Journal of Organizational Behavior, J. Organiz. Behav. **33**, 678–699 (2012)
Published online 22 August 2011 in Wiley Online Library (wileyonlinelibrary.com) **DOI**: 10.1002/job.778

A meta-analysis of the interrelationships between employee lateness, absenteeism, and turnover: Implications for models of withdrawal behavior

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Summary We meta-analyzed the correlations between voluntary employee lateness, absenteeism, and turnover to (i) provide the most comprehensive estimates to date of the interrelationships between these withdrawal behaviors; (ii) test the viability of a withdrawal construct; and (iii) evaluate the evidence for competing models of the relationships between withdrawal behaviors (i.e., alternate forms, compensatory forms, independent forms, progression of withdrawal, and spillover model). Corrected correlations were .26 between lateness and absenteeism, .25 between absenteeism and turnover, and .01 between lateness and turnover. These correlations were even smaller in recent studies that had been carried out since the previous meta-analyses of these relationships 15–20 years ago. The small-to-moderate intercorrelations are not supportive of a withdrawal construct that includes lateness, absenteeism, and turnover. These intercorrelations also rule out many of the competing models of the relationships between withdrawal behaviors, as many of the models assume all relationships will be positive, null, or negative. On the basis of path analyses using meta-analytic data, the progression of withdrawal model garnered the most support. This suggests that lateness may moderately predict absenteeism and absenteeism may moderately predict turnover. Copyright © 2011 John Wiley & Sons, Ltd.

Keywords: lateness; absenteeism; turnover; withdrawal from work; meta-analysis

Voluntary employee lateness, absenteeism, and turnover are often referred to as "withdrawal behaviors" because they each represent some physical removal from the workplace (e.g., Hulin, 1991; Johns, 2001; Koslowsky, 2000).[1] Withdrawal behaviors are costly to organizations. Employee lateness has been estimated to cost US businesses more than $3bn each year (DeLonzor, 2005), employee absenteeism has been estimated to cost businesses as much as 15 per cent of payroll (Navarro & Bass, 2006), and the cost of replacing employees has been estimated between 50 and 200 per cent of those employees' first year salaries (Fitz-enz, 1997; Hale, 1998). Sagie, Birati, and Tziner (2002) considered the costs of all withdrawal behaviors to a leading, medium-sized Israeli company and estimated the total cost to be approximately 16.5 per cent of the company's before-tax income. Other studies have documented the negative effects of withdrawal behaviors on teammates' morale and work motivation (e.g., Jamal, 1984; Koslowsky, Sagie, Krausz, & Singer, 1997). Clearly, there is value in understanding withdrawal

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[1]Other things such as leaving work early (Iverson & Deery, 2001), psychological withdrawal (Koslowsky, 2009), and retirement (Hanisch & Hulin, 1990) have been put forward as manifestations of withdrawal. This study's focus on lateness, absenteeism, and turnover does not imply that we do not believe that these other variables are manifestations of withdrawal. Rather, lateness, absenteeism, and turnover are by far the most studied withdrawal behaviors (Koslowsky, 2009; Krausz, Koslowsky, & Eiser, 1998), so we focus on these in our review of models of employee withdrawal.

Received 19 July 2010
Revised 24 June 2011, Accepted 09 July 2011

behaviors, and this study contributes to this understanding by meta-analyzing the relationships between voluntary lateness, absenteeism, and turnover.

Two general perspectives have been taken to explaining the link between withdrawal behaviors (Koslowsky, 2009). One perspective views voluntary lateness, absenteeism, and turnover as manifestations of an overall withdrawal from work construct, arguing that each behavior is a way that employees withdraw from work in response to unfavorable work attitudes such as job dissatisfaction and lack of organizational commitment (e.g., Hulin, 1991; Rosse & Hulin, 1985; Rosse & Hulin, 1984). On the basis of this withdrawal construct perspective, some have argued that an understanding of the withdrawal behaviors and their antecedents would be increased by focusing on aggregate measures that combine the withdrawal behaviors (e.g., Hanisch, Hulin, & Roznowski, 1998). In particular, on the basis of the compatibility principle (Ajzen & Fishbein, 1980), some have made the case that broad measures such as job satisfaction and organizational commitment will best predict similarly broad criteria such as aggregate measures of a withdrawal construct (e.g., Harrison, Newman, & Roth, 2006). Additionally, such aggregate measures would not suffer as much from criterion deficiency (e.g., Gupta & Jenkins, 1991).

However, the second perspective views each of the withdrawal behaviors as unique and driven by specific antecedents and therefore not reflective of an overall withdrawal construct (e.g., Price & Mueller, 1981; Steers & Mowday, 1981). Further, Mobley (1982) noted that employees do not always engage in withdrawal behaviors to avoid work (as is implied by the term "withdrawal") but, instead, are often motivated to engage in these behaviors because of alternatives and attractions such as the pleasure of sleeping in or going to a ballgame. On the basis of this uniqueness perspective, some have made the case that studying lateness, absenteeism, and turnover separately will lead to a greater understanding of each of the withdrawal behaviors (e.g., Blau, 1998; Johns, 1998). From this perspective, referring to lateness, absenteeism, and turnover as withdrawal behaviors is more of a handy umbrella term for the behaviors than an indication of them being reflective of an overall withdrawal construct.

