How to Capture Reciprocal Communication Dynamics: Comparing Longitudinal Statistical Approaches in Order to Analyze Within- and Between-Person Effects

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ORIGINAL ARTICLE

How to Capture Reciprocal Communication Dynamics: Comparing Longitudinal Statistical Approaches in Order to Analyze Within- and Between-Person Effects

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Choosing an appropriate statistical model to analyze reciprocal relations between individuals' attitudes, beliefs, or behaviors over time can be challenging. Often, decisions for or against specific models are rather implicit and it remains unclear whether the statistical approach fits the theory of interest. For longitudinal models, this is problematic since within- and between-person processes can be confounded leading to wrong conclusions. Taking the perspective of the reinforcing spirals model (RSM) focusing on media effects and selection, we compare six statistical models that were recently used to analyze the RSM and show their ability to separate within- and between-person components. Using empirical data capturing respondents' development during adolescence, we show that results vary across statistical models. Further, Monte Carlo simulations indicate that some approaches might lead to wrong conclusions if specific communication dynamics are present. In sum, we recommend using approaches that explicitly model and clearly separate within- and between-person effects.

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Communication research has for a long time been concerned with the question whether the relationship between media usage and a certain variable can be better explained under the media effects or the media selection paradigm. However, media effects and selection are not described as distinct and independent but rather as deeply connected, reciprocal, and potentially reinforcing phenomena. The reinforcing spirals model (RSM; Slater, 2007, 2015, 2017) has become a popular theoretical framework to link media use and attitudes, beliefs, or behaviors over time (Valkenburg, Peter, & Walther, 2016). In recent years, scholars investigated several reinforcing spirals between media use and associated outcomes. Examples can be found for political news use and ideological leanings (Dahlgren, Shehata, & Strömbäck, 2019), political discussion and affective polarization (Hutchens, Hmielowski, & Beam, 2019), music television consumption and smoking behavior (Slater & Hayes, 2010), or media violence and aggressive behavior (Slater, Henry, Swaim, & Anderson, 2003), to name just a few.

Most RSM-related studies contribute to advancing the RSM in the context of substantive research questions, but methodological decisions have been rather implicit and have not received full attention. However, if methodological decisions do not take into account the theoretical considerations of the applied model, they might come with biases or even present methodological artifacts (Schemer, Geiss, & Müller, 2019). This is particularly true when considering the RSM as a longitudinal model that implements both within- and between-person processes. Recently, scholars have emphasized the importance of disentangling such effects in the context of the RSM (Scharkow & Bachl, 2019; Schemer et al., 2019) and formulated more generally, "that between-person relations are different from within-person relations conceptually and empirically" (Wang & Maxwell, 2015, p. 63).

However, approaches that conceptualize the processes of the RSM as within- or between-person effects while taking into account the core dynamics of the RSM, that is, homeostasis, positive feedback-loops, and maintenance, are missing. Moreover, the variety of statistical models, which have been used to analyze the within- and between-person processes of the RSM, have never been compared systematically. Although literature in the field of statistical modeling intensively focused on the comparison of models that link two outcomes over time as well as their ability to separate within- and between-person processes (Bainter & Howard, 2016; Usami, Murayama, & Hamaker, 2019), such comparisons have been very rarely applied to the field of communication science.

This article contributes to the body of literature theoretically and empirically. Specifically, we (a) describe the core dynamics of the RSM, (b) explain the importance of disentangling within- and between-person processes, and (c) show how the RSM can be separated in within- and between-person components. Furthermore, we (d) give an overview of the statistical models that have been used to analyze the RSM and explain their RSM-related (dis-)advantages. By using (e) an empirical example and conducting (f) Monte Carlo simulations, we systematically compare the

statistical approaches. Finally, we (g) give recommendations in order to model the RSM accurately.

Dynamics of the RSM

The RSM is conceptualized as the longitudinal model. Media use at a certain time (t_1) influences attitudes, beliefs, and behaviors at a later time (t_2), representing the *media effect*. In turn, attitudes, beliefs, and behaviors serve as mediators influencing subsequent media use (t_3) representing the *selection effect* (Slater, 2007). Three dynamics can be distinguished.

Most prominently, Slater (2007) described a *positive feedback-loop* as a dynamic in which the mediation process is triggering a reciprocal, mutually reinforcing relationship between media effects and selection over time. During a positive feedback-loop, media and selection effects "grow out of control" (Slater, 2015, p. 373) leading to an increase in both individuals' media use and associated outcomes over time (Schemer et al., 2019). Positive feedback-loops appear only during limited times (Slater, 2015) triggered by specific events or salient issues that lead to selective exposure (Song & Boomgaarden, 2017).

If media and selection effects obtain individuals' media use and associated outcomes at relatively high (or low) levels, *maintenance* is achieved. During maintenance, mutual reinforcement between media effects and selection is ongoing but "will rarely lead to extremes of attitude or behavior" (Slater, 2007, p. 289), for example, due to ceiling effects. Instead, media use and associated outcomes remain stable over time.

If media and selection effects are weak or absent and adjust quickly to a stable level, individuals are in a state of *homeostasis* (Slater, 2007). During homeostasis, "selectivity of attitude- and identity-consistent content are likely to operate only to the extent necessary to maintain a reasonable level of comfort with respect to protecting identity-central attitudes and beliefs" (Slater, 2015, p. 375).

Interindividual and intraindividual effects in communication processes

Longitudinal theories and models like the RSM focus at least implicitly on two types of effects: developments *within* individuals (intraindividual effects) and differences *between* individuals (interindividual effects). *Intraindividual effects* refer to patterns of change within an individual (Curran & Willoughby, 2003). In the RSM context, such change represents, for example, a person-specific development in media use over time; for example, an individuals' increasing trajectory of reading political news over the period of adolescence due to a positive feedback-loop (Moeller, Shehata, & Kruikemeier, 2018). Intraindividual effects can be more complex when focusing on "how, when, and why the individual changes over time" (Nesselroade & Ram, 2004, p. 10). For example, an adolescent might not continuously increase the frequency of reading news articles over time, but deviate from their growing

trajectory at some points. Low interest in a current political topic could—compared with a usual day—lower the adolescents reading frequency. Analysis of such time-specific fluctuations from an individual baseline is referred to as analysis of *intraindividual variability* (Molenaar, 2004). In contrast, *interindividual* effects refer to differences between persons in intraindividual patterns of change (Bainter & Howard, 2016; Hoffman & Stawski, 2009). For example, individuals' development or baselines (as well as fluctuations from these baselines) in a specific outcome might be conditioned on person-specific characteristics like age. Older adolescents might show stable news reading frequencies over time (due to maintenance or homeostasis), while younger adolescents show growing frequencies (due to a positive feedback-loop); the dynamics differ *between* individuals.

For communication scholars, it is important to analyze both types of effects (Thomas, Otto, Ottenstein, & Maier, 2020). Often, however, theories have rather implicit assumptions about both types of effects, and substantive studies show a lack of discussion on disaggregating within- and between-person processes (Curran & Bauer, 2011). Therefore, misleading conclusions could be drawn if scholars estimate within-person effects, whereas the theoretical model actually proposes between-person relations (or vice versa) since both types of effects differ fundamentally. For instance, Baumgartner, van der Schuur, Lemmens, and te Poel (2018) investigated the reciprocal relationship between adolescents' media multitasking and attention problems in the RSM context by accurately separating within- and between-person effects. Although they found positive relations at the between-person level (adolescents with higher levels in media multitasking across time showed higher levels in attention problems across time), they did not find a reciprocal within-person relationship meaning that overall an adolescents' media multitasking did not affect their subsequent attention problems and vice versa.

Both effects are meaningful but show different processes. The within-person effects refer to time-specific media and selection effects modeling a (Granger) causal relationship between media use and effect, while the between-person effects refer to individuals' trends in media use and associated outcomes determining whether trends in both variables are correlated. Analytically, it is important to separate within- from between-person effects to be more precise about mechanisms and processes at each level. Mixing them up might confound central processes in the underlying theory. The separation of within- and between-person effects is, therefore, not only a methodological issue but also an issue that refers to the interpretation of the underlying processes in a theoretical model. Thus, if communication scholars are interested in the underlying processes of a longitudinal theory, both types of effects matter and need to be considered.

