Journal of Management Scientific Reports
Vol. 2 No. 2, May 2024 154-167
DOI: 10.1177/27550311241247833

Gain and loss cycles revisited: What to consider when testing key assumptions of conservation of resources theory

Sabine Sonnentag
School of Social Sciences, University of Mannheim, Mannheim, Germany
Laurenz L. Meier
Institute of Work and Organizational Psychology, University of Neuchâtel, Neuchâtel, Switzerland

In this editorial, we discuss approaches to the empirical test of gain and loss cycles as described within Hobfoll's conservation of resources theory (COR). We present COR theory's basic assumptions about gain and loss cycles and critically discuss typical empirical studies that aim at testing these assumptions. We highlight conceptual and empirical problems when testing gain and loss cycles of resources and provide guidance for researchers with respect to theoretical, temporal, and data-analytic aspects. We offer some suggestions for constructive replications and reproducibility.

Keywords: *conservation of resources; stress; data analysis; gain cycles; loss cycles; time*

Job stress is a topic that has fascinated organizational researchers for decades (Bliese et al., 2017). This interest is not surprising because job stress continues to be a pressing societal problem (American Psychological Association, 2021; Health and Safety Executive, 2023) and because the complexity of the phenomenon comprising organizational, interpersonal, task-related, cognitive, affective, and physiological aspects challenges researchers both theoretically and empirically. Numerous theories have been developed to explain how job stress impacts individuals (Cooper, 1998; Ganster & Rosen, 2013). These theories are—or should be—the guiding framework that informs researchers about what to investigate and how to design their empirical studies.

Corresponding Author: Sabine Sonnentag, University of Mannheim, School of Social Sciences, A5, 6, D-68159 Mannheim, Germany.

Email: sabine.sonnentag@uni-mannheim.de

In this editorial, we focus on the conservation of resources theory (COR theory; Hobfoll, 1998) as one prominent theory often used in empirical job-stress research. Specifically, we zoom in on the concepts of resource gains and resource losses and describe key aspects that researchers should consider when aiming at testing resource gains and resource losses in connection to job stress. We start by briefly summarizing some central features of COR theory and give some examples of prior empirical studies that have focused on gain and loss cycles. We critically review these studies and discuss some crucial issues that researchers should consider when testing gain and loss cycles. In particular, we will address constructs to be measured, study design, and problems with traditional cross-lagged panel analysis, when discussing theoretical, temporal, and data-analytic aspects.

In terms of the mission of JOMSR (Kraimer, 2023), our editorial is dedicated to offering guidance about how to test parts of COR theory as an already published theoretical model that—as we believe—needs continued and even better empirical tests. The need and opportunity for future tests originates, among others, in more advanced statistic-analytical approaches that have been developed and refined during the past decades. We will point out specific starting points for constructive replication (Köhler & Cortina, 2019) and constructive reproducibility (Cortina et al., 2023) of existing studies on gain and loss cycles.

Gain and loss cycles of resources within conservation of resources theory

Conservation of resources (COR) theory (Hobfoll, 1989, 1998) plays a prominent role in organizational stress research. Initially, Hobfoll (1989, p. 516) defined resources as "objects, personal characteristics, conditions, and energies" that individuals value and that help them to attain resources. Later, Halbesleben et al. (2014, p. 1338) suggested a revised definition and characterized "resources as anything perceived by the individual to help attain his or her goals." The central idea of COR theory is that resources are fundamental for people's well-being and that stress occurs when resources may be lost, when resources in fact are lost, and when resource investment is not followed by resource gain (Hobfoll, 1998).

COR's central idea about the benefits of resources found its way into major organizational job design models (e.g., job-demands resources model; Bakker et al., 2014; Demerouti et al., 2001) and hundreds of empirical studies (for meta-analyses, Downes et al., 2021; Gonzalez-Mulé et al., 2021). Hobfoll's (1989, 1998) COR theory is very successful in terms of citation counts. The article in which he introduced COR theory (Hobfoll, 1989) has received more than 19,000 citations in Google Scholar (as of February 2024), and the more recent *Annual Review* article (Hobfoll et al., 2018) has already been cited more than 3,000 times (as of February 2024).