Quantifying the magnitude of the relationships between measures of the withdrawal behaviors can provide resolution to this debate. If lateness, absenteeism, and turnover are each manifestations of an overall withdrawal construct, measures of the three behaviors should have appreciable interrelationships. There is not a consensus regarding how highly intercorrelated measures should be before aggregation can be justified or before the measures can be declared reflective of a common construct. However, it is instructive to examine how others have conceptualized these behavioral measures on the basis of their intercorrelations. For instance, Berry, Ones, and Sackett (2007) concluded that interpersonal deviance and organizational deviance were correlated factors in an overall deviance construct based in part on an intercorrelation of .62. LePine, Erez, and Johnson (2002) concluded that altruism, civic virtue, conscientiousness, courtesy, and sportsmanship were all correlated factors in an overall organizational citizenship behavior construct based in part on an average intercorrelation of .67. On the other hand, Dalal (2005) concluded that organizational citizenship behavior and counterproductive work behavior were separate constructs based in part on an intercorrelation of −.32. Thus, there is generally a precedent for expecting strong relationships (e.g., .50+; Cohen, 1992) between behaviors, instead of small or moderate relationships (e.g., .30 or lower), if those behaviors are to be considered manifestations of a common construct. Therefore, although it is not always the case that measures must be highly intercorrelated to justify aggregating them into an overall index (Bollen & Lennox, 1991; Paunonen & Gardner, 1991), relatively low intercorrelations between withdrawal behaviors would call into question the appropriateness of an aggregate withdrawal construct including the three withdrawal behaviors.

Moderate-to-strong lateness–absenteeism and absenteeism–turnover correlations have been cited as evidence in favor of the withdrawal construct perspective (Harrison et al., 2006; Koslowsky et al., 1997; Mitra, Jenkins, & Gupta, 1992). In particular, the combined results of two meta-analyses provide estimates of the relationships between lateness, absenteeism, and turnover. Mitra et al. (1992) meta-analyzed the relationship between absenteeism and turnover (mean corrected correlation of .33, $k = 33$). Koslowsky et al. (1997) meta-analyzed the relationship between lateness and absenteeism (mean corrected correlation of .40, $k = 25$) and between lateness and turnover (mean corrected correlation of .07, $k = 6$).

DOI: 10.1002/job

Present Study

Overall relationships

This study meta-analyzed the relationship between voluntary employee lateness, absenteeism, and turnover, to determine the degree of support for the withdrawal construct perspective versus the uniqueness perspective. Although these three relationships have been meta-analyzed in previous research, there is value in revisiting these relationships for a number of reasons. First, since Koslowsky et al. (1997) and Mitra et al. (1992), there has been 15–20 years of research on the interrelationships between withdrawal behaviors. The meta-analyses of Koslowsky et al. and Mitra et al. were based on modest numbers of samples (i.e., between six and 33 samples), so the addition of 20 years worth of research should lead to more comprehensive estimates. Further, the previous meta-analyses focused solely on published research, whereas this meta-analysis adds unpublished research. Thus, the present meta-analyses' estimates are based on roughly twice the total sample sizes of Koslowsky et al. and Mitra et al., which allows for a more robust test of the degree of support for the withdrawal construct perspective. Support for the withdrawal perspective would be in the form of strong intercorrelations between employee lateness, absenteeism, and turnover. Therefore,

Hypothesis 1: There will be strong intercorrelations between employee lateness, absenteeism, and turnover.

Moderator analyses

The larger numbers of samples in this meta-analysis also allowed an investigation of a number of possible moderators of the relationships between lateness, absenteeism, and turnover. This represents another incremental contribution of this study, as previous meta-analyses investigated either no moderators (in the case of Koslowsky et al., 1997) or a comparatively small set of moderators (in the case of Mitra et al., 1992).

Because of its potential to confound meta-analytic estimates, the first potential moderator investigated in this meta-analysis was whether the withdrawal behaviors were measured via "objective" versus "subjective" means. Objective measures are typically company records, whereas subjective measures usually involve asking either supervisors or employees themselves to report how often employees are late and/or absent. An especially important consideration is when the same subjective rater rates both withdrawal behaviors. This is not an issue for the relationships involving turnover because turnover was always measured via "objective" means. However, this is a common occurrence in studies reporting lateness–absenteeism relationships. When self-ratings or supervisor ratings of both lateness and absenteeism are used, the lateness–absenteeism relationship can be artificially inflated because of common method bias and/or halo error. Further, these errors may be exacerbated if the subjective raters are not provided with a time frame for their ratings (e.g., how often is Employee X absent?) or if the time frame is too long (e.g., how often was Employee X absent in the past year?). When asked to rate how often someone is late or absent in general without the frame of reference of a reasonable period, the rating likely essentially becomes a rating of employee dependability (i.e., Employee X is a dependable person, so Employee X is probably not late or absent very often). The period specification (e.g., how often was Employee X late in the past month?) acts as a frame of reference and a prime to think in terms of more objective behavior counts and mitigates the same source bias. Therefore,

Hypothesis 2a: Because of common method bias and halo error, the relationship between lateness and absenteeism will be stronger when subjective ratings of lateness and absenteeism are used than when company records of either behavior are used.

DOI: 10.1002/job

Hypothesis 2b: The relationships between lateness and absenteeism will be more inflated when a reasonably short time frame (i.e., under 1 year) is not provided for subjective raters.

