Psychological Methods

Examining Individual Differences in How Interaction Behaviors Change Over Time: A Dyadic Multinomial Logistic Growth Modeling Approach

Miriam Brinberg, Graham D. Bodie, Denise H. Solomon, Susanne M. Jones, and Nilam Ram

Online First Publication, August 10, 2023. https://dx.doi.org/10.1037/met0000605

AMERICAN PSYCHOLOGICAL ASSOCIATION

Psychological Methods

ISSN: 1082-989X

https://doi.org/10.1037/met0000605

Examining Individual Differences in How Interaction Behaviors Change Over Time: A Dyadic Multinomial Logistic Growth Modeling Approach

Miriam Brinberg[1], Graham D. Bodie[2], Denise H. Solomon[3], Susanne M. Jones[4], and Nilam Ram[5, 6]

[1] School of Communication, The Ohio State University

[2] Department of Media and Communication, School of Journalism and New Media, University of Mississippi

[3] Department of Communication Arts and Sciences, The Pennsylvania State University

[4] Department of Communication Studies, University of Minnesota

[5] Department of Psychology, Stanford University

[6] Department of Communication, Stanford University

Abstract

Several theoretical perspectives suggest that dyadic experiences are distinguished by patterns of behavioral change that emerge during interactions. Methods for examining change in behavior over time are well elaborated for the study of change along continuous dimensions. Extensions for charting increases and decreases in individuals' use of specific, categorically defined behaviors, however, are rarely invoked. Greater accessibility of Bayesian frameworks that facilitate formulation and estimation of the requisite models is opening new possibilities. This article provides a primer on how multinomial logistic growth models can be used to examine between-dyad differences in within-dyad behavioral change over the course of an interaction. We describe and illustrate how these models are implemented in the Bayesian framework using data from support conversations between strangers ($N = 118$ dyads) to examine (RQ1) how six types of listeners' and disclosers' behaviors change as support conversations unfold and (RQ2) how the disclosers' preconversation distress moderates the change in conversation behaviors. The primer concludes with a series of notes on (a) implications of modeling choices, (b) flexibility in modeling nonlinear change, (c) necessity for theory that specifies how and why change trajectories differ, and (d) how multinomial logistic growth models can help refine current theory about dyadic interaction.

Translational Abstract

Many theories in social psychology and communication suggest that how behaviors change within a dyadic interaction can impact both the individual and the dyad. The study of changes in categorically defined dyadic behavior (e.g., speech acts, conflict tactics) has been limited, in part, because of the absence of suitable methodological approaches. To address this gap, this article provides a primer on how dyadic multinomial logistic growth models can be used to examine between-dyad differences in within-dyad behavioral change. Specifically, we describe and illustrate how dyadic multinomial logistic growth models are implemented in the Bayesian framework using data from support conversations between strangers ($N = 118$ dyads) to examine (RQ1) how six types of listeners' and disclosers' behaviors change as support conversations unfold and (RQ2) how the disclosers' preconversation distress moderates the change in conversation behaviors. The article concludes with a discussion of (a) analytic considerations for researchers implementing this model, and (b) opportunities afforded by multinomial logistic growth models for refining current theory about dyadic interaction.

Keywords: categorical data, dyadic interaction, intensive longitudinal data, growth models, supportive conversations

Supplemental materials: https://doi.org/10.1037/met0000605.supp

Several theoretical perspectives suggest that dyadic experiences are shaped by patterns of behavioral change that emerge during interaction. Differences in emotion regulation or dysregulation (Butler, 2011), conflict resolution or escalation (Courtright et al., 1990), and supportive or unsupportive communication (Burleson & Goldsmith, 1998) during dyadic interactions can all produce meaningful, and often consequential, differences in individual and relational well-being. Research examining the dynamics of dyadic interpersonal interactions has primarily utilized methods that describe change in dyad members' thoughts, feelings, and behaviors that are measured and quantified using continuous variables (e.g., growth models, differential equation models). Methods for describing change when behavior is measured using categorical variables, however, are hardly ever used. Thus, the goal of this article is to provide a practical primer that introduces and increases the accessibility of methods that can be applied to longitudinal categorical time series

Miriam Brinberg https://orcid.org/0000-0001-5202-9292

This study was supported by the National Science Foundation (Grants 1749474, 1749454, 1749255).

Correspondence concerning this article should be addressed to Miriam Brinberg, School of Communication, The Ohio State University, 3016 Derby Hall, 154 N Oval Mall, Columbus, OH 43210, United States. Email: brinberg.2@osu.edu

to examine how behaviors during dyadic interactions change over time. Specifically, we illustrate how dyadic (bivariate) multinomial logistic growth models are formulated and can be fit to empirical data using a Bayesian multilevel modeling framework.

Research on interaction dynamics can be framed as addressing two types of processes: short-term fluctuations around an equilibrium/mean—within-dyad variability—and directional growth or decline—within-dyad change (Butler, 2011; Nesselroade, 1991). Examinations of within-dyad variability are relatively frequent and push forward knowledge about dyadic synchrony and covariation in interaction behaviors. Examinations of within-dyad change, however, has not yet pushed forward knowledge about how use of particular interaction behaviors increase or decrease over time (Ram & Grimm, 2015).

Various theoretical perspectives on dyadic interaction suggest increases/decreases and escalation/de-escalation of certain conversation behaviors that have yet to be tested. For instance, advice response theory posits that advice-giving behaviors are more likely to occur following emotional support behaviors, and thus will be more prevalent as a support conversation progresses (Feng, 2014). Testing these kinds of theoretical predictions are likely currently avoided because the models needed to answer such questions are notoriously difficult to formulate and estimate. In sum, there is need for methods that provide opportunities to address questions of directional change processes (i.e., increases/decreases) in how dyad members use particular behaviors over the course of an interaction when the data on interaction behaviors are categorical. Dyadic (bivariate) multinomial logistic growth models address this need.

Generalized linear models allow that many kinds of measurement scales can be used to examine change. Models for continuous scales use an identity (Gaussian) link function to map the linear relationship between the predictor variables and the continuous outcome variable. In contrast, generalized linear models for categorical scales require a link function that accounts for the nonnormality of the data when mapping the linear relationship between the predictor variables and the categorical outcome variable. The additional complexities created by the nonnormality of the categorical data often become practically intractable when using maximum likelihood estimation (MLE) in the traditional frequentist framework, especially when the sample size is modest (around 100 or 200 individuals, or, in this case, dyads; Kim et al., 2020). Advances in the accessibility and capability of modern computation and Bayesian estimation frameworks now make it much easier and possible to accommodate the nonnormally distributed outcome variables and fit dyadic models of categorical change.

This article provides a practical primer that facilitates formulation and estimation of dyadic multinomial logistic growth models that open new possibilities for examining between-dyad differences in within-dyad behavioral change over time. We (a) describe five steps for fitting dyadic multinomial logistic growth models in a Bayesian framework, (b) illustrate the method through analysis of how dyad members' use of specific behaviors changes as conversations unfold, and (c) discuss considerations for how this approach can be applied in the study of dyadic interactions, including the types of relational data needed for analysis, implications of various choices of the operationalization of time variables, and how the models can be extended to further examine why and when dyad members change their behaviors as interactions unfold.

Steps to Fitting Multinomial Logistic Growth Models

This section forwards a five-step process for fitting dyadic multinomial logistic growth models, including information about data requirements, model setup, and model interpretation.

Step 1: Formulating Research Questions and Obtaining Data

The goal of the first step in the dyadic multinomial logistic growth modeling process is to formulate research questions about dyadic change across time and obtain categorical time series data that are appropriate for answering those questions. As noted in the introduction, many theoretical accounts of interpersonal interaction provide rich grounds for developing hypotheses about how dyad members' behavior changes over the course of a conversation.

When testing these kinds of hypotheses, the changes in behavior (or other construct of interest) can be observed through repeated measurement of categorical variables. In the study of conversations, speaking turn by speaking turn behaviors may be coded with respect to the conflict tactics used by each dyad member during an argument (Courtright et al., 1990), the persuasive techniques used by dyad members during an influence interaction (Dillard, 1990), or the pragmatic function of turns (e.g., acknowledgment, question) during a support interaction (Bodie et al., 2021). In all these scenarios, provided that the behavioral categories are coded in an exhaustive and mutually exclusive manner, multinomial link functions can be leveraged into descriptions of behavioral change. Specifically, the repeated observations of behavior, Y_t, are modeled as a set of probabilities,

$$\pi_{kt} = P(Y_t = k) \quad (1)$$

that describe the probability that a dyad member engaged in behavior of category k at time t, under the constraint that the probabilities of all categories k at each time point t sum to one (separately for each dyad member),

$$\sum_{k=1}^{K} \pi_{kt} = 1. \quad (2)$$

The interest then is in formulating specific hypotheses about how these probabilities change over time for each member of the dyad.

Of note, the categorical time series obtained from the coding of dyad members' behavior may be synchronous or asynchronous. In the synchronous case, each dyad member's behavior is measured at each occasion t to obtain a bivariate categorical time series that has no intentional missingness. For instance, the emotional expressions (e.g., negative, neutral, or positive) of both dyad members may be rated during all speaking turns in a conversation, whether or not that individual is speaking or listening at each specific turn. In the asynchronous case, each dyad member's behavior would only be measured when the behaviors of interest occur, such as the content of speaking turns that alternate between dyad members, to obtain a bivariate categorical time series that has intentional missingness. For instance, the pragmatic function engaged (e.g., acknowledgment, elaboration, question) would be coded for each dyad member's speaking turns but *not* for their listening turns. Both data collection approaches are viable. Given that the latter approach produces data that are not often analyzed in dyadic growth models, we construct our illustrative example using speaking-turn only data that has “inherent” missingness.

Step 2: Data Description, Plotting, and Preparation

The goals of the second step in the dyadic multinomial logistic growth modeling process are (2a) to obtain an understanding of the categorical time series data through statistical descriptives and data visualizations and (2b) to prepare and format the data for growth modeling.

Initial descriptions of the categorical time series data obtained from multiple dyads can include the overall length of each time series (i.e., interaction length), the frequency or relative proportion of occurrence of each dyad member’s behaviors within each time series, and the across-dyad variability in length and use of behaviors. Figure 1 depicts two conversations, with turn number on the x-axis and role on the y-axis, with one dyad member’s (the listener’s) turns on the bottom half and the other dyad member’s (the discloser’s) turns on the top half. Each colored rectangle represents dyad members’ speaking turn acts across time (with gray bars indicating when a dyad member is not speaking). The multipanel configuration of Figure 1 enables examination of between-dyad differences in conversation length (as measured by the number of turns), the use of turn types across conversations, and how behaviors change over time within each conversation. Specifically, Dyad 126 on the left has more turns ($n = 102$) compared to Dyad 190 on the right ($n = 42$).[1] Furthermore, Dyad 126 had 59 elaboration turns and 31 acknowledgment turns (58% and 30% of turns in the conversation, respectively) and Dyad 190 had 25 elaboration turns and eight acknowledgment turns (60% and 19% of turns in the conversation, respectively). We also see that the listener in Dyad 126 begins the conversation using acknowledgments (red) and increasingly uses elaboration turns (green) throughout the conversation. Before formal modeling, statistical descriptives and data visualizations of the categorical time series data provide researchers valuable insight into what behaviors are (not) being used within interactions, how enacted behaviors may change over time, and how the use and change in behaviors may differ across dyads.

The determination of a common time metric is especially important in the study of dyadic interactions, so that time has the same meaning across dyads and so that we are able to align the time series of different dyads. The categorical time series obtained in Step 1 may be of equal clock-time length for all dyads in the sample, such as when every second of a 5-min laboratory-based interaction is coded, or of differing lengths across dyads, such as when each speaking turn in an interaction is coded. Stated differently, interactions may result in time series of different lengths either due to differences built into the study design or imposed by the coding procedure. When interactions are of differing lengths, researchers must determine a common time basis that provides for meaningful comparison across dyads.

