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From cross-lagged effects to feedback effects: Further insights into the estimation and interpretation of bidirectional relations

Xiaohui Luo[1] · **Hongyun Liu**[1] · **Yueqin Hu**[1]

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Abstract

Bidirectional relations have long been of interest in psychology and other social behavioral sciences. In recent years, the widespread use of intensive longitudinal data has provided new opportunities to examine dynamic bidirectional relations between variables. However, most previous studies have focused on the effect of one variable on the other (i.e., cross-lagged effects) rather than the overall effect representing the dynamic interplay between two variables (i.e., feedback effects), which we believe may be due to a lack of relevant methodological guidance. To quantify bidirectional relations as a whole, this study attempted to provide guidance for the estimation and interpretation of feedback effects based on dynamic structural equation models. First, we illustrated the estimation procedure for the average and person-specific feedback effects. Then, to facilitate the interpretation of feedback effects, we established an empirical benchmark by quantitatively synthesizing the results of relevant empirical studies. Finally, we used a set of empirical data to demonstrate how feedback effects can help (a) test theories based on bidirectional relations and (b) reveal correlates of individual differences in bidirectional relations. We also discussed the broad application prospects of feedback effects from a dynamic systems perspective. This study provides guidance for applied researchers interested in further examining feedback effects in bidirectional relations, and the shift from focusing on cross-lagged effects only to a comprehensive consideration of feedback effects may provide new insights into the study of bidirectional relations.

Keywords Bidirectional relation · Feedback effect · Cross-lagged effect · Dynamic structural equation model · Intensive longitudinal data

The bidirectional or reciprocal relation between variables is an important issue in longitudinal studies in psychology and other social and behavioral science (Pettit & Arsiwalla, 2008; Taris & Kompier, 2014; Usami et al., 2019). Traditional longitudinal studies have typically collected data at a few time points, each spanning several months or years, to study developmental or long-term change, which may not capture the micro-dynamics of variables (e.g., from day to day, or hour to hour), and the real-time interplay between variables.

In recent decades, intensive longitudinal data (ILD) obtained through methods such as daily diaries (Bolger et al., 2003) and ecological momentary assessments (EMA; Smyth & Stone, 2003) have been widely used to reveal dynamic processes within individuals over time. Due to the large number of observations in ILD (e.g., more than 20; Collins, 2006), traditional cross-lagged models (e.g., cross-lagged panel models [CLPMs] and random intercept cross-lagged panel models [RI-CLPMs]) applicable to data with only a few time points have difficulty in analyzing such data, and a new modeling approach for ILD, dynamic structural equation modeling, has been proposed.

Dynamic structural equation models (DSEMs; Asparouhov et al., 2018; McNeish & Hamaker, 2020) integrate structural equation modeling, multilevel modeling, and time series modeling approaches, and are therefore able to separate the trait components of the variables from the state components

✉ Hongyun Liu
hyliu@bnu.edu.cn

✉ Yueqin Hu
yueqinhu@bnu.edu.cn

[1] Beijing Key Laboratory of Applied Experimental Psychology, National Demonstration Center for Experimental Psychology Education (Beijing Normal University), Faculty of Psychology, Beijing Normal University, No. 19, Xin Jie Kou Wai St., Hai Dian District, Beijing 100875, People's Republic of China

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and explore the bidirectional lagged relations between the state components of the variables at the within-person level. It is worth noting that while both DSEMs and (RI-)CLPMs are cross-lagged models focusing on bidirectional relations between variables under the discrete-time modeling framework, they are applicable to data with different features and have different assumptions about the random effects of bidirectional relations (McNeish & Hamaker, 2020). (RI-)CLPMs are typically used for traditional longitudinal data (also known as panel data) with few repeated measurement occasions (i.e., 3–8) on a macro timescale (i.e., months or years), and they analyze data in a wide format. In addition, they typically assume that there are no individual differences in the autoregressive and cross-lagged parameters of the variables (i.e., they do not take into account the random effects of these parameters). In contrast, DSEMs are typically used for intensive longitudinal data with more repeated measurement occasions (i.e., more than 10, or even more than 20) on a micro timescale (i.e., hours or days), and they analyze data in a long format. They assume individual differences in the autoregressive and cross-lagged parameters of the variables (i.e., they take into account the random effects of these parameters). In addition to discrete-time models such as DSEMs, intensive longitudinal data can also be analyzed with continuous-time models, which can deal with the time-interval dependency problem (Kuiper & Ryan, 2018) encountered with DSEMs. However, these continuous-time models are often more difficult to specify in software, whereas DSEMs can be easily implemented in user-friendly software such as M*plus* (McNeish & Hamaker, 2020). Due to the unique advantages and ease of implementation of DSEMs, they have been increasingly used to examine reciprocal relations in ILD across multiple domains in psychology, including clinical (Gómez Penedo et al, 2021; Hjartarson et al., 2022; Santangelo et al, 2020; Zhu et al., 2022), developmental (Becht et al., 2021; Boele et al., 2023; Bülow et al., 2022; Xu & Zheng, 2022), health (Armstrong et al., 2021; Lewis et al., 2022), educational (Neubauer et al., 2022; Niepel et al., 2021; Rottweiler & Nett, 2021), social (Edershile & Wright, 2021), and organizational (Bourret et al., 2023; Li et al., 2023) domains.

However, previous research on bidirectional relations often estimated and interpreted the bidirectional effects[1] between variables separately, without considering the bidirectional effects as a whole. This hindered a more comprehensive understanding of the dynamic interaction process between variables, and prevented further investigation of individual differences, developmental processes, and related factors of the bidirectional relations between variables.

In fact, some researchers have theoretically discussed the bidirectional relations between variables as a whole, and referred to them as feedback loops (Boden & Berenbaum, 2010; Goldring & Bolger, 2021; Hollenstein, 2015). For example, Almeida (2005) pointed out that there may be a feedback loop in daily stress processes: stressors impair an individual's psychological and physical well-being, which may lead to more stressors due to selective exposure. Although there have been theoretical discussions of feedback loops between variables, few empirical studies have examined feedback loops between variables as a whole, and this lack of research, we believe, is largely due to the lack of methodological guidance for estimating and interpreting feedback effects. Therefore, the present study aims to illustrate how feedback effects can be estimated and interpreted based on DSEMs, providing further insights into bidirectional relations.

Theoretical and empirical studies on feedback loops

Theoretically, the idea of feedback loops has been drawn upon to answer many key research questions in psychology. For example, in studies on the dynamic processes of emotion, feedback loops have been widely used to explain the dynamic interaction between different components of emotion, particularly emotion regulation process (Gross, 2015; Hollenstein, 2015). Moreover, research on emotion-related disorders has also been inspired by the idea of feedback loops. For example, Garland et al. (2010) noted that the behavioral, cognitive, affective, and physiological attributes of depression and anxiety often reinforced each other, which led to damaging downward spirals. In contrast, some interventions (e.g., mindfulness practice) may trigger a self-perpetuating dynamic interplay between positive cognitive and emotional factors, which contributed to beneficial upward spirals (Garland et al., 2010). Similar processes have also been proposed for other disorders. For example, Jacob et al. (2019) noted that there was also a feedback loop between posttraumatic stress disorder (PTSD) and neurocognition. In addition, feedback loops have provided valuable insight into examining critical issues in multiple subareas of psychology. For example, a recent review article in educational psychology proposed a summary model of the feedback loop between motivation and achievement in learning based on previous influential theories on academic motivation (Vu et al., 2022). Taken together, abundant theoretical studies on feedback loops have suggested that this concept was not new to psychology; rather, it has received wide attention and has important theoretical and practical value.

[1] Note that when we refer to "bidirectional effects," "cross-lagged effects," "feedback effects," etc., in this paper, we do not mean a strictly causal influence, but rather a predictive relation (or, in the case with temporal precedence (or temporal ordering), a Granger causal relation; Granger, 1969). We use the term "effect" for consistency with previous research. However, we would like to remind the reader that it may be essentially a predictive relation or a Granger causal relation.

However, empirical studies that directly analyze feedback loops are limited. Though focusing on feedback processes, previous studies typically estimated the effects of one variable on another (e.g., cross-lagged effects between two variables), without considering the entire feedback loop in an integrated manner (Emerson et al., 2018; Sleddens et al., 2017; Somers et al., 2022; Xiang et al., 2020; Zhang & Wu, 2014). An exception was a recent study on daily stress processes, which was the first attempt to empirically examine feedback loops as a whole (Goldring & Bolger, 2021). Specifically, they estimated the contemporaneous bidirectional effects between stressors and psychological distress, as well as between psychological distress and physical symptoms. Then, the products of two bidirectional effects were used to calculate the corresponding feedback effects. Although this study was an encouraging attempt to estimate the overall feedback effect and its individual differences, it had several limitations in estimating and interpreting the feedback effects. First, the non-recursive structural equation model (SEM) used in this study could not be identified without instrumental variables, while selecting appropriate instrumental variables was not easy, especially in ILD. Second, the contemporaneous bidirectional effects examined in this study may reflect only contemporaneous associations rather than reciprocal effects in a feedback loop. Moreover, temporal precedence (or temporal ordering) is one of the prerequisites for causal inference, and most previous studies on bidirectional relations have conducted multiple repeated measurements and estimated cross-lagged effects to make causal inferences (i.e., Granger causality; Granger, 1969). Therefore, estimating feedback effects based on lagged effects rather than contemporaneous effects may be crucial for better understanding the bidirectional relations between variables. Furthermore, the size of the feedback effect was subjectively described (e.g., "very small," "basically zero") and its practical value was inferred accordingly (Goldring & Bolger, 2021). As mentioned in the discussion, the interpretation of feedback effects may need to be based on more empirical criteria. In conclusion, given the great value of feedback loops in theoretical and empirical research on bidirectional relations and the lack of appropriate methods for applied researchers, a methodological guidance on estimating and interpreting feedback effects based on lagged bidirectional relations was warranted.

