

Job stressors and social support seeking: A sensing-based longitudinal panel study

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Abstract

Since decades, stress researchers have considered social support as a key resource for preventing or coping with job stress. Furthermore, social support is seen as a direct contributor or precondition to wellbeing and subjective health (Danna & Griffin, 1999). Whereas the job stress literature has spent a substantial focus on the supposed moderator role of social support (the buffer hypothesis) or its direct effects on wellbeing, the stressor-support effect has gained much less attention. In addition, the focus was on *receiving* social support and less on the individual's effort to *seek* social support that underlies the stressor-support effect. From such a perspective, job stressors prompt social support seeking as a coping strategy in attempt to either cope with the stressor or the emotional stress response. The intended research project attempts to investigate the effect of job stressors on social support seeking, measured in a longitudinal triangulation study in which perceived job stressors are measured with self-reports and social support seeking is measured by relying on smartphone-based sensing data (i.e., Bluetooth-based interactions, the number of outgoing telephone calls, their duration, and the number of outgoing text messages). The longitudinal design comprises 6 months of monthly measured job stressors (workload and role ambiguity) and monthly aggregated sensing data. In addition, exploratory analyses will focus on the shape of individual daily time series, their relationship with job stressors, and inter-individual differences in the shape and relationship.

Introduction and background

In their effort to identify psychosocial resources that may help to prevent job stressors or reduce their negative consequences, researchers in the field of job stress have placed a heavy focus on the role of social support (Cohen & Wills, 1985; Daniels & Guppy, 1994; Dignam & West, 1988; Hobfoll, Freedy, Lane, & Geller, 1990; Viswesvaran, Sanchez, & Fisher, 1999). In this regard, scholars have claimed different functional roles that social support may play, that is, as a direct contributor of wellbeing (i.e., the direct effect model, Wheaton, 1985) or as a moderator of the stressor-wellbeing effect (buffer hypothesis, Cohen & Wills, 1985). In contrast, and despite substantial research (Viswesvaran et al., 1999), the role of social support as a response to stressors has gained less prominence. Combining this “stressor-support-model” with the direct effect model provides a potential to locate social support as a key mediator linking job stressors to reduced wellbeing (the mediation model, Viswesvaran et al.,

1999). This perspective would assign social support the status of a resource which the individual attempts to acquire as a coping strategy in order to either prevent continuation of the stressor or to reduce the psychological consequences (e.g., worries, tension). In this regard, *social support seeking* is a fruitful perspective on the stressor-support linkage as it emphasizes the role of the individual as an active problem solver (Folkman & Lazarus, 1988). This contrasts with the alternative models that focus on the resource function of an „existing“ degree of social support.

Having stated the importance of social support seeking as an active coping strategy, the question arises on how individuals seek for social support. While direct, face-to-face-contact with colleagues, partners, and peers may be the most intuitive strategy, additional channels provided by digital sources (e.g., smartphones) may be used that have the advantage to connect the target person with potential supporters. In this regard, telephone calls or text message conversations are an easily accessible and low-thresholded source of support. Because such channels can be directly measured via smartphones (Eagle & Pentland, 2006; Schmid Mast, Gatica-Perez, Frauendorfer, Nguyen, & Choudhury, 2015), a study using this approach, thus, avoids problems of surveys especially when both independent and dependent variables are measured with the same method (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). In this regard, social behaviour can be measured in a direct and a less reactive way which avoids response-style related errors and systematic error covariances between the independent and dependent variable.

Finally, although there are a number of studies on social support which apply longitudinal designs (Dormann & Zapf, 1999; Frese, 1999; Marcelissen, Winnubst, Buunk, & De Wolff, 1988), to our knowledge, these studies focused on the direct and interactive effects of social support, not on the effect of job stressors on social support seeking. This is disadvantageous as scholars focusing on the relationship between job stressors and social support both argued for an effect of stressors on social support as well as the effect of social support on reducing stressors (Viswesvaran et al., 1999). However, representing them as alternative models avoids recognizing that both models can be integrated and could comprise a simultaneous causal system with stressors inducing social support seeking and received social support reducing stressors (Antonakis, Bendahan, Jacquart, & Lalive, 2010). If this is true, estimating OLS regressions in cross-sectional designs (or simple structural equation models) will lead to biased or even nonsensical results. The same is true for meta-analysing correlations between both (Viswesvaran et al., 1999), as the correlation between both will be a function of both effects. As both effects would operate in opposing directions (i.e., stressors prompt seeking social support vs. getting social support reduces stressors), the bias will be severe. A longitudinal design, in contrast, allow to disentangle both and to estimate both directions. Furthermore, modern multi-level approaches (Bolger & Laurenceau, 2013) or improvements of the classical cross-lagged panel model (Hamaker, Kuiper, & Grasman, 2015) allows to estimate individual change and within-person-processes (i.e., the random intercept cross-lagged-panel model, RI-CPLM).

