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Investigating Heterogeneity in (Social) Media Effects: Experience-Based Recommendations

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We recently introduced a new, unified approach to investigate the effects of social media use on well-being. Using experience sampling methods among sizeable samples of respondents, our unified approach combines the strengths of nomothetic methods of analysis (e.g., mean comparisons, regression models), which are suited to understand group averages and generalize to populations, with idiographic methods of analysis (e.g., N=1 time series analyses), which are suitable to assess the effects of social media use on each single person (i.e., person-specific effects). Our approach challenges existing knowledge of media effects based on the nomothetic-only approach. As with many innovations, our approach has raised questions. In this article, we discuss our experience with our unified media effects approach that we have been building since 2018. We will explain what our approach exactly entails and what it requires. For example, how many observations are needed per person? Which methods did we employ to assess the meaningfulness of variation around average effects? How can we generalize our findings to our target populations? And how can our person-specific results aid policy decisions? Finally, we hope to answer questions of colleagues who are interested in replicating, extending, or building on our work.

Keywords: social media, well-being, n=1 approach, effect heterogeneity

In (social) media effects research, different categories of questions are sought to be answered. Some studies investigate how frequent media users differ from less frequent users in certain outcomes (e.g., using mean comparisons, regression models), with the goal to generalize their results to a target population. This approach has been named a "nomothetic approach" (Robinson, 2011). Other studies, based on an "idiographic approach" try to uncover if and how media use leads to changes within single individuals. While early idiographic approaches typically relied on qualitative observations or interviews, contemporary idiographic studies also employ quantitative designs, in which they rely on multiple data points within individuals across time, collected with, for example experience sampling methodology (ESM) studies, daily diaries, or within-subject experiments (Bolger et al., 2019; Conner et al., 2007, 2009).

In the past decade, a growing group of methodologists has proposed to unite the subtlety and specificity of idiographic analyses with the goal of nomothetic inference (Bolger et al., 2019; McNeish & Hamaker, 2020; Molenaar, 2004; Molenaar & Campbell, 2009; Nesselroade & Molenaar, 2010; Voelkle et al., 2014). Inspired by this methodological work, we saw opportunities to adopt their unified approach to study media effects, in particular, the effects of social media use on well-being, or indicators of well-being, such as self-esteem and friendship closeness (Beyens et al., 2021; Pouwels et al., 2021; Valkenburg, Beyens, Pouwels, et al., 2022; Valkenburg, Pouwels, et al., 2021). Our new approach thus combines the strengths of a nomothetic approach (e.g., representative samples, generalization to target populations) with those of an idiographic or person-specific approach (focus on unique within-person processes of single participants).

As of 2018, we have investigated to what extent the small average effects of social media use on well-being that are typically found in empirical studies (Jensen et al., 2019; Orben & Przybylski, 2019) and meta-analyses (Liu et al., 2019; Yin et al., 2019) apply to different adolescents. Based on the differential susceptibility to media effects model (Valkenburg & Peter, 2013) and anecdotal evidence that points at large media effects for some individuals (Lang, 2011; McGuire, 1986; Valkenburg et al., 2016), we investigated for how many adolescents the average small effects of social media use on well-being actually apply and for how many not. In addition, we aimed to explain why such potential differences in susceptibility to these effects exist by including moderators in our analytical models.

In a series of ESM studies with 100+ within-person assessments per person among representative samples of adolescents, we found striking differences in the person-specific effects of social media use on well-being, self-esteem, distraction, and friendship closeness. And although for most adolescents the within-person effects of social media use on well-being were non-existent to small, for a small subgroup these effects were moderately to strongly negative (e.g., β < -.30) and for another small subgroup these were moderately to strongly positive (e.g., β > .30). These differences in person-specific effect sizes applied to both self-reports and digital trace data of social media use (Verbeij et al., 2022) and could be partly explained by moderators, such as self-esteem instability, peer approval contingency, and social media use-induced envy and enjoyment (Valkenburg, Beyens, Pouwels, et al., 2022; Valkenburg, Pouwels, et al., 2021).