Disaggregating the RSM into intraindividual and interindividual components

Although the three dynamics of the RSM describe different patterns in the relationship between media use and associated outcomes, they share similar components

that can be interpreted as within- or between-person effects. In order to separate these effects, it is important to distinguish between long-term, trait-like *baselines* representing interindividual differences in intraindividual trends over time and short-term, state-like *fluctuations* from these baselines in media use and associated outcomes (e.g., Schemer, 2012). Slater (2007) mentioned both components when comparing homeostasis with a thermostat. During homeostasis, individuals do not change in their media use or associated outcomes over time; individuals' baselines are stable showing the same value at each point in time (flat trends, comparable to the setting of a thermostat representing the baseline temperature). However, small fluctuations might appear that adjust to individuals' baseline levels due to attitude-congruent media effects and selection (comparable to fluctuations in temperature quickly regulated to the thermostats baseline temperature).

Although individuals' underlying baselines show intraindividual developments in media use and associated outcomes over time, they are *statistically* defined as interindividual components (Baumgartner et al., 2018). The reason for this is that these baselines represent individuals' expected scores that continuously follow an underlying pattern at each point in time. Thus, patterns in individuals' baseline trends do not vary within but only between persons, for example, if an individual shows an increasing trend in its media use baseline (due to a positive feedback-loop), whereas another individual shows a stable baseline over time (due to homeostasis or maintenance). Therefore, individuals' baselines statistically represent time-unlinked, person-specific characteristics like biological sex (Bainter & Howard, 2016). Accordingly, we conceptualize individuals' baselines as between-person components (Figure 1, *a* and *b*).

Media and selection effects lead to fluctuations (or deviations) from individuals' continuous baselines (or expected scores) (Slater, 2007). If an individual seeks for attitude-congruent information (e.g., through social identity threats), their media use is higher compared with their baselines (selection effect, path *c*). In turn, fluctuations in media use affect individuals' subsequent attitudes leading to fluctuations from the underlying baseline (media effect, path *d*). If both effects are ongoing, a mutually reinforcing relationship establishes. As media and selection effects are processed and vary "within one and the same media user" (Schemer et al., 2019, p. 265), both effects can be perceived as intraindividual components (Scharkow & Bachl, 2019).

The RSM "suggest[s] that further insight can be gained by incorporating variables, such as individual differences and social influences as predictors of media use rather than as statistical controls" (Slater, 2015, p. 376). Such exogenous variables affect both individuals' baselines and corresponding fluctuations. For example, if a social-identity threat appears, individuals in a relatively closed system (e.g., due to a strong identification with a social group) might show stronger mutually reinforcing media and selection effects and growing baselines compared with individuals in an open system based on an absence of external regulatory pressure (Slater, 2007). Slater (2015) conceptualized exogenous variables like ones' social environment as
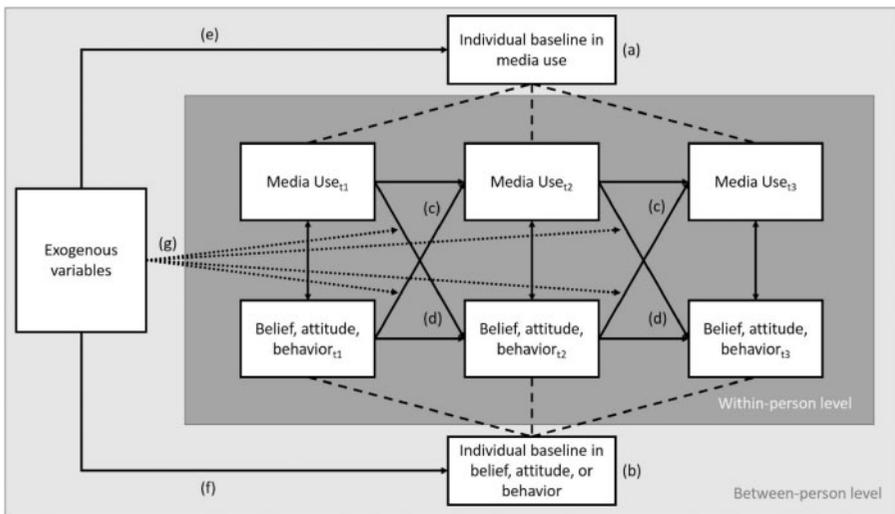
Figure 1 Within- and between-person components of the reinforcing spirals model.

person-specific characteristics representing between-person or *group-level* components that explain differences *between* individuals' personal baselines (paths *e* and *f*) but also condition the intraindividual mutual reinforcement process, that is, reciprocal media and selection effects (path *g*).

In sum, the RSM requires analysis of intraindividual variability to analyze reciprocal relations between fluctuations in media use and associated outcomes that are present during a positive feedback-loop and maintenance but absent during homeostasis (Figure 2). Moreover, modeling interindividual components is mandatory for the RSM to model interindividual differences in intraindividual continuous trends by means of individuals' baselines in both variables (that are stable over time for homeostasis and maintenance but increasing during a positive feedback-loop) and to model effects of exogenous, group-level variables that condition the reinforcement process at the within- and between-person level.

Statistical approaches to model the RSM

Recently, scholars applied six statistical models to analyze the dynamics of the RSM by following the traditions of *cross-lagged panel models* and *latent growth curve models* as recommended by Slater (2007). The (a) cross-lagged panel model (e.g., Hutchens et al., 2019), (b) the fixed effects dynamic panel model (e.g., Moeller et al., 2018), and (c) the random intercept cross-lagged panel model (e.g., Baumgartner et al., 2018) follow the former tradition. The (d) parallel latent growth curve model (e.g., Slater & Hayes, 2010), (e) the reduced autoregressive latent trajectory model (e.g., Schemer, 2012), and (f) the latent curve model with structured residuals (e.g., Thomas et al., 2020) follow the traditions of the latter one. Tables 1 and 2
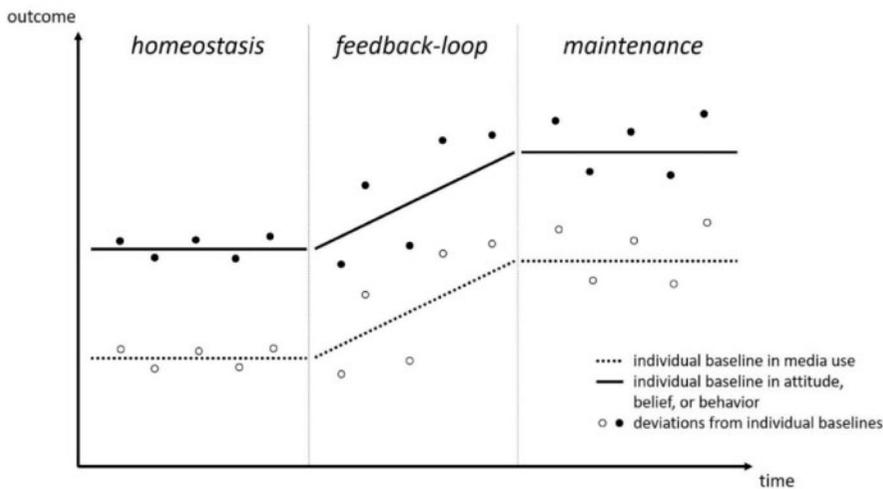
Figure 2 Dynamics of the reinforcing spirals model.

summarize the interpretations for all models and their ability to model and separate within- and between-person components.

The cross-lagged panel model (CLPM)

The simple idea of the CLPM is to model two outcomes (i.e., media use and associated outcomes) in a cross-lagged autoregressive pattern in order to analyze cause and effect (Figure 3A). The linear equations to estimate such a model can be written as follows:

$$y_{it} = \mu_{yt} + p_{yy}y_{i(t-1)} + p_{yz}z_{i(t-1)} + \nu_{y_{it}} \tag{1.1}$$

$$z_{it} = \mu_{zt} + p_{zz}z_{i(t-1)} + p_{zy}y_{i(t-1)} + \nu_{z_{it}} \tag{1.2}$$

where y_{it} and z_{it} represent outcome variables for individual i at occasion t and $\nu_{y_{it}}$ and $\nu_{z_{it}}$ describe random disturbances. The parameters μ_{yt} and μ_{zt} represent means for y and z that vary across time but not between individuals (Hamaker, Kuiper, & Grasman, 2015). The autoregressive effects p_{yy} and p_{zz} (y/z at time $t-1$ predict subsequent y/z) as well as the cross-lagged effects p_{yz} and p_{zy} (y at time $t-1$ predict subsequent z and vice versa) represent relations between deviations from these means (Usami et al., 2019), describing individuals' time-specific expected relative standings on y and z (Selig & Little, 2012).