The second potential moderator investigated in this meta-analysis was whether the primary samples were included in previous meta-analyses. The previous meta-analyses were carried out 15 to 20 years ago and were composed of primary studies published between 1955 and 1988 (for Mitra et al., 1992) and between 1952 and 1994 (for Koslowsky et al., 1997). It is possible that there have been important changes in the workplace since these times. Of particular relevance to this meta-analysis is that factors such as increased layoffs, outsourcing, and short-term contract work may have led to decreases in employee loyalty to organizations in recent years (Cooper, 1999; Sullivan, 1999). This decreased loyalty suggests that employees today may be more likely to quit or withdraw from their organizations precipitously. For instance, the unfolding model of voluntary turnover (e.g., Harman, Lee, Mitchell, Felps, & Owens, 2007) outlines a number of psychological paths that employees can take to quitting their jobs. A number of these paths to quitting involve "shocks" to employees that can cause them to quit suddenly, instead of due to escalating job dissatisfaction as is required by the withdrawal construct perspective. Although such shocks surely happened to employees in earlier research included in previous meta-analyses, the decrease in employee loyalty in recent years would be expected to make employees more susceptible to quitting suddenly because of shocks. Further, to the degree that employees have become less loyal and therefore more likely to withdraw from their organizations precipitously and without the provocation of sustained dissatisfaction, one would expect that relationships between the withdrawal behaviors would be weaker in more recent samples. If the relationships between withdrawal behaviors are considerably weaker than in previous reviews, this might challenge the idea of an overall withdrawal construct. Therefore,

Hypothesis 3: The relationships between lateness, absenteeism, and turnover will be weaker in samples not included in previous meta-analyses.

Another important moderator of the relationships between withdrawal behaviors may be the way in which withdrawal behaviors are measured. For instance, a common distinction between lateness and absenteeism measures is whether they are "frequency" versus "time lost" measures (Hackett & Guion, 1985). Time lost measures evaluate lateness and absenteeism in terms of total time lost, regardless of the number of lateness/absenteeism episodes. Frequency measures evaluate lateness/absenteeism in terms of the number of lateness/absenteeism episodes, regardless of the duration of those episodes. Because employees engaging in voluntary withdrawal are more likely to be late/absent often and for shorter intervals than employees engaging in involuntary withdrawal (e.g., sickness), frequency measures are often considered to be more sensitive to differences between employees in voluntary withdrawal. Because of the long-term illness' potential to disproportionately affect them, time lost measures may be more contaminated by involuntary withdrawal. Thus, on the basis of the idea that frequency measures may be "purer" measures of voluntary withdrawal, voluntary withdrawal models may hold better with frequency rather than time lost measures of lateness/absenteeism. This study provides moderator analyses testing this prediction. Specifically,

Hypothesis 4: The relationships between lateness, absenteeism, and turnover will be stronger when lateness and/or absenteeism are measured via frequency rather than time lost.

Another potential moderator is the unemployment rate at the time of each of the studies. The unemployment rate may affect correlations between turnover and other withdrawal behaviors, as turnover may be less likely when there is low availability of alternative job opportunities (e.g., Hulin, Roznowski, & Hachiya, 1985). If there is a low rate of voluntary turnover, this can reduce variance in turnover, which would be expected to result in lower correlations between turnover and the other withdrawal behaviors. Indeed, Mitra et al. (1992) found a correlation of −.51 between unemployment rates and absenteeism–turnover correlations in their meta-analysis. Therefore, this meta-analysis

DOI: 10.1002/job

investigated whether the unemployment rate at the time of each study moderated the relationships between turnover and the other withdrawal behaviors. Specifically,

Hypothesis 5: The greater the unemployment rate, the weaker will be the absenteeism–turnover and lateness–turnover relationships.

An additional moderator may be the industry in which primary studies were carried out (Mitra et al., 1992). Particularly, differences between organizations and industries in the norms surrounding withdrawal behaviors may affect the relationship between withdrawal behaviors. For instance, in some industries, such as the manufacturing industry or blue-collar jobs in general, there may be more vigilant surveillance (e.g., punching a time clock) of lateness and absenteeism. Such increased scrutiny might discourage voluntary withdrawal behaviors. This may limit variance and result in lower correlations between withdrawal behaviors. On the other hand, the variance in withdrawal behaviors might be limited via different mechanisms in other industries. For instance, some industries composed more of "white-collar" jobs (e.g., finance and insurance industry) may allow employees more latitude in exactly when they begin their days, which could reduce lateness behavior. The exact mechanisms are beyond the scope of the current study, but it is clear that some attempt to account for these differences would be ideal when investigating relationships between withdrawal behaviors. Because there are plausible arguments for expecting the relationships between withdrawal behaviors to be either higher or lower within industries, the following research question was posed:

Research Question: Do the relationships between withdrawal behaviors differ across industries?

