictors of the level of engagement.

Other statistical methods have been applied to semi-continuous data (see Gottard et al. 2013, for a review), including linear regression. However, unlike a two-part model, linear regression does not allow for unique or separate predictions of engagement (or not) in a behavior and the level of engagement when it does occur. The distinction could be important in cases wherein one set of predictors is needed to address whether an individual engages in a behavior and another set is needed to predict an individual's degree of engagement.

Additionally, linear regression can be influenced by the presence of zeros, a circumstance that can cloud interpretation of empirical results. Thus, methods that assume censoring or truncation have been applied to semi-continuous data. Danaher and Dagger (2013) apply a Tobit model to study measures of purchase outcome. Tobit regression assumes an underlying normally distributed response that allows left- or right-censoring of the response (Tobin 1958). The assumption of left-censoring is used in the Danaher and

Dagger study to account for zeros for those individuals who made no purchase. This assumption, however, is not well suited for the current study: specifically, zero denotes that an individual did not engage in the target behavior and values below zero are not possible. In such cases, the assumption of left-censoring is judged problematic for semi-continuous measures (Min and Agresti 2002).

Two-part mixed-effects models extend two-part models for the analysis of repeated measures of semi-continuous data. Similar to a two-part model, a two-part mixed-effects model requires the creation of two new variables, one binary and one continuous, with each having repeated measures. Distinct mixed-effects models are specified for each variable, and the two models are joined by allowing the random effects of each model to covary. For instance, Olsen and Schafer (2001) specify a model based on a joint distribution that links a mixed-effects logistic regression model for a binary repeated-measures response and a mixed-effects linear regression model for a continuous repeated-measures response. Estimation of the two model parts is simultaneous using maximum likelihood (ML) (Olsen and Schafer 2001) or Bayesian estimation (Xing et al. 2015).

A two-part mixed-effects model is a subject-specific model that includes one or more random subject effects. A general form of the model is assumed to apply to all members of a population, such as assuming that the same covariates relate to the outcome variable, but one or more of the model coefficients of each model part are unique to the individual. The covariance structure is partitioned into a within- and a between-person component. The within-person component characterizes variation and covariation of responses within persons and across occasions. The between-person component characterizes individual differences in the random effects and their covariation across the population. These considerations are relevant to the current study of media use because they allow for the study of variation in the likeliness of use and level of use within and between individuals and present opportunities to study predictors of these different aspects of media use behaviors.

Missing data and zeroes

In a mixed-effects model, individuals need not have complete data for all planned assessments to be included in the analysis. Missing data are assumed to be missing at random such that whether or not an individual has missing data, referred to as *missingness*, is independent of the missing data (see Olsen and Schafer 2001). If this assumption holds, then the missingness is ignorable and there is no need to account for it in the analysis. If the missingness is not ignorable, then methods detailed in Molenberghs and Kenward (2007) may be adapted to a two-part mixed-effects model to study potential sources of missingness (Xu and Blozis 2011). Similar to Olsen and Schafer, we assume data are missing at random.

Because two-part models include a submodel that specifically relates to the zeros of a semi-continuous response, it is important to distinguish among the types of zeros described in the statistical literature and to clarify the assumptions made about the zeros in the model developed in this paper. Three types of zeros are often described: true zeros, certain zeros, and zeros that represent censored data. True zeros represent an absence of a behavior for individuals who have a history of engaging in the behavior but the behavior is not observed for a particular assessment. Certain zeros (also called excess zeros) represent an absence of the behavior for an individual who has no history of the behavior, and so the behavior is not expected to be observed. Finally, zeros that represent censored data result from studies in which values close to zero are not reliably measured and zero is used to represent censored values that may or may not include zero. The two-part mixed-effects models developed in Olsen and Schafer (2001) assume that zeros are true zeros. The current authors also make this assumption about the two-part mixed-effects models applied to the diary measures of TV use, as we assume that all individuals have a history of TV use.

Research application, model formulation, and data analysis

Sample

To illustrate the modeling framework, we report on responses to a daily question of how much time was spent watching TV for 782 adults. Participants were interviewed by telephone to obtain daily self-reports of time spent watching TV for up to 8 consecutive days. The data were part of the longitudinal Midlife in the United States (MIDUS Refresher): Daily Diary Project (Ryff and Almeida 2012–2014). Participants were selected from a nationally representative, random-digit-dial sample of non-institutionalized, English-speaking adults residing in the contiguous United States.

The sample included 56% women. The mean age was 58 years (SD = 12.5 years). For those reporting marital status (all but two of the respondents), 70.8% were married, 12.6% divorced, 8.8% widowed, 6.5% had never married, and 1.3% were separated. About 69% reported having a college degree or higher, 26% finished high school or earned a GED, and 6% did not complete high school. The number of survey days completed ranged from 1 to 8 days with a sample average of 7.5 days (SD = 1.4). Table 1 summarizes, by day of the week, the proportion of responses for which no TV use was reported, as well as descriptive statistics on time spent in hours conditional that some time was spent. Given plans to survey participants for 8 consecutive days, respondents could contribute more than once to a daily summary (e.g., surveyed on two different Mondays). For each day, a high

Table 1 Descriptive statistics for reported time spent watching TV (n = 782)

Day	% Reports of no use	Time spent			
		Mean	SD	Minimum	Maximum
Monday	17.3	2.4	2.1	.08	20
Tuesday	17.1	2.2	2.0	.08	18
Wednesday	18.0	2.0	1.9	.08	16
Thursday	16.5	2.0	1.9	.08	16
Friday	16.6	2.1	2.1	.03	22
Saturday	19.6	2.3	2.0	.17	20
Sunday	15.7	2.7	2.2	.08	23

Individuals contribute up to 8 daily reports of TV use, so some individuals contribute more than one value to reports as given here for each day of the week. Values of time spent are conditional on any positive report of time spent. Data source: Midlife in the United States (MIDUS Refresher): Daily Diary Project, 2012–2014. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2018 06–06

proportion of respondents reported to have watched TV. Not apparent from this summary, however, is how individuals differed in their TV use across days. About 57% of the sample reported to have watched TV on all 8 survey days, with the remainder reporting a range from none to 7 days. Although a majority reported to have watched TV every day, a substantial segment did not.

Analytic strategy

In the analyses presented, it was assumed that the time frame during which a person reported TV use (i.e., a 24-h period) directly corresponded to the time during which the individual made a decision to watch TV (i.e., the same 24-h period). To begin, a set of unconditional models (no covariates are included) were fit that differed with regard to the distribution assumed for the continuous model part relating to time spent watching TV to address the positive skew in responses. In all models a logistic model was used for the binary response relating to whether or not an individual watched TV. For the continuous model part, the three distributions considered were normal, lognormal, and gamma. These three models are not nested and so were compared using the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). These models assumed homogeneity of variation for the within-person residual of the continuous model part. Based on the model with the lowest AIC and BIC values, the assumption of homogeneity was relaxed by adding a person-specific random effect to allow the day-to-day variation in time spent to differ between individuals; a likelihood ratio test was used to evaluate the need to relax this assumption of homogeneity of the within-person variation. Next, covariates were added to the model. Person-level covariates studied were age and sex, and an occasion-level indicator was used to contrast weekends from weekdays. In a final step in fitting the models, a reduced model was formed by excluding interaction effects whose estimated confidence intervals included 0 as an interior point. All first-order effects of the covariates were retained in the final model to allow for a description of TV use with regard to the covariates. Maximum likelihood estimation of the models was carried out using SAS version 9.4 with PROC NLMIXED for non-linear mixed-effects models (Wolfinger 1999).