Our focus on how media effects operate within individuals, and how this varies across these individuals has linkages to developments in several other disciplines. For instance, in the experimental research tradition in psychology, our unified idiographic/nomothetic approach has been named an effect heterogeneity approach (Bolger et al., 2019; Bryan et al., 2021). An effect heterogeneity approach aims to uncover and explain how within-person responses to stimuli or experimental treatments differ across individuals. The effect heterogeneity approach is rapidly gaining prominence in many disciplines, ranging from personality psychology, health psychology, and developmental psychology to neuroscience and communication science (Aalbers et al., 2021; Bolger et al., 2019; Bryan et al., 2021; Howard & Hoffman, 2018; Rose et al., 2013).

Aims of the Article

One aim of the current article is to answer potential questions of colleagues who consider adopting, extending, or building on our approach. Another aim is to take away the concerns about our approach raised by Johannes et al. (2024) in this volume of *Meta-Psychology*. In the remainder of this article, we describe our experiences with a unified media effects approach that we have built as of 2018. We will explain what such a unified approach exactly entails and what it requires. For example, how many observations are needed per person? Which methods did we use to assess the meaningfulness of variation around average effects? How can we generalize our findings to our target populations? And how can person-specific results aid policy decisions or inform practitioners?

Nomothetic, Group-Differential, and Idiographic Approaches in Media Effects

Our unified media effects approach unifies three common research approaches: nomothetic, group-differential, and idiographic (Lerner & Lerner, 2019). Since the second half of the 20th century, media effects research has been dominated by a nomothetic approach (Valkenburg et al., 2023). This approach is traditionally associated with between-person methods of analyses, such as mean comparisons, correlations, and regression models. Between-person methods try to establish, for example, whether individuals who use social media more often are worse off compared to others who use social media less often.

However, in the past years, media effects research has progressively embraced another type of nomothetic research that is based on average within-person media effects (Hamaker, 2012). Within-person methods try to uncover, for example, whether the well-being of persons change when they use social media more than they usually do. Within-person methods are progressively considered more valid than between-person methods to investigate media effects, because a media effect is an intraindividual change due to media use (Valkenburg et al., 2016).

A nomothetic approach, whether based on between- or within-person methods of analysis, assumes that characteristics of humans are shared by all people (Lerner & Lerner, 2019). As Table 1 shows, nomothetic media effects approaches at the between- and within-person level have comparable goals, hypotheses, levels of analysis, sampling procedures, and inference levels. Both approaches focus on aggregate or average statistics. And both aim to generalize from samples to populations.

As Table 1 shows, a group-differential media effects approach acknowledges that some characteristics of humans are not shared by all but only by some people (Lerner & Lerner, 2019). This type of research tries to understand which subgroups in a sample are more (or less) susceptible to the effects of (social) media. Such subgroups are typically compared by using group-level moderators, such as gender, age, or personality. However, group-level moderators may invariably gloss over more subtle individual differences in susceptibilities to media effects (Pearce & Field, 2016; Valkenburg et al., 2016). As Lerner and Lerner (2019, p.27) observe, "in addition to their nomothetic and group-differential characteristics, every person has idiographic characteristics that define him or her as unique." Such more subtle individual differences in susceptibility to media effects are the focus of an idiographic media effects approach (see third column of Table 1).

Table 1

Our Unified (Nomothetic + Group-Differential + Idiographic) Media Effects Approach

	Nomothetic (Between- and Within-Person)	Group-Differential	Idiographic (Person-Specific)
Goal	Establishing universal media effects	Establishing media effects for subgroups (e.g., males vs. females)	Establishing media effects for individual X
Example of hypothesis	Social media use undermines the well-being of individuals	Social media use undermines the well-being of females more than of males	Social media use undermines the well-being of individual X
Level of analysis	Whole sample	Subsamples	Individual
Estimate	Aggregated estimates for the sample	Aggregated estimates for subgroups	Person-specific estimates
Sampling	Large representative samples	Large representative subsamples	Multiple representative observations within individual X (e.g., > 50)
Inference level	From sample to population	From subsample to subpopulation	From individual X's measured results to individual X's overall functioning

Modelling Techniques for a Unified Media Effects Approach

To analyse data on the united nomothetic, group-differential and person-specific approach, several modelling techniques are available, such as Group Iterative Multiple Model Estimation (GIMME, Gates and Molenaar, 2012) or Dynamic Structural Equation Modelling (DSEM, McNeish and Hamaker, 2020). In our studies we used DSEM. DSEM is a Bayesian modelling technique that combines the strengths of multilevel analysis and Structural Equation Modeling with N=1 time-series analysis. DSEM allows researchers to investigate the between-person and average within-person effect of (social) media use (i.e., nomothetic analyses), while also allowing for the inclusion of trait and time-varying moderators (i.e., group-differential analyses).