Models of the relationships between withdrawal behaviors

The meta-analytic results are also used to test the viability of various competing models of the interrelationships between withdrawal behaviors. Johns (2001) outlined five potential models of the relationships between lateness, absenteeism, and turnover: independent forms, compensatory forms, alternate forms, spillover model, and the progression of withdrawal model (hereafter referred to as the "progression model").[2] This begs the question of which of these five models is most appropriate. Given the evidence of positive relationships between lateness, absenteeism, and turnover (Koslowsky et al., 1997; Mitra et al., 1992), the independent forms, compensatory forms, and alternate forms models (which each hypothesizes either null or negative relationships between the withdrawal behaviors) are unlikely to be the most appropriate models (see Johns, 2001, for a detailed description of all the models). The positive relationships between withdrawal behaviors are compatible with either the spillover model (which treats withdrawal behaviors as related but does not specify a temporal ordering between them) or the progression model (which explicitly hypothesizes a temporal ordering of withdrawal behaviors, such that increased levels of lateness are indicative of a greater likelihood of subsequent absenteeism and increased levels of absenteeism are indicative of a greater likelihood for subsequent turnover; Johns, 2001; Rosse, 1988).

Which model is the most appropriate has important implications for organizational practice. For instance, if the progression model is most appropriate, this means that lateness may be an early warning sign of future absenteeism and that absenteeism may be an early warning sign of future turnover. If this is the case, organizations may be best served by increasing their preventative efforts toward employee lateness in an effort to prevent more serious forms of withdrawal in the future (e.g., absenteeism) and by treating absenteeism as a more serious indicator of future voluntary turnover. On the other hand, if the spillover model is most appropriate, lateness may not be an antecedent to absenteeism, and employees who are late may be just as likely to quit as those who are absent. In this case,

[2]Other withdrawal behavior reviews (e.g., Harrison & Martocchio, 1998; Mitra et al., 1992) have outlined essentially the same possible models of the relationships between withdrawal behaviors.

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organizations may be best served by focusing their efforts on reducing all behavioral manifestations of withdrawal and by treating any withdrawal behavior as a possible early warning sign of an intent to quit.

The results of this meta-analysis can be used to shed some light on the viability of these alternative models of the interrelationships between withdrawal behaviors. Specifically, we used the meta-analytic results to create a matrix of the meta-analytic correlations between lateness, absenteeism, and turnover. We then used this correlation matrix in path analyses, testing the fit of the five competing models of the interrelationships between withdrawal behaviors (e.g., Viswesvaran & Ones, 1995). In all, the results of this meta-analysis address both the tenability of the withdrawal construct perspective and the various models of the interrelationships between withdrawal behaviors.

Method

Literature search

We conducted multiple searches to obtain studies with relevant data. We consulted the reference sections of previous reviews of these relationships (Griffeth, Hom, & Gaertner, 2000; Koslowsky et al., 1997; Mitra et al., 1992). We performed a keyword search of the PsycINFO and ABI/Inform databases, as well as a search of the Society for Industrial and Organizational Psychology annual conference programs from 1998 to present and the Academy of Management annual conference programs from 2005 to present. In addition, we contacted each of the consulting firms sponsoring the 2008 Society for Industrial and Organizational Psychology conference to try and obtain pertinent unpublished data. Finally, we inspected the reference sections of each of the identified primary studies for relevant sources of data.

For inclusion in the meta-analyses, studies needed to provide individual-level correlations or statistics that could be converted to correlations for at least one of the following relationships: lateness–absenteeism, absenteeism–turnover, or lateness–turnover. We excluded studies based on group-level data (e.g., Angle & Perry, 1981; Fleishman, Harris, & Burtt, 1955). Also, whereas Koslowsky et al. (1997) included an absenteeism–lateness correlation from Rosse (1988), this study was excluded from the present meta-analysis because we could locate no useable data in the published article. We used a number of decision rules to draw only one correlation from each sample and thus minimize violation of the assumption of independence. First, some studies reported separate correlations for both voluntary and involuntary withdrawal behaviors; in such cases, we only included the voluntary withdrawal correlations. We did not include in the meta-analyses those studies only including involuntary withdrawal measures. Second, if multiple measures of the same withdrawal construct were reported for a single sample (e.g. separate absenteeism–turnover correlations for time lost and frequency measures of absence), we used composite formulas (Ghiselli, Campbell, & Zedeck, 1981, pp. 163–164) to estimate what the correlation would be if those multiple measures were combined into a composite. If composite formulas could not be used, we used the mean sample-size-weighted correlation. In all, the lateness–absenteeism meta-analysis included 36 studies from which 57 correlations were drawn, the absenteeism–turnover meta-analysis included 35 studies from which 45 correlations were drawn, and the lateness–turnover meta-analysis included 7 studies from which 13 correlations were drawn.

Moderator analyses

Types of lateness and absenteeism measures

We sorted lateness and absenteeism measures into three categories: frequency, time lost, and subjective (this moderator analysis was not relevant for turnover measures). Frequency and time lost measures (which were defined in the Introduction section) were always "objective" measures in that they were always drawn from company records. Subjective measures asked the supervisor or employee to report their behavior (e.g., an item asking a supervisor how often a given employee was late in the past month). Subjective measures almost always measured the frequency of lateness/absenteeism, not time lost.

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Inclusion in previous meta-analyses

We ran the lateness–absenteeism and lateness–turnover meta-analyses using only those samples included in the study by Koslowsky et al. (1997) versus only those samples not included in the Koslowsky et al. study. Similarly, we ran the absenteeism–turnover meta-analysis using only those samples included in the study by Mitra et al. (1992) versus only those samples not included in the Mitra et al. study.

Industry

We classified jobs for each of the primary samples into industries using the North American Industry Classification System, 2007 two-digit code for each job, resulting in four categories: manufacturing, healthcare, finance and insurance, and other (i.e., those jobs that did not fall into any of the other three industries).