In context of the RSM, the CLPM models relations between time-specific inter-individual deviations in media use and associated outcomes (Figure 1, paths c and d) and implements person-specific predictors of these relations (path g), for example, by running multigroup or moderation analyses. Yet, these deviations do not rely on *individuals'* time-invariant baselines representing trait-like trends (a and b) but on time-variant means across *all* individuals (μ_{yt} and μ_{zt}). As such, individuals'

Table 1 Composition, Interpretation, and Requirements of the Statistical Models

	CLPM	DPM	RI-CLPM	LCM	Reduced ALT	LCM-SR
Latent factors	–	Random intercept	Random intercept	Random intercept and random slope	Random intercept and random slope	Random intercept and random slope
Between-person components	–	Random intercept	Random intercept	Random intercept and random slope	Random intercept	Random intercept and random slope
Within-person components	–	Cross-lagged, autoregressive structure	Cross-lagged, autoregressive residual structure	–	Cross-lagged structure	Cross-lagged, autoregressive residual structure
Mixed components	Cross-lagged, autoregressive structure	–	–	–	Random slope	–
Interpretations of						
Intercepts (means in the CLPM)	Mean levels in y (and z) at occasion t	Latent variable capturing between-person variance for unobserved and unmeasured variables	Interindividual differences in time-variant means (/ means of the intercepts when means are constrained to equality	Estimated starting levels in individuals' y (and z) and interindividual differences between individuals'	Estimated starting levels in individuals' y (and z) and interindividual differences between individuals' starting	Estimated starting levels in individuals' y (and z) and interindividual differences between individuals'

		across time) for y (and z)	starting levels		levels conditioned on the within-person relations between y and z	starting levels
Slopes	–	–	Mean levels of individuals' growth rates in y (and z) and interindividual differences between individuals' growth rates	Mean levels of individuals' growth rates in y (and z) and interindividual differences between individuals' growth rates	Mean levels of individuals' growth rates in y (and z) and interindividual differences between individuals' growth rates conditioned on the within-person relations between y and z	Mean levels of individuals' growth rates in y (and z) and interindividual differences between individuals' growth rates
Cross-lagged effects	Individuals' rank order in y_t predicting individuals' rank order in z_{t+1}	Higher than usual levels in y_t are predicted by individuals' levels in z_{t-1}, where higher than	Higher than usual levels in y_t predict higher than usual levels in z_{t+1}, where higher than	–	Levels of y predict subsequent deviations from linearity in the growth trajectory for z	Higher than usual levels in y_t predict higher than usual levels in z_{t+1}, where higher than

Continued

Table 1 Continued

	CLPM	DPM	RI-CLPM	LCM	Reduced ALT	LCM-SR
		usual refers to individuals' means across time	usual refers to individuals' expected scores			usual refers to individuals' growth trajectories
Autoregressive effects	Equivalent to cross-lagged effects but within outcomes	Equivalent to cross-lagged effects but within outcomes	Equivalent to cross-lagged effects but within outcomes	–	–	Equivalent to cross-lagged effects but within outcomes
Minimum occasions	Two	Three	Three	Three	Three	Three

Note: This table is based on Bainter and Howard (2016) who used a LCM as a reference point when defining within-person and between-person components. Minimum occasions refer to the minimum measurement occasions needed in order to identify the model; they might differ depending on (non-)stationary assumptions and model constraints (Usami et al., 2019). All models require evenly spaced time intervals between repeated measures and across individuals.
CLPM = cross-lagged panel model; DPM = dynamic panel model; LCM = parallel latent growth curve model; LCM-SR = latent curve model with structured residuals; reduced ALT = reduced autoregressive latent trajectory model; RI-CLPM = random intercept cross-lagged panel model.

Table 2 Modeling Relevant Components of the Reinforcing Spirals Model Across Approaches

	CLPM	DPM	RI-CLPM	LCM	Reduced ALT	LCM-SR
Explicitly models individuals' baselines? (letters *a* and *b*)	No	No	Yes	Yes	Yes[b]	Yes
Models pure within-person media and selection effects? (paths *c* and *d*)	No	Yes[a]	Yes	No	Yes	Yes
Models within-person media and selection effects between deviations from individuals' baselines?	No	Yes	Yes	No	No	Yes
Conditions reciprocal media and selection effects on exogenous variables? (path *g*)	Yes	Yes[a]	Yes	No	Yes	Yes
Models effects from exogenous variables on individuals' baselines? (paths *e* and *f*)	No	Yes	Yes	Yes	Yes[b]	Yes

Note: [a]Only for one cross-lagged effect at a time. [b]Intertwined with cross-lagged effects. CLPM = cross-lagged panel model; DPM = dynamic panel model; LCM = parallel latent growth curve model; LCM-SR = latent curve model with structured residuals; reduced ALT = reduced autoregressive latent trajectory model; RI-CLPM = random intercept cross-lagged panel model; .

time-invariant baselines as well as predictors for such trends (paths *e* and *f*) cannot be estimated and media as well as selection effects do not describe pure within-person processes. Instead, the CLPM estimates temporal rank order stability (autoregressive effect) and relations (cross-lagged effect) across waves describing within-person changes in between-person differences, not clearly separating both types of effects (Berry & Willoughby, 2017); failing to capture RSM dynamics (Schemer et al., 2019).

The fixed effects dynamic panel model (DPM)

One extension of the CLPM is the DPM (Allison, 2009; Allison, Williams, & Moral-Benito, 2017). The idea of the DPM is to estimate pure autoregressive and cross-lagged within-person effects while controlling for unobserved interindividual heterogeneity. The DPM is estimated with two separate models with the following equation:

$$y_{\text{it}} = \mu_{\text{yt}} + I_{\text{yi}} + p_{\text{yy}} y_{i(t-1)} + p_{\text{yz}} z_{i(t-1)} + \nu_{y_{\text{it}}} \tag{2}$$
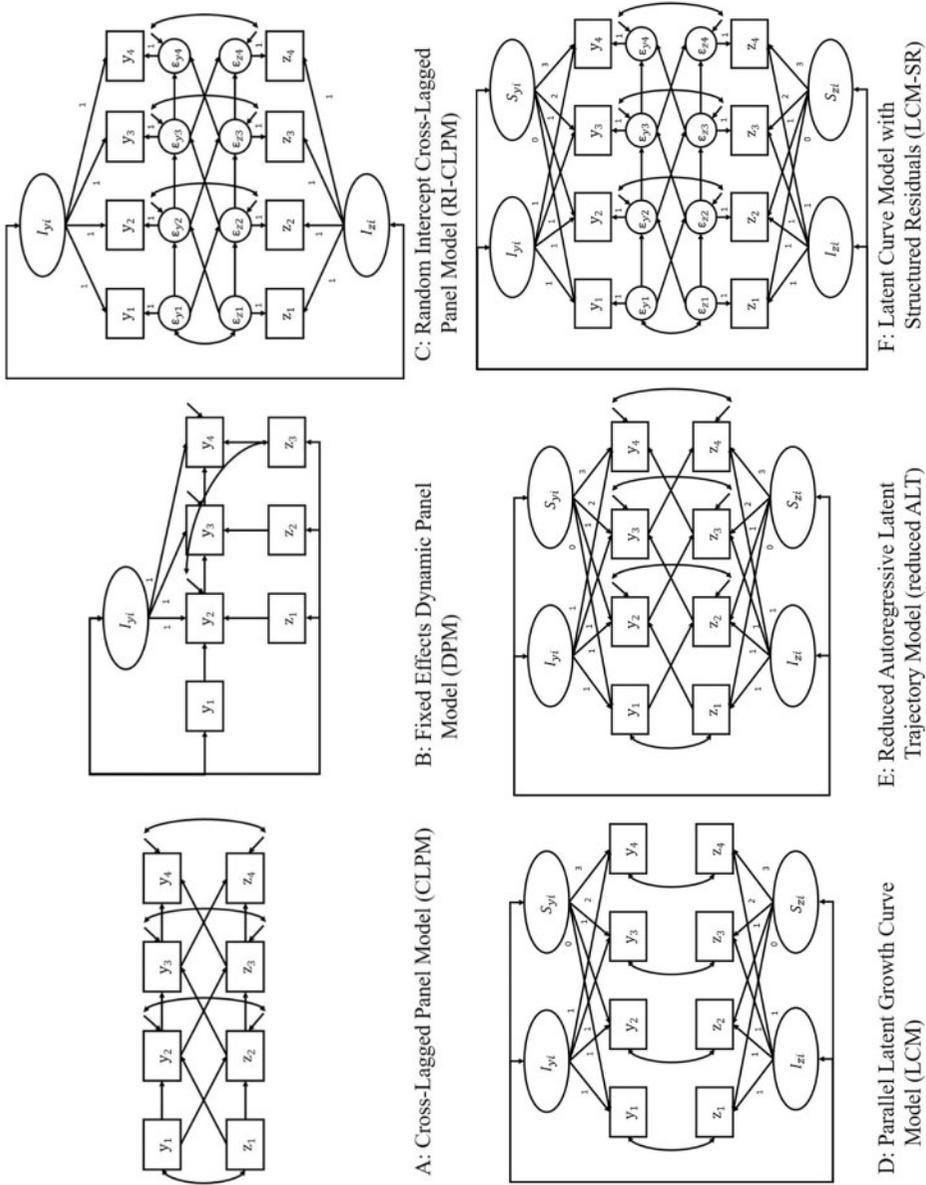
for outcome *y* and equation