Finally, the N=1 time-series analysis enables researchers to establish the longitudinal (lagged) effects of media use within each single participant (i.e., person-specific analysis). DSEM is a modelling technique for intensive longitudinal data. Such data typically require a large number of within-person observations per participant. After all, similar to the samples to detect nomothetic media effects, the number of within-person observations per person determines the power to detect a significant person-specific media effect (Howard & Hoffman, 2018). Therefore, researchers have collected as many as 80, 90, or even more than 100 within-person measurements per participant (for examples, see Howard and Hoffman, 2018). In our DSEM-based ESM studies we included 126 measurements per participant. But every ESM study includes participants with fewer observations, due to person-specific differences in compliance. It is our experience that when participants have fewer than 50 observations, their person-specific effects are only significant at $\beta \geq .20$.

The Added Value of a Unified Media Effects Approach

Our unified media effects approach unites the strengths of nomothetic and group-differential methods with those of person-specific methods. For example, in one of our studies we hypothesized that the experience of envy during social media browsing would moderate the effect of this browsing on well-being (Valkenburg, Beyens, Pouwels, et al., 2022). We indeed found a small moderating effect of envy ($\beta = .13$). By combining our N=1 time series results with a nomothetic and a group-differential approach (with browsing-induced envy as one of the group-level moderators), we could exactly specify for how many (and which) participants our moderation hypothesis could be confirmed. Our N=1 moderation analysis indicated that 25% of adolescents who felt browsing-induced envy experienced a negative effect of browsing on their well-being, while 13% of adolescents who did not feel browsing-induced envy experienced such a negative effect.

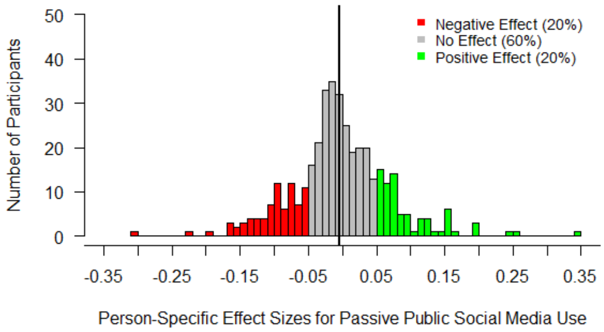
Our unified media-effect approach has three additional advantages. First, it allows us to compare the between-person and average within-person results. Many researchers have long assumed that results at the between-person level are generalizable to the within-person level. But, as has been convincingly demonstrated mathematically by Molenaar and Campbell (2009), this assumption is untenable in the social sciences. In our ESM studies, we indeed found considerable differences between the between-person associations and the average within-person effects of social media use. In some studies, the within-person effect was weaker than the between-person associations. For example, Beyens et al. (2021) found a significant negative between-person association of social media browsing with well-being (β = -.12), but no average within-person effect (β = .00). In addition, Siebers et al. (2023)found a strong between-person association between social media use and distraction (β = .48), but a small to moderate within-person effect (β = .18).

In other instances, we even found opposite between-person associations and within-person effects, a phenomenon that has been named a Simpson's paradox (Kievit et al., 2013). For example, (Valkenburg, Beyens, Pouwels, et al., 2022) found a positive between-person association of browsing with inspiration (β = .08), but a negative within-person effect (β = -.04). Finally, Pouwels et al. (2021) demonstrated that Instagram use with close friends was positively associated with friendship closeness at the between-person level (β = .17) but negatively at the within-person level (β = -.07). Together these findings demonstrate that a between-person association of (social) media use with well-being or related outcomes does not adequately describe a media effect, defined as an intraindividual (change) process.