As a summary, the intended project attempts to apply a longitudinal design to investigate the causal relationship of monthly measured perceived job stressors (workload and role ambiguity) and objective social support seeking, operationalized by smartphone-based sensing data in a design with an intended number of 6 monthly waves. This is in line with some prior research that measured smartphone-based telephone calls and text messages which was regarded as indicative for the individual's goal to initiate social interactions—especially when being faced with problems (Yu, Zhou, Zhang, Schiele, & Becker, 2013). In our study, relevant sensing data will be face-to-face social interactions measured by means of Bluetooth sensor scans as well as attempts to initiate a contact to the target person's social system (i.e., number of outgoing telephone calls, duration of calls, number of outgoing text messages). The following section specifies the confirmatory goals and optional exploratory goals.

Hypotheses

On the basis of claims of a social support inducing effect prompted by job stressors, we expect that job stressors show a positive effect on social activities initiated by the target person. Job stressors such as workload (i.e., having too much work or having to work faster than adequate), or role ambiguity (i.e., being confronted with unclear goals or lack of necessary information) have been shown to lead to severe immediate strain reactions up to negative long-term psychological and physical health consequences (Danna & Griffin, 1999). These stressors cause an overtaxation of the behavioural regulation system, for instance, when being confronted with workload or time pressure (Frese & Zapf, 1994) or lead to insecurities about relevant main goals or sub goals that underlie task assignments. These overtaxations and insecurities, in turn, cause negative emotions, tension, worries, and anxiety. As social support may consist in either instrumental support (e.g., real help), emotional support (e.g., caring or listening), informational support (i.e., giving advices), or appraisal support (i.e., providing positive feedback), phases of increased job stressors and the induced psychological discomfort will motivate target persons to approach people in their social surrounding to receive some or several of these functions. As aforementioned, this may occur via face-to-face contact as well as communication channels such as telephone calls or sending text messages.

Hypothesis 1: Job stressors are positively related to social support seeking, operationalized by a) Bluetooth-measured social contacts, b) number of outgoing telephone calls, c) duration of telephone calls, and d) number of outgoing text messages.

As the next section will explicate, job stressors will be conceptualized on „medium-trait-level“ that is on a timely level that is located between *daily* and *in general*. This allows, to analyse more dynamic changes and their short-term consequences compared to trait-level conceptualizations.

Optional exploratory research questions

Based on the main premise of the study explicated in Hypothesis 1, further goals shall be addressed in an exploratory fashion due to the lack of a theoretical basis or knowledge about the characteristics of the data that comes with a sensing study.

1. Whereas job stressors will be measured with traditional self-reports, social support seeking will be measured in a semi-continuous fashion and aggregated to a (monthly) level in order to match the number of waves and interval duration of the job stressors. On the other hand, the more fine grained measurement of the sensing data allows to investigate more dynamic (e.g., daily) trends and fluctuations of social support seeking. Further goals, thus, refer to a) investigating individual time series (Jebb, Tay, Wang, & Huang, 2015) and their inter-individual differences, b) applying clustering methods to identify groups of people with similar time series (Hyndman & Athanasopoulos, 2018) and c) analysing the characteristics of these groups. This phase of the study addresses questions for stability of social behaviour (e.g., habits), dynamic fluctuations (e.g., responsiveness to mood changes), carry-over effects (e.g., autocorrelation), or compensatory effects (e.g., restricting oneself after excessive behaviour).
2. Beyond these descriptive goals, we attempt to investigate the effect of monthly measured job stressors on day-level social support seeking. In this regard, we intend to answer questions about the effect latency and functional form of increasing social support seeking in phases with high job stressors. As reporting job stressors is based on past events, we expect that changes in social support seeking start sometime prior to the actual measured point in time.
3. As we focus on social support seeking, we rely on activities of the target individual, thus, outgoing calls or text messages. In contrast, responses by the intended interaction partner may signify a success of social support seeking (i.e., actual support). This provides a fruitful area for investigating conditions for such responsiveness or the timely gap between the initialization and response.
4. As individuals may have many contacts, the concept of social support seeking may be valid only to close relationships. In this regard, we will follow the approach by Yu, Zhou, Zhang, Schiele, and Becker (2013) who gathered data on telephone calls and text messages to identify close contacts of the target person by considering the most frequent contacts. A further goal is hence, to identify close relationships and consider interactions with those individuals as the relevant outcome.
5. The stated hypothesis focuses the number of text messages. In addition, sentiment analyses of the content of these messages may provide validity evidence for relying on these messages as expression of social support seeking. That is, there should be a correlation between job stressors and negative emotional expression in these text messages.