Coding of covariates

Respondent's age was the difference in years between a respondent's birthday and the time of their interview. Age was centered about the sample mean age of 48 years. Sex was coded and labeled as Fem, with Fem = 1 if female and Fem = 0 if male. A variable labeled Wkend represented weekend days (Wkend= 1 if the interview took place on a Saturday or Sunday) versus weekdays (Wkend = 0). The proportion of weekend days to the total number of interview days ranged across participants from 0 to 1 with a mean proportion of .26 (SD = .09). To account for the effect of these differences, the proportion of weekend days when the interviews were conducted, labeled PropWkend, was included as a covariate and centered about the sample mean. Interactions among Fem, Age, and Wkend were tested. The interaction between Age and Fem was an individual-level effect. The interactions between Wkend with Age and Fem were cross-level interactions and tested the moderating effects of Age and Fem, respectively, on the effect of Wkend on TV use.

Unconditional models for TV use

For daily reports of time spent watching TV, let y_{ij} be time spent for individual i on day j, where $i = 1,\ldots, 782$ and $j = 1,\ldots, n_i$, with n_i denoting the number of daily measures for individual i. Let t_{ij} be the day that y_{ij} was observed. From y_{ij} two new variables were created: u_{ij} was equal to 1 if $y_{ij} > 0$ and otherwise was equal to 0 (if y_{ij} was missing, then u_{ij} was coded as missing); m_{ij} was equal to y_{ij} if $y_{ij} > 0$ and was missing otherwise. Using a mixed-effects logistic model for the binary response, the logit of the probability that individual i watched TV on day j, η_{ij}, is

$$\eta_{ij} = \log\left[P\left(u_{ij} = 1\right) / \left(1 - P\left(u_{ij} = 1\right)\right)\right]. \tag{1}$$

The logit in Eq. (1) was assumed to follow a two-level model:

$$\begin{aligned} &\text{Level 1}: \ \eta_{ij} = \alpha_{0i} \\ &\text{Level 2}: \ \alpha_{0i} = \alpha_0 + a_i, \end{aligned} \tag{2}$$

where α_0 is a fixed effect for the population and a_i is a random effect that varies by individual and assumed to be independently and identically distributed (i.i.d.) as normal with mean equal to 0 and variance φ_a. The variance φ_a represents between-person variability in the logits relating to whether or not a person reported watching TV.

The model for m_{ij} included a fixed effect γ_0 assumed to be constant across the population, a random effect s_i that varies by individual, and a day-specific residual e_{ij}:

$$\begin{aligned} \text{Level 1}: \ m_{ij} &= \gamma_{0i} + e_{ij} \\ \text{Level 2}: \ \gamma_{0i} &= \gamma_0 + s_i \end{aligned}. \tag{3}$$

The random effect s_i was assumed to be i.i.d. normal with mean equal to 0 and variance φ_{s}. The variance φ_{s} is the between-person variation in positive measures of time spent watching TV. The residual e_{ij} is the difference between an individual's daily report of time spent and the individual's estimated average time across all of the individual's days of observation. The distribution of the residuals depends on the assumptions made about m_{ij}, described later.

The models for the logit η_{ij} in Eq. (2) and the continuous measure m_{ij} in Eq. (3) were joined at the second level of the larger model by the covariance φ_{sa} between the random effects a_i and s_i of the respective models. A larger matrix containing the two variances and their covariance is represented by $\boldsymbol{\Phi}$ in the larger model:

$$\boldsymbol{\Phi} = \begin{bmatrix} \varphi_{\mathrm{a}} & \\ \varphi_{\mathrm{sa}} & \varphi_{\mathrm{s}} \end{bmatrix}.$$

Assessing the distribution of time spent, m_{ij}

Two-part mixed-effects models are flexible in that different distributions can be used to represent responses (e.g., Liu et al. 2010). We take advantage of this and apply different response distributions to the continuous model part to address the positive skew in the reported measures of time spent. The first model, Model A_1, assumed that m_{ij} was normally distributed. A lognormal and a gamma distribution, both of which are positive and continuous distributions, allow for skewed responses: Model A_2 assumed that m_{ij} was lognormally distributed, and Model A_3 assumed that m_{ij} followed a gamma distribution. The lognormal and gamma distributions are described in "Appendix 1" section.

Results for unconditional models

Indices of model fit for Models A_1, A_2, and A_3 are in the upper part of Table 2. Model A_2 that assumed a lognormal distribution for m_{ij} provided the best overall fit, as this model had the lowest AIC and BIC values. Model A_2 assumed homogeneity in the parameter characterizing daily variation in time spent. In Model A_4 the assumption of homogeneity was relaxed. To do this, a model of the within-person variation coefficient was specified, similar to that used in standard regression analysis for a normally distributed response (Aitkin 1987; Cook and Weisberg 1983; Harvey 1976; Carroll and Ruppert 1988). Specifically, a model for the within-person variance of the lognormal distribution included a random subject effect u_i to allow for heterogeneity between individuals with regard to the scale parameter:

$$\theta^2 = \exp\left(\tau_0 + u_i\right). \tag{4}$$

The coefficient τ_0, when exponentiated, is the common within-person variance and u_i is the unique subject effect that permits the coefficient to vary between individuals. As a subject-level effect, u_i can covary with the other subject-level random effects a_i and s_i of the logit and continuous sub-models, respectively:

$$\boldsymbol{\Phi} = \begin{bmatrix} \phi_a & & \\ \phi_{sa} & \phi_s & \\ \phi_{ua} & \phi_{us} & \phi_u \end{bmatrix},$$

where φ_{ua} and φ_{us} are the covariances between the random effect u_i of the model for θ^2 and the random effect a_i of the logistic model in Eq. (2) and s_i of the linear regression model in Eq. (3), respectively; φ_u is the variance of u_i.

A deviance test comparing the fit of Model A_2 versus A_4 indicated a marked improvement in fit to the data [$\chi^2(3) = 475$, $p < .001$), suggesting individual differences in the daily variation in time spent watching TV, and thus, a need to allow for heterogeneity in daily variation. Under Model A_4 the estimated logit was 2.6 (SE = .11), which equates to an estimated average probability of .92 of watching TV across respondents and days. The estimated mean log time spent watching TV when individuals were watching TV was .39 h (SE = .03) averaged across respondents and days, translating (after exponentiation of the estimate) to about 1.5 h.

Table 2 Indices of model fit for unconditional and conditional two-part mixed models (n = 782)

Model	Q	−2lnL	AIC	BIC
A_1	6	21,631	21,643	21,671
A_2	6	18,686	18,698	18,726
A_3	6	18,808	18,820	18,848
A_4	9	18,211	18,229	18,271
B_1	33	18,029	18,095	18,249
B_2	23	18,044	18,090	18,198

−2lnL is −2 times the loglikelihood. AIC is the Akaike information criterion. BIC is the Bayesian information criterion. Smaller values of the AIC and BIC indicate better fitting models

To emphasize the importance of relaxing the assumption of homogeneity of variation for the within-person residual of daily variation in time spent watching TV, scores for four individuals are compared. In a model that assumes homogeneity of the daily variation across individuals, a single value of the SD of the residuals would be assumed to capture the within-person variation for all individuals. For instance, shown in Fig. 2 are scores for two individuals who have a standard deviation in time spent equal to approximately 3 h. Note that their averages in time spent across days differ (Person 1 has a mean of 3.7 h and Person 2 has a mean of 5.1 h). In a typical application of a two-part mixed-effects model, the random effect s_i in the model for m_{ij} would account for individual differences in means, and assuming homogeneity of variation across individuals might be reasonable if all individuals had a similar degree of within-person variation. To contrast this, Fig. 3 displays scores for two individuals whose means and SDs both differ (Person 3 has a mean of 4.5 h and a SD of 5.6 h; Person 4 has a mean of .6 h and a SD of .3 h). Although the typical application of a two-part mixed-effects model could again address individual differences in the means by the random subject effect, the assumption of homogeneity of variation would not be appropriate given marked individual differences in variation.