Estimation of feedback effects

A straightforward idea for estimating feedback effects is to multiply the effects in both directions, which was applied in a previous study (Goldring & Bolger, 2021). In the specific context of our study (i.e., estimating feedback effects based on lagged relations in DSEMs), feedback effects can be obtained by multiplying the cross-lagged effects estimated in DSEMs. To illustrate why this idea makes sense, we start with how bidirectional relations can be examined using DSEMs. As shown in Fig. 1a, for the two variables of interest (i.e., Y_1 and Y_2), we start by considering an autoregressive process for each variable. To explore their bidirectional relations, we add cross-lagged effects between the two variables and allow for contemporaneous associations between their residuals (see Fig. 1b). If the feedback loop is viewed from the perspective of Y_1 (i.e., the path $Y_{1,\,T-1} \rightarrow Y_{2,\,T} \rightarrow Y_{1,\,T+1}$ in Fig. 1c), it shows how the prior state of Y_1 (i.e., $Y_{1,\,T-1}$) affects its subsequent state (i.e., $Y_{1,\,T+1}$) through its dynamic interaction with Y_2. A similar illustration can be made for Y_2 (see Fig. 1d). For both Y_1 and Y_2, the effects corresponding to the feedback loops are the products of the two cross-lagged effects (i.e., $\varphi_{12} \times \varphi_{21}$), which suggests that these products can be used as quantitative indicators of the overall bidirectional relations between variables (i.e., feedback loops). In addition, since the cross-lagged effects are allowed to vary between individuals in DSEMs, both average feedback effects and person-specific feedback effects are available.

The above presentation of feedback effects is based on a bivariate model, and one might ask how to compute feedback effects in a model with three or more variables. This can be divided into two cases depending on the research interest. In one case, although there are three or more variables in the model, the research focus remains on the feedback loop between two variables. For example, in a model with a multidimensional construct A and another construct B, the researcher is interested in the loops between construct B and each dimension of construct A, respectively. In this case, the feedback effects can be computed directly using the method described above. In the other case, the researcher believes that there are multiple feedback loops in the model and is interested in the overall feedback effect. For example, a researcher builds a model with three variables (i.e., Y_1, Y_2, and Y_3), and three bivariate feedback loops between them. In this case, we can calculate the feedback effect from the perspective of one particular variable as well as the overall feedback effect between all variables (please see Supplementary Information S1 for details).

There are two other issues worth noting here. First, time-varying effects are not considered in this study. Therefore, autoregressive, cross-lagged, and feedback effects are the same for all measurement occasions (i.e., time-invariant effects). Second, autoregressive and cross-lagged effects are a function of the time interval (Hecht & Zitzmann, 2021; Kuiper & Ryan, 2018), and their estimates depend on the specific time interval. Therefore, the interpretation of these effects, as well as feedback effects, should be subject to the specific time interval.

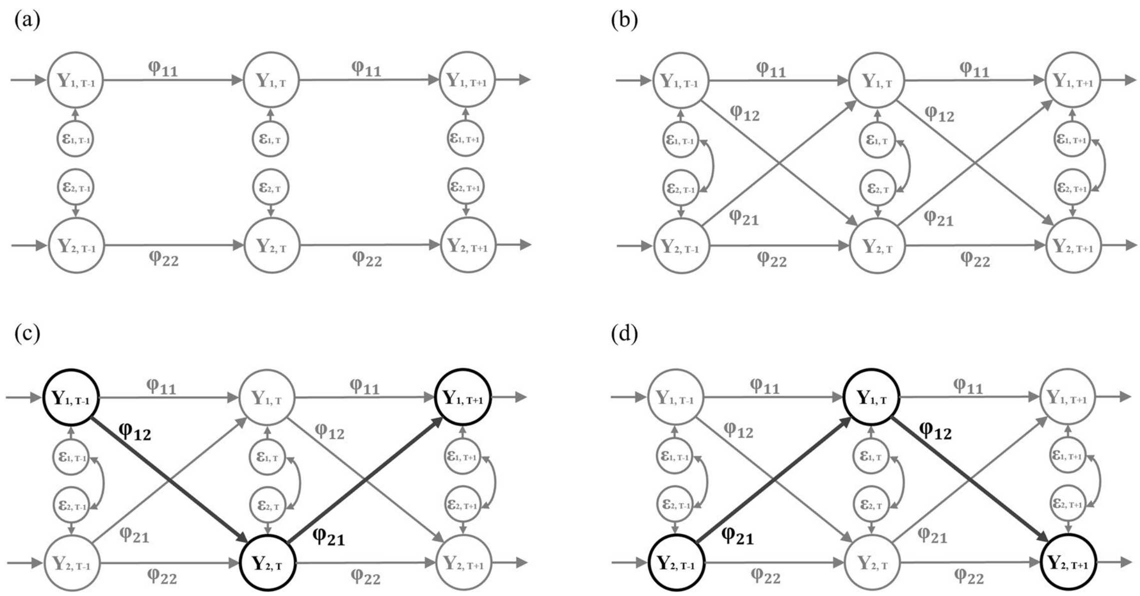

Fig. 1 Dynamic feedback process between two variables, Y_1 and Y_2, at time points T−1, T, and T+1. Model (**a**) shows the autoregressive processes of Y_1 and Y_2, and (**b**) adds cross-lagged effects and contemporaneous relations to arrive at a bivariate DSEM. Models (**c**) and (**d**) show the dynamic feedback processes from the perspective of Y_1 and Y_2, respectively. *Notes*: φ_{11} and φ_{22} denote autoregressive parameters, and φ_{12} and φ_{21} denote cross-lagged parameters. ε_1 and ε_2 are the residuals of Y_1 and Y_2

Interpretation of feedback effects

After estimating feedback effects, researchers may further consider how to interpret them. First, we may wonder what a positive or negative feedback effect means. As the product of two cross-lagged effects, a positive feedback effect indicates that the effects in both directions are of the same sign. This suggests that the two variables are mutually excitatory (Hollenstein, 2015; Yang et al., 2019), and their dynamic interaction forms a self-perpetuating loop (Garland et al., 2010). For example, some individuals may have a positive feedback loop between stressors and negative affect. This may indicate that stressors increase individuals' subsequent negative affect, which in turn exposes the individuals to more stressors; in other words, the bidirectional relation between stressors and negative affect constitutes a damaging and self-perpetuating loop. On the contrary, if a feedback effect is negative, the effects in the two directions are of different signs. This suggests that the two variables are mutually inhibitory (Hollenstein, 2015; Yang et al., 2019), and their dynamic interaction forms a self-regulating loop. Compared with the above example, other individuals may have a negative feedback loop between stressors and negative affect: while the stressor subsequently leads to more negative affect, it predicts fewer subsequent stressors. This suggests that during the dynamic interaction between stressors and individuals' negative affect, they mutually inhibit each other, contributing to individuals' adaptive dynamic equilibrium.

In addition, we may also want to know how to interpret the size of feedback effects. Similar to the interpretation of regression effects, a feedback effect between two variables (e.g., Y_1 and Y_2) equal to φ can be interpreted as follows: when one variable at time T−1 (e.g., $Y_{1,\,T-1}$) changes by 1 unit (or *SD*), the variable at time T+1 (e.g., $Y_{1,\,T+1}$) is expected to change by φ units (or *SD*) through its dynamic interplay with the other variable (i.e., through the path $Y_{1,\,T-1} \rightarrow Y_{2,\,T} \rightarrow Y_{1,\,T+1}$), after controlling for the autoregressive process of the variable (i.e., through the path $Y_{1,\,T-1} \rightarrow Y_{1,\,T} \rightarrow Y_{1,\,T+1}$).

Furthermore, researchers might wonder what are considered as small, medium, and large feedback effects. Given that feedback effects are the products of cross-lagged effects, it may occur to some researchers that the feedback effects could be regarded as the products of two correlations and interpreted based on previous criteria for correlations. It is worth noting, however, that the criteria proposed for correlations do not apply to cross-lagged effects, let alone feedback effects. The estimation of cross-lagged effects controls for the effects (i.e., autoregressive effects) of the prior states of the variables and the contemporaneous associations between variables, and thus the cross-lagged effects are expected to be smaller than common bivariate associations (Orth et al., 2022). With a particular focus on cross-lagged effects, a recent article quantitatively analyzed previous studies on bidirectional relations between variables based on CLPMs and RI-CLPMs, and proposed criteria for small, medium, and large cross-lagged effects (Orth et al., 2022). However, these criteria are not applicable to the present study. First, the cross-lagged effects they were interested in were based on (RI-)CLPMs, while feedback effects are more appropriately estimated in DSEMs. This is because most of the discussion of feedback loops is related to short-term dynamic interaction processes between components (Goldring & Bolger, 2021; Hollenstein, 2015; Kunnen et al., 2019) rather than long-term developmental processes. Such intensive interactions (which typically require dense and large numbers of measurements) are more suitably constructed with DSEMs than with (RI-)CLPMs. Moreover, (RI-)CLPMs do not consider between-person random effects on autoregressive and cross-lagged effects as DSEMs do (Usami et al., 2019). As a result, (RI-)CLPMs cannot estimate person-specific feedback effects, and therefore cannot further examine individual differences in the bidirectional relations of interest. Therefore, it is more reasonable to use DSEMs to estimate feedback effects. In addition, DSEMs differ from (RI-)CLPMs in many aspects, including not only their different considerations of random effects, as we just mentioned, but also the fact that the cross-lagged effects estimated by DSEMs usually correspond to shorter time intervals (hours or days), whereas those estimated by (RI-)CLPMs usually correspond to longer intervals (months or years). These lead to their incomparable cross-lagged effects. More importantly, the feedback effects are the products of cross-lagged effects between a pair of constructs, and in most cases, the two cross-lagged effects are not equal. Therefore, it is not appropriate to use the benchmark of cross-lagged effects to interpret the size of feedback effects (e.g., by squaring the benchmark values of cross-lagged effects), and an empirical benchmark of feedback effects is needed to promote a better understanding of feedback effects.

Potential application of feedback effects

In addition to analyzing the bidirectional relations between variables more directly, estimating and understanding feedback effects as a whole has broader value for applied research. Specifically, it could help us further explore and answer research questions about bidirectional relations. One type of question that may be of interest to researchers is whether theories based on bidirectional relations or feedback loops could be empirically supported. In answering this type of question, previous studies typically tested the relations in both directions separately, and significant relations in both directions would provide supporting evidence for the corresponding theory. However, this approach had limitations. It could not test the overall effect of a loop consisting of a bidirectional relation. Moreover, researchers could not make inferences about the overall size of the dynamic feedback processes based on the effect sizes of two directions. In contrast, the estimation procedure and the empirical benchmark of feedback effects introduced in this study allows researchers to test the statistical significance and interpret the size of feedback effects, which could effectively help applied researchers to better understand the theories based on bidirectional relations.