Different time metrics are possible depending on the time-sampling approach, such as interval- and event-contingent sampling (Ram & Reeves, 2018). Interaction studies that use interval-contingent sampling observe behaviors and assign categorical codes within specified spans of time. For instance, dyad members’ behaviors can be coded at particular moments in time, such as every second within an interaction, or by researcher-defined epochs of time (e.g., every 10 s). Although interval-contingent sampling has a built-in common time metric (e.g., seconds or epochs), interactions may differ in length based upon the nature of the interaction, such as interactions that last until the achievement of a certain goal (e.g., persuasion, conflict resolution) or task completion (as in organization research). In contrast to interval-contingent sampling, dyadic interaction studies may also use event-contingent sampling, that is, individuals’ behavior is coded only when an instance of interest occurs, such as a speaking turn or an expression of an emotion. In these cases, the length of dyads’ interaction data will differ. For instance, even when researchers code each speaking turn of support conversations that are all exactly 5-min long, some dyads may exhibit frequent back-and-forth dialogue while other dyads feature miniature monologues (e.g., Rains et al., 2021; Solomon et al., 2022).

Regardless of a study’s sampling procedure, mapping time to a common metric facilitates comparison of how the same conversational process unfolds over time across dyads. To make comparisons across interactions at specific time points (e.g., how does the use of certain behaviors change from the beginning to the end of an interaction, and do these behaviors significantly differ from dyad to dyad?), time should be rescaled to a common metric.

One approach to rescaling time across interactions is to represent when behaviors occurred with respect to the proportion of total time. When examining turn-to-turn behaviors within conversations, *turn* (as in Table 1) at observation t in a dyad’s conversation of length $TotalTurns_d$ (the maximum number of turns within the conversation for dyad d) can be rescaled such that

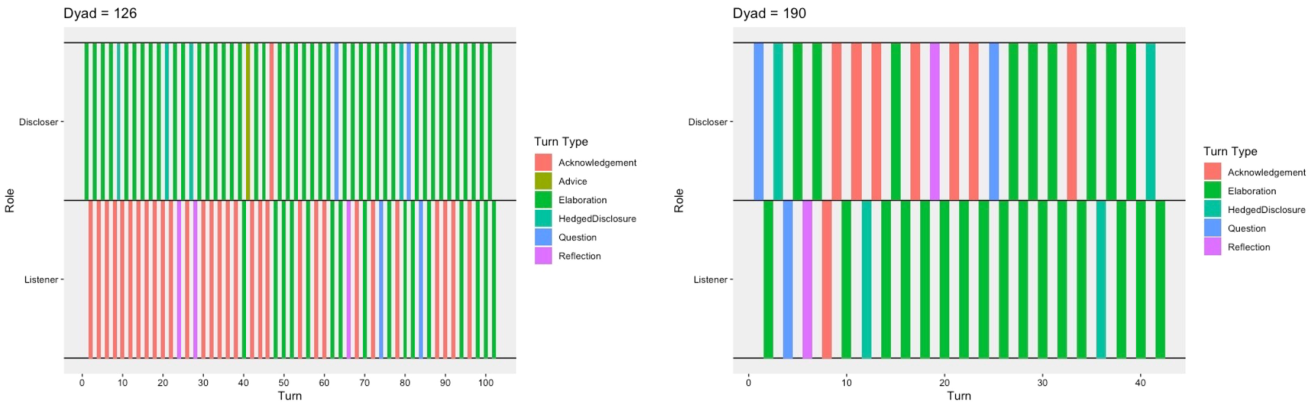
$$ConversationTime_{dt} = \frac{turn_{dt}}{TotalTurns_d}. \tag{3}$$

$ConversationTime_{dt}$ is on a scale from 0.00, which indexes the start of the conversation, to 1.00, which indexes the end of the conversation. Thus, the relative timing of each dyad’s behaviors is now represented in the time series as the proportion of time elapsed thus far in the interaction and now mimic an interval-contingent sampling procedure such that the behavior between two time points is interpolated into that interval. For instance, if an interaction had only eight speaking turns (i.e., four turn pairs), the first turn pair would “occur” from time points 0.00 to 0.25, the second turn pair would “occur” from time points 0.26 to 0.50, the third turn pair would “occur” from time points 0.51 to 0.75, and the fourth turn pair would “occur” from time points 0.76 to 1.00. Similarly, if an interaction had 20 speaking turns (i.e., 10 turn pairs), the first turn pair would “occur” from time points 0.00 to 0.10, and the 10th turn pair would “occur” from time points 0.91 to 1.00.

Note that conversion to a common time metric may not be necessary depending on the data or research question. For instance, if categorical codes are available for every second or predefined epoch (e.g., non-overlapping 10 s periods) of interaction of specified length (e.g., 5-min conversation), then interactions are likely to have the same (or at least very similar) lengths and do not require a new common time metric. In other situations, the original unit of time may be more meaningful than establishing a common beginning and end to

[1] For some research questions, the differing length of time may be of interest (e.g., what characteristics of an interaction lead to faster conflict resolution?) and thus require different methods (e.g., survival analysis; Allison, 2018).

Figure 1
Two Exemplar Dyadic Conversations



Note. The categorical time series from two dyads in our sample. The x-axis represents the turn within the conversation, and the y-axis represents the role in the conversation with discloser turns depicted on the top half and listener turns depicted on the bottom half; color indicates the turn category. See the online article for the color version of this figure.

the interaction. Regardless of whether the data need to be reconfigured, the categorical time series for all dyads must be reformatted to a synchronous, bivariate time series and aligned with respect to a common time metric that facilitates interpretation of the descriptions of change obtained from the dyadic multinomial logistic growth model.

Step 3: Specifying the Model and Priors

The goals of the third step in our dyadic multinomial logistic growth modeling process are to (3a) select a link function that specifies the relation between the categorical outcome variable and a linear combination of predictor variables (e.g., time variable), (3b) determine the appropriate change function to describe the trajectory of behavior over time, and (3c) establish from the literature whether there is prior information about the change processes of interest that can inform model specification.

First, the dyadic multinomial logistic growth model is a type of generalized linear model. All generalized linear models have three components: (a) the systematic component, which is comprised of the linear combination of the predictor variables, (b) the link component, which specifies how the mean of the outcome is related to the linear combination of the predictors, and (c) the random component, which is the outcome variable and the probability distribution associated with it (Jaccard, 2015). Typically, a continuous outcome variable is assumed to have a set of predictor variables (i.e., systematic component), a Gaussian distribution and an identity (i.e., direct) link function to model the linear association between the predictors and outcome variable (i.e., the link component), and an outcome with a normal distribution described by a mean and variance (i.e., the random component). Similarly, a multicategory outcome variable is expected to be a result of a linear combination of predictor variables (i.e., systematic component). In contrast, a multicategory outcome variable is assumed to have a multinomial distribution (i.e., random component), and a set of logit functions are used to model the linear association between the predictors and each level of the outcome variable (i.e., link component). In this case, a series of logit link functions are used, which modifies the interpretation of the predictors on the outcome, such that the linear association between the predictors is the log probability ratio of each category occurring in comparison to a reference group (Agresti, 2019).

Second, the dyadic multinomial logistic growth model requires specification of the type of change trajectories that emerge over time. The expected change trajectory can be derived from a combination of theory, data visualization, and model comparison (Grimm et al., 2016). For example, increases in behavior might be represented by a linear function, while increases followed by decreases in behavior might be represented by a quadratic function. Rather than repeating the didactic presentations on fitting many types of (nonlinear) functions (e.g., Ram & Grimm, 2015) used in growth models, we demonstrate the use of a linear trajectory model that is straightforwardly extended when modeling more complex change trajectories.

Combining the multinomial logit link function and a linear change trajectory function, a general dyadic multinomial logistic growth model for an outcome with, for example, three categories, can be written as

Level 1:

$$\log\left(\frac{P(Y_{dt[1]} = B)}{P(Y_{dt[1]} = A)}\right) = \beta_{0dB[1]} + \beta_{1dB[1]}Time_{dt}, \tag{4}$$

where the log probability ratio of Partner 1 in dyad d exhibiting behavior B at time t relative to exhibiting behavior A at time t is modeled as a function of a Partner 1 dyad-specific intercept, $\beta_{0dB[1]}$, that indicates Partner 1's baseline tendency to exhibit behavior B at the beginning

Table 1
An Example of the Potential Format of the Data Before Reformatting

Dyad ID	Turn	Partner	Turn type	Conversation time
1	1	Discloser	Elaboration	0.040
1	2	Listener	Reflection	0.080
1	3	Discloser	Elaboration	0.120
1	4	Listener	Acknowledgment	0.160
.	.	.	.	.
118	81	Discloser	Hedged disclosure	0.964
118	82	Listener	Reflection	0.976
118	83	Discloser	Elaboration	0.988
118	84	Listener	Acknowledgment	1.00

of the interaction relative to behavior A, and a Partner 1 dyad-specific slope, $\beta_{1dB[1]}$, that indicates the rate of change in Partner 1's tendency to exhibit behavior B relative to the change in behavior A. In parallel,

$$\log\left(\frac{P(Y_{dt[1]}=C)}{P(Y_{dt[1]}=A)}\right)=\beta_{0dC[1]}+\beta_{1dC[1]}Time_{dt}, \tag{5}$$

where the log probability ratio of Partner 1 in dyad d exhibiting behavior C at time t relative to exhibiting behavior A at time t is modeled as a function of a Partner 1 dyad-specific intercept, $\beta_{0dC[1]}$, that indicates Partner 1's baseline tendency to exhibit behavior C at the beginning of the interaction relative to behavior A, and a Partner 1 dyad-specific slope, $\beta_{1dC[1]}$, that indicates the rate of change in Partner 1's tendency to exhibit behavior C relative to the change in behavior A. Parallel equations are used to represent Partner 2's log odds ratio of exhibiting behaviors B and C relative to behavior A, specifically

$$\log\left(\frac{P(Y_{dt[2]}=B)}{P(Y_{dt[2]}=A)}\right)=\beta_{0dB[2]}+\beta_{1dB[2]}Time_{dt}, \tag{6}$$

$$\log\left(\frac{P(Y_{dt[2]}=C)}{P(Y_{dt[2]}=A)}\right)=\beta_{0dC[2]}+\beta_{1dC[2]}Time_{dt}. \tag{7}$$

Note that there are no error terms modeled in the Level 1 equations because the random component is incorporated into the log probability ratio of the outcome variable.

In turn, the dyad-specific intercepts and slopes are modeled for each partner at

Level 2 as

$$\begin{aligned}
\beta_{0dB[1]} &= \gamma_{00B[1]} + \gamma_{01B[1]}X_d + u_{0dB[1]},\\
\beta_{1dB[1]} &= \gamma_{10B[1]} + \gamma_{11B[1]}X_d + u_{1dB[1]},\\
\beta_{0dC[1]} &= \gamma_{00C[1]} + \gamma_{01C[1]}X_d + u_{0dC[1]},\\
\beta_{1dC[1]} &= \gamma_{10C[1]} + \gamma_{11C[1]}X_d + u_{1dC[1]},\\
\beta_{0dB[2]} &= \gamma_{00B[2]} + \gamma_{01B[2]}X_d + u_{0dB[2]},\\
\beta_{1dB[2]} &= \gamma_{10B[2]} + \gamma_{11B[2]}X_d + u_{1dB[2]},\\
\beta_{0dC[2]} &= \gamma_{00C[2]} + \gamma_{01C[2]}X_d + u_{0dC[2]},\\
\beta_{1dC[2]} &= \gamma_{10C[2]} + \gamma_{11C[2]}X_d + u_{1dC[2]},
\end{aligned} \tag{8}$$

where γ_{00} and γ_{10} are sample-level parameters that describe the baseline (i.e., $Time = 0.00$) and linear trajectory in the logit space of behaviors B and C compared to the baseline and linear trajectory of behavior A for Partners 1 and 2, separately, of the prototypical dyad; γ_{01} and γ_{11} are sample-level parameters that describe the association between a dyad-level predictor X and the baseline and linear trajectory in the logit space of behaviors B and C compared to behavior A; and the us are residual unexplained between-dyad differences in the baseline occurrence of behaviors that are assumed multivariate normally distributed.