Method

Data collection

The data will be collected within the research project *PhoneStudy* in cooperation with the LMU Munich. Detailed descriptions are contained in the respective master protocol (see <http://dx.doi.org/10.23668/psycharchives.2901>).

Survey measures

Job stressors are *workload* (i.e., having too much work or being required to work too fast) and *role ambiguity* (i.e., having unclear or ambiguous goals or too little information that is necessary to carry out a task). All measures are provided with an instruction that explicates the focus on the *current*, not general, job stressors. Responses are possible on a 7-point rating scale ranging from 1 (*do not agree*) to 7 (*do fully agree*). Workload will be measured with three items from the scale by Spector and Jex (1998). A sample item for workload is „My work requires me to work very hard these days“. Role ambiguity will be measured with two items developed by Schuler, Aldag, & Brief (1977). A sample item is „I know exactly what is expected of me“ (reversely coded).

Sensing measures

Bluetooth. Research has shown that Bluetooth sensors can be used as a passive measure of social interactions (Do, Blom, & Gatica-Perez, 2011; Eagle & Pentland, 2006; Raento, Oulasvirta, & Eagle, 2009). The smartphone scans the environment regularly and detects external Bluetooth devices which indicate the near presence of other people (i.e., the Bluetooth ID, see Padmaja, Prasad, Sunitha, Reddy, & Anil, 2019). On the one hand, bluetooth sensing is an error-prone measure: besides the occurrence of technical errors, nearby persons may have no smartphone or may have Bluetooth signal deactivated, or nearby persons may not interact with the target person. In addition, due to the low scanning frequency of up to 5 minutes, shorter interactions may be missed. On the other hand, despite these problems, its validity as a measure of social interactions have been supported (Eagle & Pentland, 2006; Fukazawa et al., 2020). In relying on Bluetooth, we take the perspective from a measurement error perspective. From this perspective, we expect the aforementioned error sources as being exogenous which, thus, should increase the error variance of the measure but do not bias the effect estimate.

In the intended project, we intend to count the number of active devices near the target person on a daily basis, then calculate a monthly mean number of daily contacts to test hypothesis 1. This procedure allows to count the same contact more than once per day which should signify an increased or prolonged interaction with that contact. It should be noted that this approach results in an objective number of personal contacts per month without considering the quality of the relationship between the target person and the contact. As an extreme, a colleague with which the person joins the office space may be counted up to 60 times a day (12 x 8h) which correctly reflects a strong prolonged proximity. Post-hoc analyses

(see research question 4) may involve a re-calculation of the number of scans with only close relationships. In addition, the number of distinct devices per day may indicate the breadth of social contacts and may differentiate a small number of intensive or prolonged interactions from a large number of short interactions (with many people).

Telephone-based measures. Sensing studies also measure the time stamp of outgoing and incoming telephone calls (Padmaja et al., 2019; Yu et al., 2013). These will be used to count the daily number of outgoing calls and the duration of accepted outgoing and received incoming calls. For testing Hypothesis 1, we intend to aggregate the number of outgoing calls and duration of calls based on outgoing calls during the month, whereas exploratory goals will focus on the daily fluctuations and trends across the month. Whereas our main procedure for testing Hypothesis 1 will consist of considering all outgoing telephone calls, an option will be to focus on those calls to interaction partners which can be identified as closely related to the target person based on the frequency of interactions over a month (Yu et al., 2013) identified through the hashed contact names.

Text-messaging. Analogous with the treatment of telephone calls, we will count the number of outgoing text-messages during the day and aggregate the daily measures to a monthly composite. Further, sentiment analysis will be conducted. The PhoneStudy applies decentralized (i.e. on-the-mobile) text analysis without gathering or recording the text of the messages.