For the current analysis, a two-part mixed-effects model was extended to allow for heterogeneity of variation in daily time spent watching TV. Specifically, Model A_4 included a random effect in the model of the residual variance. Regarding individual differences in the likeliness to watch TV, time spent watching TV, and daily variation, the estimated variances of the three random effects under Model A_4 were all large, suggesting individual differences in the likeliness to watch TV ($\hat{\varphi}_a = 4.8$, SE = .50), mean log time spent watching TV, ($\hat{\varphi}_s = .41$, SE = .01), and daily variation in time spent about an individual's mean log time spent ($\hat{\varphi}_u = .67$, SE = .07).. "Appendix 2" section displays the empirical Bayes (EB) estimates of the three random effects.

To better understand the extent of individual differences in the three aspects of watching TV and their patterns of association, the EB estimates of the random effects (Davidian and Gallant 1993) were calculated. To ease interpretation, the EB estimates of the logits were transformed to probabilities. Estimates of the mean log time spent watching were exponentiated to obtain values in hours. Estimates of the standard deviation of log mean time spent were transformed to standard deviations of time spent in hours. The bivariate associations between sets of estimates are displayed in Figs. 4, 5, and 6. Each display indicates the mean, median, lower quartile, and

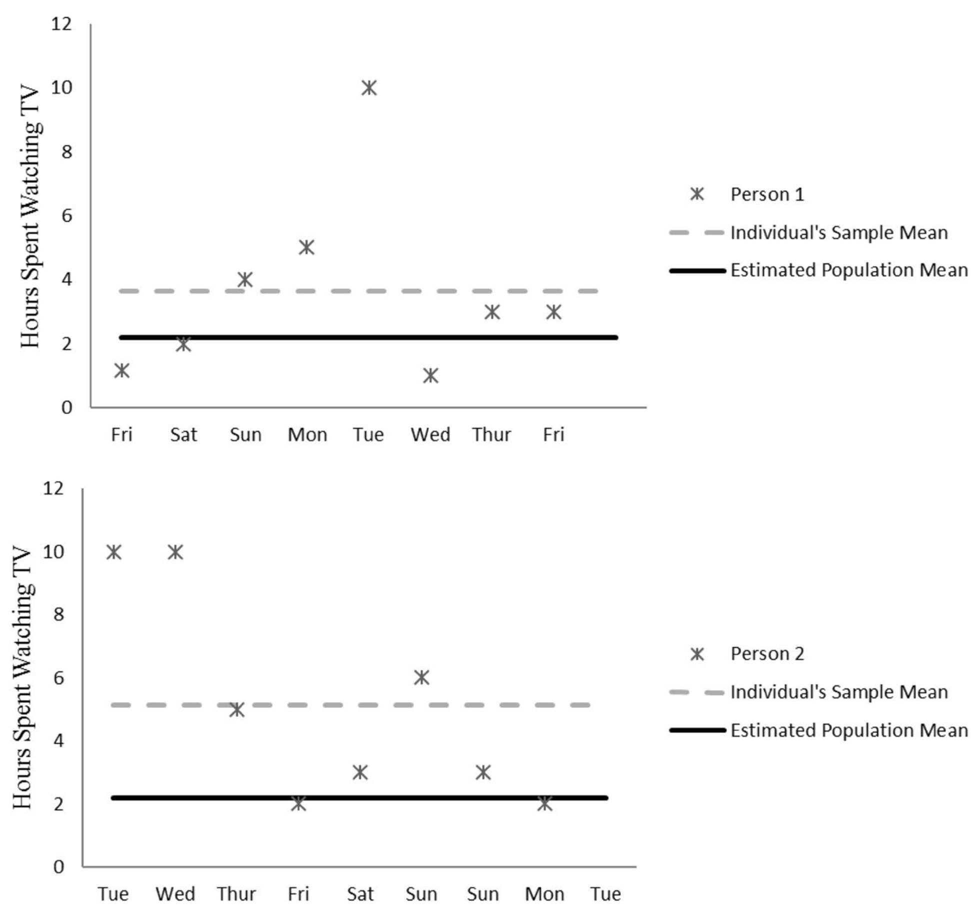


Fig. 2 Time spent watching TV for two individuals. Individual sample means and standard deviations by individual: Person 1, mean = 3.7 h, SD = 2.9 h; Person 2, mean = 5.1 h, SD = 3.3 h

Fig. 3 Time spent watching TV for two individuals. Individual sample means and standard deviations by individual: Person 3, mean 4.5 h, SD = 5.6 h; Person 4, mean = 0.6 h, SD = 0.3 h

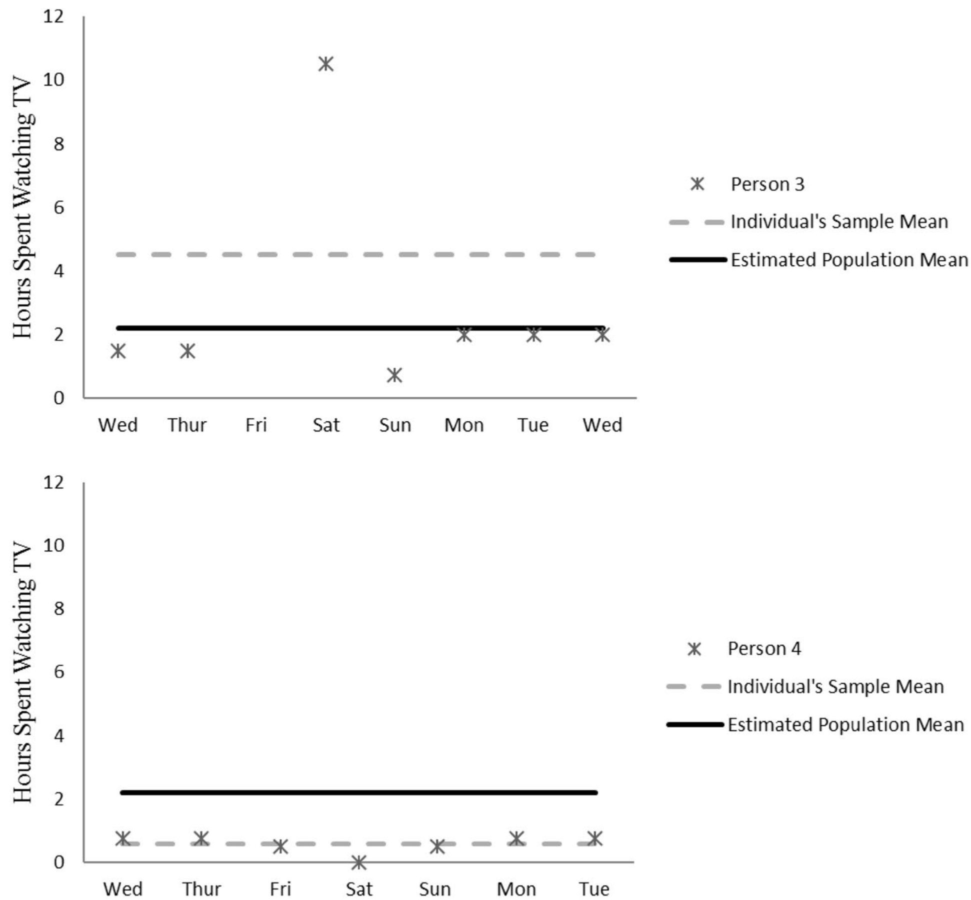


Fig. 4 Bivariate plots of empirical Bayes estimates of person-level probabilities of watching TV and mean log time spent watching TV