The symmetric between-dyads (Level 2) covariance matrix of random effects is

$$\begin{bmatrix}
\sigma^2_{u_{0B[1]}} \\
\sigma_{u_{0B[1]}u_{1B[1]}} & \sigma^2_{u_{1B[1]}} \\
\sigma_{u_{0B[1]}u_{0C[1]}} & \sigma_{u_{1B[1]}u_{0C[1]}} & \sigma^2_{u_{0C[1]}} \\
\sigma_{u_{0B[1]}u_{1C[1]}} & \sigma_{u_{1B[1]}u_{1C[1]}} & \sigma_{u_{0C[1]}u_{1C[1]}} & \sigma^2_{u_{1C[1]}} \\
\sigma_{u_{0B[1]}u_{0B[2]}} & \sigma_{u_{1B[1]}u_{0B[2]}} & \sigma_{u_{0C[1]}u_{0B[2]}} & \sigma_{u_{1C[1]}u_{0B[2]}} & \sigma^2_{u_{0B[2]}} \\
\sigma_{u_{0B[1]}u_{1B[2]}} & \sigma_{u_{1B[1]}u_{1B[2]}} & \sigma_{u_{0C[1]}u_{1B[2]}} & \sigma_{u_{1C[1]}u_{1B[2]}} & \sigma_{u_{0B[2]}u_{1B[2]}} & \sigma^2_{u_{1B[2]}} \\
\sigma_{u_{0B[1]}u_{0C[2]}} & \sigma_{u_{1B[1]}u_{0C[2]}} & \sigma_{u_{0C[1]}u_{0C[2]}} & \sigma_{u_{1C[1]}u_{0C[2]}} & \sigma_{u_{0B[2]}u_{0C[2]}} & \sigma_{u_{1B[2]}u_{0C[2]}} & \sigma^2_{u_{0C[2]}} \\
\sigma_{u_{0B[1]}u_{1C[2]}} & \sigma_{u_{1B[1]}u_{1C[2]}} & \sigma_{u_{0C[1]}u_{1C[2]}} & \sigma_{u_{1C[1]}u_{1C[2]}} & \sigma_{u_{0B[2]}u_{1C[2]}} & \sigma_{u_{1B[2]}u_{1C[2]}} & \sigma_{u_{0C[2]}u_{1C[2]}} & \sigma^2_{u_{1C[2]}}
\end{bmatrix}, \tag{9}$$

where $\sigma^2_{u_{0B[1]}}$ and $\sigma^2_{u_{1B[1]}}$ are the variances of Partner 1's baseline and linear trajectories, respectively, in the logit space of behaviors B compared to the baseline and trajectory of behavior A and $\sigma^2_{u_{0B[2]}}$ and $\sigma^2_{u_{1B[2]}}$ are the variances of Partner 2's baseline and linear trajectories, respectively, in the logit space of behaviors B compared to the baseline and trajectory of behavior A, with similar interpretations for behavior C for both partners; the off-diagonal elements are the covariances among the intercepts and slopes across behaviors and partners. As typical in multilevel modeling, the residual covariance structures can be constrained to match substantive hypotheses (e.g., homogeneity of effects) or data constraints.

Third, fitting the dyadic multinomial logistic growth model in a Bayesian framework allows/requires explicit specification of prior distributions that inform the model-fitting process. Prior distributions range from "informative" o "uninformative." Informative priors are derived from previous findings. For instance, when findings from previous studies consistently show that the frequency with which questions are asked decreases as support interactions unfold, the prior distribution for the slope estimate can reflect the existing knowledge that as time increases the log probability ratio of question asking behavior decreases (i.e., a normal distribution with a mean below zero and small standard deviation) relative to the reference category. In contrast, when findings from previous studies are inconsistent or no *a priori* hypotheses about parameter values are available, the prior distributions can explicitly reflect the lack of knowledge and be specified as uninformative—that is, a distribution where all parameter values are equally likely.

After the appropriate link functions, change functions, and prior distributions have been identified and specified, the dyadic multinomial logistic growth model can be fit to the categorial time series data.

Step 4: Estimating the Model Parameters

The goal of the fourth step in our dyadic multinomial logistic growth modeling process is to estimate the model parameters that summarize and describe between-dyad differences in within-dyad change and check for model convergence of parameter estimation. The accessibility and use of Bayesian estimation approaches has increased rapidly during the past decade, in part because of improving computational power and availability of easy-to-use statistical software that implements the estimation algorithms. Accessibility of Bayesian analytic tools is not the sole reason for their increased popularity. The Bayesian approach has several advantages over frequentist approaches. First, Bayesian analyses use Markov Chain Monte Carlo (MCMC) algorithms, which iteratively sample from the underlying probability distribution to obtain a collection of probable estimates for each parameter in the model. MCMC methods can be particularly advantageous when the nonnormality of categorical data creates complexities in the numerical integration process, which can be problematic for MLE methods (Kim et al., 2020). Here, we find the Bayesian estimation approach particularly useful because it enables the estimation of informative dyadic models that include all the desired fixed effects and random effects while accommodating the categorical outcome variables. Furthermore, the Bayesian framework can be particularly helpful when working with small sample sizes, which is common in dyadic studies, by increasing the precision (i.e., smaller standard errors) of estimates (Hox et al., 2012). Other advantages, including incorporating prior information, obtaining distributions for each estimated parameter, and ease of making inferences from the results, are well-outlined elsewhere (e.g., van de Schoot et al., 2014).

Fitting a model using a Bayesian approach requires multiple decisions, including establishing the MCMC sampling procedure. Researchers must determine how samples of the parameter estimates will be selected from the iterative computations of the probability distribution. Specifically, choices include the length of the burn-in period, the number of sampling iterations, and the thinning rate.

To begin, the burn-in period refers to the number of initial iterations that are used to hone in on a reasonable estimate before determining the estimated posterior distribution. Recent literature suggests that at least 10,000 iterations should be used in the burn-in period (Depaoli & van de Schoot, 2017). Next, the number of sampling iterations following the burn-in period needs to be chosen. Prior work suggests the number of iterations should be large enough to achieve an effective sample size (ESS; to be described in more depth below) of at least 1,000 (Zitzmann & Hecht, 2019), but others have recommended at least 10,000 iterations regardless of the number of iterations needed to achieve a reasonable ESS (Depaoli & van de Schoot, 2017). Generally, the number of iterations should be large enough that the model can obtain stable estimates of the model parameters without wasting computational time. The number of iterations needed will depend on the specific model and data being used. Finally, a thinning rate needs to be chosen. A thinning process helps avoid potential autocorrelation of parameter estimates that may manifest in the sampling procedure. By not retaining all parameter estimates (e.g., only retaining every other parameter estimate or every fifth parameter estimate), the final sampling distribution is less likely to be influenced by any autocorrelation of estimates. Some prior work has shown that thinning can reduce the precision of parameter distributions, so should only be used when computational memory is an issue (Link & Eaton, 2012). In practice, estimation is often pretested using a relatively small number of burn-in and estimation iterations to make sure that the model is programmed and running correctly. More extended computational time is then invested to obtain actual modeling results and output.

After the model is fit, the model output should be checked for indication that the iterative sampling procedure converged and produced reliable results. Convergence of the MCMC algorithms is determined through graphical checks of the chains and posterior distributions (they should look like "hairy caterpillars"; Roy, 2020), inspection of R-hat values (<1.1; Gelman et al., 2014), and the ESS of both the bulk and tail of the parameter distributions (>10,000, Kruschke, 2015; >1,000, Zitzmann & Hecht, 2019).

Step 5: Obtaining and Configuring Model Output

The goal of the fifth and final step in our dyadic multinomial logistic growth modeling process is to interpret the model results. This is achieved through two substeps: (5a) transforming the parameter estimates into an interpretable scale and (5b) using the transformed parameters to describe and visualize between-dyad differences in within-dyad change.

First, inference about the parameter estimates in the Bayesian framework makes use of 95% credible intervals (instead of confidence intervals) and transformation into relative risk (RR) ratios (given the multinomial nature of the outcome variable). Another useful metric for interpretation is the probability of direction, which is the probability that a parameter (based upon its posterior distribution) is positive or negative, that is, different from zero (Makowski et al., 2019). The probability of direction ranges from 50% to 100%, with 50% indicating that the parameter is equally likely to be positive or negative and 100% indicating the parameter is very likely to be either positive or negative.

Second, after considering the interpretive relevance of each parameter (using the credible intervals and probability of direction), the parameters of the dyadic multinomial logistic growth model provide information about whether and how the predictors are related to the expected log probability ratio of each behavior, relative to a reference category. These parameters are often much easier to interpret after back-transformation into a probability metric using the inverse link function (Agresti, 2019). Specifically, exponentiated model parameters provide an informative description of the model-implied baselines and trajectories of change. Finally, visualizations of the model-implied trajectories provide an intuitive understanding of the (nonlinear) change in the observed interaction behaviors, reporting of findings, and interpretation with respect to the study hypotheses.

In sum, we presented five steps for dyadic multinomial logistic growth modeling, from data preparation to model interpretation. The accompanying online supplemental materials and online tutorial (https://www.lhama.osu.edu/methods-tutorials/categorical-multinomial-logistic-growth-curve-models/) include annotated R code that covers all the data preparation and analytic steps involved in fitting a dyadic multinomial logistic growth model (R Core Team, 2020). Although there are a variety of proprietary (e.g., Mplus; Muthén & Muthén, 1998–2015) and open source programs (e.g., JAGS, Plummer, 2003; Stan, Stan Development Team, 2019) and R packages (e.g., *rjags*, Plummer, 2019), our illustration makes use of freely available packages in R, specifically *dplyr* for data preparation (Wickham et al., 2020) and *brms* (Bürkner, 2017) for fitting the dyadic multinomial logistic growth model in a Bayesian framework.

Illustrative Empirical Example

We next present an illustrative empirical example using dyadic categorical time series data obtained through speaking turn by turn coding of dyadic support conversations between two strangers. We use the dyadic multinomial logistic growth model to examine how six types of listeners' and disclosers' pragmatic verbal behaviors—acknowledgment, advice, elaboration, hedged disclosure, question, and reflection turns (Bodie et al., 2021)—change over time as the support conversation unfolds.

Participants and Procedures

The data were obtained during a laboratory study of undergraduate students ($N = 236$, 118 dyads) recruited from general education courses at a large university in the southern region of the United States (Bodie et al., 2015). The 236 participants were between the ages of 18 and 52 years ($M = 20.80$, $SD = 4.05$) and identified as White/European American ($n = 177$), Black/African American ($n = 37$), Asian/Asian American ($n = 8$), or Hispanic/Latinx ($n = 14$). A research assistant solicited informed consent and randomly assigned participants to conversational roles (listener or discloser roles). Participants assigned to the discloser role were asked to talk about one of two upsetting events (e.g., illness, academic performance) they identified in a preconversation questionnaire. Participants assigned to the listener role were asked to behave as they usually would in an interaction with a friend. All conversations lasted 5 min and were video recorded.

Measures

Speaking Turn Behavior

The conversations were transcribed and segmented into utterances. Utterances were coded for the presence/absence of verbal response modes characteristic of therapeutic interactions (per Stiles, 1992) and were assigned (for both disclosers and listeners) according to a six-category typology of speaking turn types: *acknowledgment*, which conveys the reception of another's message; *advice*, which guides another by making suggestions or giving directions; *question*, which requests information or guidance; *elaboration*, which shares an individual's thoughts and states objective information; *reflection*, which restates another person's experience and explains, labels, or evaluates the other's experience; and *hedged disclosure*, which qualifies elaboration statements with pauses and sentence fragments (e.g., "I mean," "I don't know"; see Bodie et al., 2021) for an in-depth description of the creation and composition of this turn typology).

Preconversation Distress

Before the support conversations, disclosers reported the severity of their distress on a scale from 1 (*not at all emotionally distressing*) to 7 (*very emotionally distressing*). This preconversation distress variable ($M = 3.25$, $SD = 1.12$, range = 1–5) was sample mean-centered and used as a dyad-level predictor in the dyadic multinomial logistic growth model.