A second type of question that may also be of interest is that related to individual differences in bidirectional relations. Specifically, researchers may wonder to what extent the feedback effects between variables varied from person to person, and furthermore, whether there are individual difference factors that could explain the interpersonal variability in dynamic feedback processes. For this type of question, previous studies usually explored whether some individual difference factors were associated with the effects in either direction and explained individual differences in effects in the two directions separately. However, we argue that this may obscure the associations of some individual difference factors with dynamic feedback processes. The bidirectional relations emphasize the whole of the two variables. A factor that is not associated with the effect in either direction may still be associated with the entire dynamic feedback process. Considering that previous studies generally explored individual differences in the effects of the two directions separately, this study describes how individual differences in dynamic feedback processes could be better explored and explained in an integrated manner. This may reveal more effective explanatory factors for individual differences in dynamic feedback processes and help researchers answer questions about individual differences in dynamic bidirectional relations in greater depth.

The present study

The main purpose of the present study was threefold. First, we used a set of empirical data to illustrate how to estimate feedback effects and their individual differences based on DSEMs. Then, we aimed to facilitate better interpretation of feedback effects by establishing an empirical benchmark for feedback effects. Specifically, we established a distribution of feedback effects based on previous empirical studies examining bidirectional relations with DSEMs, and operationalized small, medium, and large feedback effects as the 25th, 50th, and 75th percentiles of the distribution. In addition, possible moderators of the size of feedback effects were tested. Finally, we used another set of empirical data to further demonstrate how feedback effects could be applied to (a) test theoretical models of feedback loops, and (b) make a unique contribution to understanding the dynamic feedback process and its related factors.

Procedure for estimating feedback effects

In this section, we introduce the procedure for estimating average and person-specific feedback effects with empirical data. Inspired by Goldring & Bolger (2021), we collected diary data on daily stress processes and investigated possible feedback loops between daily stressors and physical symptoms based on their cross-lagged relations. Specifically, we estimated the average feedback effect between stressors and physical symptoms. We also estimated person-specific feedback effects and examined the individual differences in the dynamic feedback process between stressors and physical symptoms.

Method

Participants and procedures

A total of 252 Chinese female college students participated in this study. Their mean age was 20.325 years (ranging from 17 to 25, $SD = 1.474$). All participants were of Chinese Han ethnicity. The majority of the sample were undergraduates (86.905%), including 12.698% freshmen, 26.587% sophomores, 24.603% juniors, and 23.016% seniors. The other participants were master's degree-seeking students (12.698%) or PhD degree-seeking students (0.397%).

This study was approved by the university's ethics committee. First, informed consent was obtained from each participant, and they all completed an online questionnaire to provide demographic information. Then, participants received a smartphone message containing a link to an online diary at 11 p.m. every day for 34 consecutive days to measure their daily stressors and physical symptoms. They were asked to complete the daily diary before going to bed each day. Participants' compliance with the study was satisfactory, with 94.888% ($n = 8130$) of all diaries ($N = 8568$; 252 participants × 34 days) being completed. At the individual level, 100 participants completed all diaries, 127 participants completed 30–33 diaries, and only 25 participants completed fewer than 30 diaries. Participants were rewarded according to their compliance, with average compensation of ¥103.31 per participant.

Measures

Daily stressors Daily stressors were measured with the Daily Inventory of Stressful Events (DISE; Almeida et al., 2002). Participants were asked to report whether they experienced the following stressful events: (a) having an argument or disagreement with anyone, (b) avoiding an argument or disagreement (i.e., having something they could have argued about but decided to let it pass), (c) experiencing a work- or school-related stressor, (d) experiencing a home-related stressor, (e) experiencing discrimination, (f) experiencing a network stressor (usually related to close friends or relatives), and (g) experiencing any other stressful event. They responded to each item with 0 ("No") or 1 ("Yes"). The total score of the seven items was calculated.

Physical symptoms Based on previous studies (Goldring & Bolger, 2021; Kroenke et al., 2002; Larsen & Kasimatis, 1991), we adapted 20 items to measure physical symptoms, including various aches (e.g., headaches, backaches, and joint pain), gastrointestinal or diet-related symptoms (e.g., nausea, poor appetite, and diarrhea), and symptoms related to the five senses (e.g., eye-, ear-, and nose-related symptoms). Participants reported whether they had each symptom with 0 ("No") or 1 ("Yes"). The total score of the 20 items was calculated.

Data analyses

A bivariate DSEM with daily stressors and physical symptoms was modeled to test their bidirectional relation (see Fig. 2). Within-person autoregressive effects of daily stressors and physical symptoms as well as their cross-lagged effects were estimated for each participant (i.e., allowing for between-person variance of all these effects), and the mean values and variances of these effects were estimated across all participants. It should be noted that these autoregressive and cross-lagged effects were estimated using a time interval of one day. Therefore, the effects should be interpreted based on the specific time interval.[2] The same is true for the feedback effect between daily stressors and physical symptoms, as it is the product of the cross-lagged effects between daily stressors and physical symptoms. The variances and covariance of the within-person residuals of daily stressors and physical symptoms were fixed to be equal for all individuals. At the between-person level, the correlations among the mean values of daily stressors and physical symptoms and their autoregressive and cross-lagged effects were freely estimated. The within-person standardization approach (Schuurman et al., 2016) was used to obtain standardized coefficients. Specifically, we first calculated the within-person variances based on the person-specific covariance matrix in each iteration, and then calculated the person-specific standardized coefficients in each iteration using the equation proposed by Schuurman et al. (2016). The average standardized coefficients (i.e., standardized fixed effects) were estimated by averaging the person-specific standardized coefficients across persons in each iteration. Therefore, we obtained the posterior distribution of each standardized coefficient, from which we derived its point estimate and credible interval.

[2] We also considered the results of parameter estimates based on another time interval (i.e., a two-day interval) using the parameter transformation method (Kuiper & Ryan, 2018; 2020). Specifically, we transformed the person-specific standardized effects based on a time interval of one day to a time interval of two days for each individual, and then averaged the transformed effects across all individuals. Results are presented in Supplementary Information S2.

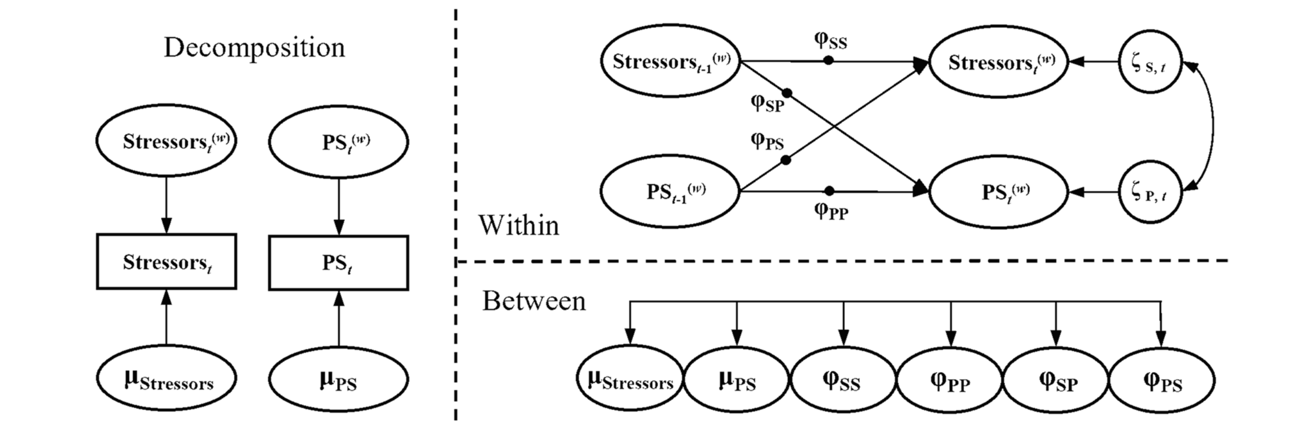

Fig. 2 Dynamic structural equation model for daily stressors and physical symptoms. *Note*: PS = physical symptoms. Black dots indicate person-specific autoregressive and cross-lagged effects

The model parameters were estimated in M*plus* version 8.10 (Muthén & Muthén, 1998-2017) using Bayesian estimation with noninformative priors and the Markov chain Monte Carlo (MCMC) algorithm. We used two Gibbs-sampler chains with 25,000 iterations each, 50% burn-in, and a thinning value of 1. The fixed number of iterations was determined considering stopping criteria including potential scale reduction (PSR; Asparouhov & Muthén, 2010) and effective sample size (ESS; Zitzmann et al., 2021; Zitzmann & Hecht, 2019), as well as trace plots of parameters (Hamaker et al., 2018). Details of model and analysis settings in M*plus* are provided in Supplementary Information S3.

To obtain the point estimate and the 95% credible interval (CI) of the feedback effect, the MODEL CONSTRAINT command and the following equation were used:

$$FE = \varphi_{PS} \times \varphi_{PS} \tag{1}$$

where FE is the feedback effect between stressor and physical symptoms for the average person, and φ_{SP} and φ_{PS} are the fixed effects (i.e., averaged across people) of cross-lagged effects between daily stressors and physical symptoms.

In addition, the standardized feedback effect for the average person (i.e., FE*) and the standardized person-specific feedback effects (i.e., FE_i^*) were calculated using the following equations:

$$FE^* = \varphi_{SP}^* \times \varphi_{PS}^* \tag{2}$$

$$FE_i^* = \varphi_{SP,i}^* \times \varphi_{PS,i}^* \tag{3}$$

where φ_{SP}^* and φ_{PS}^* are the fixed effects of standardized cross-lagged effects between daily stressors and physical symptoms, and $\varphi_{SP,i}^*$ and $\varphi_{PS,i}^*$ are the person-specific standardized cross-lagged effects between daily stressors and physical symptoms. Notably, the person-specific standardized cross-lagged effects were obtained from the STDRESULTS command in the SAVE section in M*plus*, and the person-specific feedback effects were then calculated according to Eq. 3 in R. All data, M*plus* syntax, and R code for feedback effect estimation are available at https://osf.io/psxw6/?view_only=52220fd7fb08434aa4d5fb832da09ce8.

Results

Descriptive analysis

The intraclass correlations for daily stressors and physical symptoms were .447 and .606, respectively, suggesting that more than half of the variance in stressors and approximately 40% of the variance in physical symptoms were within-person. At the within-person level, daily stressors were positively associated with physical symptoms ($r = .137$, $p < .001$), which suggests that when individuals encountered more stressors than their average levels, they experienced more physical symptoms than usual. At the between-person level, there was a strong positive association between daily stressors and physical symptoms ($r = .518$, $p < .001$). This suggests that people who encountered more stressors on average had more physical symptoms on average.