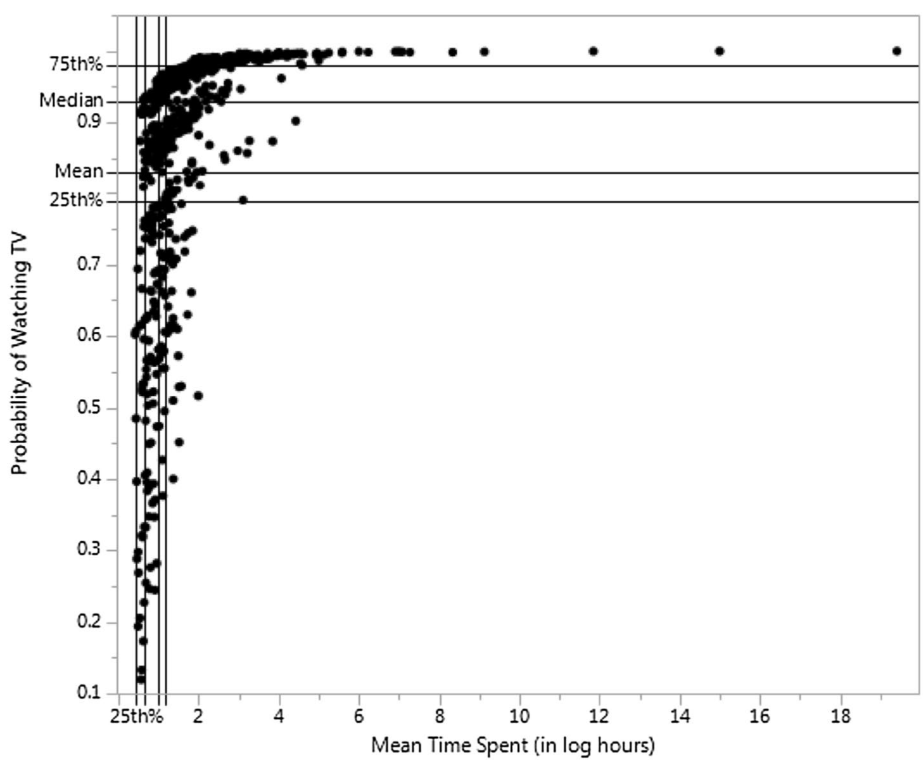


Fig. 5 Bivariate plots of empirical Bayes estimates of person-level probabilities of watching TV and standard deviation of log time spent watching TV

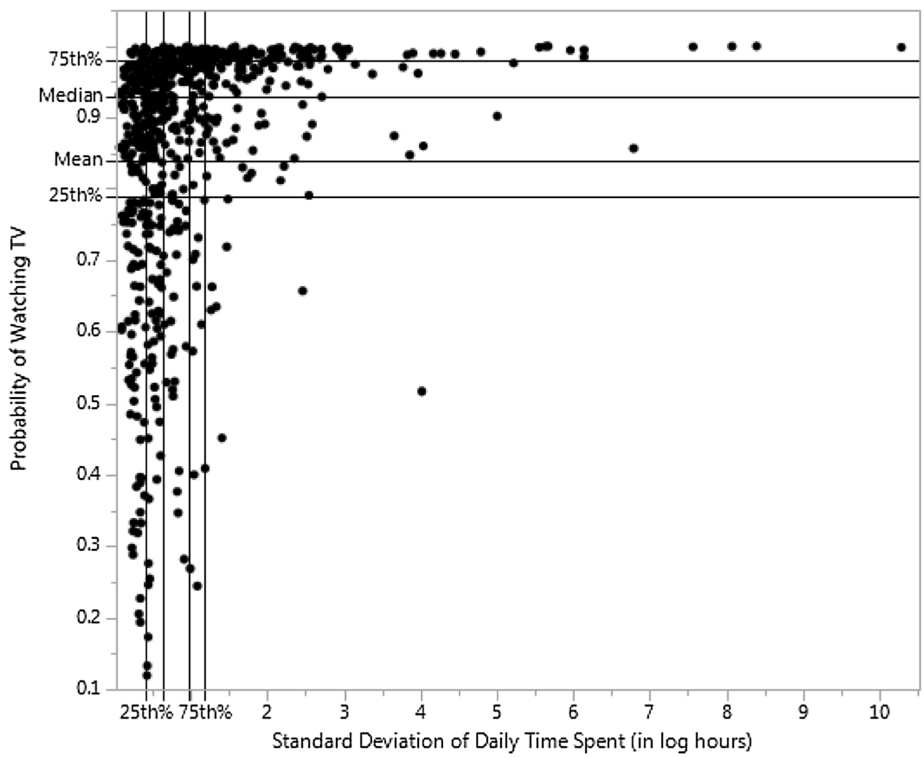
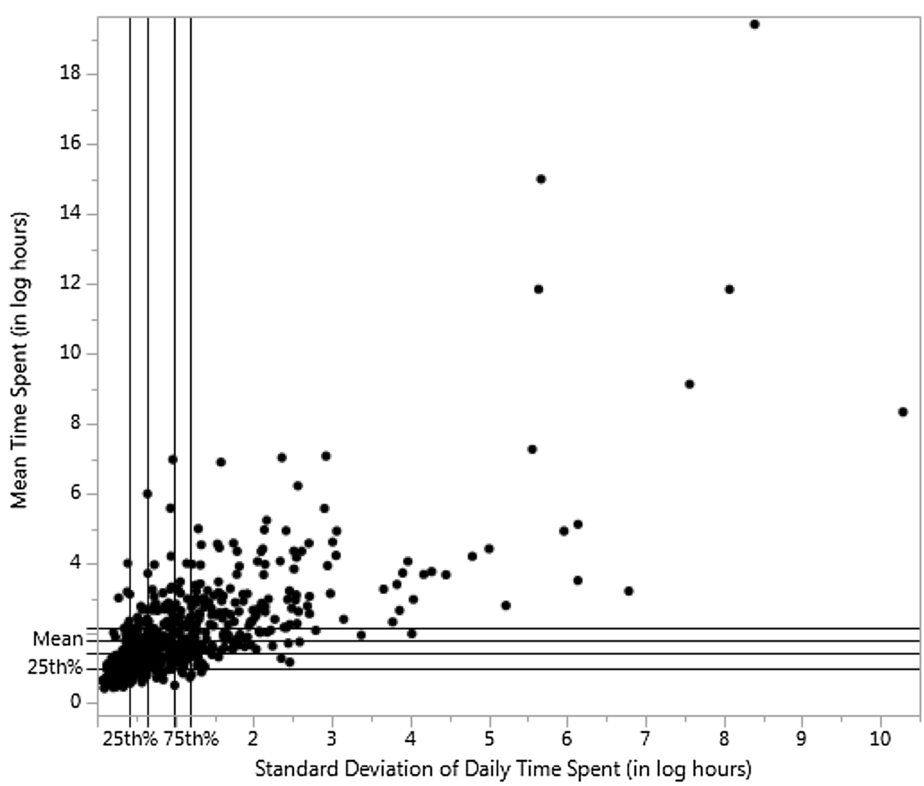


Fig. 6 Bivariate plots of empirical Bayes estimates of person-level log mean time spent watching TV and standard deviation of log time spent watchingTV



upper quartile. A high concentration of respondents ($n=415$) have an average probability of watching TV across days ranging between .83 (25th percentile) and .98 (75th percentile) and a mean time spent watching TV ranging from 1.3 (25th percentile) to 2.7 (75th percentile) hours (see Fig. 4). A high concentration of respondents ($n=408$) (middle display) have probabilities ranging between .83 and .98 and a standard deviation in time spent ranging from 2.2 (25th percentile) to 4.1 h (75th percentile) (see Fig. 5). A high concentration of respondents ($n=388$) have a mean time spent ranging from 1.3 to 2.7 h and a standard deviation in daily time spent ranging from 2.2 to 4.1 h (see Fig. 6). All effects had positive associations with each other, indicating that individuals with higher probabilities of watching TV also had higher means in time spent and greater daily variation, and those with higher means in time spent also had greater daily variation.