Illustrative Dyadic Multinomial Logistic Growth Model

In this section, we illustrate each of the five steps presented above for fitting a dyadic multinomial logistic growth model.

Step 1: Formulating Research Questions and Obtaining Data

The goal of the first step in the dyadic multinomial logistic growth modeling process is to formulate our research questions about how dyad members' behaviors change during support conversations and obtain categorical time series data of these behaviors. Prior work on "troubles talk" (Jefferson, 2015) has described multiple phases in how listeners and disclosers exchange messages during a support conversation, including how listeners acknowledge discloser comments, ask questions, and further elaborate on an issue toward the beginning of the conversation with a decrease in listener questions and discloser elaborations and an increase in listener reflections and advice as the conversation unfolds. However, the implied hypotheses about how behaviors change have not yet been formally tested. Complementary to the overall changes in behavior outlined by Jefferson, prior work has shown that emotional distress motivates increased processing of support at moderate levels of distress (compared to mild distress) and diminishes processing ability at high levels of distress (Bodie et al., 2011), and thus may impact the pragmatic verbal behaviors enacted within a support conversation. For instance, disclosers with low levels of emotional distress may be able to engage in verbal behaviors that require more processing ability, such as reflecting on their stressor. Taken together, the theory and prior empirical work suggest the formulation of two research questions:

> *RQ1*: How do listeners' and disclosers' conversation behaviors change as support conversations unfold?

> *RQ2*: How does disclosers' preconversation distress impact baseline levels and the rate of change of listeners' and disclosers' conversation behaviors?

Step 2: Data Description, Plotting, and Preparation

The goal of the second step in our process is to (2a) describe and visualize the categorical time series and (2b) to prepare and format the data for the growth model. Across the dyads, we can summarize the categorical time series at both the level of dyads and the level of conversational role (listener, discloser). At the dyadic level, conversations were, on average, 63.19 turns long ($SD = 29.92$, range = 2–147), with elaboration turns being the most common ($n = 3{,}320$, 45%) and advice turns being the least common ($n = 137$, 2%). At the conversational role level, disclosers used elaboration turns most frequently ($n = 2{,}552$, 69%) and advice turns least frequently ($n = 31$, 1%), whereas listeners used acknowledgment turns most frequently ($n = 1{,}467$, 40%) and advice turns least frequently ($n = 106$, 3%). A full summary of turn type use is displayed in Table 2.

The aggregate description of turn type use masks the timing of these behaviors and the differences across conversations. Visual depictions of the conversations can provide an intuitive understanding of the timing and change of conversation behaviors within and between dyads. General observations from the time series plots shown in Figure 1 provide insights into the many ways that conversations might differ, particularly how listeners' and disclosers' conversation behaviors change as the conversations unfold. Dyadic multinomial logistic growth models can help quantify the changes we observe in these plots.

Table 2
Turn Type Occurrence as Proportion

Turn type	Listener	Discloser
Acknowledgment	0.40 (1,467)	0.10 (359)
Advice	0.03 (106)	0.01 (31)
Elaboration	0.21 (768)	0.69 (2,552)
Hedged disclosure	0.06 (237)	0.15 (571)
Question	0.11 (414)	0.04 (143)
Reflection	0.18 (667)	0.01 (37)

Note. Frequency of turn type occurrence is reported in the parentheses.

Finally, before specifying the models, we reformatted the categorical time series data into "long" format data where each row contains information about a single turn pair. As shown in Table 3, the reformatted data have five columns: the dyad ID variable, the turn pair number variable, the turn type category variable for listeners, the turn type category variable for disclosers, and a common time metric variable ("conversation time") that aligns conversation trajectories across dyads with respect to proportional length. Although all these laboratory-based support conversations lasted approximately 5 min (clock time), the turn-level coding procedures produced speaking turn-level time series that ranged in length from 2 to 147 speaking turns. In line with the temporally structured nature of the task, we chose to rescale time with respect to total conversation time, so that the time variable used in the analysis aligns all conversations with respect to the beginning of the conversation = 0.00 and the end of the conversation = 1.00. As per Equation 3, the conversation time variable was obtained by dividing the turn pair number indexing each row of data by the total number of turn pairs in that dyad's conversation. The resulting variable locates each turn pair with respect to where it occurred in the 5 min conversation.

Step 3: Specifying the Model and Priors

The third step in our process had three goals: (3a) identify the appropriate link function, (3b) determine the appropriate change function to describe the trajectories of behavior across the support conversations, and (3c) incorporate prior theory about support conversation dynamics into model specification.

First, the six-category categorical variable suggests using a multinomial logit link function that represents the outcome variables in terms of the log probability ratio that a dyad member will use a specific turn type relative to a comparison category, chosen here to be the *acknowledgment* turn type. The ultimate selection of a reference category is arbitrary, that is, the choice does not change the model results[2] (Agresti, 2019, p. 160). However, selecting a reference category that facilitates theoretical framing and results interpretation is always useful. Second, we defaulted to using a linear function to describe the change trajectories of all six turn types (acknowledgment, advice, elaboration, hedged disclosure, question, and reflection) because there is no specific theoretical guidance about what kinds of change are expected during a support conversation and we sought didactic simplicity. Third, the complete dyadic multinomial logistic growth model was specified to describe how both listeners' and disclosers' conversation behaviors change as support conversations unfold and how the discloser's level of preconversation distress impacts the level and rate of change in turn type use during the support conversations. The model follows the form

$$\begin{aligned}
&\log\left(\frac{P(TurnType_{dt[L]} = Advice)}{P(TurnType_{dt[L]} = Acknowledgement)}\right) = \\
&\quad \beta_{advice0d[L]} + \beta_{advice1d[L]} ConversationTime_{dt[L]}, \\
&\log\left(\frac{P(TurnType_{dt[L]} = Elaboration)}{P(TurnType_{dt[L]} = Acknowledgement)}\right) = \\
&\quad \beta_{elaboration0d[L]} + \beta_{elaboration1d[L]} ConversationTime_{dt[L]}, \\
&\log\left(\frac{P(TurnType_{dt[L]} = HedgedDisclosure)}{P(TurnType_{dt[L]} = Acknowledgement)}\right) = \\
&\quad \beta_{hedgeddisclosure0d[L]} + \beta_{hedgeddisclosure1d[L]} ConversationTime_{dt[L]}, \\
&\log\left(\frac{P(TurnType_{dt[L]} = Question)}{P(TurnType_{dt[L]} = Acknowledgement)}\right) = \\
&\quad \beta_{question0d[L]} + \beta_{question1d[L]} ConversationTime_{dt[L]}, \\
&\log\left(\frac{P(TurnType_{dt[L]} = Reflection)}{P(TurnType_{dt[L]} = Acknowledgement)}\right) = \\
&\quad \beta_{reflection0d[L]} + \beta_{reflection1d[L]} ConversationTime_{dt[L]},
\end{aligned} \tag{10}$$

where the log probability ratio of listener L in dyad d enacting an *advice* behavior at proportional turn pair t relative to enacting an *acknowledgment* behavior is modeled as a function of a person-specific intercept, $\beta_{advice0d[L]}$, that indicates a listener's baseline tendency to enact an advice turn at the beginning of the conversation ($Time_{Ldt} = 0$) relative to an acknowledgment turn, and a person-specific slope, $\beta_{advice1d[L]}$, that indicates how listener L in dyad d's tendency to enact advice changes during the conversation. We chose acknowledgment turns as the reference category, in this case, because it was the most frequently used turn type for listeners across conversations and the use of acknowledgments was expected to decrease throughout the conversation; thus, we wanted to compare the use of the other turns in relation to acknowledgment turns given our expectations of acknowledgment use. For disclosers, the model follows the same form as the listeners' model.

Table 3
An Example of the Data Format for Conducting a Dyadic Multinomial Logistic Growth Model

Dyad ID	Turn pair	Listener turn type	Discloser turn type	Conversation time
1	1	Reflection	Elaboration	0.000
1	2	Acknowledgment	Elaboration	0.080
.	.	.		.
118	41	Reflection	Hedged disclosure	0.952
118	42	Acknowledgment	Elaboration	0.976

[2] Although the model results do not change, the run time of the model seems to be impacted by the reference category. In our experience, small base rate categories had substantially longer run times as compared to categories that occurred more frequently. Further work is needed to determine if there is indeed a computational advantage in the choice of reference category.

In turn, the person-specific intercepts and slopes for the listener within the dyad are modeled as

$$\begin{aligned}
&\beta_{advice0d[L]} = \gamma_{advice00[L]} + \gamma_{advice01[L]}Distress_d + u_{advice0d[L]},\\
&\beta_{elaboration0d[L]} = \gamma_{elaboration00[L]} + \gamma_{elaboration01[L]}Distress_d\\
&\quad + u_{elaboration0d[L]},\\
&\beta_{hedgeddisclosure0d[L]} = \gamma_{hedgeddisclosure00[L]} + \gamma_{hedgeddisclosure01[L]}Distress_d\\
&\quad + u_{hedgeddisclosure0d[L]},\\
&\beta_{question0d[L]} = \gamma_{question00[L]} + \gamma_{question01[L]}Distress_d + u_{question0d[L]},\\
&\beta_{reflection0d[L]} = \gamma_{reflection00[L]} + \gamma_{reflection01[L]}Distress_d + u_{reflection0d[L]},\\
&\beta_{advice1d[L]} = \gamma_{advice10[L]} + \gamma_{advice11[L]}Distress_d + u_{advice1d[L]},\\
&\beta_{elaboration1d[L]} = \gamma_{elaboration10[L]} + \gamma_{elaboration11[L]}Distress_d\\
&\quad + u_{elaboration1d[L]},\\
&\beta_{hedgeddisclosure1d[L]} = \gamma_{hedgeddisclosure10[L]} + \gamma_{hedgeddisclosure11[L]}Distress_d\\
&\quad + u_{hedgeddisclosure1d[L]},\\
&\beta_{question1d[L]} = \gamma_{question10[L]} + \gamma_{question11[L]}Distress_d + u_{questionL1d[L]},\\
&\beta_{reflection1d[L]} = \gamma_{reflection10[L]} + \gamma_{reflection11[L]}Distress_d + u_{reflection1d[L]},
\end{aligned} \tag{11}$$

where $\gamma_{advice00[L]}$ and $\gamma_{advice10[L]}$ are sample-level parameters that describe the baseline level and trajectory of *advice* use for the prototypical listener relative to the comparison category, *acknowledgments* (the same interpretation follows for the other turn types); $\gamma_{advice01[L]}$ and $\gamma_{advice11[L]}$ are sample-level parameters that describe the association between the disclosers' preconversation distress and the baseline level and trajectory of *advice* use for the prototypical listener relative to the comparison category, *acknowledgments* (the same interpretation follows for the other turn types); and the *u*s are residual unexplained between-person differences in baseline turn type use and change in turn use that are assumed multivariate normally distributed. The random effects for the *u*s were structured to allow for all possible correlations within-dyad members and across-dyad members (as in Equation 9). For disclosers, the model follows the same form as the listeners' model.