A particularly interesting aspect of COR theory is the assumption that resources can dynamically decline (resource loss) and increase (resource gain) over time, resulting in loss versus gain cycles. Specifically, in Corollary 1, Hobfoll (1998, p. 80) states "that those with greater resources are less vulnerable to resource loss and more capable of orchestrating resource gain" and that "those with fewer resources are more vulnerable to resource loss and less capable of achieving resource gain." He continues by proposing that "those who lack resources are not only more vulnerable to resource loss, but this initial loss begets further loss" (Corollary 2; p. 81) and "that those who possess resources are more capable of gain, and that initial resource gain begets further gain" (Corollary 3; p. 82).

Moreover, COR states that “gain cycles are … predicted to have less momentum (e.g., speed) and less impact than loss cycles” (Hobfoll, 1998, p. 82). In addition, the dynamic interplay of resources may not only express itself in gain and loss cycles but also in gain and loss spirals, defined as “amplifying loops in which cyclic relationships among constructs build on each other positively over time“ (Salanova et al., 2010, p. 119).

Examples of studies aiming at a test of gain and loss cycles of resources

The attractiveness of Hobfoll’s (1998) writing on gain and loss cycles is reflected in both theoretical and empirical research. For instance, the concept of gain and loss cycles has been incorporated in the extended version of the job–demands–resources model in its theorizing on occupational well-being in general (Bakker, Demerouti et al., 2023) and burnout in particular (Bakker & Costa, 2014; Bakker & de Vries, 2021). Over the years, numerous empirical studies have been published that refer to the idea of gain and loss cycles (Bakker, Xanthopoulou et al., 2023; Hakanen et al., 2011) and spirals (Salanova et al., 2006; Stollberger et al., 2022). These studies included various job and personal resources such as social support and self-efficacy. In addition, they often studied volatile resources (ten Brummelhuis & Bakker, 2012) such as work engagement and flow versus the lack of such volatile resources (e.g., emotional exhaustion). Job demands have been included in these studies as well.

Researchers took up the idea of gain and loss cycles in both a univariate and bivariate (or even multivariate) way. For instance, in a sample of 265 nurses, Paustian-Underdahl et al. (2023) studied gain and loss cycles in a univariate way. Specifically, they examined how exhaustion shows a resource-loss cycle and how work engagement shows a resource-gain cycle over 30 months (time lags between measurement points: 6 months). They assumed that exhaustion and work engagement would increase and that the degree of change in both exhaustion and work engagement would increase over time as well. However, they refrained from making any assumption about how (change in) exhaustion might predict (change in) work engagement or vice versa. Paustian-Underdahl et al. (2023) applied a latent change score modeling approach (McArdle, 2009) for assessing the trajectories of exhaustion and work engagement, respectively. Findings were largely in line with the notion of gain and loss cycles, with both exhaustion and work engagement showing increases over time, and in addition, exhibited acceleration effects (i.e., the rate of change increased over time). These did not directly compare the model parameters for exhaustion versus work engagement, missing the opportunity to test Hobfoll’s (1998) assumption that loss cycles have more momentum and more impact than gain cycles.

Bivariate tests of gain and loss cycles are more common than univariate tests. Such bivariate tests often used cross-lagged panel designs. A traditional cross-lagged panel design needs at least two measurement points and specifies a cross-lagged path from the initial level of variable A at Time 1 to variable B at Time 2 and vice versa, in addition to autoregressive paths for both variables. Thus, with this approach, researchers test if initial individual differences in a Resource A predict change in individual differences in a Resource B (cf. Orth et al., 2021).

For instance, Halbesleben (2010) examined how exhaustion (as a state of depleted resources) relates to safety workarounds (i.e., at-risk behaviors that “work around” safety procedures) and how safety workarounds relate to injuries. Applying a traditional cross-lagged panel model to three-wave data (time lags: 6 months), Halbesleben also tested if injuries predicted subsequent exhaustion. Overall, Halbesleben found support for such a loss cycle (i.e., exhaustion predicting injuries and injuries predicting exhaustion) in one of the two samples studied.