Figure 3 Statistical approaches to model the reinforcing spirals model for four repeated measures.

$$z_{it} = \mu_{zt} + I_{zi} + p_{zz}z_{i(t-1)} + p_{zy}y_{i(t-1)} + v_{z_{it}} \tag{3}$$

for outcome z, where I_{yi} and I_{zi} represent random intercepts that have means of zero, vary between individuals, and have factor loadings constrained to 1 starting with the second occasion since the first measure is treated as an exogenous predictor (Figure 3B). The random intercept represents interindividual mean differences and is treated as a set of unobserved time-invariant variables that have constant effects on y (or z) (Allison et al., 2017). When correlating the intercept with the independent time-variant variable, only within-person variation is left leading to unbiased autoregressive and cross-lagged effects (Bollen & Brand, 2010).

Therefore, the DPM models intraindividual variability: Autoregressive and cross-lagged relations rely on individuals' time-specific deviations from their personal means in media use (or associated outcomes) over time (Figure 1, paths c and d). Thus, media and selection effects are modeled as processes within the same media user. Further, the DPM accounts for individuals' trends in one outcome each (a and b) and models effects of exogenous variables on these baselines (paths e and f), but does not explicitly model the specific (static or growth) form of these trends (Hamaker & Muthén, 2020). Thus, it is impossible to determine unbiased stable or growing, potentially correlated baselines to test for the dynamics of the RSM. Because of two separated models, conditions for the mutual reinforcement process (path g) need to be estimated for media and selection effects separately. Mediation processes cannot be tested.

The random intercept cross-lagged panel model (RI-CLPM)

Another extension of the CLPM is the RI-CLPM (Hamaker et al., 2015). The basic idea of the RI-CLPM is to fully separate state-like, within-person from trait-like, between-person components. The RI-CLPM can be written as follows:

$$y_{it} = \mu_{yt} + I_{yi} + p_{yy}\varepsilon_{yi(t-1)} + p_{yz}\varepsilon_{zi(t-1)} + v_{y_{it}} \tag{4.1}$$
$$z_{it} = \mu_{zt} + I_{zi} + p_{zz}\varepsilon_{zi(t-1)} + p_{zy}\varepsilon_{yi(t-1)} + v_{z_{it}} \tag{4.2}$$

where I_{yi} and I_{zi} are the latent random intercepts with means of zero and factor loadings constrained to 1 (Figure 3C). The autoregressive and cross-lagged effects are explicitly modeled between the residuals ($\varepsilon_{y_{it}}$ and $\varepsilon_{z_{it}}$).

In the RI-CLPM, latent intercepts represent individuals' time-invariant deviations from the time-variant means μ_{yt} and μ_{zt}. Together, they form individuals' expected scores in y and z that account for trends over time (Usami et al., 2019), while the RI-CLPM does not explicitly assume specific (e.g., stable or growing) trends. However, when constraining the time-variant means to equality over time and estimating means for the random intercepts, the RI-CLPM explicitly models individuals' *stable* mean levels across time (Hamaker et al., 2015). For both the constrained and the unconstrained RI-CLPM, the residuals represent time-specific

deviation from individuals' trait-like trends in y and z that predict subsequent deviations in individuals' trends in z and y accounting for intraindividual variability.

In the RSM context, latent intercepts in the constrained RI-CLPM represent mean levels of individuals' stable baselines and corresponding interindividual differences for media use and associated outcomes across time (Figure 1, a and b) according to homeostasis and maintenance. The residuals—ordered in an autoregressive, cross-lagged structure—represent deviations from these stable personal baselines allowing to model intraindividual media and selection effects (paths c and d). Exogenous variables can be modeled as predictors for both individuals' baselines (paths e and f) and intraindividual media and selection effects (path g).

The parallel latent growth curve model (LCM)

The LCM is a statistical approach that explicitly models individuals' trajectories over time to observe a (non)linear development (Bollen & Curran, 2006). In its simplest form, the LCM estimates two latent growth factors a random intercept (I) and a random slope (S) for y and z, respectively (Figure 3D). This LCM can be written as follows:

$$y_{it} = I_{yi} + S_{yi} + \varepsilon_{y_{it}} \tag{5.1}$$
$$z_{it} = I_{zi} + S_{zi} + \varepsilon_{z_{it}} \tag{5.2}$$

where I_{yi}, S_{yi}, I_{zi}, and S_{zi} are in each case composed of an overall mean and interindividual deviations from that mean. Factor loadings are constrained to 1 for the random intercepts and to a function of time for the random slopes. The random intercepts represent mean levels of the initial starting point in individuals' growth trajectories for y as well as z and corresponding interindividual differences. The random slopes represent mean levels of the growth rates in individuals' growth trajectories for both outcomes and corresponding interindividual differences. The slopes are trait-like between-person components representing individuals' baselines in y and z (Bainter & Howard, 2016). The LCM, however, does not structure time-specific deviations from these slopes ($\varepsilon_{y_{it}}$ and $\varepsilon_{z_{it}}$) in an autoregressive, cross-lagged pattern.

With regards to the RSM, the LCM allows for linearly growing trends in individuals' baselines in media use and associated outcomes (Figure 1, a and b) potentially catching a positive feedback-loop, while individuals might still differ in their individual baselines (e.g., through decreasing, increasing, or stable trajectories over time). The LCM ignores reciprocal media and selection effects, mediation processes (paths c and d), and exogenous variables conditioning intraindividual effects (path g). However, the LCM can model effects of exogenous variables on individuals' trajectories at the between-person level (paths e and f) and covariance between the slopes testing for parallel growth processes (Slater & Hayes, 2010).

The reduced autoregressive latent trajectory model (reduced ALT)

In the RSM context, scholars extended the LCM with cross-lagged effects (Moeller & de Vreese, 2019; Schemer, 2012). This model can be seen as a reduced version of the ALT (Bollen & Curran, 2004). The idea is to implement time-specific relations to the LCM in order to test whether the covariance between the latent slopes is conditioned on an intraindividual reinforcement process. The reduced ALT can be written as follows:

$$y_{it} = I_{yi} + S_{yi} + p_{yz}z_{i(t-1)} + v_{y_{it}} \tag{6.1}$$
$$z_{it} = I_{zi} + S_{zi} + p_{zy}y_{i(t-1)} + v_{z_{it}} \tag{6.2}$$

with cross-lagged effects (p_{yz} and p_{zy}) modeled between manifest variables and latent growth factors (I_{yi}, S_{yi}, I_{zi}, and S_{zi}) modeled like in the LCM (Figure 3E). The interpretation of the growth factors, however, differs fundamentally. Cross-lagged effects and latent slopes are intertwined; both are modeled between manifest variables and thus define the trajectories for y and z (Usami et al., 2019). The reduced ALT estimates conditional random intercepts and slopes controlling for within-person cross-lagged effects (Bainter & Howard, 2016), which results in nonlinear growth curves that cannot be interpreted like in the LCM (Jongerling & Hamaker, 2011). Cross-lagged effects show how y predicts subsequent z after controlling for the underlying growth processes (Curran & Bollen, 2001).