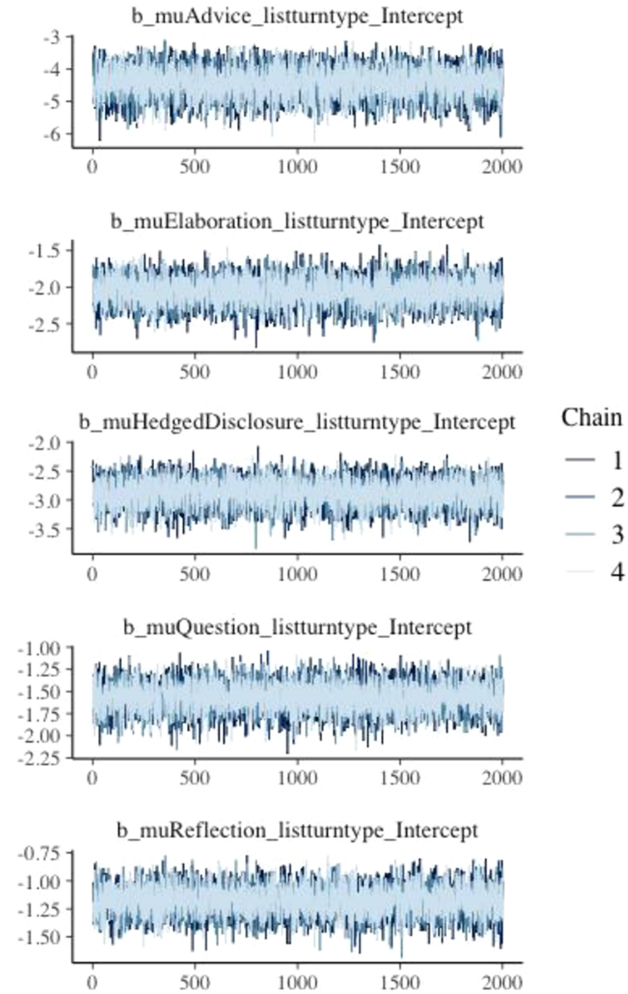
Third, the prior distributions for the parameters were, in the absence of a strong guiding theory, specified on the uninformative end of the continuum. Specifically, we use the default mildly informative priors available in the R program *brms* (Bürkner, 2017), which include flat priors for the intercepts and time/growth parameters (i.e., gammas), half student *t* distribution priors with three degrees of freedom, a mean of zero, and (for our data) standard deviations of 2.5, and Lewandowski–Kurowicka–Joe distribution priors for the correlations among random effects.

Step 4: Estimating the Model Parameters

The goal of the fourth step is to estimate the model and check for model convergence. The above model was fit to the data using a Bayesian approach, as implemented with the *brms* package in R (Bürkner, 2017; R Core Team, 2020). In line with current guidelines (e.g., Depaoli & van de Schoot, 2017), MCMC estimation was done using 20,000 iterations, with a 10,000 iteration burn-in period, four chains, and a thinning rate of 5.

Inspection of model convergence criteria indicated that all four MCMC chains successfully converged. As can be seen in Figure 2 depicting the MCMC chains for listeners' fixed effect intercept parameters, the MCMC chains did not show any noticeable trends and indeed looked like "hairy caterpillars" (Roy, 2020). All R-hat values were <1.1 (Gelman et al., 2014), and the ESS of both bulk and tail of all parameter distributions were $>1,000$ ($>2,000$, Oravecz & Muth, 2018; $>1,000$, Zitzmann & Hecht, 2019). In sum, the model convergence criteria provide confidence that the model results are accurate and trustworthy.

Figure 2
Convergence Plots of Select Model Parameters



Note. See the online article for the color version of this figure.

Step 5: Obtaining and Configuring Model Output

The fifth and final step in our dyadic multinomial logistic growth modeling process involves (5a) transforming the parameter estimates into an interpretable scale, and (5b) using the transformed parameters to describe and visualize within-dyad differences in within-dyad change.

Interpretation of model parameters was facilitated by back-transforming the mean parameter estimates to an interpretable scale using the inverse of the logit link function. The exponentiated model parameters for the fixed effects—that is, risk ratios—are displayed in

Table 4, the correlation of the random effects is displayed in Table 5, and plots of the expected trajectories of (conditional) prototypical turn type use are shown in probability metric in Figure 3.

How Does Turn Type Use Change?

To address our first research question, we examined how conversation behaviors changed during support conversations. In accordance with theory articulating phases of "troubles talk" (Jefferson, 2015), the intercept parameters indicate that there is a high probability that these conversations open with listeners expressing *acknowledgments*. Specifically, for the prototypical listener, the log probability ratio of using an *advice* ($\gamma_{advice00[L]} = -4.41$, probability of direction (pd) = 100%; RR = 0.01 with 95% CI = [0.00, 0.03]), *elaboration* ($\gamma_{elaboration00[L]} = -2.05$, pd = 100%; RR = 0.13 with [0.09, 0.18]), *hedged disclosure* ($\gamma_{hedgeddisclosure00[L]} = -2.88$, pd = 100%; RR = 0.06 with [0.04, 0.08]), *question* ($\gamma_{question00[L]} = -1.57$, pd = 100%; RR = 0.21 with [0.15, 0.28]), or *reflection* turn ($\gamma_{reflection00[L]} = -1.18$, pd = 100%; RR = 0.31 with [0.24, 0.39]) was significantly lower relative to the use of an *acknowledgment* turn at the beginning of the support conversation.

Although listeners are expected to begin conversations with acknowledgment of their partner's experience, listeners are expected to increasingly offer their own reflections and advice as the conversation unfolds. We found that the use of *advice* ($\gamma_{advice10[L]} = 1.47$, pd = 98.03%; RR = 4.36 with 95% CI = [1.08, 15.11]), *elaboration* ($\gamma_{elaboration10[L]} = 2.10$, pd = 100%; RR= 8.14 with [4.87, 13.38]), *hedged disclosure* ($\gamma_{hedgeddisclosure10[L]} = 1.62$, pd = 100%; RR = 5.06 with [2.65, 9.41]), and *reflection* ($\gamma_{reflection10[L]} = 0.63$, pd = 99.91%; RR = 1.88 with [1.27, 2.74]) turns (but not *question* turns; $\gamma_{question10[L]} = 0.26$, pd = 85.03%; RR = 1.29 with [0.78, 2.07]), significantly increase across the support conversation relative to the use of *acknowledgment* turns. As seen when moving left to right in the top panels of Figure 3, the trajectories of the conversation behavior probabilities indicate that listeners' tendency to use *advice* (yellow), *elaboration* (red), *hedged disclosure* (orange), and *reflection* (purple) conversation behaviors increased relative to the use of *acknowledgment* (blue) behaviors from the beginning to the end of the conversations.

Theory on "troubles talk" (Jefferson, 2015) also hypothesizes that conversations are likely to begin with disclosers elaborating on their stressor. We found that for the prototypical discloser, the log probability ratio of using an *advice* ($\gamma_{advice00[D]} = -1.55$, pd = 100%; RR = 0.21 with 95% CI = [0.07, 0.53]), *question* ($\gamma_{question00[D]} = -1.39$, pd = 100%; RR = 0.25 with [0.12, 0.50]), or *reflection* turn ($\gamma_{reflection00[D]} = -3.26$, pd = 100%; RR = 0.04 with [0.01, 0.12]) was significantly lower than the log probability ratio of using an *acknowledgment* turn at the beginning of the support conversation, and the log probability ratio of using an *elaboration* ($\gamma_{elaboration00[D]} = 2.90$, pd = 100%; RR = 18.16 with [13.02, 25.63]) or *hedged disclosure* ($\gamma_{hedgeddisclosure00[D]} = 1.59$, pd = 100%; RR = 4.91 with [3.32, 7.33]) turn was significantly higher than the log probability ratio of using an *acknowledgment* turn at the beginning of the support conversation. These findings support Jefferson's model of troubles talk.

As the conversation continues, disclosers are expected to engage in fewer elaboration turns as they instead respond to the hypothesized increase in listener reflection and advice turns (Jefferson, 2015). We found that the use of *advice* ($\gamma_{advice10[D]} = -4.66$, pd = 99.96%; RR = 0.01 with 95% CI = [0.00, 0.18]), *elaboration* ($\gamma_{elaboration10[D]} = -1.26$, pd = 100%; RR = 0.28 with [0.17, 0.47]), and *hedged disclosure* ($\gamma_{hedgeddisclosure10[D]} = -1.98$, pd = 100%; RR = 0.14 with [0.08, 0.25]) turns significantly decreased across the support conversation relative to the use of *acknowledgment* turns. Moving left to right in the bottom panels of Figure 3, the trajectories indicate the probability that disclosers engage in particular behaviors throughout the conversation. For example, the probability of elaboration (red) behaviors remained at about 0.75 throughout the conversation, and acknowledgment (blue) behaviors increased from 0.05 probability at the beginning of the conversation to about 0.20 at the end of the conversation.

Notably, there were substantial between-dyad differences in both the log probability ratio of listeners and disclosers using each of the different conversation behaviors at the initiation of the support conversations and the linear change in conversation behavior use across the support conversations. With respect to modeling of dyadic change, the correlation among random effects was generally low across-dyad members (see Table 5); however, there were a few random effects that were moderately correlated, including (a) a moderate negative correlation between listeners' hedged disclosure intercepts and disclosers' elaboration intercepts ($r = -.45$) and hedged disclosure intercepts ($r = -.41$), indicating that dyads in which listeners' used more hedged disclosures at the beginning of the conversation were likely to have disclosers' who used fewer elaborations and hedged disclosures at the beginning of the conversation, and (b) a moderate negative correlation between listeners' elaboration intercepts and disclosers' hedged disclosure intercepts ($r = -.40$), indicating that dyads in which listeners' used more elaborations at the beginning of the conversation were likely to have disclosers' who used fewer hedged disclosures at the beginning of the conversation.

Does Preconversation Stress Impact Turn Type Use Change?

To address our second research question, we examined whether disclosers' preconversation distress impacted the baseline use and rate of change of listeners' and disclosers' conversation behaviors. We found that the level of discloser's preconversation distress was not associated with differences in listeners' or disclosers' conversation behavior use at the beginning of the conversation and did not impact the rate of change in listeners' or disclosers' conversation behavior use throughout the conversation.

Specifically, for the prototypical listener, the log probability ratio of discloser's preconversation distress did not impact using an *advice* ($\gamma_{advice01[L]} = 0.05$, pd = 56.09%; RR = 1.05 with 95% CI = [0.55, 2.03]), *elaboration* ($\gamma_{elaboration01[L]} = 0.03$, pd = 56.70%; RR = 1.03 with [0.74, 1.42]), *hedged disclosure* ($\gamma_{hedgeddisclosure01[L]} = -0.05$, pd = 60.28%; RR = 0.95 with [0.66, 1.37]), *question* ($\gamma_{question01[L]} = -0.22$, pd = 94.21%; RR = 0.80 with [0.60, 1.06]), or *reflection* turn ($\gamma_{reflection01[L]} = -0.14$, pd = 88.08%; RR = 0.87 with [0.69, 1.09]) at the beginning of the support conversation relative to the use of *acknowledgment* turns. Furthermore, the discloser's preconversation distress did not moderate how the use of *advice* ($\gamma_{advive11[L]} = 0.74$, pd = 93.18%; RR = 2.10 with [0.80, 5.66]), *elaboration* ($\gamma_{elaboration11[L]} = -0.09$, pd = 66.29%; RR = 0.91 with [0.58, 1.43]), *hedged disclosure* ($\gamma_{hedgeddisclosure11[L]} = 0.11$, pd = 65.83%; RR = 1.12 with [0.65, 1.91]), *question* ($\gamma_{question11[L]} = 0.12$, pd = 71.01%; RR = 1.12

Table 4
Results From Dyadic Multinomial Logistic Growth Model Examining How Listeners' and Disclosers' Turn Type Use Changes During a Support Conversation as Moderated by Preconversation Distress