Also using a traditional cross-lagged panel model, Hakanen et al. (2011) analyzed how job and home resources reciprocally relate to experiences of resourcefulness, namely work engagement (as outcome and predictor of job resources) and marital satisfaction (as outcome and predictor of home resources). In addition, these authors examined reciprocal relations between work-to-family enrichment and work engagement and between family-to-work enrichment and marital satisfaction. In their two-wave study (time lag: 3 years), job resources assessed at Time 1 predicted an increase in work engagement at Time 2 and vice versa. Similarly, home resources assessed at Time 1 predicted an increase in marital satisfaction at Time 2 and vice versa. Hakanen et al. also reported reciprocal relationships between work-to-family enrichment and work engagement.

As the traditional cross-lagged panel model has been criticized for providing biased estimates for the cross-lagged paths, researchers started to use more sophisticated data-analytic approaches such as refined versions of the cross-lagged panel model (random intercept cross-lagged panel model, Hamaker et al., 2015; Mulder & Hamaker, 2021; general cross-lagged panel model, Zyphur et al., 2020) and latent-change score models (McArdle, 2009). For instance, using a random intercept cross-lagged panel model, De Cuyper et al. (2022) examined how qualitative job insecurity (i.e., a potential resource loss) related to work-related learning (i.e., a process resulting in knowledge and skills as personal resources). Analyzing their three-wave data (time lags: 3 months), these authors found significant negative cross-lagged paths from qualitative job insecurity to participation in formal and some types of informal learning as well as reverse negative paths from participation in formal learning to qualitative job insecurity.

Ford et al. (2023) relied on a general cross-lagged panel model and analyzed how energetic and attentional resources relate to work-family conflict (work-to-family conflict, family-to-work conflict) over time. Using four-wave data (time-lags: 1 month), they found that low energetic and attentional resources predicted an increase in work-to-family conflict from one month to the next, and that work-to-family conflict predicted a decrease in attentional—but not energetic—resources. For family-to-work conflict, cross-lagged paths were not significant. In addition, the authors found little evidence for loss spirals over two months, neither for work-to-family conflict nor for family-to-work conflict.

Using latent change score modeling, Jiang et al. (2023) examined if self-esteem, sense of belonging, and perceived social support (i.e., resources) predict a reduction in job insecurity (i.e., reduced threat of stable employment as a resource) over six years (7 measurement points with time lags of 1 year). In addition, these authors tested if job insecurity predicts changes in self-esteem, sense of belonging, and perceived social support. They found that self-esteem and sense of belonging predicted a decrease in job insecurity, but job insecurity did neither predict change in self-esteem nor sense of belonging. Perceived social support predicted a decrease in job insecurity, and job insecurity predicted a decrease in job insecurity as well.

Taken together, we see a huge variety of study features in empirical research testing gain and loss cycles. First, studies covered diverse constructs, including job and personal resources as well as constructs that refer to volatile resources. Often, it remains unclear why specific constructs have been chosen and not others. This problem could be partially attributed to COR theory itself as COR theory does not provide a detailed description of which resources should be most relevant as predictors and outcomes of other resources (Halbesleben et al., 2014). Second, there was heterogeneity in the time lags between measurement points. Time lags ranged from one month (Ford et al., 2023) to three years (Hakanen et al., 2011). This variety in time lags implies that it is difficult to draw firm conclusions about how much time is needed for gain and loss cycles to unfold. Again, this problem is partly caused by COR theory itself because COR theory is mute about the duration of gain and loss processes (Halbesleben et al., 2014). However, this problem is not limited to COR theory, but is also very common in the broader organizational literature, where decisions about time lags are often made in a somewhat arbitrary way (Dormann & Griffin, 2015). Third, studies used a variety of data-analytic approaches. These approaches span from the traditional cross-lagged panel model to its revised versions (random-intercept cross-lagged panel model; general cross-lagged panel model) and latent change score models. The use of these diverse statistical methods reflects advancement in statistical approaches for analyzing longitudinal panel data. Importantly, these various approaches may lead to different results and conclusions (Orth et al., 2021), mainly because they differ in what is analyzed. Therefore, the selection of a specific data-analytic method profoundly impacts conclusions about gain and loss cycles. In the remainder of this editorial, we describe key points researchers should consider when testing gain and loss cycles in the future.