A second advantage of our unified media effects approach is that it allows researchers to investigate to what extent the person-specific effects (i.e., the within-person effects for each single person) are consistent with the average within-person effect. In other words, to what extent can we translate the average within-person effect of social media use on well-being to each person in the sample? In our studies, we found significant discrepancies between the average within-person effects and the person-specific effects. The histogram in Figure 1 shows the distribution of the person-specific effect sizes of the effect of browsing on well-being found in Beyens et al. (2021). The X-axis of the histogram shows the different person-specific effect sizes, which ranged from moderately negative (β = -.30) to moderately positive (β = +.35). The Y-axis shows the number of participants experiencing the specific effect sizes listed on the X-axis. The vertical black line represents

Figure 1

Distribution of the person-specific effect sizes of the effects of social-media scrolling on well-being (adapted from Beyens et al., 2021)



Note. Results are based on an ESM study among 387 adolescents with 126 within-person assessments across three weeks. The vertical black line represents the average within-person effect of β = .00. Figure taken from Beyens et al. (2021).

the average within-person effect of scrolling on well-being (i.e., β = .00). We found that only 9% of the person-specific effect sizes fell within the 95% credible interval [-.022, -.014] around the average within-person effect. Together, these discrepant results between the average and person-specific effects of social media use suggest that the average person is rare (Rose et al., 2013).

A final advantage of our approach is that it allows researchers to reveal for how many participants a media effects hypothesis is confirmed and for how many it is rejected. Recently, we investigated a recurrent hypothesis in the literature, the Passive Social Media Use Hypothesis (Verduyn et al., 2017). This hypothesis states that passive social media use (browsing/scrolling) results in lower well-being because it leads to upward social comparison and envy, which in turn negatively affects one's well-being. We found that the Passive Social Media Hypothesis was confirmed for 20% of participants (the red bars in Figure 1), while it was unconfirmed for 80% of participants (the grey and green bars in Figure 1). We found that 20% of participants even experienced an effect opposite to the hypothesis (the green bars in Figure 1). Thus, to speak in Popperian terms, our approach enabled us to falsify the Passive Social Media Hypothesis.

Approaches to Detect the Meaningfulness of Heterogeneity in Media Effects

A potential concern regarding our unified media effects paradigm is that there is always variation around averages and that such variation is the foundation of nomothetic statistics based on averages. We agree that there is always noise around average media effects. But the modelling technique that we use is pre-eminently suited to distinguish between true variation and noise. In our early multilevel models, we used a model comparison approach (Beyens et al., 2020; Siebers et al., 2022). In such an approach, a fixed effects model is compared with a random slopes model. When the fit of the model significantly improves by adding random slopes, evidence exists for heterogeneity in the effect at the sample level. However, model comparison is a suboptimal method to distinguish true variation from noise, because adding random slopes almost always improves model fit. Moreover, model comparison does not work with Bayesian modelling techniques such as DSEM (McNeish & Hamaker, 2020).

Smallest Effect Size of Interest

DSEM allows for more sophisticated approaches to investigate the validity of heterogeneity in media effects. DSEM yields the standardized effect sizes for the sample as a whole and for each single person. As a result, it allows researchers to assess how the average within-person effect and person-specific effects compare to their set smallest effect size of interest (SESOI, Anvari and Lakens, 2021). We relied on the SESOI in our later studies (e.g., Beyens et al., 2021; Valkenburg, Beyens, Pouwels, et al., 2021, 2022). Based on our preregistered SESOI, we were able to classify individuals according to the principles of Grice et al. (2020) as supporting theory or rejecting theory. For example, in our test of the Passive Social Media Use Hypothesis (Verduyn et al., 2017), we classified 20% of participants as supporting theory and 80% as rejecting theory (Valkenburg, Beyens, Pouwels, et al., 2022).

However, in the media effects literature there is still no agreed-upon standard to interpret between-person and within-person media effect sizes. This lack can be inferred from the fierce academic debates on the small aggregate effects of video game violence on aggression (e.g., Bushman et al., 2010; Ferguson and Kilburn, 2010) and that on the small aggregate effects of social media use on well-being (see Valkenburg, Meier, and Beyens, 2022, for such differences in interpretations). Likewise, there are no set standards for the SESOI. Therefore, in our studies, we preregistered our SESOI. We used a SESOI of $\beta = .10$ for between-person associations and β=.05 for within-person effects. These decisions were based on recommendations by Gignac and Szodorai (2016) and a recent meta-review of media effects (Meier & Reinecke, 2021).

Significance Levels for Person-Specific Effects

What makes DSEM even more powerful is that it can assess whether a person-specific effect is statistically significant. Figure 2 shows the significance levels of the person-specific effects of browsing on well-being (left forest plot) and the effects of social media use on distraction (right forest plot). Each of the two forest plots shows a unique distribution of person-specific effects. The left plot shows that most person-specific effects of browsing on well-being center around the average within-person effect of $\beta = .00$ (60%). In addition, 20% of participants experience a negative effect of browsing on well-being (red dots), of which 5% was significantly negative (dark red dots). Conversely, about an equal percentage of 20% of participants experience a positive effect of browsing on well-being (green dots), of which 3% was significantly positive (dark green dots).