Conditional models to study between-person differences and within-person variation in TV use

Accounting for individual differences in the three aspects of watching TV, including differences in the daily variation in time spent across days, was done by incorporating covariates into the model. In Model B_1, the logit in Eq. (2) was extended to include the occasion-specific covariate Wkend_{ij}, the person-level covariates Age_i and Fem_i, and their interactions, adjusting for PropWkend_i:

$$\begin{aligned}
&\text{Level 1}: \eta_{ij} = \alpha_{0i} + \alpha_{1i}\text{Wkend}_{ij} \\
&\text{Level 2}: \alpha_{0i} = \alpha_{00} + \alpha_{01}\text{Fem}_i + \alpha_{02}\text{Age}_i \\
&\qquad + \alpha_{03}\text{Fem}_i * \text{Age}_i + \alpha_{04}\text{PropWkend}_i \\
&\alpha_{1i} = \alpha_{10} + \alpha_{11}\text{Fem}_i + \alpha_{12}\text{Age}_i + \alpha_{13}\text{Fem}_i * \text{Age}_i.
\end{aligned} \tag{5}$$

In Eq. (5), α_{00} is the logit for men on weekends at the sample mean age and sample mean proportion of weekend days; the coefficients α_{01}, α_{02}, and α_{03} are the effects of Fem_i, Age_i, and their interaction, respectively, and on the logit. The binary variable Wkend_{ij} was person-centered about the individual's proportion of weekend days relative to their total number of days interviewed. Thus, the effect of Wkend, α_{10}, represents the pooled within-person effect of weekend, and the effect of PropWkend α_{04} is the between-person effect of the proportion of weekend days when interviewed. The coefficients α_{11}, α_{12}, and α_{13} are cross-level interaction effects between Wkend_{ij} and Fem_i and Age_i and their interaction, respectively. Thus, α_{11}, α_{12}, and α_{13} are the moderating effects of Fem_i and Age_i and their interaction, respectively, on the effect of Wkend_{ij} on η_{ij}. The interpretation of the fixed effects and their interactions follows that for a mixed-effects logistic model (Larsen et al. 2000). The random effect a_i is now the conditional subject effect after accounting for the covariates on the logit; a_i has an expected value of 0 and variance φ_a. The variance φ_a is the between-subject variance of individual logits conditional on the covariates.

Similarly, the continuous model part for m_{ij} in Model B_1 included the effects of the covariates and their interactions, adjusting for PropWkend_i:

$$\begin{aligned}
&\text{Level 1}: m_{ij} = \gamma_{0i} + \gamma_{1i}\text{Wkend}_{ij} + e_{ij} \\
&\text{Level 2}: \gamma_{0i} = \gamma_{00} + \gamma_{01}\text{Fem}_i + \gamma_{02}\text{Age}_i \\
&\qquad + \gamma_{03}\text{Fem}_i * \text{Age}_i + \gamma_{04}\text{PropWkend}_i + s_i \\
&\gamma_{1i} = \gamma_{10} + \gamma_{11}\text{Fem}_i + \gamma_{12}\text{Age}_i + \gamma_{13}\text{Fem}_i * \text{Age}_i.
\end{aligned} \tag{6}$$

In Eq. (6), γ_{00} is time spent watching TV for men on weekends at the mean sample age and the sample mean proportion of weekend days. The coefficients γ_{01}, γ_{02}, and γ_{03} are the effects of Fem_i, Age_i, and their interaction, respectively, on time spent. The effect γ_{10} represents the pooled within-person effect of Wkend_{ij}, and the effect γ_{04} is the between-person effect of PropWkend_i. The coefficients γ_{11}, γ_{12}, and γ_{13} are the effects of Wkend_{ij} and its cross-level interactions with Fem_i, Age_i, and their interaction, respectively. Thus, γ_{11}, γ_{12}, and γ_{13} are the moderating effects of Fem_i and Age_i and their interaction, respectively, on the effect Wkend_{ij} on m_{ij}. The fixed effects are interpreted as in a linear mixed-effects model (Laird and Ware 1982). The residual at the first level of the model, e_{ij}, is the deviation of an individual's observed score from the fitted score and is assumed to follow a lognormal distribution. The random effect s_i is the subject effect, conditional on the covariates, with mean equal to 0 and variance φ_s. The variance φ_s is the between-subject variance of individual levels of mean time spent conditional on the covariates.

The model of the variance of the level 1 residual of the continuous model part was extended to include the covariates:

$$\theta^2 = \exp\left(w'\tau + u_i\right),$$

where w is the covariate set (with the first value equal to 1 for the reference value), and τ is the set of effects of the covariates to be estimated:

$$\tau = \left(\tau_0, \tau_1, \tau_2, \tau_3, \tau_4, \tau_5, \tau_6, \tau_7, \tau_8\right), \tag{7}$$

where τ_0 is the residual variance when all covariates are equal to 0. The remaining effects are τ_1 for Fem_i, τ_2 for Age_i, τ_3 for the interaction between Fem_i and Age_i, τ_4 for Wkend_{ij}, τ_5 for PropWkend_i, τ_6 for the cross-level interaction between Fem_i and Wkend_{ij}, τ_7 for the cross-level interaction between Age_i and Wkend_{ij}, and τ_8 for the cross-level interaction between Fem_i, Age_i, and Wkend_{ij}. The coefficient θ^2 increases if an effect is positive and decreases if an effect is negative. The residual of the regression is given by u_i. The variance of u_i, φ_u, is the between-subject variance of daily variation coefficient conditional on the covariates.

Results for conditional models

ML estimates and 95% confidence intervals relating to Model B_1 are in the first two columns of results in Table 3. We then excluded any interaction effects whose estimated confidence interval included 0 as an interior point but retained all first-order effects of the covariates regardless of whether the interval included 0 to draw inference about

Table 3 Estimated covariate effects on likeliness to watch and time spent watching TV (n = 782)

Parameter	Model			
	B_1	95% CI	B_2	95% CI
α_{00}	3.0 (.35)	[2.3,3.7]	3.0 (.35)	[2.3, 3.7]
Fem_i, α_{01}	− .47 (.18)	[− .82, − .11]	− .46 (.18)	[− .81, − .11]
Age_i, α_{02}	.04 (.01)	[.01,.06]	.03 (.01)	[.02, .05]
Age_i*Fem_i, α_{03}	− .00 (.01)	[− .03,.02]		
$\mathrm{PropWkend}_i$ α_{04}	− .37 (1.2)	[−2.7,1.9]	− .37 (1.2)	[−2.7,1.9]
Wkend_j, α_{10}	− .03 (.16)	[− .34,.29]	− .07 (.10)	[− .26, .13]
Wkend_{ij}*Fem_i, α_{11}	− .11 (.21)	[− .51,.30]		
Wkend_{ij}*Age_i, α_{12}	− .02 (.01)	[− .05,.00]		
Wkend_{ij}*Age_i*Fem_i, α_{13}	.01 (.02)	[− .02,.05]		
γ_{00}	.23 (.07)	[.09,.38]	.23 (.07)	[.09, .38]
Fem_i, γ_{01}	− .01 (.03)	[− .08,.05]	− .01 (.03)	[− .08, .05]
Age_i, γ_{02}	.01 (.00)	[.01,.02]	.01 (.00)	[.01, .02]
Age_i*Fem_i, γ_{03}	.00 (.00)	[− .01,.01]		
$\mathrm{PropWkend}_i$ γ_4	.64 (.26)	[.13,1.1]	.64 (.26)	[.13,1.1]
Wkend_{ij}, γ_{10}	.20 (.02)	[.15,.25]	.21 (.02)	[.16, .26]
Wkend_{ij}*Fem_i, γ_{11}	− .09 (.03)	[− .15, − .02]	− .10 (.03)	[− .17, − .04]
Wkend_{ij}*Age_i, γ_{12}	− .00 (.00)	[− .01,.00]	− .01 (.00)	[− .01, − .00]
Wkend_{ij}*Age_i*Fem_i, γ_{13}	− .00 (.00)	[− .01,.00]		

Estimates are based on maximum likelihood. Standard errors are in parentheses

the effects, or the lack thereof. Based on an evaluation of test results from Model B_1, a final model, Model B_2, is used for interpretation. Estimates of effects and their confidence intervals for Model B_2 appear in the last two columns of Table 3. In interpreting any one of the effects of Model B_2, an effect is statistically adjusted for all other effects included in the model.