Key points when testing gain and loss cycles

Studying resource gain and loss cycles is attractive to many researchers interested in explaining how people stay healthy and engaged within organizations. Although the general idea of gain and loss cycles is appealing, empirical tests can be challenging, and the decisions researchers need to make are not trivial. In the following sections, we describe some key issues researchers need to tackle when planning empirical research that tests gain and/or loss cycles. Specifically, we discuss theoretical aspects, temporal issues, and data-analytic approaches.

Theoretical aspects

Before empirically testing gain and loss cycles, researchers need to address theoretical issues. The most pressing theoretical issues refer to two main questions: (1) the choice of the specific resources to be tested and (2) the differentiation between a within-person and a between-person perspective.

With respect to the first question, examining gain and loss cycles requires researchers to thoughtfully select the resources that “take part” in the gain and loss cycles. As described above, COR theory uses the concept of resources very broadly. Resources as “anything perceived by the individual to help attain his or her goals” (Halbesleben et al., 2014, p. 1338) comprise a broad set of factors such as conditions, objects, individual prerequisites, and energies (Hobfoll, 1998). Which ones among these very diverse factors should operate within gain and loss cycles? COR theory does not offer clear guidance here.

Within COR theory, resources are characterized by equifinality and multifinality (Halbesleben et al., 2014, p. 1339). This equifinal and multifinal nature of resources implies that different resources can be useful for attaining the same specific goal and that one specific resource can be used for attaining multiple different goals. When conceptualizing further resource gain as a goal, it becomes obvious that—according to COR theory—a specific resource is not linked to a specific set of other resources that benefit from the initial resource. Rather, resources within gain and loss cycles are replaceable—at least to some degree. This poses challenges for researchers because the number of combinations through which various resources can operate within gain and loss cycles becomes endless. Therefore, researchers might be tempted to test—or even selectively report—gain and loss cycles of arbitrarily chosen resources.

To develop their research model and their specific hypotheses, researchers need to select resources that are influential and malleable at the same time. Thus, resources that operate well in gain and loss cycles must be impactful in the sense that their presence (absence) has the power to affect other resources. In addition, to be effective within gain and loss cycles, these resources need to have some degree of plasticity so that the other resources can have an impact on them.

With respect to resources that are particularly influential, Hobfoll (2002, p. 308) points to key resources as resources that help in "selecting, altering, and implementing their other resources." Such key resources include self-efficacy, self-esteem, optimism, and goal-directed behavior as personal resources, but also social support and social power as job-related and societal resources (Hobfoll, 2002; ten Brummelhuis & Bakker, 2012). These resources should be highly relevant because their general nature makes them functional in many different situations. For instance, generalized self-efficacy can be utilized for many different purposes (different tasks, different skill sets), whereas the benefit of task-specific self-efficacy is limited to a certain task and the skills needed to perform this task. Thus, the availability (lack) of these key resources should be particularly important within gain and low cycles because they have the potential to influence other resources. Most of these key resources are also malleable to some degree, so they can be changed by influential other resources. For instance, self-efficacy and self-esteem can change over time and can be influenced by specific experiences (Meier et al., 2011; Sitzmann & Yeo, 2013), and social support may be changed by job-crafting efforts (Tims et al., 2013). Social power is probably the most stable key resource, but over longer periods of time, even social power might be influenced by other resources.