Voluntariness

We did not include lateness, absenteeism, and turnover measures that were purely involuntary (e.g., sick days, being fired) in this meta-analysis. However, we did include measures of combined voluntary and involuntary withdrawal behaviors. For instance, it was common for studies to state that they included all instances of withdrawal (e.g., both voluntary and involuntary absenteeism). We included such combined measures, and thus, there were two types of withdrawal measures in this meta-analysis: purely voluntary measures (hereafter referred to as “voluntary” measures) and combined measures that included all forms of withdrawal (hereafter referred to as “combined” measures). We were concerned that the inclusion of these combined measures might affect relationships between withdrawal behaviors. Thus, we carried out separate analyses for voluntary versus combined measures of withdrawal behaviors.

Unemployment rates

For primary studies including absenteeism–turnover or lateness–turnover correlations, we recorded the average unemployment rate during the collection of turnover data. As opposed to the other moderators, which were all categorical, unemployment rate was a continuous moderator variable. If the primary study reported the unemployment rate, we used this rate in our analysis. For studies that did not report the unemployment rate, we used archival sources to determine the average unemployment rate in the area during the period over which turnover data were collected. For the 13 studies that did not report the period over which turnover data were collected, we assumed that the data were collected 3 years prior to the publication of the study, as Carsten and Spector (1987) reported that the average lag time between data collection and publication date was 3.17 years. We also ran analyses excluding these 13 samples and results did not change significantly. We obtained unemployment rates for primary studies carried out in the USA from the Bureau of Labor Statistics (BLS). The BLS reports national unemployment rates, regional rates, and divisional rates (more specific than regional rates). When the division or the region that the data were collected in could be determined, we used those rates; otherwise, we used the national unemployment rate (analyses were also run excluding the 18 samples for which national unemployment rates were used and results did not change significantly). For two primary studies that were not carried out in the USA, we used unemployment estimates from the United Nations Economic Commission for Europe. We note that unemployment rates from the BLS and the United Nations Economic Commission for Europe are estimates that are not perfectly reliable/accurate (e.g., Tiller, 1992). To the degree that the unemployment estimates contain error, the relationships between the unemployment rate and other variables will be underestimates.

Accuracy checks

The coders were the second author (MA in I/O Psychology) and the third author (PhD in I/O Psychology); both have extensive experience in coding and have carried out multiple meta-analyses. The coders both independently coded

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all articles and then compared their coding. We discussed any disagreements between the second and third authors, and when agreement could not be reached, we asked the first author (who has a PhD in I/O and has published multiple meta-analyses) to code the information and to provide a third independent rating; after which, we discussed disagreements until agreement was met.

Meta-analytic procedure

We used the Hunter and Schmidt (2004) meta-analysis approach and made corrections for the following three statistical/methodological artifacts. First, meta-analyses of turnover relationships typically correct point-biserial correlations for uneven numbers of stayers and leavers in the turnover measure, as a failure to do so would result in some between-study variance simply due to study differences in turnover rates (e.g., Griffeth et al., 2000; Mitra et al., 1992), which could confound estimates of the construct–level relationships. Thus, when the turnover rate for a given sample deviated from 50 per cent, we corrected the correlations to what they would have been with a 50 per cent turnover rate using formulas provided by Hunter and Schmidt (2004). Two studies (Beehr & Gupta, 1978; Jahn, 1998) did not report turnover rates, so we used the average population turnover rate of 21 per cent (Steel, Shane, & Griffeth 1990) for these studies. Second, because absenteeism is naturally a continuous variable, we made corrections for dichotomization for four studies that artificially dichotomized the absenteeism measure. Third, we corrected correlations for unreliability of lateness and/or absenteeism. Reliability information was rarely provided for lateness or absenteeism measures. Thus, we constructed artifact distributions to assist in the correction of absenteeism and lateness unreliability. When correcting objective absenteeism measures (mostly company records of absenteeism) for unreliability, we used the artifact distributions from Hackett and Guion (1985), who reported average reliabilities of .51 ($k = 27$) for frequency measures of absence and .66 ($k = 29$) for time lost measures of absence. No previous research has reported artifact distributions for subjective measures of absenteeism, so we created an artifact distribution on the basis of four primary samples in this meta-analysis (average internal consistency reliability of .67). Similarly, we created an artifact distribution for subjective lateness measures with an average reliability of .53 ($k = 5$). For objective lateness measures (mostly company records of lateness), seven samples reported both reliability and a period over which the lateness data were recorded. Using the Spearman–Brown formula, we adjusted each of these seven reliabilities to a 1-month period (see Ones, Viswesvaran, & Schmidt, 2003 for another example of the use of this method of reliability estimation). The average 1-month reliability for lateness measures was .331. We then used the Spearman–Brown formula to adjust this mean 1-month reliability to the periods within each primary study in this meta-analysis (e.g., if Study A incorporated a 6-month lateness period, the Spearman–Brown formula estimates that the reliability of that lateness measure would be .748, as the 6-month period is six times as long as the mean 1-month artifact reliability).

We did not make corrections for unreliability of turnover. We are unaware of methods for estimating the reliability of turnover or of previous research that has estimated the reliability of turnover. However, Schmidt and Hunter (1996) made the point that even if outcomes such as turnover are recorded accurately, the underlying turnover process may not be perfectly reliable. So, we performed sensitivity analyses wherein the degree of changes to study conclusions resulting from correcting correlations for varying levels of turnover reliability was assessed. Even when turnover reliability was quite low (i.e., .50), this had very little effect on any results and no effect on any conclusions; full sensitivity analysis results are available upon request from the first author.