Regarding likeliness to watch TV, there was a clear direction in the difference in the logit between men and women ($\hat{\alpha}_{01} = -.46$, SE = .18, CI [− .81, − .11]) but not between weekdays and weekends ($\hat{\alpha}_{10} = -.07$, SE = .10, CI [− .26, .13]). The difference between men and women translates to an estimated difference of .03 in the probability, with men having on average a slightly higher daily probability of watching TV. The estimated effect of *Age* on the logit suggests that older respondents were more likely to watch TV relative to younger individuals ($\hat{\alpha}_{02} = .03$, SE = .01, CI [.02, .05]).

With regard to log time spent watching TV, the estimated difference between men and women was moderated by whether the interview fell on a weekday or weekend. For men the estimated difference in log time spent on weekdays versus weekends was $\hat{\gamma}_{10} = .21$ (SE = .02, CI [.16, .26], suggesting a higher average on weekends. For weekdays there was no clear difference between men and women in mean log time spent ($\hat{\gamma}_{01} = -.01$ (SE = .03, CI [− .08, .05]). Men and women differed, however, in their mean log time spent on weekends ($\hat{\gamma}_{01} + \hat{\gamma}_{11} = -.12$, SE = .5, CI [− .21, − .02]), indicating a lower average in time spent for women. The estimated effect of Age was moderated by whether the survey was done on a weekday versus a weekend, with a positive effect of Age for weekdays being $\hat{\gamma}_{02} = .01$ (SE = .001, CI [.01, .02]) and the effect of Age essentially canceled out after adding the weekend effect of $\hat{\gamma}_{12} = -.01$ (SE = .001, CI [− .01, − .003]), indicating that older respondents tended to report more time spent on weekdays but not weekends.

With regard to heterogeneity in daily variation in the log of time spent watching TV, estimates of the effects of covariates are in Table 4. Only the estimated effect of Age was clear in its direction, indicating greater stability in time spent across days for older participants ($\hat{\tau}_2 = -.01$, SE = .003, CI [− .02, − .01]).

Discussion and implications

It is not uncommon for media use studies to focus on cross-sectional, aggregate data, and further, to make no explicit mention of zeros in the data collected and analyzed (e.g., Cheon et al. 2018; La Ferle and Lee 2005). When zeros are not explicitly mentioned in media use studies, one may question the conclusions and inferences drawn from the data analysis, such as in cases where a sample is comprised of only individuals who reported positive use of the medium of interest (e.g., Mora 2016). In such cases, any understanding of media use behaviors relate only to those who used at the time of measurement. A second point of concern is that when zeros are included in the analysis of time

Table 4 Estimated covariate effects on daily variation in time spent watching TV (n = 782)

Parameter	Model			
	B_1	95% CI	B_2	95% CI
θ^2	.30(.05)		.30(.05)	
τ_1, Fem_i	.06(.07)	[− .08,.20]	.06(.07)	[− .09,.20]
τ_2, Age_i	− .02(.00)	[− .03, − .01]	− .01(.00)	[− .02, − .01]
τ_3, Fem_i*Age_i	.01(.01)	[− .00,.02]		
τ_4, $PropWkend_i$	− .29(.55)	[−1.4, .78]	− .26(.55)	[−1.3,.82]
τ_5, $Wkend_{ij}$	.08(.09)	[− .10,.25]	.11(.06)	[− .01,.23]
τ_6, $Wkend_{ij}$*Fem_i	.06(.12)	[− .18,.30]		
τ_7, $Wkend_{ij}$*Age_i	.01(.01)	[− .00,.03]		
τ_8, $Wkend_{ij}$*Fem_i*Age_i	− .01(.01)	[− .03,.01]		

Estimates are based on maximum likelihood. Standard errors are in parentheses

spent, summary measures such as the sample mean will be reduced. This can also lead to misunderstandings about the level of use.

Contrary to cross-sectional studies that use aggregate measures of media use, the current study takes a three-step process. Step 1, conceptual in nature, embraces the fact that media use is continuous by nature and that zeros commonly result through the measurement of media use and should be explicitly addressed. Step 2 was to collect data commensurate with the continuous nature of media use. Here the study used daily diary data to capture TV use on a daily basis for eight days. Step 3 then applied a two-part mixed-effects model to account for variation in time spent, where zeros were specifically addressed. Using a mixed-effects model, it was possible to evaluate media use at the individual level.

This approach resulted in the identification of and integration of three important media behavior variables: probability of using a medium, time spent with the medium, and variation in use across time. The results suggest the importance of understanding these variables and their implications for reach and frequency. Unlike cross-sectional, aggregate data approaches, the results from the approach followed here shed light on media use patterns across time, both within and between individuals.

Using the 3-step approach described above, the findings were in line with expectations. That is, accounting for the zeros allowed for assessing the probability of TV use for study participants. Understanding the probability of using TV is important because it sheds light on the relative importance of the medium in terms of age, gender, and day of week, each important variables for media practitioners.

Of the three variables the methodological and statistical approached revealed, two were most pertinent to behavioral revelations when considered concurrently, namely individual differences in time spent and in the within-person day-to-day variation. The joint effect of these two variables has both conceptual and practical implications. From a conceptual perspective, reach and frequency are typically discussed in terms of non-time use behaviors like brand usage level (Nelson-Field et al. 2012) and stimulus involvement (Schmidt and Eisend, 2015). There are more general considerations that influence when reach or frequency goals are appropriate. For example, reach is appropriate for convenience products (O'Guinn et al. 2019) and when brands want to affect top-of-mind awareness (Kelly and Jones, 2012), whereas frequency is best for new products, products with many features (O'Guinn et al. 2019) and repositioning a brand (Kelly and Jones 2012). The results of the present study conceptually suggest that time use and variation in time use should be considered given their implications for reach and frequency.

From a theoretical and practical perspective, the results suggest that media behavior researchers and media planners may need to reconsider traditional beliefs about how reach and frequency relate to media behavior. That is, traditional thinking suggests that frequency is best suited for those who spend a lot of time watching TV. The results from this study, however, suggest that those with the highest probability of watching TV also have the highest degree of instability in time spent across days. Instability in time spent across days suggests that reach goals might be more appropriate. This counter-intuitive result is also reflected in the positive relationship between higher mean hours spent watching TV and higher levels of instability. This result, too, suggests that reach might be more appropriate rather than frequency.