The above list of key resources is not necessarily exhaustive. For instance, the experience of job control might also be influenced by making use of control opportunities that are available (Daniels et al., 2013). However, not all resources described as key resources in the broader literature qualify for resources within gain and loss cycles. As an example, researchers characterized conscientiousness (Russell et al., 2017) and transformational leadership (Widianto & Wilderom, 2023) as key resources. It is conceivable that conscientiousness and transformational leadership are influential in that they elicit or strengthen other resources. However, conscientiousness and transformational leadership are not easily malleable and therefore, they are not the most obvious resources to be included in gain and loss cycles.

To sum up, researchers need to consider the resources' features of being both influential and malleable when designing studies to test gain and loss cycles. Moreover, when testing a model with multiple resources (e.g., Resources A and B), it is not sufficient to simply point out that both are resources and, therefore, reciprocally influence each other. Instead, researchers need to explain the mechanisms by which Resource A is influential and malleable for Resource B (and vice versa). For instance, Jiang et al. (2023) do this in an exemplary way. Researchers may even go one step further and test various resources against one another so that the field gets a better understanding of which resources are particularly influential within gain and loss cycles. Such an approach would clearly contribute to the mission of JOMSR that aims to answer questions such as "why these specific dimensions and no others?" (Kraimer et al., 2023, p. 13).

The second question with respect to theoretical issues of the COR framework is whether researchers are mainly interested in between-person differences or within-person processes. The between-person perspective, on the one hand, focuses on individual differences in initial resource levels and the consequences these differences have for subsequent resource levels. The within-person perspective, on the other hand, concentrates on a person's momentary resource level relative to that same person's usual level. For instance, one may ask if employees are more likely to gain (lose) more resources during times when their personal resource level is comparably high (low).

In his discussion on gain and loss cycles, Hobfoll (1998, p. 80) referred to between-person differences when stating "that those with greater resources are less vulnerable." And indeed, gain and loss cycles are often studied with a between-person perspective (Hakanen et al., 2011; Llorens-Gumbau & Salanova-Soria, 2014). However, a within-person perspective is theoretically plausible as well. For instance, it is conceivable that when a person is in a state of high resourcefulness, further resource gain is more likely because resource abundance helps the acquisition or better use of other resources. Similarly, when a person is in a state of high vulnerability, further resource loss is more likely, for instance, because it is less feasible to compensate for lacking resources. Empirical studies used such a within-person approach, for instance when studying cycles between job insecurity and reduced workplace learning (De Cuyper et al., 2022). Some daily survey studies examined parts of gain (McGrath et al., 2017) and loss cycles (Bakker, Xanthopoulou et al., 2023), using a within-person approach. Although the COR framework initially focused on between-person differences, we think that both between-person and within-person approaches are important. Systematically extending COR research to the study of within-person processes will provide opportunities for constructive replication—a key goal of JOMSR (Kraimer et al., 2023).

It is also possible to combine the within-person with the between-person perspective. For instance, it could be interesting to examine if persons differ in their within-person processes, such that some persons might benefit more from momentarily high states of resourcefulness (and subsequent resource gain) and others might be harmed more severely by momentarily high states of vulnerability (and subsequent resource loss). Within the thinking of COR theory, one could argue that the availability of resources (as a between-person variable) might predict these different response patterns to states of resourcefulness versus vulnerability. A similar idea is expressed in the gain paradox principle that states that “resource gain increases in salience in the context of resource loss” (Hobfoll et al., 2018, p. 106). Empirically testing a single principle of a larger theory—such as the gain paradox principle in COR theory—fits the mission of JOMSR.

Temporal aspects

Researchers planning studies that test gain and loss cycles need to address temporal issues, including questions about the duration of cycles and about the shape of the change processes happening within the cycles. As a starting point, researchers must make assumptions about how long it takes for the effects of one resource to impact another resource (in the case of multivariate cycles) or how long it takes for the change in a resource to become evident (in the case of univariate cycles). These assumptions are important when designing a study because they inform the decision about time lags between measurement points. This decision is not trivial as findings from one study often do not generalize to another study when the two studies differ in time intervals between measurement points (Voelkle et al., 2012).