Path analyses based on the meta-analytic findings

We used LISREL 8.8 (Jöreskog & Sörbom, 2006) for the path analyses. We constructed intercorrelation matrices between lateness, absenteeism, and turnover using the results of the meta-analyses and performed path analysis using these meta-analytic intercorrelation matrices. Because the sample sizes for each of the correlations within

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the meta-analytic matrices differed, we used the conservative harmonic mean sample size in the path analyses (Viswesvaran & Ones, 1995). When assessing model fit, Hu and Bentler (1999) suggested a two-index presentation strategy wherein adequate model fit can be inferred when both of the following "rule of thumb" conditions are met: the comparative fit index (CFI) is 0.95 or higher and the standardized root mean square residual (SRMR) is 0.09 or lower.

Results

Lateness–absenteeism meta-analysis

Initial analyses including subjective measures
We initially ran the lateness–absenteeism meta-analysis using all 57 samples ($N = 13\,800$). The mean corrected correlation was .38 ($SD_\rho = 0.31$, 95 per cent confidence interval [CI] = 0.35–0.40). This would appear to provide partial support for Hypothesis 1: that there would be strong relationships between the withdrawal behaviors. However, Hypothesis 2a suggested that this relationship could be inflated because of the use of subjective ratings of both lateness and absenteeism. In support of Hypothesis 2a, the lateness–absenteeism correlation was much higher in the 23 samples in which lateness and absenteeism were rated subjectively by the same source (corrected mean $r = .60$, $SD_\rho = 0.42$, 95 per cent CI = 0.56–0.64) than in the 34 samples in which this was not the case (corrected mean $r = .27$, $SD_\rho = 0.23$, 95 per cent CI = 0.24–0.30).

Hypothesis 2b suggested that, amongst the samples with subjective ratings of both lateness and absenteeism, the lateness–absenteeism correlation would be especially inflated if subjective raters were given no time frame or too long of a time frame for reporting lateness and absenteeism. Thus, we sorted the 23 double-subjective ratings samples into two categories. In 19 samples, the subjective raters were not provided a time frame or were provided a time frame of more than 12 months; the corrected mean correlation in these 19 samples was .85 ($SD_\rho = 0.31$, 95 per cent CI = 0.81–0.89). The remaining four double-subjective ratings samples provided time frames between 2 weeks and 6 months for raters, and the corrected mean correlation in these four samples was .14 ($SD_\rho = 0$, 95 per cent CI = 0.07–0.22). Therefore, in support of Hypothesis 2b, amongst the samples in which subjective raters rated both lateness and absenteeism, the lateness–absenteeism correlation was significantly higher in the 19 samples in which no time frame or an unreasonable time frame was provided to raters. Thus, we excluded the 19 inflated samples from all of the following analyses, whereas the four other samples were retained.

Overall lateness–absenteeism relationship
As shown in Table 1, the overall meta-analytic lateness–absenteeism correlation was .256 (for the sake of space and ease of presentation, we reported corrected correlations in the text; see tables for uncorrected correlations). Although this is a moderate and appreciable correlation, this is not a strong correlation, as was predicted by Hypothesis 1 and the withdrawal construct perspective. There was a great deal of variability around this mean correlation ($SD_\rho = 0.219$; only 14 per cent of the variance was accounted for by sampling error and other statistical artifacts), and the credibility interval (which represents the 80 per cent interval within which corrected correlations vary) was wide and overlapped with zero, suggesting the presence of moderators.

Moderator analyses
We list the results of each of the lateness–absenteeism moderator analyses in Table 1. Support for the moderator analyses are in the form of sizable mean correlation differences and non-overlapping confidence intervals between the moderator categories. In support of Hypothesis 3, the mean correlation for samples included in Koslowsky et al. (1997) was significantly higher than for samples not included in Koslowsky et al. Hypothesis 4 was not supported for lateness measures, as the mean lateness–absenteeism correlation did not vary depending on whether frequency

DOI: 10.1002/job

Table 1. Meta-analysis results for the relationships between lateness, absenteeism, and turnover.