Therefore, the reduced ALT accounts for intraindividual variability but does not fully disaggregate within- and between-person components. In the RSM context, the reduced ALT predicts deviations from aggregate-level (rather than *individuals'*) baselines in media use and associated outcomes (Figure 1, *a* and *b*) testing for time-specific nonlinearity in these baselines (paths *c* and *d*) (Bainter & Howard, 2016). Exogenous variables predict *conditional* slopes at the between-person level (paths *e* and *f*) and condition media as well as selection effects at the within-person level (path *g*).

The latent curve model with structured residuals (LCM-SR)

Another extension of the LCM is the LCM-SR (Curran, Howard, Bainter, Lane, & McGinley, 2014). The idea of the LCM-SR is to model a parallel growth process with an autoregressive, cross-lagged residual structure while fully separating within- from between-person components simultaneously. The linear equation for the LCM-SR is as follows:

$$y_{it} = I_{yi} + S_{yi} + p_{yy}\varepsilon_{yi(t-1)} + p_{yz}\varepsilon_{zi(t-1)} + v_{y_{it}} \tag{7.1}$$
$$z_{it} = I_{zi} + S_{zi} + p_{zz}\varepsilon_{zi(t-1)} + p_{zy}\varepsilon_{yi(t-1)} + v_{z_{it}} \tag{7.2}$$

where the latent growth factors (I_{yi}, S_{yi}, I_{zi}, and S_{zi}) are modeled like in the LCM. Autoregressive and cross-lagged effects are explicitly modeled between the residuals ($\varepsilon_{y_{it}}$ and $\varepsilon_{z_{it}}$) similar to the RI-CLPM (Figure 3F). Like in the LCM, random intercepts and slopes are mean levels in individuals' estimated starting values and growth rates for individuals' growth trajectories that vary between individuals. Individuals'

growth trajectories represent a trait-like baseline, whereas the residuals represent time-specific deviations from individuals' growth trajectories predicting time-specific deviations from individuals' trajectories at a subsequent time (Bainter & Howard, 2016).

In the RSM context, the random slopes allow for linearly growing trends in individuals' baselines according to a positive feedback-loop (Figure 1, *a* and *b*). Individuals' deviations from these baselines and reciprocal relations between them (paths *c* and *d*) are captured in the residual structure representing intraindividual variability in media selection and effects. The influence of exogenous variables can be tested on both the between-person level (paths *e* and *f*) by regressing the latent growth factor on exogenous predictors and the within-person level by modeling heterogeneity across groups when conditioning the intraindividual mutual reinforcement process on exogenous variables (path *g*) (Curran et al., 2014).

Summary

Models that consider intraindividual variability *and* fully separate within- and between-person components are the DPM, the RI-CLPM, and the LCM-SR. These approaches are similar and lead—under specific conditions—to equivalent estimates (Hamaker & Muthén, 2020). The DPM, however, does not explicitly model the form of individuals' baseline trends making it impossible to determine whether a positive feedback-loop or maintenance is present, while the constrained RI-CLPM explicitly models stable baselines (testing for homeostasis and maintenance) and the LCM-SR explicitly models linear trajectories allowing for parallel growing baselines (as predicted for a positive feedback-loop).

Empirical comparison of the statistical models

As the six models capture quite different relations between media use and associated outcomes, the choice of a particular model might fundamentally affect (or restrict) conclusions that can be drawn for the RSM. In an empirical comparison, we show how the parameter estimates of the models differ and how the models fit to the empirical data at hand. As a theoretical basis, we rely on the reinforcing spiral between political interest and news consumption since recent studies showed the theoretical relevance and empirical evidence for a reciprocal relationship between both outcomes (Kruikemeier & Shehata, 2017; Moeller et al., 2018, Strömbäck & Shehata, 2010, 2019). To do so, we used a six-wave panel study conducted in Sweden from 2010 to 2015.[1] Respondents' first participation in the panel was at the age of 13/14 participating with a time interval of approximately 1 year between each measurement. Therefore, the dataset captures respondents' development during adolescence. During this period, positive feedback-loops are likely to occur "since personal and social identities are still in formation" (Slater, 2015, p. 380). Therefore, we assume to find both growth in individuals' baselines on average (between-person level) and an

Table 3 Means, Standard Deviations, Cronbach's α, and *N*s for Political Interest and News Consumption

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6
Political interest						
M	4.50	4.66	4.64	5.26	5.63	6.16
SD	2.32	2.49	2.46	2.47	2.44	2.40
α	0.62	0.73	0.79	0.81	0.81	0.82
Total news use						
M	3.87	4.13	3.92	3.94	4.01	4.27
SD	2.12	2.10	2.21	2.09	1.98	2.03
α	0.69	0.70	0.75	0.71	0.70	0.72
N (minimum)	900	861	820	707	682	659

intraindividual mutual reinforcement process. Moeller et al. (2018, for more details on the data) already showed reinforcing spirals between political interest and online media use by using exactly the same dataset. In contrast to this study and in line with Kruikemeier and Shehata (2017), we, however, rely on the relationship between political interest and total news use.

Measures
We rely on the same scales used by Moeller et al. (2018). Accordingly, adolescents' political interest was measured with two items ("how interested are you in politics?" and "how interested are you in what is happening in society?") and total news use with four items asking for the frequency of adolescents' daily newspaper, radio, television, and Internet news use. All items were measured on a scale ranging from 1 (not at all interested/at least 5 days a week) to 5 (very interested/never; reversed for total news use). The mean scores for political interest and total news use were recoded to a scale ranging from 0 to 10 (Table 3).

Model constraints
We constrained each autoregressive, cross-lagged, and contemporaneous effects to equality over time for comparing the estimates properly. Accordingly, we were not able to estimate indirect effects to test for mediation as described by Slater (2007). However, by relaxing these constraints, all models can potentially test for intraindividual mediation except the DPM and the LCM. For simplicity, we did not model exogenous variables but focused on the between-person components *a* and *b* as well as the within-person components *c* and *d* (Figure 1). The DPM was modeled with two separated models. For the RI-CLPM, we constrained the means to equality over time and estimated means for the latent intercepts assuming homeostasis or maintenance. All models were calculated with the *R* package *lavaan* version 0.6-5

(Rosseel, 2012). For the DPMs, we used the *xtdpdml* command in *Stata* version 16 (Williams et al., 2018). *Lavaan* code for the models is shared in the online supplementary material (see also the OSF-link in the "ReadMe"-file).

Results

Table 4 shows the results for all approaches. The models that explicitly allowed for linearly increasing trends in individuals' baselines for total news use and political interest (LCM, reduced ALT, and LCM-SR) or accounted for such trends (DPMs) showed good or acceptable fit indices. In contrast, models that did not model individual trends (CLPM) or modeled stable individual baselines over time assuming homeostasis or maintenance (RI-CLPM) showed rather weak fits (see root mean square error of approximation, comparative fit index, and Tucker–Lewis index). A reason for this might be the underlying parallel growth process for both outcomes in individuals' baselines indicated by the growth rates of the unconditional linear slopes of the LCM and the LCM-SR (see means of slopes correlated for the LCM, see covariance between slopes). In line with our theoretical assumptions, thus, political interest and news consumption increased during adolescence.

When looking at cross-lagged effects, we found reciprocal rank order relations (CLPM), an intraindividual mutual reinforcement process (DPMs), predictions of nonlinearity in total news use trajectories (reduced ALT), and intraindividual selection effects relying on stable (RI-CLPM) and growing (LCM-SR) individual baselines in total news use and political interest. These findings show that the choice of different models would result in quite different conclusions with respect to the effects postulated in the RSM. Following interpretations of RSM-related studies, the CLPM (based on mixed cross-lagged effects), the DPMs (based on intraindividual cross-lagged effects), and the LCM (based on correlated slopes, interindividual level) indicated positive feedback-loops, while the RI-CLPM, the reduced ALT, and the LCM-SR (based on intraindividual cross-lagged effects) showed selection effects only. Further, the RI-CLPM (intercepts) and the reduced ALT (slopes) showed significant correlations between the underlying baselines (interindividual level).