Generally, decisions about time intervals should be informed by theory. However, COR theory is not specific about how long it takes until cycles of resource gains and losses unfold. Nevertheless, the statement that gain cycles “have less momentum (e.g., speed)” (Hobfoll, 1998, p. 82) implies that loss cycles become manifest within shorter time intervals than gain cycles. However, it remains unclear how long the respective time intervals should be. Hamaker (2023) discussed how researchers might address questions of study design related to time intervals, number of measurement waves, and time frame of the measurements. Moreover, continuous time modeling approaches provide an empirical approach to identifying the time interval within which specific processes operate (Driver & Voelkle, 2018). Nevertheless, theoretical considerations are important when deciding about time lags.

In addition, when deciding about time lags, researchers should also consider that the various parts of a cycle might not need the same time to unfold. For instance, Resource A might have a rather immediate impact on Resource B, whereas it might need more time until Resource B has the reverse effect on Resource A. Moreover, the impact of one resource on another within a gain or loss cycle might not always follow a linear but a higher-order trend. For instance, a resource might have a linear impact on the other resource immediately after the onset of the process, but this impact might slow down over time (in case of a gain cycle) or it might accelerate over time (in case of a loss cycle). To test these more complex time trends, more than the usual two to three measurement points are needed (Hopwood et al., 2022).

Taken together, there are not yet simple solutions for deciding about temporal issues. But without doubt, researchers need to move beyond “intuition, chance, convenience, or tradition” (Mitchell & James, 2001, p. 533) when addressing temporal aspects of gain and loss cycles. It will be particularly important to keep in mind that different resources most likely act on different temporal trajectories. Therefore, most published studies on gain and low cycles that we described above (e.g., Hakanen et al., 2011; Jiang et al., 2023; Paustian-Underdahl et al., 2023) could be subject to constructive replication as time lags received relatively little attention in these studies. For instance, it would be interesting to see if the gain and loss cycles of work engagement and exhaustion that Paustian-Underdahl et al. (2023) identified over six-month periods may become evident at even shorter time intervals.

Data-analytic aspects

Researchers used various statistical approaches when aiming to test gain and loss cycles, ranging from the traditional cross-lagged panel model to its revised versions and latent change score models. The cross-lagged paths estimated in the various approaches include the most important information pertaining to gain and loss cycles. Importantly, the various approaches can result in different estimates of the cross-lagged paths (Usami et al., 2019), leading to different conclusions (Orth et al., 2021). For instance, Jiang et al. (2023) illustrated how the traditional cross-lagged panel model, the random-intercept cross-lagged panel model, and the latent change score model resulted in huge differences in parameter estimates.

Although the traditional cross-lagged panel model is easy to understand and has been quite popular in empirical tests of gain and loss cycles (Hakanen et al., 2011; Halbesleben, 2010), it does not provide unbiased estimates for the cross-lagged paths. This problem is caused by the estimation of the autoregressive paths that conflates stable trait-like differences between persons and dynamic temporal within-person processes (Hamaker et al., 2015). Thus, because the autoregressive path does not only capture temporal stability in the variables but also enduring trait-like between-person differences, the cross-lagged paths are biased and do not adequately represent the relationship between the initial level of Resource A on change in Resource B and vice versa.

To avoid this problem, researchers can use a random-intercept cross-lagged panel model instead. This model specifies trait-like influences that may have an impact on all measurement points as a random intercept (Hamaker et al., 2015; Mulder & Hamaker, 2021). The study by De Cuyper et al. (2022) is a good example of this. When interpreting findings from a random-intercept cross-lagged panel model, a caveat, however, is needed. Because the random-intercept cross-lagged panel model specifies trait-like influences as a random intercept, the substantive cross-lagged paths should be interpreted as within-person coefficients (Hamaker, 2023). Thus, a significant cross-lagged path from Resource A to Resource B implies that a higher-than-usual level of Resource A predicts change in Resource B.