Results from this investigation also provide more nuanced reach and frequency implications. The decision matrices in Figs. 7 and 8 summarize the implications. For probability of using by variation in time spent (stability), Fig. 7 presents a decision matrix for gender (figure on the left) and age (figure on the right), respectively. For gender, the figure suggests that men may be better targets for reach, whereas women may be better targets for frequency. The implications are that media planners can adjust media strategies so that media plans for men take into account reach goals, whereas those for women will reflect frequency goals. For age, the figure suggests that older viewers may be better targets for

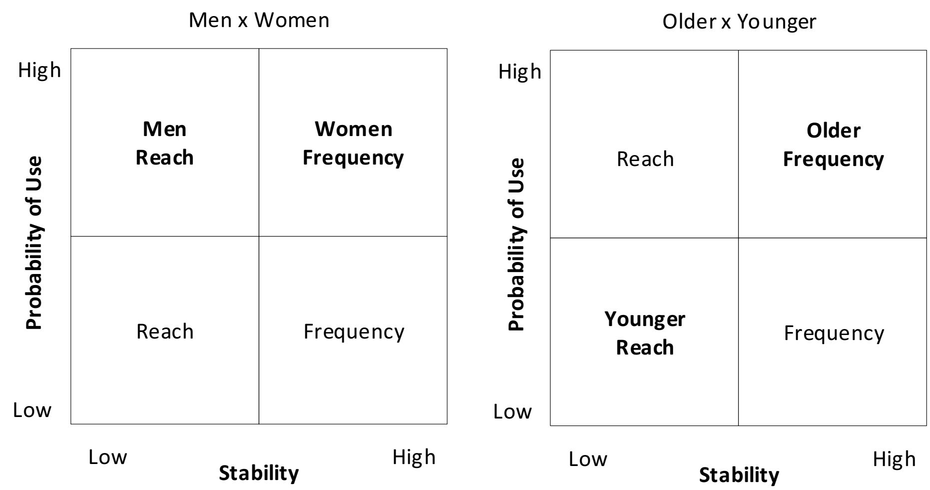


Fig. 7 Reach or frequency decision matrix based on probability of use and stability in time spent

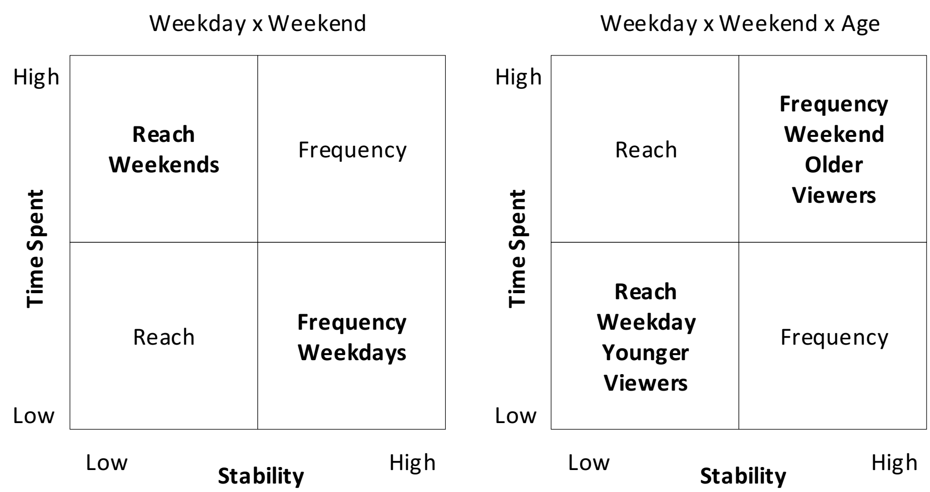


Fig. 8 Decision matrix for weekday viewing versus weekend and weekday by weekend viewing given age

frequency, whereas younger viewers may be better targets for reach. Similar to the implications for gender, here media planners would ensure that programming for older viewers are used for frequency goals, whereas programming for younger viewers are used for reach goals.

For time spent by stability in time spent, Fig. 8 presents a decision matrix for weekday versus weekend (figure on the left) and weekday versus weekend by age (figure on the right), respectively. Independent of age and gender, the figure on the left suggests that for weekday versus weekend only, weekends would generally be good for reach, whereas weekdays would generally be good for frequency. Here, media planners would use the weekends for reach goals and weekdays for frequency goals. One possible way to execute such a plan would be to use a vehicle that tends to be popular with a general audience, such as a news program. However, when considering age in terms of weekday versus weekend, the figure on the right suggests that frequency would be good for older viewers on weekends, whereas reach would be good for younger viewers on weekdays. Similar to the implications of gender and age, here, too, media planners would consider a media vehicle popular for older viewers on weekends to execute frequency goals, whereas a media vehicle popular with younger viewers on weekdays to execute reach goals. The findings regarding younger viewers and reach are in line with work by Hallward (2008) that suggests recall is greater among younger viewers who watch fewer hours of TV during the week.

Importantly, the findings of the current study can also be considered in terms of earlier research on reach and frequency. For example, research conducted by Nelson-Field et al. (2012) suggests that reach and frequency should be considered in terms of usage level, that is, heavy versus light users. Citing McDonald and Ehrenberg (2003), they suggest that frequency goals are best for heavy users and that reach goals for best for light users. The rationale is that heavy users require top-of-mind awareness given their usage level. On the contrary, reaching light users in the hopes of converting them to heavy users is more likely with reach goals. With these findings in mind, the results of the current study can be integrated thusly (see Fig. 2).

The work by Schmidt and Eisend (2015) suggests that reach and frequency goals should take into account level of involvement. They suggest that reach goals are best for high involvement products and that frequency is best for low involvement products. The results of their meta-analysis suggest that "high involvement needs less repetitions to achieve maximum impact" (p. 425) and that "low involvement… enhance advertising exposure effects on attitudes towards the brand…(p. 425). Figure 9 integrates their findings into those of the present study.

Implications of using a two-part mixed-effects model

A two-part mixed-effects model provides a description of media behaviors at both the individual and population levels. The model distinguishes between those who are and those who are not likely to use media. Aggregated across days, patterns of use provide profiles of likely users and non-users and provide information about the overall target audience base. Having a more precise understanding of which consumers are likely to engage with a given media could help to ensure a more efficient use of media dollars and perhaps a more accurate attribution of media effects.

With regard to measures of time spent, a two-part mixed-effects model separates the zeros in summarizing measures of time spent. An important aspect of separating days of no use is that it removes the impact of including non-users in describing the central tendency in use, as zeros in measures of central tendency depress the mean. In using a two-part mixed-effects model, summary measures of time spent are based on those times when individuals were actively engaged with the media. This framework can allow media planners to select the best days, age groups, and times to target males and females for media and message placement. Lastly, having a description of the degree of stability in individual measures of time spent improves understanding of the likeliness for exposure to a given message. Thus, one implication of using this statistical model with individual-level, repeated-measures data is that it allows media planners to more specifically define and attain reach and frequency goals and do so in a manner that optimizes media budget and spending dollars where they are most likely to have impact.