Average effects

Table 1 presents the unstandardized and standardized parameter estimates for the dynamic bidirectional relation between daily stressors and physical symptoms. There were positive autoregressive effects of daily stressors and physical symptoms, suggesting carryover effects from current stressors and physical symptoms to subsequent stressors and physical symptoms. More importantly, there were significant cross-lagged effects between daily stressors and physical symptoms. Specifically, individuals who had more stressors reported more physical symptoms the next day ($\varphi_{SP}^* = .060$, 95% CI = [.031, .088]), which in turn led to more subsequent

Table 1 Results of parameter estimation from the dynamic structural equation model for daily stressors and physical symptoms

Parameter	Unstandardized estimates		Standardized estimates
	Fixed effects	Random variances	Fixed effects
φ_{SS}	.256 [.221, .291]	.031 [.020, .046]	.255 [.226, .282]
φ_{PP}	.451 [.413, .489]	.033 [.022, .048]	.451 [.420, .480]
φ_{SP}	.033 [.013, .053]	.008 [.004, .013]	.060 [.031, .088]
φ_{PS}	.071 [.024, .117]	.020 [.008, .040]	.042 [.016, .068]
FE	.002 [.000, .005]	–	.002520[a]

φ_{SS} and φ_{PP} denote the autoregressive effects of daily stressors and physical symptoms, respectively; φ_{SP} and φ_{PS} denote the cross-lagged effects between daily stressors and physical symptoms, respectively. FE denotes the feedback effect between daily stressors and physical symptoms; 95% credible intervals (CIs) are in the brackets. [a]The standardized feedback effect is the product of two standardized cross-lagged effects

stressors the following day (φ^*_{PS}= .042, 95% CI = [.016, .068]). This suggested a self-perpetuating loop between daily stressors and physical symptoms (unstandardized feedback effect [FE] = .002, 95% CI = [.000, .005]). According to the empirical benchmark of feedback effects established in the next section, this is a medium to large feedback effect. In addition, the random variances in autoregressive and cross-lagged effects suggested that there was some interindividual variation in the bidirectional relation between daily stressors and physical symptoms. This prompted us to further investigate individual differences in the feedback effects between daily stressors and physical symptoms.

Person-specific feedback effects

Figure 3 shows the distribution of the person-specific standardized feedback effects between daily stressors and physical symptoms, which reveals substantial individual differences in feedback effects (*Mdn* (median) = .002; range = −.007 to .041). Notably, the majority of the sample (n = 203, 80.56%) exhibit a feedback effect above zero. This suggests that most people had a self-perpetuating loop between daily stressors and physical symptoms that led to instability. In contrast, approximately 19% of people (n = 49) had a feedback effect below zero, suggesting that only a small proportion of individuals tended to have self-regulating processes between daily stressors and physical symptoms.

Interpretation of feedback effects

Inspired by Orth et al. (2022), we established an empirical benchmark for feedback effects to promote a better understanding of the size of feedback effects. Specifically,

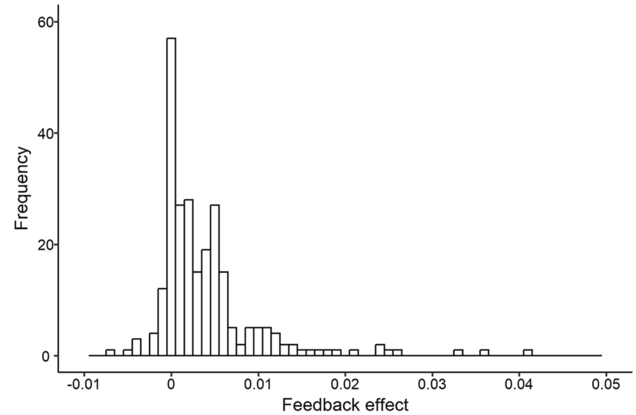

Fig. 3 Distribution of the person-specific standardized feedback effects between stressors and physical symptoms

we first systematically reviewed previous empirical studies that examined the bidirectional relations between variables using DSEMs. Then, we calculated feedback effects using standardized cross-lagged effects for corresponding variables in each study, and established an empirical distribution of feedback effects. Small, medium, and large feedback effects were operationally defined as the 25th, 50th, and 75th percentiles of the empirical distribution, and benchmark values were defined as surrounding anchors (Bosco et al., 2015; Orth et al., 2022) rather than cutoff values (i.e., lower bounds). We also examined the distribution of feedback effects in different disciplines of psychology. In addition, to test whether the empirical benchmark for feedback effects could be applied to various contexts, we explored possible moderators for feedback effects, such as sample size, number of observations, and time interval.

Method

Literature search and study selection

We conducted a literature research on March 23, 2023, in the following eight databases: Web of Science, MEDLINE, PsycINFO, APA PsycArticles, ProQuest Dissertations & Theses Global, the Psychology Database, ScienceDirect, and Scopus. The following Boolean search terms were used: ("dynamic structural equation model*") OR (dynamic multilevel model*) OR (dynamic mixed model*) OR (dynamic hierarchical model*).

A total of 1288 potentially relevant records (760 records after removing duplicates) were identified. The inclusion criteria were as follows: (a) peer-reviewed articles written in English, (b) use of multilevel DSEM, (c) testing bidirectional cross-lagged relations, (d) reporting standardized cross-lagged effects, (e) use of human subjects, and (f) exclusion of inconsistent results (e.g., studies with extremely

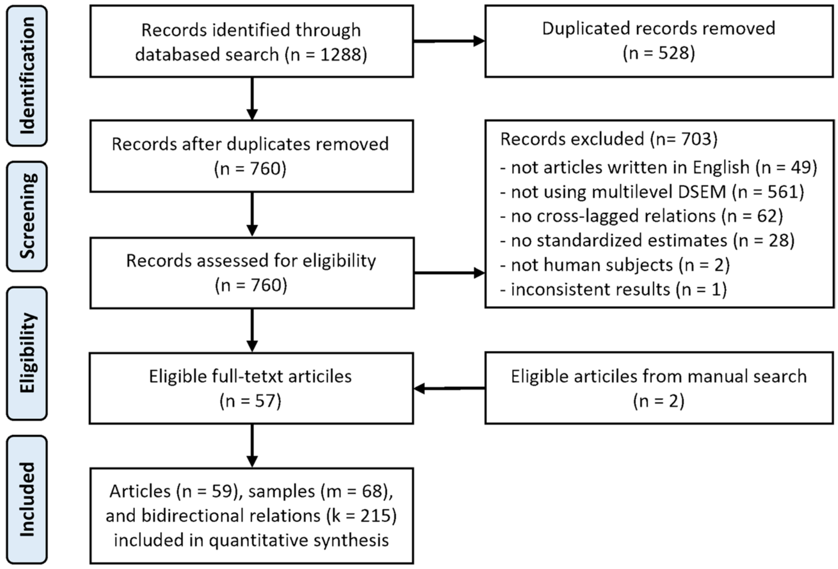

Fig. 4 PRISMA flow diagram of the study selection process

inconsistent results with other studies of feedback effects). For articles that did not report standardized cross-lagged effects, an email request for standardized results was sent to the authors.[3] The full text of the records was screened by two graduate students in psychology. The first 10% of articles ($n = 76$) were independently screened by two raters, and the differences in screening results were discussed with all authors to reach consensus on the inclusion criteria. The next 10% of articles were used to estimate interrater agreement, and the results indicated high interrater agreement in study selection (kappa coefficient = .93). The remaining articles were evaluated separately by the two raters. In addition, we manually checked the citation records of two highly cited articles on DSEM (Asparouhov et al., 2018; Hamaker et al, 2018) to include additional articles that may have met our requirements. These resulted in the inclusion of 215 records of feedback effects ($k = 215$) from 68 samples ($m = 68$) in 59 articles ($n = 59$). The references of the included articles are available at https://osf.io/psxw6/?view_only=52220fd7fb08434aa4d5fb832da09ce8. The study selection process is outlined in the PRISMA [Preferred Reporting Items for Systematic Reviews and Meta-Analyses] flow diagram in Fig. 4.

[3] We sent emails to the corresponding authors of 30 articles requesting standardized results and received responses from eight researchers for ten articles. Based on the authors' responses, five of the ten articles were eligible to be included in this study. For example, three articles were excluded because these studies used a probit link function so that the cross-lagged effects were in probit units. These effects are not directly comparable with the cross-lagged effects in other studies and therefore were not included in this study to establish an empirical benchmark for feedback effects.

Data extraction

Three types of information were extracted from each study. First, we coded the basic information about each study, including the author(s), publication year, and disciplines (i.e., developmental, health-clinical, educational, social-personality, or other disciplines of psychology). Then, the following sample characteristics were coded: sample type (i.e., college/university students, clinical sample, or community sample), sample size, mean age, percentage of female participants, country in which the sample was collected, whether the sample was dyadic (i.e., a categorical variable was coded as 0 if two constructs were within a person, coded as 1 if two constructs were within a dyad/between persons, coded as 2 for other cases; Xu & Zheng, 2022). Finally, we extracted the following study design and effect size information: construct A, construct B, autoregressive effect of construct A, autoregressive effect of construct B, cross-lagged effect from construct A to construct B, cross-lagged effect from construct B to construct A, feedback effect between construct A and construct B, number of observations, time interval, multiple constructs in a model (i.e., a dichotomous variable coded as yes if three or more constructs were included in one model), covariates in within-level model (i.e., a dichotomous variable coded as yes if one or more covariates were included at the within-level model), covariates in between-level model (i.e., a dichotomous variable coded as yes if one or more covariates were included at the between-level model), innovative (co)variances (i.e., a dichotomous variable coded as yes if innovative variance and/or innovative covariance were estimated), and shared method variance (i.e., a dichotomous variable coded as yes if measures of construct A and construct B were based on reports/ratings from the same person; Orth et al., 2022). Standardized results were coded for autoregressive and cross-lagged effects, and standardized feedback effects were calculated as the products of two corresponding standardized cross-lagged effects. More details on data extraction are provided in the coding manual (https://osf.io/psxw6/?view_only=52220fd7fb08434aa4d5fb832da09ce8).

All included articles were double-coded by the two raters. Approximately half of the articles ($n=30$) were used to estimate interrater agreement. The average interrater agreement was .91 for continuous variables (i.e., mean correlation coefficient) and .87 for categorical variables (i.e., mean kappa coefficient). Inconsistent coding results were discussed until consensus was reached.

Data analyses

First, descriptive statistics about samples and study designs were reported. According to the rationale provided by Orth et al. (2022), the signs of the effects were determined by the specific constructs in empirical studies and were irrelevant when establishing effect size benchmarks, and the absolute values of feedback effects were used to generate the empirical distribution and establish the empirical benchmark for the feedback effects. In addition, we conducted simple regression analysis for each presumed moderator (i.e., sample type, sample size, mean age, gender, dyads, number of observations, time interval, multiple constructs, covariates in within-level model, covariates in between-level model, innovative (co)variances, and shared method variance) to test its potential influence on feedback effects.