That said, we would even go a step further and wonder whether cross-lagged panel models are at all appropriate to test gain and loss cycles (see also Taris & Kompier, 2014). By definition, gains and losses in resources reflect changes in the levels of one's resources from one time point to the next. As such, they indicate within-person changes. Such changes, however, are not the focus of cross-lagged panel models, neither in the traditional nor in the random-intercept cross-lagged panel model. Using a traditional cross-lagged panel model, one could for example examine whether individuals who are low (relative to others) in resource A will experience a subsequent (rank-order, i.e., relative standing compared to others) decrease in Resource B. This model is thus silent about (within-person) changes in resources. In contrast, a random-intercept cross-lagged panel model could be used to examine whether individuals with lower than usual Resource A (i.e., relative to their trait level) will experience a subsequent increase in Resource B. While this model now focuses on within-person fluctuations, it still does not capture moment-to-moment changes. Having lower (higher) resources at a specific moment than *usual* does not necessarily reflect a decrease (increase). To properly study decreases and increases, we need to know whether one's resources at a specific moment are lower (or higher) than at *the previous moment.*

A suitable model for capturing changes from one moment in time to the next is the latent change score model (McArdle, 2009). Latent change score models can be applied to univariate and multivariate (i.e., bivariate) research questions (for a description of best practices in latent change score models within the organizational science, see Matusik et al., 2021). As a univariate model, researchers can test how a resource develops over time (see Paustian-Underdahl et al., 2023, for an example). In its bivariate version, a latent change score model allows researchers to examine the dynamic relationship between two variables over time (e.g., if the initial level in Resource A predicts change in Resource B and vice versa). The study by Jiang et al. (2023) is an example of applying a latent change score model to test cycles within COR theory. Moreover, an extension of the latent change score model allows one to examine whether a recent change (as opposed to the recent level) in Resource A predicts a subsequent change in Resource B (change-to-change extension of the latent change score model, Grimm et al., 2012). This approach could be particularly instrumental in testing Collorary 2 and Collorary 3 that focus on the consequences of initial resource loss and resource gain, respectively.

Therefore, the latent change score models are an interesting analytical approach for investigating gain and loss cycles, but a note of caution should be added. As stated above in the critique of traditional cross-lagged panel model, it is necessary to account for stable inter-individual differences by separating between-person and within-person variance to estimate effects from one variable (e.g., Resource A) to another (e.g., Resource B). However, latent change score models do not decompose the observed variance into between-person and within-person variance (Usami et al., 2019); thus, problems identified with the cross-lagged panel model may also exist here.

As there is not yet a "perfect" data-analytic approach to testing gain and loss cycles, researchers need to decide which limitations they may want to accept. Whereas the random-intercept cross-lagged panel model tests if a temporary deviation from a person's average level of a Resource A predicts a temporary deviation from this person's average level of Resource B, the latent-change score model tests if a person's latent score in Resource A predicts change in this person's latent score in Resource B (Orth et al., 2021). In any case, researchers should be aware of what they are actually testing and should communicate this clearly in their articles.

Several of the studies mentioned above could be re-analyzed using alternative data-analytic approaches. For instance, the Halbesleben (2010) study could be a good candidate for constructive reproducibility (Cortina et al., 2023). Instead of using a traditional cross-lagged panel approach data could be analyzed by using a random-intercept cross-lagged panel model or a latent change score model. Similarly, it would be interesting to see if the findings reported by De Cuyper et al. (2022) hold when analyzing the data with a latent change score approach.

It is without saying that before starting to test the model of interest, preliminary analyses are needed. Researchers should examine construct validity (Jackson et al., 2009), test for measurement invariance (Vandenberg, 2002), and consider power issues (Mulder, 2023; Zhang & Liu, 2018).

Conclusion

More than 25 years after Hobfoll's (1998) book was published, COR theory is still widely used within the organizational sciences, and researchers are particularly fascinated by the idea of gain and loss cycles. However, testing these gain and loss cycles is far from trivial. We hope that this editorial encourages researchers to embrace these challenges and develop innovative ways to move COR research forward. Novel empirical insights might even fuel back into theory development, resulting in a refined version of COR theory.

Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Laurenz L. Meier https://orcid.org/0000-0002-5675-1562

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