Analytical approaches

Tests of factor models and longitudinal invariance. As the first step, we will specify and test longitudinal measurement models of the two job stressor variables. This step provides a test of the supposed causal structure underlying the measures (Greiff & Heene, 2017; Hayduk, Cummings, Boadu, Pazderka-Robinson, & Boulianne, 2007) as well as testing for longitudinal invariance (Millsap & Hartog, 1988; Vandenberg & Self, 1993). As in any other study applying structural equation modelling, is likely that we will face a misfit of the basic model via the chi-square test and/or failures to support full or partial measurement invariance (Bryne, Shavelson, & Muthén, 1998). As the workload scale by Spector and Jex comprises two items that emphasize the quantitative overload and one item focusing on time pressure, it is of special interest whether all three items measure one underlying latent workload variable or two separate variables.

Intended responses to misfit of the model structure will be to use diagnostics to respecify the model. These diagnostics are a) the *standardized residuals* (i.e., normalized deviations of the model-implied covariances from the empirical covariances) and b) the approach by Bollen (2019) to identify *model-implied instrumental variables* to test the specification of specific relationships between a latent variable and each of its measured indicators. As any data-informed model respecification, this approach implies the risk for capitalization on chance and will be reported as a proposal implying the need for future replication.

Beyond the test of the overall structure, longitudinal measurement invariance means that a) the model structure and b) parameters of interest (most noteworthy, the factor loadings) do not significantly change across time which could indicate a change of the measurement intervals or even the overall validity of the measure (Steinmetz, Schmidt, Tina-Booh, Wieczorek, & Schwartz, 2009). In case of a failure to show invariance, results should be interpreted with care.

Cross-lagged panel models. Based on the former steps, the main approach for testing hypothesis 1 is the random-intercept cross-lagged-panel model (RI-CLPM, Hamaker et al., 2015; Mund & Nestler, 2019). This model is an improvement over the classical autoregressive CLPM, in which the independent variable and the dependent variable are both measured within certain intervals. The backbone of this model are autoregressive effects of each variable on their version measured later in time which denotes the between-subjects stability (or rank-order stability). The substantive effects are then tested by estimating effects of the variables on their counterpart one point in time later. Applied to our study, this would mean testing the effects of job stressors at point t on social support seeking at $t+1$ and vice versa. As it is intended to specify latent variable models for the job stressors, these will be kept in the structural model.

Mixed effects models. A statistical problem which may occur will be related to the distribution of the sensing data: Whereas the daily number of Bluetooth scans, calls, and messages are count variables which are inadequate for usual general linear models (such as OLS regression or structural equation modelling), a highly aggregated form of these variables may have distributional properties with which can be dealt by using robust estimators. If this is not the case, we will consider possibilities to test Hypothesis 1 and the exploratory questions by using generalized linear mixed effects models (Barber & Thompson, 2004) which allow other forms of error distributions (e.g., tweedie or gamma distributions).

Time series analysis. For analysing the exploratory questions, there are several analytical options which will be explored. As a first step, we will apply time series analysis (Box-Steffensmeier, Freeman, Hitt, & Pevehouse, 2014; Jebb et al., 2015) to the sensing data. This serves not only to identify errors, missing data, and outliers and to correct the data accordingly (Hyndman & Athanasopoulos, 2018) but also to identify constituting elements of individual time series, that is, linear and non-linear trends and systematic variations (i.e., seasonality) if they exist. A further step, we intent to apply clustering methods to time series features (e.g., seasonal strength, trend strength, linearity) to identify groups of individuals with similar time profiles (Wang, Smith, & Hyndman, 2006) and to associate the features with person-level predictors.

For the prediction of day-level sensing data by the monthly survey measures (see research question 2), we attempt to use the continuous time modelling approach (Boker & Wenger; de Haan-Rietdijk, Voelkle, Keijsers, & Hamaker, 2017; Driver, Oud, & Voelkle, 2017; Driver & Voelkle, 2018) which allows modelling continuous dynamic functions underlying coarsely measured time data (as in the case of job stressors). This should allow to investigate continuous effects of job stressors on social support

seeking. We regard this phase of the project as exploratory due to the innovativeness and lack of experience with the approach.

Software

All of these analyses will be conducted using R (R Core Team, 2020). Relevant packages will be

- *dplyr* and *tidyr* (for data wrangling)
- *lubridate* (for wrangling timestamp data)
- *ggplot2* (for graphics)
- *lavaan* (for structural equation modelling)
- *MIIVsem* (for diagnosing factor model misspecification)
- *lme4* (for generalized mixed effects models with count and gamma distributions)
- *cplm* (for modelling mixed-effects models with tweedie distributions).