Results

Descriptive statistics

A total of 68 samples were included in the quantitative synthesis and showed substantial heterogeneity; 45.59% were community samples, 29.41% were clinical samples, and 25% were college students. The average number of participants per sample was 258.63, ranging from 37 to 3388 ($Mdn=140$, $SD=436.72$), and the total number of participants included was 17,587. The mean age of participants ranged from 2.25 to 73.03 years ($M=28.31$, $SD=15.66$), and the proportion of female participants ranged from 0.11 to 1.00 ($M=0.60$, $SD=0.21$). Twenty-five percent of the samples were from Germany, 22.06% from the United States, 10.29% from the Netherlands, 7.35% from Switzerland, 5.88% from Canada, 5.88% from China, 10.29% from other countries, and 13.24 % from unknown countries. The number of observations per sample ranged from 4 to 2000 ($M=78.01$, $Mdn=41$, $SD=245.09$). The average time interval was 24.77 h, with 36.76% of the intervals between 0.25 h and 12 h, 42.65% between 12 h and 24 h, 2.94% shorter than 0.25 h (actually 30 seconds or less), and 5.88% longer than 24 h (actually one week or more). Notably, in some studies, there were unequal and/or varied time intervals across individuals due to missing observations. For these cases, researchers typically used the TINTERVAL command in M*plus* to rescale the data into a specific time interval to maintain a constant interpretation of autoregressive and cross-lagged effects based on this time interval (McNeish & Hamaker, 2020).

Cross-lagged and feedback effects were coded for each pair of constructs ($k=215$). Of these, 57.67% were estimated in models with multiple constructs (i.e., three or more); 10.23% had covariates at the within-person level, and 28.84% had covariates at the between-person level. Innovative variances and/or covariance(s) were estimated in models of 19.53% pairs of constructs. Shared method variance was shown in 74.42% pairs of constructs.

In addition, for the disciplines of the 59 included articles, it should be noted that the numbers of the samples (m) and the records (k) of feedback effects were unbalanced across disciplines: developmental ($m=13$, $k=67$), health-clinical ($m=43$, $k=114$), educational ($m=5$, $k=24$), social-personality ($m=4$, $k=6$), or other disciplines ($m=3$, $k=4$) of psychology. Therefore, we only analyzed and present the distribution percentiles for feedback effects in developmental, health-clinical, and educational psychology.

Distribution of feedback effects

The distribution of feedback effects is presented in Fig. 5, and the distribution percentiles are shown in Table 2. The 25th, 50th, and 75th percentiles correspond to values of .0003, 0014, and .0060, respectively. It is worth noting that there were two outliers (i.e., not within $M \pm 3\,SD$) in the distribution, and thus we examined whether the results would be affected by these outliers. As shown in Table 2, the 25th, 50th, and 75th percentiles remain essentially unchanged after excluding the outliers.

In addition, we examined the distribution percentiles for feedback effects in developmental, health-clinical, and educational psychology. As shown in Table 2, the 25th, 50th, and 75th percentiles of the distributions in these disciplines differed only slightly from those of the original distribution, and most of the deviations (with the exception of the 75th percentile of the distribution in educational psychology) were relatively small. Taking into account the distribution percentiles of the original distribution as well as the distributions in specific disciplines, we propose an empirical benchmark for feedback effects of .0003, .0015, and .0060 for small, medium, and large effects, respectively.

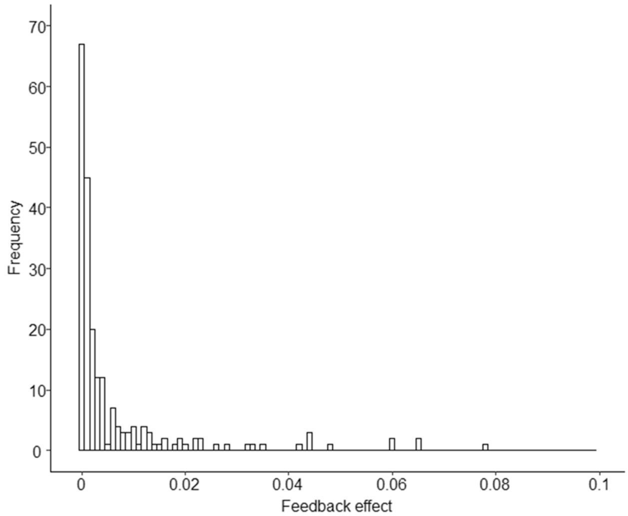

Fig. 5 Distribution of feedback effects in DSEMs. *Note*: Two feedback effects greater than 0.2 are not presented in the figure for plotting purposes

Moderator analyses

To further explore the applicability of the empirical benchmark of feedback effects, we tested the moderating effects of the presumed variables. As shown in Table 3, the feedback effects are not significantly affected by any of the presumed moderators, indicating that the empirical benchmark of feedback effects can be applied across a wide range of conditions.

Broader application of feedback effects

After showing how to estimate and interpret feedback effects, we further demonstrated how feedback effects could be used to help answer research questions about empirical evidence of relevant theories, and explanatory factors of the individual differences in feedback effects. Specifically, we used a set of empirical data on state mindfulness and psychological distress, and took the spiral model in mindfulness practice (Garland et al., 2010) as an example. The spiral model in mindfulness practice proposed multiple possible mechanisms by which mindfulness practice may enhance individuals' psychological well-being (Garland, 2010). In natural settings without interventions, researchers may also be interested in how people's state mindfulness interacts with their psychological well-being, for example, whether higher levels of state mindfulness lead to lower levels of psychological distress, which promote subsequent state mindfulness. This bidirectional relation contributes to a self-perpetuating feedback loop, which would support the

Table 2 Distribution percentiles for feedback effects in DSEMs

Percentile	Original distribution ($k=215$)	Outlier excluded ($k=213$)	Developmental ($k=67$)	Health-clinical ($k=114$)	Educational ($k=24$)
5	.000009	.000008	.000041	.000000	.000098
10	.000093	.000092	.000100	.000082	.000118
15	.000103	.000102	.000100	.000145	.000145
20	.000200	.000200	.000201	.000200	.000288
25	**.000312**	**.000300**	**.000351**	**.000400**	**.000377**
30	.000450	.000443	.000518	.000572	.000482
35	.000600	.000600	.000655	.000600	.000598
40	.000706	.000700	.000840	.000800	.001037
45	.001100	.001052	.001200	.001144	.001246
50	**.001400**	**.001292**	**.001400**	**.001550**	**.001611**
55	.001845	.001718	.001994	.002100	.001719
60	.002400	.002400	.002778	.002400	.001862
65	.003200	.002999	.003492	.003387	.002071
70	.003985	.003700	.004163	.004318	.003420
75	**.006150**	**.006000**	**.006512**	**.007233**	**.003712**
80	.009100	.008300	.008640	.011232	.004802
85	.011988	.011775	.010258	.013961	.007153
90	.019560	.018560	.016472	.021950	.009215
95	.042380	.033840	.039650	.032571	.056939

The 25th, 50th, and 75th percentiles are bolded. For the social-personality psychology and other disciplines of psychology, only six and four records of feedback effects are included, respectively, which is not sufficient to obtain distribution percentiles for feedback effects. Thus, the results of these disciplines are not presented

Table 3 Test of presumed moderators

Moderators	*B*	*SE*	*p*
Sample type			
Clinical vs. college students	−.004	.006	.542
Community vs. college students	−.002	.005	.759
Sample size	−.000	.000	.788
Mean age	−.000	.000	.218
Gender	−.011	.012	.339
Dyads			
Dyads vs. not dyads	−.001	.004	.887
Other cases vs. not dyads	.000	.009	.993
Number of observations	−.000	.000	.566
Time interval (t)			
$0.25\,\text{h} \le t < 12\,\text{h}$ vs. $t < 0.25\,\text{h}$	.007	.009	.434
$12\,\text{h} \le t \le 24\,\text{h}$ vs. $t < 0.25\,\text{h}$	.009	.008	.236
$t > 24\,\text{h}$ vs. $t < 0.25\,\text{h}$	.009	.012	.448
Multiple constructs	−.005	.004	.240
Covariates in within-level model	−.007	.006	.298
Covariates in between-level model	−.004	.004	.361
Innovative (co)variances	−.003	.005	.587
Shared method variance	−.002	.004	.716

There are four types of time intervals (t): (**a**) second level: $t < 0.25\,\text{h}$ (actually 30 seconds or less); (**b**) hourly level: $0.25\,\text{h} \le t < 12\,\text{h}$; (**c**) daily level: $12\,\text{h} \le t \le 24\,\text{h}$; (**d**) weekly level: $t > 24\,\text{h}$ (actually 1 week or more)

effectiveness of mindfulness practice in alleviating psychological distress. Therefore, we investigated the feedback effects between the three dimensions of state mindfulness (i.e., acting with awareness, present moment attention, and nonjudgmental acceptance) and psychological distress to test whether the spiral model proposed by Garland et al. (2010) could be empirically supported.

For the individual differences in the bidirectional relation between mindfulness and psychological well-being, we focused on the following potentially related factors. The first one was self-regulation, a factor generally associated with feedback processes (Garland et al., 2010). The second category was possibly protective factors in the dynamic interaction between mindfulness and psychological distress: self-compassion (Bluth & Blanton, 2015) and self-esteem (Michalak et al., 2011). The third category was indicators of individuals' psychological well-being (Garland et al., 2010), including general psychological well-being, anxiety symptoms, depressive symptoms, and perceived stress.

For these individual difference factors, we were particularly interested in whether estimating feedback effects as a whole could constitute a unique contribution to understanding the associations between dynamic feedback processes and related factors. To this end, we tested how each factor was associated with two cross-lagged effects between state mindfulness and psychological distress as well as their feedback effect. If a factor was significantly associated with only the cross-lagged effects and not with the feedback effect, the feedback effect did not make a unique contribution to understanding how this factor played a role in the dynamic feedback process. In contrast, if a factor was significantly associated with only the feedback effect and not with the cross-lagged effects, this suggested that the feedback effect did make a unique contribution to a more comprehensive understanding of the relation between this factor and the dynamic feedback process. There was another situation that supported the unique contribution of the feedback effect. For a factor that was significantly associated with both the cross-lagged effects and the feedback effect, the association between the factor and the feedback effect may indicate a unique contribution of the feedback effect, or it may be that the feedback effect is the product of two cross-lagged effects. Thus, we further tested whether the factor was significantly associated with the feedback effect by calculating the partial correlation between the factor and the feedback effect after controlling for the associations between the factor and the two cross-lagged effects. A significant partial correlation suggests that the feedback effect still contributes uniquely to our examination of relevant individual difference factors.