Parameter	Relative to acknowledgment							p-direction (%)
	Estimate (*SE*)	95% CI	R-hat	Bulk ESS	Tail ESS	Risk ratio	95% CI	
Fixed effects								
Intercept								
Listener								
Advice, $\gamma_{advice00[L]}$	−4.41 (0.44)	[−5.31, −3.59]	1.00	6,523	7,283	0.01	[0.00, 0.03]	100
Elaboration, $\gamma_{elaboration00[L]}$	−2.05 (0.18)	[−2.41, −1.71]	1.00	7,452	7,040	0.13	[0.09, 0.18]	100
Hedged disclosure, $\gamma_{hedgeddisclosure00[L]}$	−2.88 (0.21)	[−3.32, −2.47]	1.00	8,082	7,638	0.06	[0.04, 0.08]	100
Question, $\gamma_{question00[L]}$	−1.57 (0.16)	[−1.88, −1.26]	1.00	7,952	7,770	0.21	[0.15, 0.28]	100
Reflection, $\gamma_{reflection00[L]}$	−1.18 (0.13)	[−1.44, −0.94]	1.00	7,610	7,560	0.31	[0.24, 0.39]	100
Discloser								
Advice, $\gamma_{advice00[D]}$	−1.55 (0.53)	[−2.71, −0.64]	1.00	7,384	7,876	0.21	[0.07, 0.53]	100
Elaboration, $\gamma_{elaboration00[D]}$	2.90 (0.17)	[2.57, 3.24]	1.00	7,238	7,306	18.16	[13.02, 25.63]	100
Hedged disclosure, $\gamma_{hedgeddisclosure00[D]}$	1.59 (0.20)	[1.20, 1.99]	1.00	7,879	7,556	4.91	[3.32, 7.33]	100
Question, $\gamma_{question00[D]}$	−1.39 (0.37)	[−2.13, −0.68]	1.00	7,467	7,850	0.25	[0.12, 0.50]	100
Reflection, $\gamma_{reflection00[D]}$	−3.26 (0.61)	[−4.54, −2.14]	1.00	7,494	7,369	0.04	[0.01, 0.12]	100
Time								
Listener								
Advice, $\gamma_{advice10[L]}$	1.47 (0.67)	[0.08, 2.72]	1.00	5,605	7,114	4.36	[1.08, 15.11]	98.03
Elaboration, $\gamma_{elaboration10[L]}$	2.10 (0.25)	[1.58, 2.59]	1.00	7,858	7,595	8.14	[4.87, 13.38]	100
Hedged disclosure, $\gamma_{hedgeddisclosure10[L]}$	1.62 (0.32)	[0.97, 2.24]	1.00	7,855	7,771	5.06	[2.65, 9.41]	100
Question, $\gamma_{question10[L]}$	0.26 (0.25)	[−0.25, 0.73]	1.00	7,875	7,954	1.29	[0.78, 2.07]	85.03
Reflection, $\gamma_{reflection10[L]}$	0.63 (0.20)	[0.24, 1.01]	1.00	7,636	7,423	1.88	[1.27, 2.74]	99.91
Discloser								
Advice, $\gamma_{advice10[D]}$	−4.66 (1.69)	[−8.47, −1.70]	1.00	7,273	7,520	0.01	[0.00, 0.18]	99.96
Elaboration, $\gamma_{elaboration10[D]}$	−1.26 (0.26)	[−1.76, −0.75]	1.00	7,492	7,730	0.28	[0.17, 0.47]	100
Hedged disclosure, $\gamma_{hedgeddisclosure10[D]}$	−1.98 (0.30)	[−2.56, −1.38]	1.00	7,810	7,787	0.14	[0.08, 0.25]	100
Question, $\gamma_{question10[D]}$	−0.63 (0.54)	[−1.76, 0.36]	1.00	7,376	7,757	0.53	[0.17, 1.44]	88.78
Reflection, $\gamma_{reflection10[D]}$	0.74 (0.82)	[−0.91, 2.32]	1.00	7,795	7,630	2.10	[0.40, 10.21]	82.79
Preconversation distress								
Listener								
Advice, $\gamma_{advice01[L]}$	0.05 (0.33)	[−0.60, 0.71]	1.00	7,873	7,973	1.05	[0.55, 2.03]	56.09
Elaboration, $\gamma_{elaboration01[L]}$	0.03 (0.17)	[−0.30, 0.35]	1.00	7,312	7,650	1.03	[0.74, 1.42]	56.70
Hedged disclosure, $\gamma_{hedgeddisclosure01[L]}$	−0.05 (0.18)	[−0.41, 0.31]	1.00	7,775	7,702	0.95	[0.66, 1.37]	60.28
Question, $\gamma_{question01[L]}$	−0.22 (0.14)	[−0.51, 0.06]	1.00	8,075	7,108	0.80	[0.60, 1.06]	94.21
Reflection, $\gamma_{reflection01[L]}$	−0.14 (0.12)	[−0.37, 0.09]	1.00	7,830	7,955	0.87	[0.69, 1.09]	88.08
Discloser								
Advice, $\gamma_{advice01[D]}$	0.22 (0.36)	[−0.47, 0.93]	1.00	7,902	8,013	1.25	[0.62, 2.53]	73.78
Elaboration, $\gamma_{elaboration01[D]}$	0.23 (0.15)	[−0.06, 0.51]	1.00	7,774	8,053	1.26	[0.94, 1.67]	94.05
Hedged disclosure, $\gamma_{hedgeddisclosure01[D]}$	0.34 (0.18)	[−0.02, 0.69]	1.00	7,809	7,849	1.40	[0.98, 1.99]	96.95
Question, $\gamma_{question01[D]}$	0.12 (0.28)	[−0.43, 0.68]	1.00	7,509	7,348	1.13	[0.65, 1.98]	66.44
Reflection, $\gamma_{reflection01[D]}$	0.89 (0.49)	[−0.02, 1.88]	1.00	7,845	7,761	2.43	[0.98, 6.55]	97.19
Preconversation Distress × Time								
Listener								
Advice, $\gamma_{advice11[L]}$	0.74 (0.50)	[−0.23, 1.73]	1.00	7,897	7,700	2.10	[0.80, 5.66]	93.18
Elaboration, $\gamma_{elaboration11[L]}$	−0.09 (0.23)	[−0.54, 0.35]	1.00	7,908	7,238	0.91	[0.58, 1.43]	66.29
Hedged disclosure, $\gamma_{hedgeddisclosure11[L]}$	0.11 (0.27)	[−0.43, 0.65]	1.00	7,805	7,784	1.12	[0.65, 1.91]	65.83
Question, $\gamma_{question11[L]}$	0.12 (0.21)	[−0.31, 0.54]	1.00	7,704	7,750	1.12	[0.74, 1.71]	71.01
Reflection, $\gamma_{reflection11[L]}$	0.28 (0.18)	[−0.06, 0.64]	1.00	7,459	7,640	1.32	[0.94, 1.90]	94.54
Discloser								
Advice, $\gamma_{advice11[D]}$	−0.77 (0.86)	[−2.49, 0.84]	1.00	8,102	7,874	0.46	[0.08, 2.32]	81.90
Elaboration, $\gamma_{elaboration11[D]}$	−0.32 (0.22)	[−0.74, 0.12]	1.00	7,224	7,949	0.73	[0.47, 1.12]	92.48
Hedged disclosure, $\gamma_{hedgeddisclosure11[D]}$	−0.16 (0.27)	[−0.68, 0.39]	1.00	7,647	7,569	0.85	[0.51, 1.47]	72.33
Question, $\gamma_{question11[D]}$	−0.27 (0.40)	[−1.06, 0.48]	1.00	7,657	7,345	0.76	[0.35, 1.61]	74.95
Reflection, $\gamma_{reflection11[D]}$	−0.99 (0.69)	[−2.35, 0.35]	1.00	7,753	7,829	0.37	[0.10, 1.42]	92.70
Random effects								
Intercept								
Listener								
$\sigma_{advice\_u0[L]}$	1.80 (0.32)	[1.20, 2.48]	1.00	7,215	7,291			100
$\sigma_{elaboration\_u0[L]}$	1.25 (0.14)	[0.98, 1.54]	1.00	7,684	7,614			100
$\sigma_{hedgeddisclosure\_u0[L]}$	1.13 (0.16)	[0.83, 1.47]	1.00	7,777	7,591			100
$\sigma_{question\_u0[L]}$	1.00 (0.13)	[0.78, 1.27]	1.00	7,688	7,833			100
$\sigma_{reflection\_u0[L]}$	0.80 (0.10)	[0.61, 1.01]	1.00	7,482	7,768			100
Discloser								
$\sigma_{advice\_u0[D]}$	0.72 (0.50)	[0.03, 1.84]	1.00	6,232	7,266			100

(*table continues*)

Table 4 (*continued*)

Parameter	Relative to acknowledgment							p-direction (%)
	Estimate (SE)	95% CI	R-hat	Bulk ESS	Tail ESS	Risk ratio	95% CI	
$\sigma_{elaboration\_u0[D]}$	0.80 (0.12)	[0.56, 1.05]	1.00	7,709	7,640			100
$\sigma_{hedgeddisclosure\_u0[D]}$	1.10 (0.15)	[0.82, 1.39]	1.00	6,761	7,297			100
$\sigma_{question\_u0[D]}$	1.51 (0.25)	[1.07, 2.04]	1.00	8,012	8,047			100
$\sigma_{reflection\_u0[D]}$	1.08 (0.39)	[0.24, 1.85]	1.00	6,503	5,471			100
Time								
Listener								
$\sigma_{advice\_u1[L]}$	1.73 (0.62)	[0.42, 2.94]	1.00	3,553	4,073			100
$\sigma_{elaboration\_u1[L]}$	1.24 (0.27)	[0.71, 1.78]	1.00	4,689	5,210			100
$\sigma_{hedgeddisclosure\_u1[L]}$	0.86 (0.44)	[0.07, 1.70]	1.00	3,197	4,825			100
$\sigma_{question\_u1[L]}$	0.63 (0.35)	[0.04, 1.34]	1.00	4,441	6,748			100
$\sigma_{reflection\_u1[L]}$	0.43 (0.27)	[0.02, 0.99]	1.00	5,273	6,824			100
Discloser								
$\sigma_{advice\_u1[D]}$	3.60 (1.02)	[1.84, 5.78]	1.00	6,923	7,010			100
$\sigma_{elaboration\_u1[D]}$	0.86 (0.26)	[0.29, 1.32]	1.00	5,458	4,160			100
$\sigma_{hedgeddisclosure\_u1[D]}$	0.89 (0.38)	[0.11, 1.58]	1.00	5,609	5,481			100
$\sigma_{question\_u1[D]}$	0.94 (0.52)	[0.06, 2.02]	1.00	6,487	6,470			100
$\sigma_{reflection\_u1[D]}$	0.80 (0.56)	[0.03, 2.07]	1.00	6,801	7,552			100

Note. Model based on $N = 118$ support conversations. Parameter estimates and 95% CI [lower, upper] from Bayesian fitting of the multinomial logistic growth curve model with *acknowledgment* turns as the reference category. Temporal progression across the conversation operationalized as the proportion of time within the conversation. CI = credible intervals; ESS = effective sample size.

with [0.74, 1.71]), or *reflection* turns ($\gamma_{reflection11[L]} = 0.28$, $pd = 94.54\%$; RR = 1.32 with [0.94, 1.90]) changed across the support conversation relative to the use of *acknowledgment* turns.

For the prototypical discloser, the log probability ratio of discloser's preconversation distress did not impact using an *advice* ($\gamma_{advice01[D]} = 0.22$, $pd = 73.78\%$; RR = 1.25 with 95% CI = [0.62, 2.53]), *elaboration* ($\gamma_{elaboration01[D]} = 0.23$, $pd = 94.05\%$; RR = 1.26 with [0.94, 1.67]), *hedged disclosure* ($\gamma_{hedgeddisclosure01[D]} = 0.34$, $pd = 96.95\%$; RR = 1.40 with [0.98, 1.99]), *question* ($\gamma_{question01[D]} = 0.12$, $pd = 66.44\%$; RR = 1.13 with [0.65, 1.98]), or *reflection* turn ($\gamma_{reflection01[D]} = 0.89$, $pd = 97.19\%$; RR = 2.43 with [0.98, 6.55]) at the beginning of the support conversation relative to the use of *acknowledgment* turns. Furthermore, the discloser's preconversation distress did not moderate how the use of *advice* ($\gamma_{advice11[D]} = -0.77$, $pd = 81.90\%$; RR = 0.46 with [0.08, 2.32]), *elaboration* ($\gamma_{elaboration11[D]} = -0.32$, $pd = 92.48\%$; RR = 0.73 with [0.47, 1.12]), *hedged disclosure* ($\gamma_{hedgeddisclosure11[D]} = -0.16$, $pd = 72.33\%$; RR = 0.85 with [0.51, 1.47]), *question* ($\gamma_{question11[D]} = -0.27$, $pd = 74.95\%$; RR = 0.76 with [0.35, 1.61]), or *reflection* ($\gamma_{reflection11[D]} = -0.99$, $pd = 92.70\%$; RR = 0.37 with [0.10, 1.42]) turns changed across the support conversation relative to the use of *acknowledgment* turns.