According to our conceptualization of the dynamics of the RSM, we rely on the constrained RI-CLPM and the LCM-SR because both approaches *explicitly* model and fully separate within- and between-person components providing proper interpretations of effects. Given that the LCM-SR showed a good fit to the data capturing linear trends in individuals' baselines and the constrained RI-CLPM showed a weak fit when estimating individuals' stable baselines over time, we conclude that the process captured by the data is a parallel growth process. In contrast to our theoretical assumptions, however, this process was based on intraindividual selection effects only and does not represent an ideal positive feedback-loop.

Table 4 Results of the Empirical Model Comparison

	CLPM	DPM	RI-CLPM	LCM	Reduced ALT	LCM-SR
Effects on PI						
Autoregressive	0.62 (0.01)***	0.28 (0.03)***	0.57 (0.03)***	–	–	0.28 (0.04)***
Cross-lagged	0.10 (0.02)***	0.10 (0.04)**	0.02 (0.03)	–	−0.01 (0.02)	0.06 (0.03)
Effects on NU						
Autoregressive	0.59 (0.01)***	0.25 (0.03)***	0.26 (0.03)***	–	–	0.17 (0.03)***
Cross-lagged	0.08 (0.01)*	0.09 (0.03)**	0.08 (0.02)***	–	0.04 (.01)**	0.07 (0.03)**
Contemporaneous Effects						
Covariance at time *t*	0.82 (0.05)***	–	0.71 (0.06)***	0.46 (0.04)***	0.42 (0.04)***	0.61 (0.07)***
Slope (PI)						
Mean	–	–	–	0.32 (0.02)***	0.33 (0.02)***	0.33 (0.02)***
Variance	–	–	–	0.16 (0.02)***	0.12 (0.02)***	0.07 (0.03)*
Intercept (PI)						
Mean	–	–	5.08 (0.06)***	4.33 (0.07)***	4.35 (0.08)***	4.34 (0.07)***
Variance	–	–	1.25 (0.29)***	3.42 (0.24)***	2.86 (0.25)***	2.04 (0.37)***
Slope (NU)						
Mean	–	–	–	0.04 (0.02)*	0.01 (0.02)	0.05 (0.02)**
Variance	–	–	–	0.10 (0.01)***	0.08 (0.01)***	0.06 (0.02)***
Intercept (NU)						
Mean	–	–	4.02 (0.05)***	3.93 (0.06)***	3.84 (0.07)***	3.92 (0.06)***
Variance	–	–	1.98 (0.14)***	2.92 (0.19)***	2.59 (0.20)***	2.37 (0.24)***
Covariance growth factors						
Intercept–intercept	–	–	1.13 (0.15)***	2.02 (0.17)***	1.87 (0.18)***	1.44 (0.23)***
Slope–slope	–	–	–	0.06 (0.01)***	0.05 (0.01)***	0.01 (0.02)
Fit indices						
RMSEA	0.076	0.015/0.030	0.082	0.060	0.051	0.047

Continued

Table 4 Continued

	CLPM	DPM	RI-CLPM	LCM	Reduced ALT	LCM-SR
CFI	0.919	0.998/0.991	0.896	0.948	0.965	0.970
TLI	0.911	0.996/0.983	0.897	0.945	0.961	0.966
χ^2 (*df*)	420.36 (60), $p < .001$	25.80 (21), $p = .214/40.36$ (21), $p = .007$	531.70 (67), $p < .001$	296.72 (63), $p < .001$	212.28 (58), $p < .001$	190.85 (58), $p < .001$
N	1,029	1,028/1,029	1,029	1,029	1,029	1,029

Note: DPMs were calculated in separate models with dependent variables PI/NU. Values in parentheses represent standard errors.
Covariance between intercepts and slopes is modeled but not depicted.
CFI = comparative fit index; CLPM = cross-lagged panel model; DPM = dynamic panel model; LCM = parallel latent growth curve model; LCM-SR = latent curve model with structured residuals; NU = total new use; PI = political interest; reduced ALT = reduced autoregressive latent trajectory model; RI-CLPM = random intercept cross-lagged panel model; RMSEA = root mean square error of approximation; TLI = Tucker–Lewis index.
***$p < .001$,
**$p < .01$,
*$p < .05$.

Comparing the models in ideal scenarios using Monte Carlo simulations

Although the empirical model comparison showed that the statistical models lead to quite different conclusions, we do not know how the approaches react in the presence of the three dynamics of the RSM. In fact, we still do not know whether a positive feedback-loop was present for our empirical data. Therefore, we compare the models by simulating three scenarios representing homeostasis, a positive feedback-loop, and maintenance. The benefit of such simulations is that we know the exact parameter values of each scenario and thus are able to figure out in how far the estimates of the models deviate from the true values in the data (e.g., Hamaker et al., 2015 for a similar procedure). As a population-generating model creating artificial data, we used the LCM-SR, which is the only model that clearly separates and models within- and between-person effects and additionally models random slopes representing individuals' trajectories. We varied the within- and between-person parameter values of the LCM-SR as described below to create artificial bivariate data with six repeated measures for each scenario. After that, we used the data generated with the LCM-SR to estimate all statistical models for each scenario. Applying Monte Carlo simulations, we generated 1,000 replications for each model per scenario to get stable estimates using a sample size of $N = 1,000$, similar to our empirical example.

For all scenarios, we set the parameter values for the variances of the intercepts to 2 (indicating interindividual differences for starting levels/baselines across time) and the covariance between the intercepts to 0.4 (indicating correlated starting levels/baselines across time). The residual variance was set to 1 (indicating interindividual differences in individuals' deviations from their baselines) and the autoregressive effects to 0.2 or 0.25 depending on the outcome (assuming some within-person stability). For the homeostasis and maintenance scenario, we set the means and variances of the slopes to zero and did the same for all covariance involving slopes indicating flat trajectories, that is, no change in both outcomes over time for both scenarios. In contrast, we modeled positive growth rates on average, interindividual differences in individuals' growth rates (slope variance), and correlated slopes in the positive feedback-loop scenario (Table 5 for all parameter values). Covariance between the residuals at the same time and cross-lagged effects were set to the same values for the positive feedback-loop and the maintenance scenario and to larger values compared with the homeostasis scenario (modeled with cross-lagged effects close to zero) representing intraindividual reinforcement between media use and associated attitudes for the former two scenarios only. In general, the autoregressive effects were larger than the cross-lagged effects and the means of the intercepts increased across scenarios. Overall, the parameter values are roughly oriented on the values of our empirical example but adjusted to simulate ideal scenarios reflecting the theoretical assumptions of the RSM as pointed out above.

We used *Mplus 7.3* (Muthén & Muthén, 1998 − 2015) to run Monte Carlo simulations (*Mplus* outputs including code for generating and analyzing the data are

Table 5 Parameter Values for Within- and Between-Person Effects Across Scenarios

Scenario	Homeostasis		Positive feedback-loop		Maintenance	
	y	*z*	*Y*	*Z*	*y*	*z*
Between-person effects						
Intercept mean	3.5	2.5	4	3	4.5	3.5
Intercept variance	2	2	2	2	2	2
Slope mean	0	0	0.8	0.9	0	0
Slope variance	0	0	0.1	0.1	0	0
Covariances						
Intercept$_z$_intercept$_y$	0.4		0.4		0.4	
Slope$_z$_slope$_y$	0		0.05		0	
Intercept$_z$_slope$_z$	0		0.1		0	
Intercept$_y$_slope$_y$	0		0.1		0	
Intercept$_z$_slope$_y$	0		0.2		0	
Intercept$_y$_slope$_z$	0		0.2		0	
Within-person effects						
Cross-lagged effects on *y*/*z*	0.015	0.01	0.15	0.1	0.15	0.1
Autoregressive effects on *y*/*z*	0.2	0.25	0.2	0.25	0.2	0.25
Residual variance	1	1	1	1	1	1
Residual covariance at time *t*	0.03		0.3		0.3	

shared in the online supplementary material). The analysis models were modeled with the same constraints reported in the empirical model comparison. However, due to slope variances set to zero in the data, many replications showed estimation problems for the reduced ALT (308/980) and the LCM-SR (865/865) in the homeostasis/maintenance scenarios. When setting slope variance for both outcomes slightly above zero (0.025) in the analysis models, the LCM-SR (0/4) showed only small estimation issues whereas the reduced ALT (0/422) showed problems in the maintenance scenario. Thus, we set the slope variance of the reduced ALT in this scenario to 0.05 leading to 20 replications with estimation problems. Overall, these estimation problems might be a result of overspecified models.