Method

Participants and procedures

A total of 270 Chinese female college students with a mean age of 20.701 years (ranging from 18 to 25, $SD = 1.569$) participated in this study. The majority of the sample were undergraduates (88.889%), including 18.519% freshmen, 34.444% sophomores, 19.630% juniors, and 16.296% seniors. The other participants were master's degree-seeking students (4.074%), and PhD degree-seeking students (0.741%). All participants were of Chinese Han ethnicity.

First, all participants signed an informed consent and completed a questionnaire that included demographic questions and trait measures. For the following seven days, an online questionnaire link was sent to each participant at 11 a.m., 2 p.m., 5 p.m., 8 p.m., and 11 p.m. each day to assess their state mindfulness and psychological distress. Participants' compliance with the study was satisfactory, with 90.582% ($n = 8560$) of all repeated measures ($N = 9450$; 270 participants × 35 measures) completed. At the individual level, 62 participants completed all repeated measures, 154 participants completed 30–34 repeated measures, and only 20 participants completed fewer than 25 repeated measures. Participants were rewarded according to their compliance, with average compensation of ¥ 68.89 per participant. This study was approved by the university's ethics committee.

Measures

Psychological distress The four-item Patient Health Questionnaire (PHQ-4) was used to measure individuals' anxiety and depressive symptoms in everyday contexts (Kroenke et al., 2009; Löwe et al., 2010). The items were as follows: (1) feeling nervous, anxious, or on edge; (2) not being able to stop or control worrying; (3) little interest or pleasure in doing things; (4) feeling down, depressed, or hopeless. Participants were asked to rate the extent to which they had experienced these feelings since they had completed the last questionnaire, from 1 ("not at all") to 5 ("very much"). The average score of the four items were calculated. Higher scores represent higher levels of psychological distress.

State mindfulness The Multidimensional State Mindfulness Questionnaire (MSMQ; Blanke & Brose, 2017) was used to measure state mindfulness. It included three subscales for three dimensions: acting with awareness (three items; example item: "I did things without paying attention," reverse-scored), nonjudgmental acceptance (three items; example item: "I thought some of my thoughts/feelings were slightly off," reverse-scored), and present moment attention (three items; example item: "I focused my attention on the present moment"). Participants were asked to rate the extent to which they agreed with the description of each item since they had completed the last questionnaire, from 1 ("not at all") to 7 ("very much"). The average score of the items in each dimension was calculated. Higher scores represent higher levels of state mindfulness.

Self-regulation We used the short version of the Self-Regulation Questionnaire (SSRQ; Carey et al., 2004) to measure individuals' general ability to regulate their own behaviors. It consisted of 31 items (example item: "As soon as I see a problem or challenge, I start looking for possible solutions"). Participants were asked to rate the extent to which they agreed with the description of each item on a five-point scale (1 = strongly disagree, 5 = strongly agree). In this study, Cronbach's alpha and the coefficient omega of the SSRQ were .952 and .961, respectively.

Self-compassion and self-esteem Self-compassion was measured with the 12-item Self-Compassion Scale–Short Form (SCS-SF; Raes et al., 2011). Participants were asked to rate how often they had the experience described in each item (example item: "I try to be understanding and patient towards those aspects of my personality I don't like"), from 1 ("never") to 5 ("always"). Cronbach's alpha and the coefficient omega of the SCS-SF were .832 and .879, respectively.

Self-esteem was measured with the 10-item Rosenberg Self-Esteem Scale (RSES; Rosenberg, 1965). Participants were asked to indicate their levels of agreement with the statement in each item (example item: "On the whole, I am satisfied with myself") on a five-point scale (1 = strongly disagree, 5 = strongly agree). Cronbach's alpha and the coefficient omega of the RSES were .915 and .941, respectively.

Indicators of psychological well-being A positive indicator of psychological well-being was individuals' general levels of psychological well-being, as measured by the 18-item Psychological Well-Being Scale (PWBS; Ryff, 1989). Participants were asked to rate the extent to which they agreed with the description of each item (example item: "In general, I feel I am in charge of the situation in which I live"), from 1 ("strongly disagree") to 7 ("strongly agree"). In this study, Cronbach's alpha and the coefficient omega of PWBS were .881 and .916, respectively.

Negative indicators of psychological well-being included anxiety symptoms, depressive symptoms, and perceived stress. Anxiety symptoms and depressive symptoms were measured with the seven-item General Anxiety Disorder Questionnaire (GAD-7; Spitzer et al., 2006) and the nine-item Patient Health Questionnaire (PHQ-9; Kroenke & Spitzer, 2002), respectively. Participants were asked to rate how often they were bothered by anxiety (example item: "worrying too much about different things") and depressive symptoms (example item: "feeling down, depressed, or hopeless") during the past week, from 0 ("never") to 3 ("almost every day"). In this study, Cronbach's alpha and coefficient omega for the GAD-7 were 0.920 and 0.949, respectively, and for the PHQ-9 were 0.898 and 0.914, respectively. In addition, perceived stress was measured with the Perceived Stress Scale (PSS; Cohen et al., 1983). Participants were asked about their feelings and thoughts during the past week (14 items; example item: "How often have you been upset because of something that happened unexpectedly?"). Each item was rated on a five-point scale (1 = never, 5 = very often). In this study, Cronbach's alpha and the coefficient omega of the PSS were .906 and .935, respectively.

Data analyses

Descriptive and correlational analyses were first conducted in R version 4.2.2 (R Core Team, 2020) with the *psych* (Revelle, 2017) package. Then, we established a dynamic structural equation model for the three dimensions of state mindfulness and psychological distress (see Fig. 6[4]). The

[4] We did not include the cross-lagged effects between the dimensions of state mindfulness because the focus of this empirical illustration was to examine the feedback effects between state mindfulness and psychological distress. Nevertheless, whether to estimate the cross-lagged effects between the dimensions of state mindfulness and psychological distress may affect the results. Therefore, we conducted supplementary analyses and present the results of the adjusted model with cross-lagged effects between the dimensions of state mindfulness (see Supplementary Information S3). The results were similar to those in the original model, and the main conclusions remained unchanged.

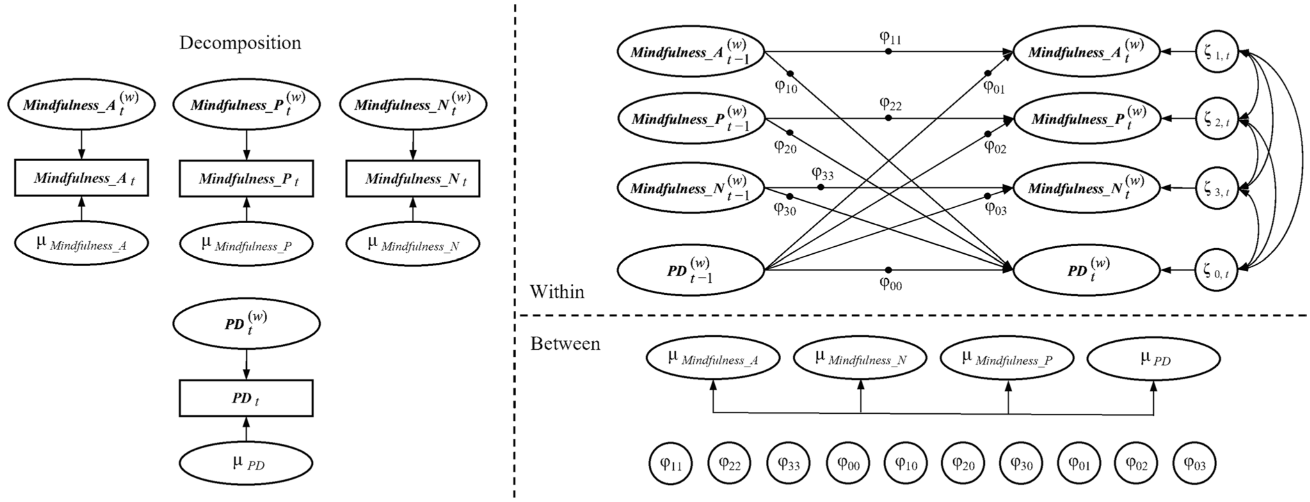

Fig. 6 Dynamic structural equation model for the three dimensions of state mindfulness and psychological distress. *Notes*: Mindfulness_A = acting with awareness; Mindfulness_P = present moment attention; Mindfulness_N = nonjudgmental acceptance. Black dots indicate person-specific autoregressive and cross-lagged effects

model parameters and the feedback effects between the three dimensions of state mindfulness and psychological distress were estimated in M*plus* version 8.10. We used two Gibbs-sampler chains with 25,000 iterations each, with 50% burn-in and a thinning value of 1. Following the procedure introduced in the first section (i.e., "Procedure for estimating feedback effects"), we used the MODEL CONSTRAINT command to obtain the point estimate and the 95% credible interval for the feedback effects for the average person. In addition, the standardized person-specific feedback effects were obtained by calculating the products of corresponding standardized cross-lagged effects saved using the STDRESULTS command. As we noted in the first application, the interpretation of autoregressive, cross-lagged, and feedback effects here should also be based on the specific time interval of the study (i.e., 3 hours). Finally, to explore whether feedback effects could make a unique contribution to further understanding the associations between dynamic feedback processes and related factors, we computed the correlations among seven individual difference factors and person-specific cross-lagged effects as well as person-specific feedback effects for each dimension of state mindfulness. All data, M*plus* syntax, and R code are available at https://osf.io/psxw6/?view_only=52220fd7fb08434aa4d5fb832da09ce8.

Results

Descriptive analysis

The descriptive statistics and correlations between the three dimensions of state mindfulness, psychological distress, and relevant factors are shown in Table 4. The intraclass correlations for the three dimensions of state mindfulness and psychological distress were .648, .601, .677, and .636, respectively, suggesting that approximately 40% of their variances were within-person. At both the between- and within-person levels, the three dimensions of state mindfulness were positively associated with each other, and negatively associated with psychological distress. This suggests that individuals with higher average levels of state mindfulness have lower average levels of psychological distress, and when individuals have higher levels of state mindfulness than their average levels, they have lower levels of psychological distress than usual.

Empirical tests of the theory based on feedback loops

The results of the dynamic bidirectional relations between the three dimensions of state mindfulness and psychological distress are presented in Table 5. The autoregressive effects of the three dimensions of state mindfulness and psychological distress are significantly positive, indicating their small to moderate carryover effects: when people had higher/lower levels of state mindfulness and psychological distress at a particular moment, they would also subsequently have higher/lower levels of state mindfulness and psychological distress.