Discussion

In this article, we outlined five steps for fitting dyadic multinomial logistic growth models in a Bayesian framework and illustrated how the model can be applied to dyadic categorical time series data in ways that facilitate the examination of between-dyad differences in within-dyad change. We will discuss modeling implications in greater depth below, but we first touch on the substantive results of the empirical demonstration. Our empirical example illustrated how the dyadic multinomial logistic growth model can be used to examine how pragmatic conversation behaviors enacted by listeners and disclosers unfold over time and whether those trajectories were impacted by the discloser's level of preconversation distress. Consistent with work on the phases of "troubles talk" (Jefferson, 2015), we found that disclosers were likely to begin the conversation elaborating on their problem and then shift their behaviors throughout the conversation by decreasing their use of elaboration turns relative to their use of acknowledgment turns. In contrast, listeners' use of elaboration turns greatly increased as the conversations unfolded. Surprisingly, and inconsistent with prior work that expects emotional distress to augment the processing of support messages (Bodie et al., 2011), the discloser's preconversation distress did not appear to impact listeners' or disclosers' baseline use of conversation behaviors or how those behaviors changed over time. Beyond the specific results, our analysis illustrates the potential for applying multinomial logistic growth models to examine changes in theoretically meaningful behaviors across a variety of dyadic interactions. We hope that this primer and illustration will spur further applications that will expand our understanding of interpersonal interaction.

Considerations for Studying Dyadic Dynamics With Multinomial Logistic Growth Models

The process of fitting multinomial logistic growth models follows five steps: (a) formulating hypotheses and obtaining data, (b) data description, plotting, and preparation, (c) specifying the model and priors, (d) estimating the model parameters, and (e) obtaining and configuring model output. We next discuss additional considerations for the first three steps, as well as opportunities for theory refinement that can emerge from using this modeling approach in analyses of dyadic interaction data. We then conclude with a series of notes on (a) implications of modeling choices, (b) flexibility in modeling nonlinear change, (c) necessity for theory that specifies how and why change trajectories differ, and (d) how multinomial logistic growth models can help refine current theory about dyadic interaction.

The first step in our model-fitting process is related to obtaining or identifying categorical time series data where the behaviors (or constructs of interest) have been coded with an exhaustive and mutually exclusive category set. In our illustrative example, each speaking

Table 5

Correlations Between Residual Random Effects of Dyadic Multinomial Logistic Growth Model Examining How Listeners' and Disclosers' Turn Type Use Changes During a Support Conversation After Accounting for Differences Related to Preconversation Distress

Parameter	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Listener																			
1. $\sigma_{advice\_u0[L]}$	—																		
2. $\sigma_{elaboration\_u0[L]}$	.31	—																	
3. $\sigma_{hedgeddisclosure\_u0[L]}$	.33	.33	—																
4. $\sigma_{question\_u0[L]}$	.42	.22	.28	—															
5. $\sigma_{reflection\_u0[L]}$	.17	.11	.25	.29	—														
Discloser																			
6. $\sigma_{advice\_u0[D]}$	**.05**	**.04**	**−.02**	**.01**	**.01**	—													
7. $\sigma_{elaboration\_u0[D]}$	**−.30**	**−.39**	**−.45**	**−.29**	**−.11**	.07	—												
8. $\sigma_{hedgeddisclosure\_u0[D]}$	**−.14**	**−.40**	**−.41**	**−.15**	**−.23**	.01	.46	—											
9. $\sigma_{question\_u0[D]}$	**.20**	**.37**	**.15**	**−.03**	**−.10**	.14	.12	−.04	—										
10. $\sigma_{reflection\_u0[D]}$	**−.08**	**.02**	**−.05**	**−.31**	**−.11**	.04	.13	−.05	.16	—									
Time																			
Listener																			
11. $\sigma_{advice\_u1[L]}$	−.08	.19	.17	.25	.21	−.02	−.27	−.17	−.13	−.12	—								
12. $\sigma_{elaboration\_u1[L]}$	.07	−.22	.18	.07	.01	−.04	−.14	−.27	−.02	.00	−.01	—							
13. $\sigma_{hedgeddisclosure\_u1[L]}$	.14	.05	−.16	.08	−.07	−.02	−.12	−.04	−.07	.02	.14	.15	—						
14. $\sigma_{question\_u1[L]}$	−.01	.05	−.01	−.14	.07	.02	.06	−.05	.18	.02	−.07	.08	−.04	—					
15. $\sigma_{reflection\_u1[L]}$	.08	.01	.08	.19	−.11	.03	−.07	−.04	.00	−.06	.07	.01	.01	.00	—				
Discloser																			
16. $\sigma_{advice\_u1[D]}$	−.11	−.07	−.12	−.22	−.30	−.06	.22	.04	.29	.27	**−.16**	**−.01**	**−.03**	**.06**	**.00**	—			
17. $\sigma_{elaboration\_u1[D]}$	−.05	.14	.02	.01	.07	.07	−.13	−.01	.21	.06	**−.06**	**−.31**	**−.21**	**.08**	**.03**	.09	—		
18. $\sigma_{hedgeddisclosure\_u1[D]}$	−.04	−.09	−.15	−.11	.04	−.01	.24	−.03	.05	.09	**−.13**	**−.14**	**−.07**	**.06**	**−.05**	.01	.13	—	
19. $\sigma_{question\_u1[D]}$	−.06	.01	−.06	−.16	−.11	.03	.00	−.03	−.07	.10	**−.06**	**.10**	**.04**	**.00**	**−.07**	.15	.01	−.03	—
20. $\sigma_{reflection\_u1[D]}$	−.01	.01	−.03	−.11	.00	.03	.05	−.05	.06	−.05	**−.04**	**.04**	**.00**	**.01**	**−.03**	.07	.00	.04	.04

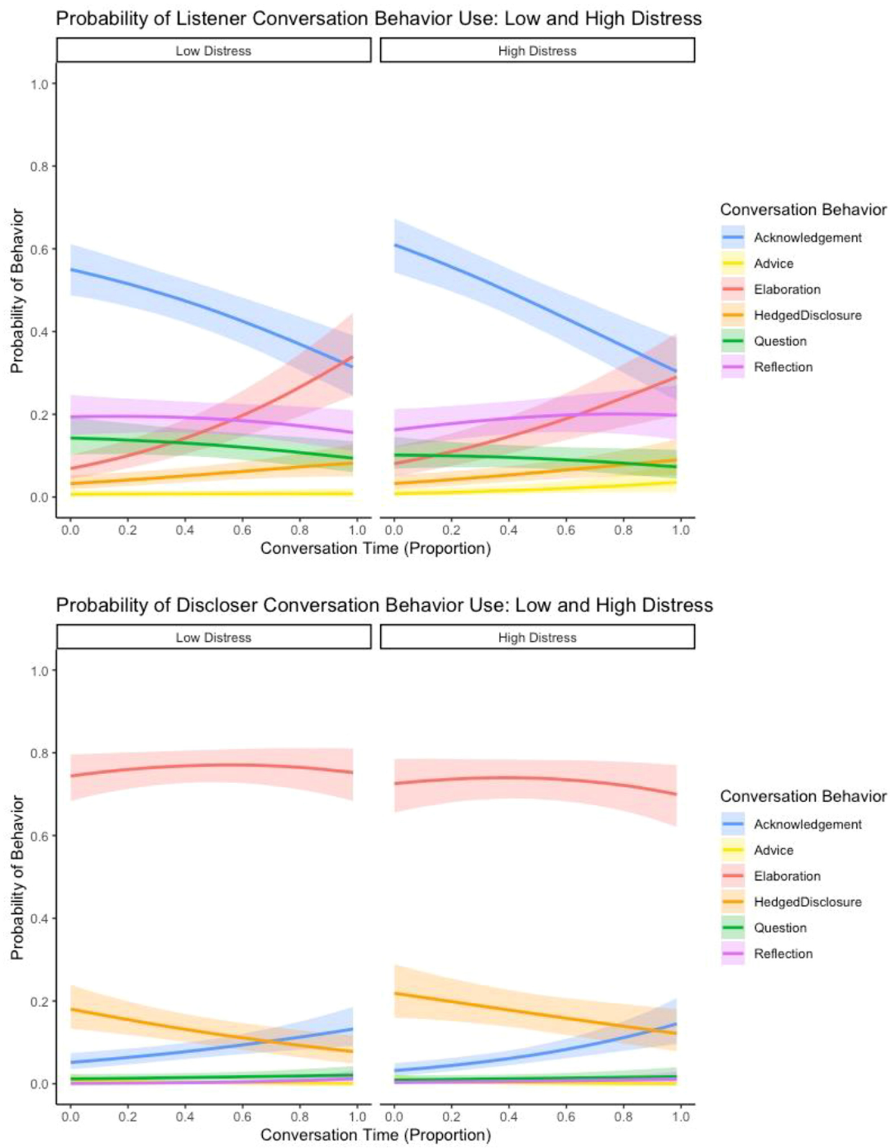
Note. The cross-dyad correlations have been bolded.

turn was coded with one of six conversation behaviors that described the pragmatic function of the speech act (Bodie et al., 2021). Although the multinomial logistic growth model can accommodate any set or size of categories, the number of categories and the selection of reference category will impact results and subsequent interpretation. For example, if we had reduced our theoretically driven six-category coding scheme into a three-category scheme by collapsing the three least frequently observed behaviors into one category, we would have glossed over potential differences in how those specific behaviors changed over time (and ended up with a difficult-to-interpret catch-all category). Relatedly, reference categories should also be chosen thoughtfully since the initial level and change in behaviors will be compared to the reference category. Researchers can consider the impact of changing reference categories for model interpretation. For example, we chose the acknowledgment conversation behavior as our reference category due to its relative frequency and anticipated rate of change during a support conversation. Notably, although the mathematics suggest that the choice of reference category is arbitrary (Agresti, 2019), our experience suggests that computation time may be substantially longer when the reference category has a low base rate (further simulation work to test this would be useful). Even though careful selection of an appropriate coding scheme is crucial, the necessary data requirements for the multinomial logistic growth model are relatively flexible when the categorical repeated measures are coded with an exhaustive and mutually scheme.

The second step in our model-fitting process involves choosing an appropriate and interpretable time metric. We have noted that the categorical time series data obtained in many studies of dyadic interactions may result in time series of similar or different length, either because of interval-contingent sampling (e.g., interactions that last different lengths because interactions went until a task was completed) or event-contingent sampling (e.g., interactions that have a different number of speaking turns). Interpretation of parameters from all growth models, including the dyadic multinomial logistic growth model, rests on an assumption that the time metric has the same meaning for all individuals/dyads. Aligning all the time series with respect to a specific event (where time = 0) and metric (e.g., proportion of total interaction) facilitates the between-person/dyad comparisons. In our illustrative example, we chose to scale the time variable used in the analysis to represent the proportion of time within the conversation, with 0.0 representing the beginning of the conversation and 1.0 representing the end of the conversation. Although our scaling of the time variable enables us to align the time series and make comparisons across dyads, the proportional nature of the variable is not so easy to interpret substantively. For instance, our calculation of conversation time as turn pair divided by the total turns assumes that all turn pairs are of equal length. Turns and turn pairs that contained many utterances are treated as though they are the same length as turns and turn pairs that contained a single utterance. As of this writing, we do not have any good solutions that dyadic interaction researchers might find especially insightful. One possibility for recapturing some of the information embedded in the length of conversation might be to include the total number of turns as a dyad-level covariate to examine whether the number of turns impacts the baseline level or rate of change in conversation behavior use. Although this possibility helps quantify the extent of the problem, we are not yet

Figure 3

Change in Conversation Behavior Use During a Support Conversation by Disclosers Who Reported Low and High Preconversation Distress



Note. The top panel depicts how the prototypical listener's use of six types of conversation behaviors changes over the course of the conversation, with the panels on the left and right distinguishing listener behaviors by dyads in which the discloser reported low and high preconversation distress. The bottom panel depicts how the prototypical discloser's use of six types of conversation behaviors changes over the course of the conversation, with the panels on the left and right distinguishing listener behaviors by dyads in which the discloser reported low and high preconversation distress. See the online article for the color version of this figure.

convinced that it completely solves the problem. Further work is needed to understand if and how different kinds of temporal information can be obtained during data collection and/or incorporated into the data analysis. For now, we simply raise the issue so that researchers take special care when rescaling the time variables used in their growth models and consider how those rescalings impact the interpretation of the within-dyad changes.