Results

We focus on the aforementioned indicators to determine reinforcing spirals: cross-lagged effects and covariance between the slopes. The estimates and standard errors presented in Table 6 are average values across the 1,000 replications and the "% Sig."-column represents the proportion of replications for which the effects significantly differ from zero at the 0.05 level.

Based on cross-lagged effects, the RI-CLPM, the DPMs, the reduced ALT, and the population-generating LCM-SR estimated values that showed no or small deviations from the true parameter values in the homeostasis scenario. These models did

Table 6 Average Effects and Covariance for all Statistical Models Across Replications

	CLPM			DPM			RI-CLPM		
	Est.	S.E.	% Sig.	Est.	S.E.	% Sig.	Est.	S.E.	% Sig.
Homeostasis									
Cross-lagged effect on y	0.04	(0.01)	**0.97**	0.02	(0.03)	**0.10**	0.02	(0.02)	**0.15**
Cross-lagged effect on z	0.03	(0.01)	**0.93**	0.01	(0.03)	**0.06**	0.01	(0.02)	**0.09**
Covariance slope$_y$-slope$_z$	-			-			-		
Positive Feedback-loop									
Cross-lagged effect on y	0.12	(0.01)	**1**	0.21	(0.04)	**1**	0.48	(0.02)	**1**
Cross-lagged effect on z	0.11	(0.01)	**1**	0.16	(0.04)	**0.99**	0.41	(0.02)	**1**
Covariance slope$_y$-slope$_z$	-			-			-		
Maintenance									
Cross-lagged effect on y	0.02	(0.01)	**0.67**	0.15	(0.03)	**1**	0.15	(0.02)	**1**
Cross-lagged effect on z	0.01	(0.01)	**0.10**	0.10	(0.03)	**0.91**	0.10	(0.02)	**1**
Covariance slope$_y$-slope$_z$	-			-			-		

	LCM			Reduced ALT			LCM-SR (pop. model)		
	Est.	s.e.	% Sig.	Est.	s.e.	% Sig.	Est.	s.e.	% Sig.
Homeostasis									
Cross-lagged effect on y	–	–	–	0.00	(0.01)	**0.09**	0.01	(0.02)	**0.10**
Cross-lagged effect on z	–	–	–	0.00	(0.01)	**0.06**	0.01	(0.02)	**0.07**
Covariance slope$_y$-slope$_z$	0.00	(0.00)	**0.13**	0.00	(0.00)	**0.14**	0.00	(0.00)	**0.10**
Positive Feedback-loop									
Cross-lagged effect on y	–	–	–	0.07	(0.01)	**1**	0.15	(0.02)	**1**
Cross-lagged effect on z	–	–	–	0.04	(0.01)	**0.94**	0.10	(0.02)	**1**
Covariance slope$_y$-slope$_z$	0.07	(0.01)	**1**	0.05	(0.01)	**1**	0.05	(0.01)	**1**
Maintenance									
Cross-lagged effect on y	–	–	–	0.03	(0.01)	**0.86**	0.13	(0.02)	**1**
Cross-lagged effect on z	–	–	–	0.02	(0.01)	**0.48**	0.08	(0.02)	**0.98**
Covariance slope$_y$-slope$_z$	0.02	(0.00)	**1**	0.04	(0.00)	**1**	0.02	(0.00)	**1**

Note: Values represent average values across replications. DPMs were calculated in separate models.
% Sig. = Proportion of replications for which the estimate significantly differs from zero at the .05-level; CLPM = cross-lagged panel model; DPM = dynamic panel model; Est. = Estimate; LCM = parallel latent growth curve model; LCM-SR = latent curve model with structured residuals; pop. model = population-generating model; reduced ALT = reduced autoregressive latent trajectory model; RI-CLPM = random intercept cross-lagged panel model; S.E. = standard error.

not indicate a reciprocal relationship between both outcomes for most replications, which is in line with the true parameter values of the generated data. For example, the RI-CLPM estimated in only 15% of the replications a cross-lagged effect from z on y that significantly differs from zero. In contrast, the CLPM overestimated the cross-lagged effects and showed in 97% of the replications a cross-lagged effect from z on y even though this effect was absent in the data. In the positive feedback-loop

scenario, all models estimated cross-lagged effects that significantly differ from zero in most of the replications and thus are able to detect the reciprocal relationship between y and z. The RI-CLPM and the DPM, however, overestimated the true parameter values, while the CLPM and the reduced ALT underestimated the cross-lagged effects. In the maintenance scenario, the RI-CLPM, the DPM, and the population-generating LCM-SR estimated values close to the true parameter values. In contrast, the CLPM and the reduced ALT underestimated the cross-lagged effects. The CLPM showed in only 10% and the reduced ALT in only 48% of the replications a significant effect from y on z although the effect was present in the data.

The covariance between the slopes showed similar results for the LCM, the reduced ALT, and the population-generating LCM-SR. The models captured the true parameter in the homeostasis scenario and showed only small deviations for the LCM in the positive feedback-loop scenario. In the maintenance scenario, however, all models estimated for all replications a covariance that significantly differed from zero although the true parameter was zero. In line with maintenance, the means of the slopes indicated—on average—flat trajectories for all models, not significantly differing from zero in most replications (see *Mplus* outputs).

To conclude, if a positive feedback-loop is present in the data, all approaches that model reciprocal effects are able to detect them, albeit the precision of estimation differed across the models. However, if another dynamic is present, model choice might lead to wrong conclusions. Particularly, the CLPM might lead to wrong conclusions in both the homeostasis and the maintenance scenario while the reduced ALT might lead to wrong conclusions in the maintenance scenario when looking at cross-lagged effects if data contain within- and between-person processes according to the LCM-SR. In contrast, the RI-CLPM and the DPM showed almost unbiased estimates in the homeostasis and the maintenance scenario. Unsurprisingly, this was true for the population-generating LCM-SR as well, in all scenarios albeit this model might produce estimation problems due to overparameterization when there actually was zero slope variance in the population. When looking at the covariance between the latent slopes, misleading conclusions could be drawn in the maintenance scenario (this might be affected by the fixed slope variance of the reduced ALT and the LCM-SR; however, the LCM showed similar results with freely estimated slope variance).

Discussion

The RSM has gathered increasing scholarly interest during the last decade. However, methodological decisions to analyze the RSM were rather implicit and it was unclear in how far recently used statistical approaches captured the dynamics of the RSM. Therefore, the aim of the current article was to emphasize the importance of disentangling within- and between-person effects and to compare six statistical approaches in order to show their (dis)advantages when investigating the RSM and its core dynamics, that is, homeostasis, positive feedback-loops, and maintenance.

By using empirical data to compare the six statistical approaches, we demonstrated that whether a reinforcing spiral is statistically observed highly depends on the applied modeling approach and corresponding interpretations of effects. Moreover, Monte Carlo simulations showed that some statistical approaches might lead to biased results for specific RSM dynamics if data contain both within- and between-person processes. This was particularly true for the often-used CLPM that indicated, for example, reciprocal media and selection effects although such patterns were absent at the within-person level.

Recommendations

Although the six models have both advantages and disadvantages, some approaches are more powerful in identifying underlying RSM processes. Further, every empirical application is unique and might require even more specialized models to explain patterns in the data. Having said that, we recommend models that fully separate and explicitly model within- and between-person effects and simultaneously allow for the inclusion of exogenous variables (i.e., person-specific and contextual factors). Moreover, approaches that model state-like deviations from individuals' trait-like baselines accurately model the processes of homeostasis, positive feedback-loops, and maintenance. If within- and between-person effects are confounded, it is impossible to draw conclusion about reinforcing spiral processes.