More importantly, the average cross-lagged effects between two dimensions of state mindfulness (i.e., acting with awareness, and nonjudgmental acceptance) and psychological distress were significant. Individuals who had higher levels of acting with awareness and nonjudgmental acceptance reported lower levels of psychological distress subsequently (standardized $\varphi_{10} = -.052$, and standardized $\varphi_{30} = -.048$, respectively), which in turn led to higher levels of acting with awareness and nonjudgmental acceptance (standardized $\varphi_{01} = -.082$, and standardized $\varphi_{03} = -.085$, respectively).

Furthermore, significant feedback effects were observed between acting with awareness and psychological distress (standardized feedback effect = .004), and between nonjudgmental acceptance and psychological distress (standardized feedback effect = .004). Moreover, both feedback effects were medium to large effects according to the empirical benchmarks established in the second section (i.e., "Interpretation of feedback effects"). In contrast, the averaged cross-lagged effects and the feedback effect between present moment attention and psychological distress were nonsignificant (unstandardized feedback effect = .000, 95% CI = [−.001, .002], standardized feedback effect = .000), indicating no feedback effect.

It should be noted that all of these effects, including autoregressive, cross-lagged, and feedback effects, were based on a specific time interval (i.e., three hours). Therefore, they should be interpreted under this specific time interval and should not be generalized to other time intervals. This also reminds us that a more accurate statement of our conclusion would be that the current findings provide supportive evidence for the spiral model of mindfulness under the specific time interval of three hours.

In addition, for the random variances in the effects of interest, we found some variability, albeit relatively small, for the cross-lagged effects of the three dimensions of state mindfulness on psychological distress, whereas the variability for the reversed effects (i.e., the cross-lagged effects of psychological distress on the three dimensions of state mindfulness) was substantial. This suggests that it is necessary to examine the person-specific feedback effects between the three dimensions of state mindfulness and psychological distress to explore possible correlates of their individual differences.

Unique contributions of feedback effects

The correlations of relevant factors with person-specific standardized cross-lagged and feedback effects between state mindfulness and psychological distress are shown in Table 6. For the dimension of present moment attention, if we focused only on the correlations between relevant factors and the cross-lagged effects, we might conclude that none of these factors was related to the dynamic reciprocal relation between present moment attention and psychological distress. However, a closer look at the correlations between relevant factors and feedback effects refuted this conclusion. All the factors were significantly associated with the feedback effect, suggesting that they could effectively explain the between-person differences in the bidirectional relation between present moment attention and psychological distress. People with higher levels of self-regulation, self-compassion, self-esteem, and psychological well-being were more likely to have a self-regulating loop between present moment attention and psychological distress.

Table 4 Descriptive statistics and correlations between the three dimensions of state mindfulness, psychological distress, and relevant factors

		M (*SD* between)	ICC	Correlations									
				1	2	3	4	5	6	7	8	9	10
1	Mindfulness_A	5.011 (1.184)	.648	–	.481***	.247***	−.302***	–	–	–	–	–	–
2	Mindfulness_P	4.886 (0.976)	.601	.772***	–	.086***	−.216***	–	–	–	–	–	–
3	Mindfulness_N	4.072 (1.194)	.677	.477***	.216***	–	−.227***	–	–	–	–	–	–
4	Psychological distress	1.719 (0.716)	.636	−.617***	−.516***	−.455***	–	–	–	–	–	–	–
5	Self-regulation	3.505 (0.646)	–	.604***	.588***	.363***	−.491***	–	–	–	–	–	–
6	Self-compassion	3.231 (0.569)	–	.453***	.488***	.408***	−.486***	.736***	–	–	–	–	–
7	Self-esteem	3.485 (0.788)	–	.439***	.458***	.371***	−.519***	.762***	.757***	–	–	–	–
8	Psychological well-being	4.630 (0.862)	–	.574***	.571***	.428***	−.556***	.835***	.756***	.835***	–	–	–
9	Anxiety symptoms	1.992 (0.751)	–	−.456***	−.448***	−.368***	.586***	−.609***	−.628***	−.660***	−.651***	–	–
10	Depressive symptoms	1.904 (0.655)	–	−.469***	−.423***	−.387***	.546***	−.653***	−.606***	−.663***	−.683***	.845***	–
11	Perceived stress	2.806 (0.704)	–	−.532***	−.533***	−.429***	.484***	−.755***	−.735***	−.720***	−.791***	.769***	.780***

Mindfulness_A = acting with awareness; Mindfulness_P = present moment attention; Mindfulness_N = nonjudgmental acceptance. ICC = intraclass correlation. Between-person correlations are presented below the diagonal, and within-person correlations are presented above the diagonal. *** $p < .001$

Table 5 Results of parameter estimation from the dynamic structural equation model for the three dimensions of state mindfulness and psychological distress

Parameter	Unstandardized estimates		Standardized estimates
	Fixed effects	Random variances	Fixed effects
φ_{00}	.234 [.193, .276]	.061 [.048, .078]	.234 [.207, .262]
φ_{11}	.225 [.195, .254]	.019 [.012, .028]	.225 [.201, .249]
φ_{22}	.162 [.128, .196]	.037 [.024, .046]	.163 [.140, .189]
φ_{33}	.198 [.164, .233]	.034 [.024, .046]	.197 [.171, .223]
φ_{10}	−.036 [−.058, −.013]	.011 [.006, .016]	−.052 [−.081, −.025]
φ_{01}	−.143 [−.203, −.081]	.086 [.060, .123]	−.082 [−.114, −.052]
φ_{20}	−.004 [−.031, .022]	.021 [.014, .029]	−.008 [−.035, .024]
φ_{02}	−.048 [−.105, .007]	.074 [.050, .107]	−.033 [−.063, −.003]
φ_{30}	−.031 [−.050, −.012]	.006 [.002, .012]	−.048 [−.074, −.020]
φ_{03}	−.131 [−.195, −.067]	.100 [.062, .154]	−.085 [−.114, −.053]
FE_1	.005 [.002, .010]	–	.004264[a]
FE_2	.000 [−.001, .002]	–	.000264[a]
FE_3	.004 [.001, .008]	–	.004080[a]

φ_{00}, φ_{11}, φ_{22}, and φ_{33} denote the autoregressive effects of psychological distress and the three dimensions of state mindfulness, respectively; φ_{10} and φ_{01} denote the cross-lagged effects between acting with awareness and psychological distress, respectively; φ_{20} and φ_{02} denote the cross-lagged effects between present moment attention and psychological distress, respectively; φ_{30} and φ_{03} denote the cross-lagged effects between nonjudgmental acceptance and psychological distress, respectively. FE_1, FE_2, and FE_3 denote feedback effects of psychological distress with acting with awareness, present moment attention, and nonjudgmental acceptance, respectively; 95% credible intervals (CIs) are in the brackets.
[a] The standardized feedback effects are the products of two corresponding standardized cross-lagged effects

For the dimension of acting with awareness, we found that self-esteem was significantly associated with the cross-lagged effect of acting with awareness on psychological distress (i.e., φ_{10}). Self-compassion and all indicators of psychological well-being were (nearly) significantly associated with the cross-lagged effect of psychological distress on acting with awareness (i.e., φ_{01}). In addition, more novel findings emerged from the perspective of feedback effects. For example, although self-regulation was not significantly associated with the cross-lagged effects between acting with awareness and psychological distress, it was significantly associated with the feedback effect between them. Furthermore, anxiety symptoms, depressive symptoms, and perceived stress were also significantly associated with the feedback effect even after controlling for the impacts of the corresponding cross-lagged effects. These results suggested that people with higher levels of self-regulation and lower levels of psychological well-being tended to have a self-regulating loop between acting with awareness and psychological distress (e.g., increased levels of psychological distress would subsequently decrease through its interaction with acting with awareness).

For the dimension of nonjudgmental acceptance, self-compassion, self-esteem, anxiety symptoms, and perceived stress were (nearly) significantly associated with both the cross-lagged effect of nonjudgmental acceptance on psychological distress (i.e., φ_{30}) and the feedback effect between them. However, it should be noted that the associations between these factors and the feedback effect were not significant after controlling for the impacts of the corresponding cross-lagged effects. This suggests that these significant associations may simply be due to the fact that the feedback effect is a product of the corresponding cross-lagged effects. Nevertheless, depressive symptoms were not significantly associated with the cross-lagged effects between nonjudgmental acceptance and psychological distress, but rather their feedback effect. To conclude, the above results suggest that estimating feedback effects constitutes a unique contribution in revealing related factors of bidirectional relations between the dimension of state mindfulness and psychological distress.

General discussion

Bidirectional relations between variables have long been a key issue in psychological research (Pettit & Arsiwalla, 2008; Taris & Kompier, 2014; Usami et al., 2019). With the increasing use of ILD and the rapid development of related data collection and analysis techniques, there has been growing interest in the dynamic interplay between variables. Although numerous previous studies have theoretically discussed the bidirectional relations (or feedback loops) between variables, they remain stuck in estimating the effect from one variable to another rather than the overall effect representing the bidirectional relations as a whole. It

Table 6 Correlations of relevant factors and person-specific standardized cross-lagged and feedback effects between state mindfulness and psychological distress

	φ_{10}	φ_{01}	FE_1	φ_{20}	φ_{02}	FE_2	φ_{30}	φ_{03}	FE_3
Self-regulation	.077	.106	**−.147***	.085	.016	**−.139***	.108	.048	−.092
Self-compassion	.023	**.142***	−.092	.079	.049	**−.211*****	**.123***	.100	−.116†(−.017)
Self-esteem	**.122***	.071	−.112†(−.026)	.058	.041	**−.150***	**.128***	.085	−.119†(−.029)
Psychological well-being	.054	.115†	**−.139***(.101)	.109	.019	**−.152***	.110	.060	−.099
Anxiety symptoms	−.016	**−.130***	**.152***(**.144***)	−.028	−.011	**.189****	−.114†	−.114†	**.121***(.017)
Depressive symptoms	−.053	−.117†	**.192****(**.180****)	−.030	.066	**.175****	−.066	−.104	**.125***
Perceived stress	−.036	**−.124***	**.179****(**.170****)	−.026	−.063	**.221*****	**−.151***	−.103	**.166***(.069)

φ_{10} and φ_{01} denote the person-specific standardized cross-lagged effects between acting with awareness and psychological distress; φ_{20} and φ_{02} denote the person-specific standardized cross-lagged effects between present moment attention and psychological distress; φ_{30} and φ_{03} denote the person-specific standardized cross-lagged effects between nonjudgmental acceptance and psychological distress. FE_1, FE_2, and FE_3 denote person-specific standardized feedback effects of psychological distress with acting with awareness, present moment attention, and nonjudgmental acceptance. For the factors that are (nearly) significantly correlated with the feedback effect and any corresponding cross-lagged effects, the partial correlation between the factor and the feedback effect (after controlling for the impacts of two corresponding cross-lagged effects) is calculated and presented in the parentheses. Significant correlations ($p < .05$) are bolded. $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; $^{\dagger}p < .07$ (nearly significant)

is worth noting that the causal dominance of variables is a matter of great interest in studies of bidirectional relations, and can usually be inferred by comparing the absolute value of the effect from one variable to the other (i.e., cross-lagged effects). However, as demonstrated in the second application study and discussed below, it is also valuable to look beyond this to examine the overall effects (i.e., feedback effects) of bidirectional relations and, more importantly, their individual differences. Previous research has rarely examined bidirectional relations from an integrative perspective, which we believe may be due to a lack of relevant methods and demonstrations. Therefore, comprehensive methodological guidance is provided for estimating and interpreting feedback effects and applying this approach to answer more research questions of interest, which we hope will enable researchers to gain further insights into bidirectional relations and help research on bidirectional relations to move forward.