The third step of our model-fitting process is to identify the appropriate functional form of the trajectory of change. Researchers can choose the appropriate trajectory to model change using a combination of theory- and data-driven approaches (Ram & Grimm, 2015). In our illustrative example, we modeled change in conversation behaviors using a linear function. However, we could have chosen a more complex representation. Jefferson's multiple phases of "troubles talk" (2015) might be more precisely articulated using spline models (e.g., Backer et al., 2022) where the phases of the conversation are modeled using a series of connected linear functions (e.g., dividing each conversation into thirds to approximate the three phases likely present in our support conversations; Solomon et al., 2022). We could have also specified different change trajectories for each conversation behavior, such as a quadratic increase in elaboration turns for listeners. Notably, even as the functions get more complicated, the probabilities across categories must still sum to one. Future work using dyadic multinomial logistic growth models should take advantage of the flexibility in specifying different functional forms of change to examine the (potential) nonlinear trajectories in how behavior changes across an interaction.

The implementation and results of dyadic multinomial logistic growth models highlight the trajectories of change in behaviors during interactions. Although many theoretical perspectives emphasize the importance of the content or topic of a given interaction, most current research on dyadic interactions focuses on the impact of individual messages (i.e., one speaking turn) or on Gestalt-like perceptions of the whole interaction (Solomon et al., 2021). As a result, there is little empirical work describing how specific behaviors change during an interaction. We believe dyadic multinomial logistic growth models can help fill this gap by modeling behavioral trajectories within interactions. While our empirical example only illustrated fitting a linear change model, there are opportunities to fit multiple models with different change functions and develop an empirical understanding of the trajectory space that might inform new theoretical models of interaction. Those analyses can, of course, all be complemented with an exploration of the characteristics of individuals (e.g., emotional distress) or dyads (e.g., relational context) that contribute to differences in the change trajectories. We hope the insights gained from dyadic multinomial logistic growth models contribute to the theoretical refinement about dyadic interaction by providing a foundational description of how dyads' behaviors change over time, how those changes differ across dyads, and what characteristics impact or are related to the uncovered differences in within-dyad change.

Finally, we see a variety of directions for methodological work building upon our current demonstration. Additional methodological work is needed to determine (a) the impact of missing data on parameter estimation, (b) the impact of model misspecification, either in the measurement (i.e., the incorrect number of categories) or in the change function, (c) how different trajectories (i.e., subtype mixtures) can be discovered, and (d) how the model can be extended to a multivariate—that is, greater than bivariate—space. Simulation work, in particular, will extend and refine knowledge about how variants of the dyadic multinomial logistic growth model perform in a wide variety of empirical situations.

Conclusion

This article provides a primer that outlines and illustrates how dyadic multinomial logistic growth models can be used to examine categorical behavioral change within dyadic interactions. We outlined five steps for implementing this model and demonstrated the approach using turn by turn pragmatic conversation behaviors during support conversations between strangers to understand how the use of these conversation behaviors changed and whether discloser's preconversation emotional distress impacted these changes during the interaction. We look forward to the many new discoveries that will emerge as the model is applied to a wide variety of categorical time series data to test and refine a range of theories on dyadic interaction.

References

Agresti, A. (2019). *An introduction to categorical data analysis* (3rd ed.). Wiley.

Allison, P. D. (2018). *Event history and survival analysis* (pp. 86–97). Routledge.

Backer, P., Ram, N., & Stifter, C. (2022). Trajectories of infant positive emotion during the still face paradigm are associated with toddler temperament. *Infant Behavior and Development*, *67*, Article 101716. https://doi.org/10.1016/j.infbeh.2022.101716

Bodie, G. D., Burleson, B. R., Holmstrom, A. J., McCullough, J. D., Rack, J. J., Hanasono, L. K., & Rosier, J. G. (2011). Effects of cognitive complexity and emotional upset on processing supportive messages: Two tests of a Dual-Process Theory of Supportive Communication Outcomes. *Human Communication Research*, *37*(3), 350–376. https://doi.org/10.1111/j.1468-2958.2011.01405.x

Bodie, G. D., Jones, S. M., Brinberg, M., Joyer, A. M., Solomon, D. H., & Ram, N. (2021). Discovering the fabric of supportive conversations: A typology of speaking turns and their contingencies. *Journal of Language and Social Psychology*, *40*(2), 214–237. https://doi.org/10.1177/0261927X20953604

Bodie, G. D., Vickery, A. J., Cannava, K., & Jones, S. M. (2015). The role of "active listening" in informal helping conversations: Impact on perceptions of listener helpfulness, sensitivity, and supportiveness and discloser emotional improvement. *Western Journal of Communication*, *79*(2), 151–173. https://doi.org/10.1080/10570314.2014.943429

Burleson, B. R., & Goldsmith, D. J. (1998). How the comforting process works: Alleviating emotional distress through conversationally induced reappraisals. In P. A. Andersen & L. K. Guerrero (Eds.), *Handbook of communication and emotion: Research, theory, applications, and contexts* (pp. 245–280). Academic Press.

Butler, E. A. (2011). Temporal interpersonal emotion systems. *Personality and Social Psychology Review*, *15*(4), 367–393. https://doi.org/10.1177/1088868311411164

Bürkner, P. (2017). Brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*(1), 1–28. https://doi.org/10.18637/jss.v080.i01

Courtright, J. A., Millar, F., Rogers, L. E., & Bagarozzi, D. (1990). Interaction dynamics of relational negotiation: Reconciliation versus termination of distressed relationships. *Western Journal of Speech Communication*, *54*(4), 429–453. https://doi.org/10.1080/10570319009374354

Depaoli, S., & van de Schoot, R. (2017). Improving transparency and replication in Bayesian statistics: The WAMBS-checklist. *Psychological Methods*, *22*(2), 240–261. https://doi.org/10.1037/met0000065

Dillard, J. P. (1990). A goal-driven model of interpersonal influence. In J. P. Dillard (Ed.), *Seeking compliance: The production of interpersonal influence messages* (pp. 41–56). Gorsuch-Scarisbrick.

Feng, B. (2014). When should advice be given? Assessing the role of sequential placement of advice in supportive interactions in two cultures. *Communication Research*, *41*(7), 913–934. https://doi.org/10.1177/0093650212456203

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2014). *Bayesian data analysis*. Chapman & Hall/CRC.

Grimm, K. J., Ram, N., & Estabrook, R. (2016). *Growth modeling: Structural equation and multilevel modeling approaches*. Guilford Press.

Hox, J., van de Schoot, R., & Matthijsse, S. (2012). How few countries will do? Comparative survey analysis from a Bayesian perspective. *Survey Research Methods*, *6*(2), 87–93. https://doi.org/10.18148/srm/2012.v6i2.5033

Jaccard, J. (2015). *Complex statistics made accessible: Binary, categorical and count outcomes*. Applied Scientific Analysis.

Jefferson, G. (2015). *Talking about troubles in conversation*. Oxford University Press.

Kim, S.-Y., Huh, D., Zhou, Z., & Mun, E.-Y. (2020). A comparison of Bayesian to maximum likelihood estimation for latent growth models in the presence of a binary outcome. *International Journal of Behavioral Development*, *44*(5), 447–457. https://doi.org/10.1177/0165025419894730

Kruschke, J. (2015). *Doing Bayesian data analysis: A tutorial with R, JAGS, and Stan* (2nd ed.). Academic Press.

Link, W. A., & Eaton, M. J. (2012). On thinning of chains in MCMC. *Methods in Ecology and Evolution*, *3*(1), 112–115. https://doi.org/10.1111/j.2041-210X.2011.00131.x

Makowski, D., Ben-Shachar, M. S., Chen, S. H. A., & Lüdecke, D. (2019). Indices of effect existence and significance in the Bayesian framework. *Frontiers in Psychology*, *10*, Article 2767. https://doi.org/10.3389/fpsyg.2019.02767

Muthén, L., & Muthén, B. (1998–2015). *Mplus user's guide* (7th ed.).

Nesselroade, J. R. (1991). The warp and the woof of the developmental fabric. In R. M. Downs, L. S. Liben, & D. S. Palermo (Eds.), *Visions of aesthetics, the environment & development: The legacy of Joachim F. Wohlwill* (pp. 213–240). Lawrence Erlbaum Associates.

Oravecz, Z., & Muth, C. (2018). Fitting growth curve models in the Bayesian framework. *Psychonomic Bulletin & Review*, *25*(1), 235–255. https://doi.org/10.3758/s13423-017-1281-0

Plummer, M. (2003). JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling. In K. Hornik, F. Leisch, & A. Zeileis (Eds.), *Proceedings of the 3rd International Workshop on Distributed Statistical Computing (DSC 2003), Vienna, Austria, March 20–22, 2003* (Vol. 124, No. 125, pp. 1–10). http://www.ci.tuwien.ac.at/Conferences/DSC.html

Plummer, M. (2019). *rjags: Bayesian graphical models using MCMC* (R package version 4-10) [Computer software]. https://CRAN.R-project.org/package=rjags

R Core Team. (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Rains, S. A., Ashtaputre, A., Nemcova, K., Lutovsky, B. R., Tsetsi, E., Pavlich, C. A., & Akers, C. (2021). The evolution of supportive conversations: Tracking within-discussion changes in support seeking and provision messages. *Communication Monographs*, *88*(4), 483–505. https://doi.org/10.1080/03637751.2021.1889009

Ram, N., & Grimm, K. J. (2015). Growth curve modeling and longitudinal factor analysis. In W. F. Overton, P. C. M. Molenaar, & R. M. Lerner (Eds.), *Handbook of child psychology and developmental science: Theory and method* (pp. 758–788). John Wiley & Sons. https://doi.org/10.1002/9781118963418.childpsy120

Ram, N., & Reeves, B. (2018). Time sampling. In M. H. Bornstein, M. E. Arterberry, K. L. Fingerman, & J. E. Lansford (Eds.), *Encyclopedia of lifespan human development* (pp. 2247–2248). Sage Publications.

Roy, V. (2020). Convergence diagnostics for Markov Chain Monte Carlo. *Annual Review of Statistics and Its Application*, *7*(1), 387–412. https://doi.org/10.1146/annurev-statistics-031219-041300

Solomon, D. H., Brinberg, M., Bodie, G. D., Jones, S. M., & Ram, N. (2021). A dynamic dyadic systems approach to interpersonal communication. *Journal of Communication*, *71*(6), 1001–1026. https://doi.org/10.1093/joc/jqab035

Solomon, D. H., Jones, S. M., Brinberg, M., Bodie, G. D., & Ram, N. (2022). Using sequence analysis to identify conversational motifs in supportive interactions. *Journal of Social and Personal Relationships*, *39*(10), 3155–3179. https://doi.org/10.1177/02654075211066618

Stan Development Team. (2019). *Stan modeling language users guide and reference manual* (Version 2.27) [Computer software]. https://mc-stan.org

Stiles, W. B. (1992). *Describing talk: A taxonomy of verbal response modes*. Sage Publications.

van de Schoot, R., Kaplan, D., Denissen, J., Asendorpf, J. B., Neyer, F. J., & van Aken, M. A. G. (2014). A gentle introduction to Bayesian analysis: Applications to developmental research. *Child Development*, *85*(3), 842–860. https://doi.org/10.1111/cdev.12169

Wickham, H., François, R., Henry, L., & Müller, K. (2020). *dplyr: A grammar of data manipulation* (R package version 1.0.2) [Computer software]. https://CRAN.R-project.org/package=dplyr

Zitzmann, S., & Hecht, M. (2019). Going beyond convergence in Bayesian estimation: Why precision matters too and how to assess it. *Structural Equation Modeling: A Multidisciplinary Journal*, *26*(4), 646–661. https://doi.org/10.1080/10705511.2018.1545232

Received October 3, 2022
Revision received March 7, 2023
Accepted June 22, 2023 ■