The right plot in Figure 2 shows the effects of social media use on distraction. Here the average within-person effect is significantly positive ($\beta = .18$). Although, again, there is heterogeneity in the effects of social media use on distraction, we found positive effects for 76% of participants, of which 38% were significantly positive. As our comparison of the two distributions show, our unified media-effects approach can be used to determine whether a media effect is more idiographic (left distribution) or more nomothetic (right distribution).

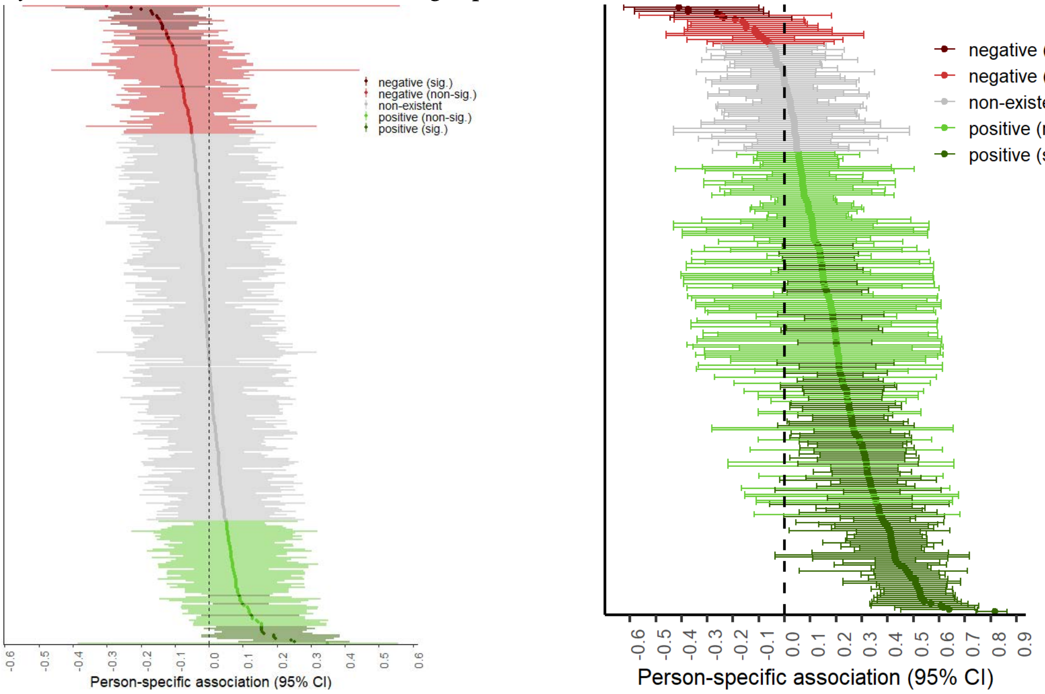
Generalizing to Target Populations

Like in a nomothetic-only approach, generalization to target populations is a matter of sample size and sampling technique in our unified approach. In our studies, we paid substantive attention to both. First, we based our sample sizes on preregistered power analyses. Second, as for our sampling technique, we started with conducting a national survey among middle adolescents (van Driel et al., 2019), which we used as a benchmark against which we compared our school-based samples of the same age group. Our school-based samples contained all educational levels and did not deviate from the national survey and from key indicators in the target population.

Non-representative samples, which are common in (social) media effects research (Odgers and Jensen, 2020) may contain participants who deviate in a host of characteristics from the target population but also from

Figure 2

Distribution of the Person-Specific Effects of Social Media Browsing on Well-Being (left panel) and the Person-Specific Effects of Social Media Use on Distraction (right panel).



Note. The dashed vertical lines in both panels represent a $\beta = .00$. The horizontal lines represent the credible intervals around the person-specific media effects. Right panel of the figure is taken from Siebers et al. (2023).

other non-representative samples. Therefore, when relying on non-representative samples, it is highly likely that the average statistics derived from these samples (a) are incomparable to those in other samples, and (b) cannot be generalized to the target population. As a result, finding consistent average effect sizes for the association of social media with well-being across non-representative samples is a nearly impossible odyssey.