In the present study, we first introduced the concept of why the feedback effect between two variables could be understood as the extent to which the prior state of one variable affected its subsequent state through its dynamic interplay with the other variable, and that the feedback effect could therefore be quantified as the product of the cross-lagged effects between the two variables. Then, we used a set of empirical data to show how to estimate the averaged feedback effects, as well as the person-specific feedback effects.

To help applied researchers understand feedback effects, we explained the meaning of positive (i.e., the two variables are mutually excitatory and form a self-perpetuating loop) and negative (i.e., the two variables are mutually inhibitory and form a self-regulating loop) feedback effects (Garland et al., 2010; Hollenstein, 2015; Yang et al., 2019), and established an empirical benchmark for feedback effects by quantitatively synthesizing previous empirical studies examining bidirectional relations based on DSEMs. Based on previous studies on establishing an empirical benchmark for effect sizes (Lovakov & Agadullina, 2021; Orth et al., 2022), we operationalized small, medium, and large feedback effects as the 25th, 50th, and 75th percentiles of the distribution of feedback effects, and proposed .0003 (small effect), .0015 (medium effect), and .0060 (large effect) as the empirical benchmark values for feedback effects. Further investigation of the distribution of feedback effects in different disciplines of psychology revealed similar benchmark results for developmental, health-clinical, and educational psychology. This suggests that the empirical benchmark of feedback effects can be used across these disciplines, and may also provide a basic reference for interpreting the magnitude of feedback effects in other disciplines.

In addition, the results showed that the size of the feedback effect was not affected by presumed moderators. This suggests that the empirical benchmark for feedback effects has the potential to be applied in a wide variety of research contexts. However, it should be noted that although these factors did not show significant moderating effects in this study, they may still be relevant to the size of feedback effects. It is still possible that sample characteristics and design characteristics may influence the magnitude of feedback effects when examining bidirectional relations between specific variables. For example, some bidirectional relations may be stronger for females than for males, and some bidirectional relations may be stronger within days (e.g., with a time interval of a few hours) than across days. Thus, researchers should carefully consider the impact of these study characteristics on the magnitude of the feedback effect. Nevertheless, the results regarding moderators support the applicability of our empirical benchmark of feedback effects across conditions. In addition, the number of feedback effects was relatively balanced at the different levels of study characteristics, which further supports the applicability of the benchmark across conditions. For example, the number of feedback effects from bivariate models (42.33%) and from models with three or more variables (57.67%) are comparable, so it is reasonable to assume that the benchmark for feedback effects proposed in this study are applicable to models with different numbers of variables.

Finally, we further illustrated how the estimation and interpretation of feedback effects as a whole could help researchers better answer the questions of interest. Researchers could more directly examine whether theoretical models and perspectives based on loops are reasonable by testing the statistical significance of feedback effects and interpreting the size of the effects (based on the empirical benchmark proposed in this study). Further exploration of person-specific feedback effects could reveal the extent to which the bidirectional relations between variables of interest differ from person to person. And examining the associations of relevant individual difference factors with feedback effects, rather than just with cross-lagged effects, could help reveal more related factors for interindividual variability in dynamic interaction processes between variables, providing more opportunities for finding antecedents and outcomes of dynamic feedback processes.

Notably, estimating and interpreting feedback effects as a whole should have greater potential for application in psychology and other social behavioral sciences. Feedback effects can be used to examine the bidirectional relations between a broad variety of variables, and could serve as an effective indicator to facilitate further understanding of the dynamic feedback process of interest. For example, emotion regulation is a topic of great interest in various subfields of psychology (Gross, 2015), and feedback loops are widely accepted to explain emotion-related dynamic processes (Hollenstein, 2015). However, previous studies on the dynamic interaction between physiology, experience, and behavioral components of individuals' emotion systems only quantitatively examined the effects of one component on another (Somers et al., 2022), or classified individuals into categories based on the combination of positive and negative values of different effects (Yang et al., 2019). In contrast, this study proposed an approach to estimate and interpret feedback effects as a whole, which provides a comprehensive quantitative indicator of the entire emotion regulation process. This promotes a more direct and accurate representation of the dynamic feedback processes of individuals' emotion systems, and helps researchers further explore individual differences in the dynamic process as well as its causes and consequences.

It is also worth noting that emotions interact not only within individuals but also between individuals (Butler et al., 2011). In fact, many dynamic interactive processes occur between individuals. For example, if we consider family members as variables (Butler et al., 2011), the interactive processes between family members could also be described by feedback loops (e.g., a mutually reinforcing feedback loop was found between mothers' and infants' positive affect; Somers et al., 2022). Furthermore, considering that the process of socialization is bidirectional (Pettit & Arsiwalla, 2008), for many interpersonal relationships, such as parents and children, romantic partners, peers, therapists and patients/clients, teachers and students, supervisors and subordinates, feedback effects could be used to integrate and quantitatively describe the bidirectional relations between individuals. This suggests a broad application potential of feedback effects in a wide range of psychological domains, including developmental, clinical, social, educational, and organizational domains.

More importantly, these two types of feedback effects (i.e., feedback effects within and between individuals) can be unified from a dynamic systems perspective. A dynamic system is a system composed of mutually interacting components, which focuses on dynamic bidirectional relations between components (Kunnen et al., 2019). Interactions between components within an individual constitutes intraindividual dynamic systems (e.g., an individual's emotion systems), whereas interactions between components between individuals constitutes interpersonal dynamic systems (e.g., a family dynamic system). From this perspective, feedback effects integrally describe how the components of a dynamic system interact with each other, reflecting the characteristics of the dynamic system as a whole, rather than a specific component or a specific effect. Since bidirectional relations emphasize the two variables as a whole, the shift from a focus on the local to a description of the entire system may provide further insights into the study of bidirectional relations.

Limitations and future directions

There are several limitations to this study that need to be noted. First, the study established an empirical benchmark for feedback effects based on studies that used DSEMs to explore bidirectional relations, but the number of relevant studies was not large, even though DSEMs have been increasingly used in recent years. Nevertheless, since this study found similar distribution percentiles for feedback effects in different disciplines in psychology (i.e., developmental, health-clinical, and educational psychology), and no significant differences in the size of feedback effects across various conditions, we believe that the benchmark established based on the currently available feedback effects is valuable for interpreting feedback effects in future empirical studies. With the increasing use of ILD in psychology and further exploration of bidirectional relations and feedback effects, future studies could accumulate more adequate empirical evidence to establish criteria for the interpretation of feedback effects. Moreover, as the number of relevant studies increases and the understanding of the magnitude of feedback effects deepens, researchers can further consider the statistical power of the empirical benchmark for feedback effects. In addition, since most of the articles and samples included were from specific disciplines of psychology (i.e., developmental and health-clinical psychology), analyzing and comparing empirical benchmarks for feedback effects in these specific disciplines of psychology may also be informative and be of interest for future research.

Second, the empirical benchmark established in this study was based only on the standardized results of previous studies. However, there may be other statistical indicators that could be used to interpret the size of feedback effects. For example, it may occur to some researchers that a relative criterion for the feedback effect can be obtained based on the ratio of the product of the cross-lagged effects and the product of the corresponding autoregressive effects. However, it is worth noting that some researchers have pointed out that such relative effect size indicators have many limitations (Miočević et al., 2018; Preacher & Kelley, 2011). Nevertheless, we encourage future researchers to explore other effect size indicators for feedback effects to further enhance our understanding of bidirectional relations.

Third, we only considered time-invariant feedback effects in bidirectional relations, and it may also be of interest to examine how these effects change over time. In dynamic interactions between variables, researchers may wonder how long or how many loops it takes for feedback effects to decay to a certain level, or the system may encounter an external stimulus and exhibit time-varying characteristics. Such questions are not uncommon in applied research focusing on dynamic interactions between variables. However, since the main purpose of this paper is to advocate for feedback effects as effective indicators of bidirectional relations, it is difficult for us to explore this issue further within the limited space of this paper. Nevertheless, to better understand feedback effects from a dynamic systems perspective, we suggest that future research further explore how the feedback effect varies over time (e.g., by drawing on impulse response plots, which are commonly used in dynamic time-series modeling; Koop et al, 1996).

Finally, this study focused on DSEM, a discrete-time model, to estimate feedback effects, and thus the interpretation of feedback effects should be based on the time interval in specific studies. Although our study showed the non-significant moderating effect of time interval on feedback effects, it should be noted that time interval may still influence the size of feedback effects. In fact, in the discrete-time modeling framework, the interpretation of many parameters depends on the time interval between two consecutive measurements, which is known as the problem of time-interval dependency (Hecht & Zitzmann, 2021; Kuiper & Ryan, 2018). An effective solution to this problem is to estimate the parameters based on continuous-time models (e.g., continuous time structural equation models; Driver et al., 2017; differential equation models; Hu et al., 2014; Luo & Hu, 2022). In addition, continuous-time models can also better deal with unevenly spaced measures—another common problem in intensive longitudinal data—than discrete-time models such as DSEMs. Moreover, the effects estimated by continuous-time models are not limited to a particular time interval, which may facilitate comparisons between studies with different time intervals. Currently, there are few studies examining bidirectional relations based on continuous-time models (De Moor et al., 2021), and with an increase in such studies, future research could further explore the estimation and interpretation of feedback effects under the continuous-time modeling framework.

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