Consequently, the RI-CLPM and the LCM-SR are probably the most adequate tools to investigate reinforcing spirals since they disaggregate within- from between-person effects, *explicitly* model individuals' trait-like baselines, and analyze the RSM at both the intraindividual and interindividual level. When constraining the means of the RI-CLPM to equality over time—which is necessary to determine the processes of homeostasis and maintenance—the RI-CLPM is basically equivalent to the LCM-SR without a latent slope. Accordingly, the constrained RI-CLPM is nested under the LCM-SR (Usami et al., 2019). This is beneficial since researchers could implement a formal test of improvement in model fit. Then, scholars could start with a RI-CLPM and empirically test whether the additional slope significantly improves model fit. If the additional slope does not improve model fit, this can be an indicator that individuals' development in media use and associated outcomes is stable (or flat) over time and therefore captures the processes of homeostasis or maintenance (depending on the magnitude of the mean levels of the intercepts and whether an intraindividual reinforcement process exists, represented by the cross-lagged effects). In contrast, if the additional slope improves model fit, individuals' media use and associated outcomes do most likely linearly develop over time and the model captures a positive feedback-loop (depending on the means of the slopes representing growth rates and whether an intraindividual reinforcement process exists).

Yet, the dynamics under investigation can be more complex; the underlying growth mechanisms might differ across outcomes. Media use might be stable

whereas attitudes, beliefs, or behaviors change over time leading, for example, to the RI-CLPM for media use and the LCM-SR for the associated outcome. Therefore, we recommend a stepwise modeling strategy as shown by Curran et al. (2014). This procedure allows to find the optimal function of time and thus to model the optimal individual development for both outcomes separately.

In case that both the RI-CLPM with constrained means and the LCM-SR show insufficient model fits, we recommend (a) to test whether nonlinear functions of time in the LCM-SR improve the model fit or (b) to relax the equality constraints on the means in the RI-CLPM (Hamaker et al., 2015). Then, the RI-CLPM takes into account the temporal patterns in the data through means that vary across time for both outcomes, but the form of individuals' baselines is not explicitly modeled. In both the cases, the data would not ideally capture the dynamics of homeostasis, positive feedback-loops, or maintenance as conceptualized here but rather phases in between.

This general recommendation, however, does not mean that other approaches are not suitable to analyze the RSM. Moeller et al. (2018), for example, combined DPM and reduced ALT to investigate reinforcing spirals. With the DPM, they estimated pure within-person effects and then estimated individuals' baselines for each outcome while controlling for cross-lagged within-person relations using the reduced ALT. Combining statistical models might provide a more robust test of the RSM.

Alternative approaches

Besides the recently used approaches presented here (based on structural equation modeling, SEM), other approaches might be interesting to properly model the RSM. For instance, (a) multilevel models allow to capture such dynamics (Otto & Thomas, 2019; Slater et al., 2003) by disaggregating within- from between-person effects (Curran & Bauer, 2011). Although there might be situations in which multilevel modeling might be superior to SEM approaches (and vice versa), both approaches are related to each other if not mathematically equivalent in many situations (Curran, 2003; Hamaker & Muthén, 2020).

Another promising approach to model reciprocal effects between media use and effect are (b) (multilevel) vector-autoregressive models (Otto et al., 2017). Such models are particularly interesting when analyzing many repeated measures for each respondent collected, for example, via experience sampling methods (Hamaker et al., 2018).

Furthermore, scholars implemented (c) approaches that model nonlinear developments in media use and associated outcomes (Otto et al., 2020). For instance, the function of time could be sequential: different growth sequences within the period under investigation might show completely different dynamics, for example, when events trigger growth in media use and associated outcomes leading to a positive feedback-loop for a specific sequence, whereas other sequences indicate homeostasis

or maintenance. Therefore, transitions between the dynamics of the RSM could be modeled allowing to examine under what circumstances homeostasis or maintenance lead to a positive feedback-loop (or vice versa). Although the approaches presented here might be limited in capturing such transitions, approaches that model growth trajectories (e.g., LCM or LCM-SR) can be combined with spline (or piecewise regression) models to analyze sequential communication dynamics (Thomas et al., 2020).

Moreover, (d) simulation-based approaches could be extended to test conditions of a reinforcing spiral. Song and Boomgaarden (2017), for example, used agent-based modeling simulations to test how interpersonal communication and the context of election campaigns affect media exposure and selection. By "employing multiple simulations over extended time periods with varying setups" (p. 274), they were able to model long-term and conditional spiral processes that are hard to capture with real data. Further, the Monte Carlo simulations presented here could be extended, for example, by varying sample size, number of waves, magnitude of effects, and implementing exogenous variables. This procedure would allow to evaluate statistical approaches across specific data scenarios.

Finally, (e) multiverse approaches could be beneficial for the RSM. Multiverse approaches do not provide a certain modeling approach but suggest a framework considering that specific (often subjective and arbitrary) decisions during data construction and analysis influence results (Steegen et al., 2016). Examining how these decisions condition results (e.g., by applying different statistical models) could strengthen claims about the RSM.

Challenges of the RSM

One challenge is to determine the *optimal time lag* for media and selection effects. The timing of communication dynamics is notoriously understudied and often lack theoretical substantiation (Lecheler & de Vreese, 2011); for most situations and outcomes, we simply do not know how long it takes until media effects and selection appear. Further, we expect large variance in the timing of media and selection effects between individuals. For one person the effect might occur after the first exposure within minutes, another person might be affected after several months. Although this problem concerns all models analyzing longitudinal data, it needs to be considered when collecting data (Dormann & Griffin, 2015).

Related to this, another challenge might occur during data collection: *Intraindividual and interindividual variability in the length of time lags* between each wave. Individuals might submit their questionnaires on different occasions (even within each wave) potentially leading to different time lags between waves across respondents. This issue becomes salient when collecting data with event-based designs (e.g., experience sampling, Otto et al., 2020) but also with large-scale panel data if respondents are not accurately resurveyed for each wave. Under specific circumstances, variability in the length of time lags might lead to biases; then,

models that account for uneven time lags (within and/or between individuals) are required (Voelkle et al., 2012).

Another challenge is *stability in self-reported media use* (Scharkow, 2019; Scharkow & Bachl, 2019). When media use is stable, a positive feedback-loop is unlikely to occur and media effects and selection might best lead to homeostasis (if media effects and selection are weak or absent) or maintenance. In order to identify positive feedback-loops, scholars do not only need the right statistical model but data that capture the mutually reinforcing relationship between media use and associated outcomes. It is, however, difficult to collect such data as true positive feedback-loops represent highly atypical communication dynamics (Slater, 2015).

Maybe, the largest challenge is the RSM itself. The requirements described by Slater (2007, 2015, 2017) lead to rather strict modeling approaches. Although we presented models that capture important components at the within- and between-person level, it seems to be unlikely to measure these requirements at the same time. This is, of course, not to say that it is impossible to find reinforcing spirals or the assumptions are wrong. It simply shows the difficulty of modeling reinforcing spirals due to the many proposed conditioning factors that are hard to measure and analyze in a single statistical model. This directly leads to the (dis-)advantages of complex theoretical frameworks like the RSM: although the RSM is useful in generating propositions and relationships between media use and associated outcomes, it is difficult to capture empirically when considering the whole theoretical model. Simpler models that focus on specific propositions of the RSM instead of trying to capture the whole framework might be better suited for statistical modeling. Therefore, framing every study on dynamic relationships as reinforcing spirals might be counterproductive and limit our way of thinking about other dynamics. After all, reinforcing spirals are only one possibility of linking media use and associated outcomes over time. Hence, implementing additional (and depending on the outcome more specific) theories as possible explanations for communication dynamics (Noelle-Neumann, 1974; Norris, 2000; Shah, McLeod, Rojas, Cho, Wagner, & Friedland, 2017, to name just a few) could broaden our view when studying the complex dynamics between media use, attitudes, beliefs, and behaviors (Schemer et al., 2019, for a similar discussion).

Finally, being more precise in describing and modeling within- and between-person processes in communication helps to better understand relations between media use and effect. The statistical approaches presented here show only a small but valuable part of the large methods repertoire that is needed to tackle the challenges of accurately investigating media use and effect over time.

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Note

1. The empirical data underlying this article will be shared on reasonable request to the author, Shehata, A.

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