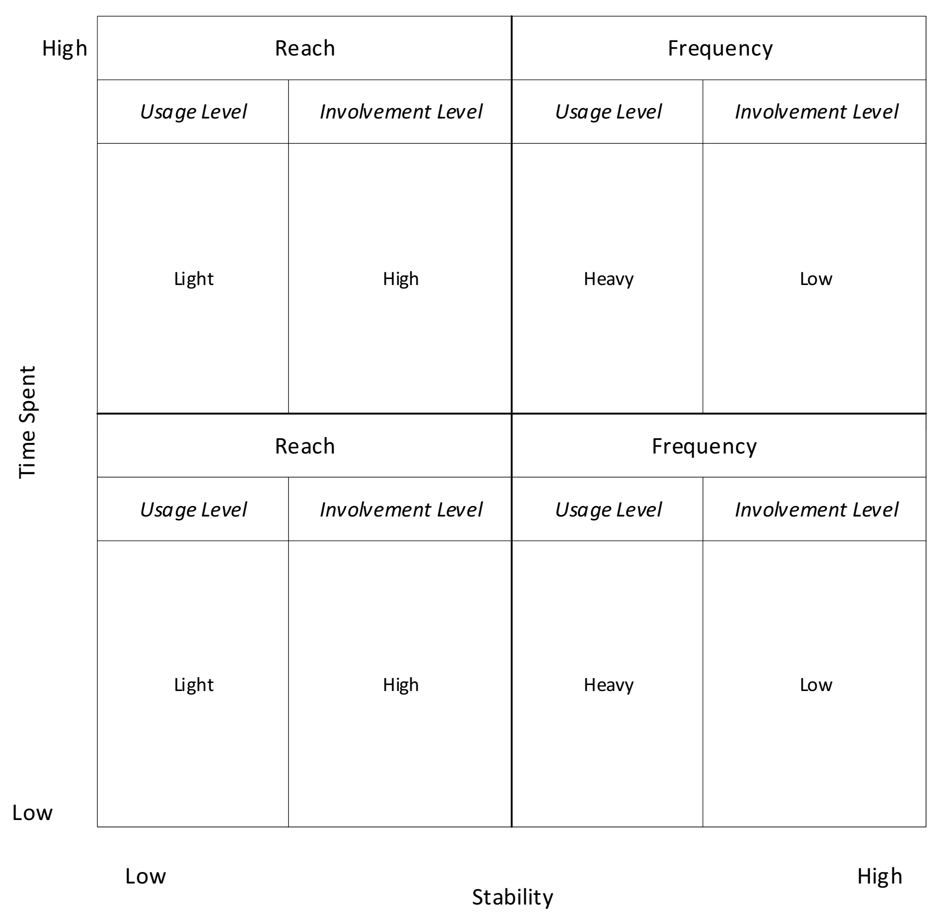


Fig. 9 Decision matrix for reach and frequency by product usage level and product involvement level

Limitations and future research

The modeling framework used in the current study suggests new insights for media strategy; its limitations provide a direction for future research. Arguably, the first limitation is that the study scrutinized a single medium. TV, however, remains important. As Geoffrey Precourt, editor emeritus of *Journal of Advertising Research* (*JAR*), noted in an introductory article that set the stage and theme for an entire issue of JAR (2017):

> '…this is still…The Age of Television. The most powerful medium in terms of reach and even frequency is still a behemoth among all means of consumer engagement.'

The research that was reported in the issue was replete with data and observations that provided quantitative support for Precourt's contention.

It is also worth noting that the method developed in this paper for a single medium can be expanded to simultaneously handle multiple media forms (Xu et al. 2014). That is, the methodology developed here could readily be extended to include multiple forms of media use to understand the three aspects of use and their interrelations in multiple forms of media.

Arguably, one could consider the age of the data as a limitation. The main focus of the current study, however, was to provide an example of the utility of two-part mixed-effects models in conjunction with daily diary data. The method sheds light on media behavior regarding reach and frequency for media planning purposes. In other words, the age of the data is unlikely to have characteristics or to become a factor that would alter an assessment of the utility of the model demonstrated here.

Despite the limitations of this study, the modeling approach used does provide media planning insight worthy of further study. To this end, the relevance of the modeling framework would be enhanced with applications to more current data sets that include multiple media, from traditional to digital. The results of such studies would have particular relevance to CMOs contemplating omnichannel strategies. Doing so would shed light on the outcomes associated with each of the three metrics utilized here. With an updated sample and multiple media a number of questions become evident: What does the likeliness to use look like when other media options are also measured? Does time spent with one media have a negative effect on other media use? What does stability look like when more than one medium is considered? Are relationships the same for both traditional and digital media?

Given the ability to collect repeated-measures data in this fragmented, medium-rich time, it seems that two-part modeling is a viable approach in helping media planners gain better insight into what is happening at the individual level. And as noted in the introduction, in the measurement of any phenomena, it essential to ensure consistency between the conceptual definition of what's being measured with the level of measurement (i.e., individual level, group level, household level) in operationalizing the concept. This study suggests that doing so is possible, important, and informative.

Appendix 1

The lognormal and gamma distributions are part of a class of generalized gamma distributions. Depending on their parameters, both can be monotonically declining or bell-shaped and skewed to the right. The lognormal distribution can be characterized by a mean ($\mu_{\log(y)}$) and a variance ($\sigma^2_{\log(y)}$), both of which relate to the log of y: log(y). The probability density function (PDF) of the lognormal distribution for a random variable Y can be given as

$$f\left(y|\mu_{\log(y)},\sigma^2_{\log(y)}\right)=\frac{1}{y_{i\sqrt{2\sigma^2\pi}}}\exp\left\{-\frac{1}{2}\left(\frac{\left(\log\left(y_i\right)-\mu_{\log(y)}\right)}{\sigma^2_{\log(y)}}\right)\right\}.$$

Note that $y>0$ and both μ and $\sigma^2>0$.

The gamma distribution can be characterized by two parameters, namely a shape (γ) and scale (θ) parameter. The PDF of the gamma distribution for a random variable Y with γ and θ parameters can be given as

$$f(y|\gamma,\theta)=-\theta\log\{\gamma\}-\log\{\Gamma(\theta)\}+(\theta-1)\log\{y\}-y/\gamma,$$

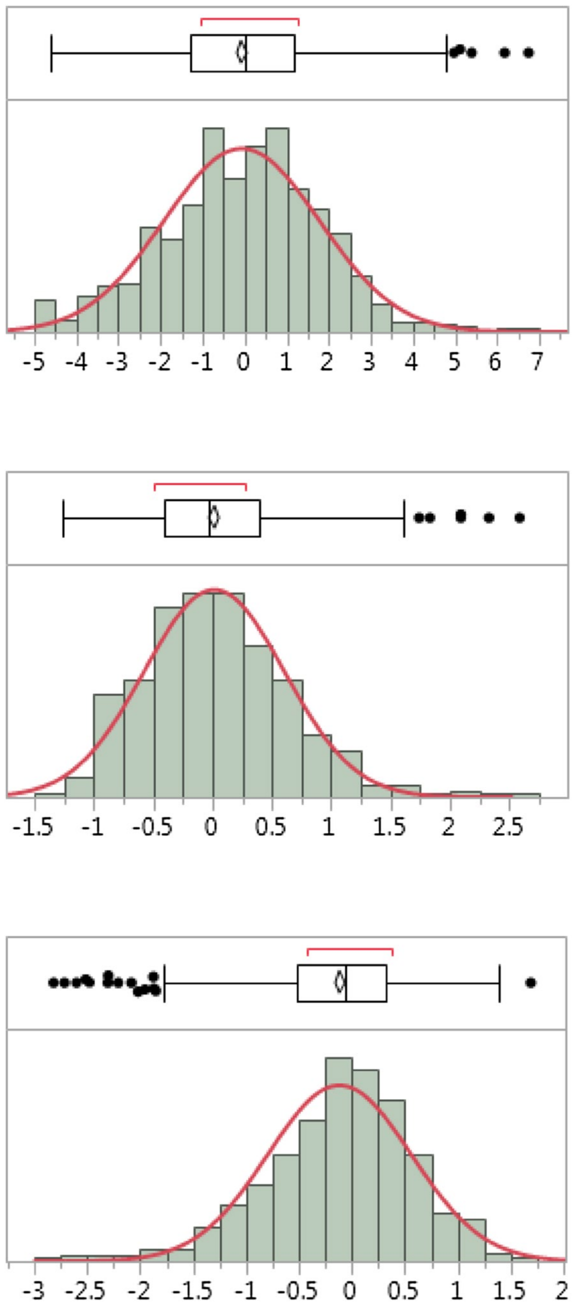
where $\Gamma(\theta)$ is the standard gamma function of the scale parameter θ. Note that $y>0$, $\gamma>$, and $\theta>0$. It is useful to relate the shape and scale parameters to the mean, variance, and standard deviation of y:

$$\mu_Y=\gamma\theta,\ \sigma^2_Y=\gamma\theta^2,\sigma_Y=\sqrt{\gamma\theta^2}, \tag{8}$$

respectively.

Appendix 2

Empirical Bayes estimates of the random effects based on a two-part mixed-effects model. Values are the random effects relating to the individual estimated logits (upper figure), log time spent (middle figure), and variance of log time spent (bottom figure).



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