	N	k	r_m	SD_r	ρ	SD_ρ	CV_{10}	CV_{90}	CI_L	CI_U	% var
Lateness–absenteeism meta-analysis											
Overall relationship	10 397	38	.176	0.147	.256	0.219	−.024	.536	0.227	0.284	14.26
Inclusion in previous meta-analysis											
Included in Koslowsky et al.	5304	22	.261	0.129	.376	0.217	.099	.654	0.338	0.415	15.26
Not included	5093	16	.088	0.108	.133	0.139	−.044	.310	0.092	0.174	26.91
Type of lateness measure											
Frequency	8842	27	.200	0.158	.270	0.248	−.048	.588	0.241	0.300	9.09
Time lost	721	4	.144	0.258	.238	0.339	−.197	.672	0.134	0.342	8.86
Subjective	2236	6	.090	0.061	.150	0.062	.070	.230	0.080	0.220	66.06
Type of absence measure											
Frequency	4258	20	.289	0.137	.414	0.239	.108	.719	0.372	0.456	13.90
Time lost	5879	17	.134	0.145	.184	0.207	−.080	.449	0.148	0.221	12.20
Subjective	1988	5	.064	0.078	.107	0.101	−.023	.236	0.033	0.180	40.72
Voluntariness of absenteeism											
Voluntary measures only	3370	15	.174	0.122	.260	0.167	.046	.474	0.210	0.310	26.02
Combined measures only	2964	11	.191	0.149	.247	0.233	−.052	.545	0.196	0.297	11.76
Industry											
Manufacturing	4498	13	.208	0.113	.283	0.186	.045	.521	0.241	0.324	14.15
Healthcare[a]	331	4	.239	0.091	.349	0.000	.349	.349	0.200	0.498	100
Finance and insurance	1574	7	.120	0.101	.195	0.153	−.001	.391	0.110	0.280	36.20
Other	4723	17	.168	0.178	.252	0.262	−.083	.588	0.210	0.295	10.42
Absenteeism–turnover meta-analysis											
Overall relationship	9594	45	.196	0.141	.253	0.165	.043	.464	0.228	0.278	21.42
Inclusion in previous meta-analysis											
Included in Mitra et al.	3566	24	.250	0.122	.331	0.138	.154	.507	0.289	0.372	36.16
Not included	6028	21	.165	0.142	.212	0.163	.003	.421	0.180	0.243	16.87
Type of absenteeism measure											
Frequency	4259	21	.193	0.164	.272	0.217	−.006	.550	0.231	0.314	16.61
Time lost	4472	19	.201	0.140	.250	0.158	.047	.453	0.215	0.285	19.76
Subjective	1021	6	.177	0.086	.210	0.040	.160	.261	0.140	0.280	82.98
Voluntariness of absenteeism											
Voluntary measures only	4124	12	.234	0.113	.302	0.131	.134	.469	0.264	0.339	20.22
Combined measures only	2554	12	.184	0.161	.234	0.194	−.014	.482	0.185	0.283	16.43
Voluntariness of turnover											
Voluntary measures only	6591	29	.198	0.130	.254	0.144	.070	.439	0.224	0.284	24.52
Combined measures only	2643	14	.206	0.167	.272	0.214	−.003	.547	0.222	0.322	16.30
Industry											
Manufacturing	1631	10	.283	0.100	.371	0.076	.273	.469	0.313	0.429	60.26
Healthcare	2418	10	.118	0.143	.157	0.183	−.077	.392	0.102	0.212	18.78
Finance and insurance	2375	10	.295	0.093	.370	0.107	.232	.507	0.323	0.417	33.15
Other	2163	10	.105	0.104	.132	0.098	.006	.257	0.079	0.184	42.47
Lateness–turnover meta-analysis											
Overall relationship[b]	2499	12	.005	0.120	.011	0.114	−.134	.157	−0.035	0.057	33.74
Inclusion in previous meta-analysis											
Included in Koslowsky et al. (1997)	1009	8	.129	0.070	.137	0	.137	.137	0.071	0.203	100
Not included	1490	4	−.079	0.059	−.100	0.028	−.136	−.064	−0.163	−0.037	83.76

Note: r_m, mean sample-size-weighted correlation (corrected for unequal *ns*); SD_r, sample-size-weighted observed standard deviation of correlations; ρ, mean sample-size-weighted correlation corrected for statistical artifacts; SD_ρ, corrected standard deviation of corrected correlations; CV_{10} and CV_{90}, 10 per cent and 90 per cent credibility values respectively; CI_L and CI_U, lower and upper bounds, respectively, of the 95 per cent confidence interval around the corrected mean correlation; % var, percentage of variance attributable to artifacts.

[a]This estimate excludes one influential outlier (Jamal, 1981) that was 3.2 standard deviation units higher than the mean correlation. When Jamal is included, the correlation rises to $r_m = .40$ ($SD_r = 0.16$; $\rho = .62$; $SD_\rho = 0.28$).

[b]This estimate excludes one influential outlier (Oh, 1995, Korean sample) that was 4.5 standard deviation units higher than the mean correlation. When Oh (1995) is included, the correlation rises to $r_m = .07$ ($SD_r = 0.21$; $\rho = 0.08$; $SD_\rho = 0.24$).

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Table 2. Weighted least squares regressions[a] wherein the fully corrected lateness–absenteeism or absenteeism–turnover correlations were regressed on the significant moderating variables.

Dependent variable	Predictors	β	R
Fully corrected lateness–absenteeism correlations[b]			.639*
	Inclusion in Koslowsky et al.	.426*	
	Absenteeism frequency	.329*	
Fully corrected absenteeism–turnover correlations[c]			.624*
	Manufacturing	.363*	
	Finance and insurance	.543*	
	Healthcare	.326*	
	Inclusion in Mitra et al.	−.013	
	Unemployment rate	−.347*	

β, standardized regression weight; R, multiple correlation; for "inclusion in Koslowsky et al.", 0 means the sample was not included in Koslowsky et al. (1997) and 1 means that it was; for manufacturing, finance and insurance, and healthcare, 0 means the sample did not come from that industry, whereas 1 means the sample did come from that industry (the "other" industry category was excluded as the "comparison group"); for "inclusion in Mitra et al.," 0 means the sample was not included in Mitra et al. (1992), and 1 means it was; "unemployment rate" is the unemployment rate at the time that each sample's turnover data were collected.
[a]We used the weighted least squares correlation with the weights being a multiplicative factor of each study's sample size and compound statistical artifacts attenuation factor (Hunter & Schmidt, 2004).
[b]Corrected for unreliability in lateness and absenteeism.
[c]Corrected for unreliability and dichotomization in absenteeism, and for uneven numbers of stayers and leavers in turnover measures.
*$p < .05$.

versus time lost measures of lateness were used. However, Hypothesis 4 was supported for absenteeism measures, as the mean lateness–absenteeism correlation was significantly higher when frequency measures of absenteeism were used. As evidenced by overlapping confidence intervals and a lack of sizable mean correlation differences, the answer to Research Question 1 is that industry does not moderate the lateness–absenteeism correlation. Also, the voluntariness of absenteeism did not moderate the lateness–absenteeism relationship, as mean correlations were not significantly different for voluntary versus combined absenteeism measures.