Estimation of time series models will rely on using the packages

- *tsibble* (for data wrangling in time series data sets)
- *feasts* (for calculation of auto-correlation, decomposition time series components, handling multiple time series, and for feature extraction)
- *fable* (for estimating time series models)
- *ctsem* (for continuous time modelling).

References

- Antonakis, J., Bendahan, S., Jacquart, P., & Lalive, R. (2010). On making causal claims: A review and recommendations. *The Leadership Quarterly*, 21, 1086-1120. doi:10.1016/j.leaqua.2010.10.010
- Barber, J., & Thompson, S. (2004). Multiple regression of cost data: use of generalised linear models. *Journal of Health Services Research & Policy*, 9(4), 197-204. doi:10.1258/1355819042250249
- Boker, S. M., & Wenger, M. J. *Data analytic techniques for dynamical systems*. Mahwah: Lawrence Erlbaum Associates.
- Bolger, N., & Laurenceau, J.-P. (2013). *Intensive longitudinal methods: An introduction to diary and experience sampling research*: Guilford Press.
- Bollen, K. A. (2019). Model implied instrumental variables (MIIVs): An alternative orientation to structural equation modeling. *Multivariate Behavioral Research*, 54(1), 31-46.
- Box-Steffensmeier, J. M., Freeman, J. R., Hitt, M. P., & Pevehouse, J. C. (2014). *Time series analysis for the social sciences*: Cambridge University Press.
- Bryne, B. M., Shavelson, R. J., & Muthén, B. (1998). Testing for the equivalence of factor covariance and mean structure: The issue of partial measurement in variance. *Psychological Bulletin*, 105(3), 456-466.
- Cohen, S., & Wills, T. A. (1985). Stress, social support, and the moderating hypothesis. *Psychological Bulletin*, 98, 310-357.
- Daniels, K., & Guppy, A. (1994). Occupational stress, social support, job control and psychological well-being. *Human Relations*, 47(12), 1523-1154.
- Danna, K., & Griffin, R. W. (1999). Health and well-being in the workplace: A review and synthesis of the literature. *Journal of Management*, 25(3), 357-384. doi:10.1177/014920639902500305
- de Haan-Rietdijk, S., Voelkle, M. C., Keijsers, L., & Hamaker, E. L. (2017). Discrete- vs. Continuous-Time Modeling of Unequally Spaced Experience Sampling Method Data. *Frontiers in Psychology*, 8(1849). doi:10.3389/fpsyg.2017.01849
- Dignam, J. T., & West, S. G. (1988). Social support in the workplace: Tests of six theoretical models. *American Journal of Community Psychology*, 16(5), 701-724. doi:10.1007/BF00930022
- Do, T. M. T., Blom, J., & Gatica-Perez, D. (2011). *Smartphone usage in the wild: a large-scale analysis of applications and context*. Paper presented at the Proceedings of the 13th international conference on multimodal interfaces.
- Dormann, C., & Zapf, D. (1999). Social support, social stressors at work, and depressive symptoms: Testing for main and moderating effects with structural equations in a three-wave longitudinal study. *Journal of Applied Psychology*, 84(6), 874-884.
- Driver, C. C., Oud, J. H., & Voelkle, M. C. (2017). Continuous time structural equation modeling with R package ctsem. *Journal of Statistical Software*.
- Driver, C. C., & Voelkle, M. C. (2018). Hierarchical Bayesian continuous time dynamic modeling. *Psychological Methods*, 23(4), 774-799. doi:10.1037/met0000168
- Eagle, N., & Pentland, A. S. (2006). Reality mining: sensing complex social systems. *Personal and ubiquitous computing*, 10(4), 255-268.
- Folkman, S., & Lazarus, R. S. (1988). *Manuals of the ways of coping questionnaire*: Consulting Psychologists.
- Frese, M. (1999). Social support as a moderator of the relationship between work stressors and psychological dysfunctioning: A longitudinal study with objective measures. *Journal of Occupational Health Psychology*, 4(3), 179-192.
- Frese, M., & Zapf, D. (1994). Action as the core of work psychology: A german approach. In H. C. Triandis & M. D. Dunnette (Eds.), (pp. 271-340). Palo Alto, California: Consulting Psychologists press.
- Fukazawa, Y., Yamamoto, N., Hamatani, T., Ochiai, K., Uchiyama, A., & Ohta, K. (2020). Smartphone-based mental state estimation: A survey from a machine learning perspective. *Journal of Information Processing*, 28, 16-30.
- Greiff, S., & Heene, M. (2017). Why psychological assessment needs to start worrying about model fit. *European Journal of Psychological Assessment*, 33(5), 313-317.

- Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. P. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods*, 20(1), 102-116.
- Hayduk, L. A., Cummings, G. G., Boadu, K., Pazderka-Robinson, H., & Boulianne, S. (2007). Testing! Testing! One, two, three - testing the theory in structural equation models! *Personality and Individual Differences*, 42(5), 841-850.
- Hobfoll, S. E., Freedy, J., Lane, C., & Geller, P. (1990). Conservation of social resources: Social support resource theory. *Journal of Social and Personal Relationships*, 7, 465-478. doi:10.1177/0265407590074004
- Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: principles and practice*: OTexts.
- Jebb, A. T., Tay, L., Wang, W., & Huang, Q. (2015). Time series analysis for psychological research: examining and forecasting change. *Frontiers in Psychology*, 6, 727.
- Marcelissen, F. H. G., Winnubst, J. A. M., Buunk, B., & De Wolff, C. J. (1988). Social support and occupational stress: A causal analysis. *Social Science Medicine*, 26(3), 365-373.
- Millsap, R. E., & Hartog, S. B. (1988). Alpha, beta, and gamma change in evaluation research. *Journal of Applied Psychology*, 73, 564-574.
- Mund, M., & Nestler, S. (2019). Beyond the cross-lagged panel model: Next-generation statistical tools for analyzing interdependencies across the life course. *Advances in Life Course Research*, 41, 100249.
- Padmaja, B., Prasad, V. R., Sunitha, K., Reddy, N. C. S., & Anil, C. (2019). *DetectStress: A novel stress detection system based on smartphone and wireless physical activity tracker*. Paper presented at the First International Conference on Artificial Intelligence and Cognitive Computing.
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879-903.
- R Core Team. (2020). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from www.R-project.org
- Raento, M., Oulasvirta, A., & Eagle, N. (2009). Smartphones: An emerging tool for social scientists. *Sociological Methods & Research*, 37(3), 426-454.
- Schmid Mast, M., Gatica-Perez, D., Fraendorfer, D., Nguyen, L., & Choudhury, T. (2015). Social sensing for psychology: Automated interpersonal behavior assessment. *Current Directions in Psychological Science*, 24(2), 154-160. doi:10.1177/0963721414560811
- Schuler, R. S., Aldag, R. J., & Brief, A. P. (1977). Role conflict and ambiguity: A scale analysis. *Organizational Behavior and Human Performance*, 20(1), 111-128. doi:[http://dx.doi.org/10.1016/0030-5073\(77\)90047-2](http://dx.doi.org/10.1016/0030-5073(77)90047-2)
- Spector, P. E., & Jex, S. M. (1998). Development of four self-report measures of job stressors and strain: Interpersonal conflict at work scale, organizational constraints scale, quantitative workload inventory, and physical symptoms inventory. *Journal of Occupational Health Psychology*, 3(4), 356-367.
- Steinmetz, H., Schmidt, P., Tina-Booh, A., Wieczorek, S., & Schwartz, S. H. (2009). Testing measurement invariance using multigroup CFA: Differences between educational groups in human values measurement. *Quality and Quantity*, 43(4), 599-616. doi:10.1007/s11135-007-9143-x
- Vandenberg, R. J., & Self, R. M. (1993). Assessing newcomers' changing commitments to the organization during the first 6 months of work. *Journal of Applied Psychology*, 78(4), 557-568.
- Viswesvaran, C., Sanchez, J. I., & Fisher, J. (1999). The role of social support in the process of work stress: A meta-analysis. *Journal of Vocational Behavior*, 54, 314-334.
- Wang, X., Smith, K., & Hyndman, R. (2006). Characteristic-based clustering for time series data. *Data Mining and Knowledge Discovery*, 13(3), 335-364. doi:10.1007/s10618-005-0039-x
- Wheaton, B. (1985). Models for the stress-buffering functions of coping resources. *Journal of health and social behavior*, 352-364.
- Yu, Z., Zhou, X., Zhang, D., Schiele, G., & Becker, C. (2013). Understanding social relationship evolution by using real-world sensing data. *World Wide Web*, 16(5-6), 749-762.