Fortunately, the combined problem of non-representative samples and inconsistent effect sizes can be salvaged. Our unified media effects approach allows researchers to identify what percentage of participants respond according to the hypothesized effects and what percentage does not (Grice et al., 2020). Such an approach allows researchers (a) to generalize to subgroups based on these percentages, (b) discover how and why these subgroups differ from each other, and (c) compare these percentages across samples. Especially in the case of non-representative samples, our approach may hold great promise. It has even been suggested that our unified approach may resolve the replication crisis in psychology (Bryan et al., 2021). However, an important question that remains is whether and to what extent researchers can validly generalize the inconsistent average statistics obtained via non-representative samples and "heterogeneity-naïve" designs to target populations (Bryan et al., 2021, p. 32).

Practical and Policy Implications of Our Person-Specific Results

Interviewer: "What is the influence of social media on you?" Adolescent 1 (16): "Social media changed me in a positive way because now I am more open-minded and down to earth." Adolescent 2 (14): "On social media you should not compare yourself to others. But that is easier said than done. It has been a difficult time for me. I have been seeing a psychologist for a while now…"

These quotes from Dutch adolescents in one of our focus group studies (van der Wal et al., 2023) reflect what media theorists have emphasized for decades: Individuals differ strongly in their susceptibility to the effects of (social) media. But these quotes may also underscore the societal implications of our unified approach. In fact, our knowledge could be of vital importance for the development of prevention and intervention programs. After all, if practitioners would base their programs on average results, they may conclude that such programs are not necessary, because most studies, including our own, report only very small or even non-existent average within-person effects of social media.

However, our results clearly show that a considerable minority of adolescents does experience meaningful negative effects of social media use. Even if we are conservative in our interpretations, it may be safe to assume that 5% of young people experience negative effects of social media use on their well-being. Knowing that the US count 75 million young people, these negative effects may generalize to nearly four million US minors. These young people may run the risk to experience mental health problems due to their social media use. We cannot deny that we need to take such percentages seriously. Our results indicate that small or even non-existent average media effects may have huge implications for some vulnerable adolescents.

Conclusion

When the terms nomothetic and idiographic were coined at the end of the 19th century (by Windelband), “a false tendency to see these two terms as antagonistic rather than complementary” arose (Robinson, 2011, p. 32). It is quite possible that such a dichotomy was an unavoidable reality in the first decades of the 20th century, when the methods of analysis were not yet sophisticated enough to unify both approaches. In part due to seminal methodologists, such as Nesselroade (1991), Molenaar (2004), and Hamaker (2012), the idiographic approach not only experienced a revival in the new millennium but it can also be successfully integrated with nomothetic and group-differential approaches (Hamaker & Wichers, 2017).

There used to be a time that researchers had to make a choice between a nomothetic or an idiographic method. Aided by technological developments, new study designs have rapidly been gaining prominence, such as phone-based ESM studies and big data samples of social media interactions (Bolger et al., 2019; Conner et al., 2007; Grice et al., 2020; van Roekel et al., 2019). In addition, rising computational power as well as statistical groundwork have resulted in new modelling tools, such as DSEM (McNeish & Hamaker, 2020), which allow us to combine the best of two worlds. Our recent ESM studies on the effects of social media use on well-being, which have been using these modelling tools, convincingly demonstrated that we no longer “have to make a choice” as suggested by Johannes et al. (2024) in this volume of *Meta-Psychology*.

Years of methodological work have taught us that nomothetic group estimates are often invalid to understand processes that operate within individuals. And as our research team has theorized, this concern also applies to the study of media effects. Between-person estimates do not tap into media effects. Moreover, individuals differ in how they respond to media use – which may render conclusions based on averages invalid, especially when they are based on non-representative samples. Our approach allows us to understand how individuals function, how they differ from each other, and how to generalize results to target populations. In our view, our approach will not only help researchers to obtain more valid estimates of how media affect individuals in their everyday lives, but it will also allow them to develop theories to understand how, when, and why individuals differ in their susceptibility to media effects.

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Author Contributions

Conceptualization: PV, IB, LK; Draft preparation: PV; Reviewing, writing, and editing: PV, IB, LK.

Open Science Practices

This article earned the Open Data, and Open Code badge for making the data, and code openly available. It has been verified that the analysis reproduced the results presented in the article. The entire editorial process, including the open reviews, is published in the online supplement.

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