To tease apart the unique effects of the two significant moderators (inclusion in Koslowsky et al. and type of absenteeism measure), we simultaneously regressed the fully corrected lateness–absenteeism correlations on two 0–1 dummy variables. The first dummy variable represented inclusion in Koslowsky et al. (0 = *not included*, 1 = *included*), and the second dummy variable represented whether a frequency measure of absenteeism was used (0 = *not a frequency measure*, 1 = *frequency measure*). We used the weighted least squares (WLS) regression with the weights being a multiplicative factor of each study's sample size and compound statistical artifacts attenuation factor (Hunter & Schmidt, 2004).[3] We list the results in Table 2, and the results show that the standardized regression weights for both "inclusion in Koslowsky et al." and "absenteeism frequency" were sizable and significant, suggesting that both have unique effects and supporting Hypotheses 3 and 4.

Absenteeism–turnover meta-analysis

Overall absenteeism–turnover relationship

The overall meta-analytic absenteeism–turnover correlation was .253 (Table 1). Although this is a moderate and appreciable correlation, this is not a strong correlation, as was predicted by Hypothesis 1 and the withdrawal construct

[3]Because SPSS miscalculates significance tests when using WLS with meta-analytic data (Lipsey & Wilson, 2001), we used an SPSS macro add-on by Wilson (2005) that correctly estimates standard errors.

perspective. There was a great deal of variability around this mean correlation ($SD_\rho = 0.165$; only 21 per cent of the variance was accounted for), suggesting the presence of moderators.

Moderator analyses

We list the results of each of the categorical absenteeism–turnover moderator analyses in Table 1. As evidenced by overlapping confidence intervals and a lack of sizable mean correlation differences, type of absenteeism measure, voluntariness of absenteeism, and voluntariness of turnover did not moderate the absenteeism–turnover relationship. Thus, Hypothesis 4 regarding frequency measures of absenteeism was not supported. However, in support of Hypothesis 3, inclusion in the previous absenteeism–turnover meta-analysis (Mitra et al., 1992) moderated the absenteeism–turnover relationship, with correlations being higher for samples that were included in Mitra et al. Also, in response to Research Question 1, industry moderated the absenteeism–turnover relationship, with correlations being higher in the "manufacturing" and "finance and insurance" industries. We used the WLS regression to determine whether unemployment rates moderated the absenteeism–turnover relationship (Hypothesis 5). We used the same methods as described earlier for the lateness–absenteeism WLS regression analyses, with the only differences being that the criterion was the fully corrected absenteeism–turnover correlations and the only predictor was the unemployment rate. In support of Hypothesis 5, there was a significant negative relationship between unemployment rate and the absenteeism–turnover correlation ($\beta = -.49$, $p < .05$, $df = 36$).

To tease apart the unique effects of the three significant moderators (inclusion in Mitra et al., industry, and unemployment rate), we simultaneously regressed the fully corrected absenteeism–turnover correlations on (i) a dummy variable representing inclusion in Mitra et al. (0 = *not included*, 1 = *included*); (ii) three 0–1 industry dummy variables (representing whether correlations were drawn from manufacturing, finance and insurance, or healthcare industries, respectively; the other category was excluded as the "comparison group"); and (iii) the continuous unemployment rates variable. We used the same methods as in the lateness–absenteeism WLS regression analyses. We list the results in Table 2. The results show that the standardized regression weights for each of the industry variables and unemployment rate were sizable and significant, suggesting that both have unique effects and supporting Hypothesis 5. The regression weight for "inclusion in Mitra et al." was essentially zero and non-significant, suggesting that the lower mean absenteeism–turnover correlation in studies not included in Mitra et al. was a function of changes in unemployment rates and/or greater concentration of recent studies in industries with lower absenteeism–turnover correlations. Thus, Hypothesis 3 was ultimately not supported in the absenteeism–turnover meta-analysis.

Lateness–turnover meta-analysis

Overall lateness–turnover relationship

The overall meta-analytic lateness–turnover correlation was .011 (Table 1). Thus, the lateness–turnover correlation is near zero, which does not support Hypothesis 1 and the withdrawal construct perspective.

Lateness–turnover moderator analyses

The mean correlation of .011 was based on only 12 samples. Because there would be too few samples in most moderator categories, we did not carry out for the lateness–turnover meta-analysis most of the moderator analyses carried out for the lateness–absenteeism and absenteeism–turnover meta-analyses. The exception was the "inclusion in previous meta-analysis" moderator analysis. Because the lateness–absenteeism and absenteeism–turnover relationships were much lower in studies not included in the Koslowsky et al. (1997) and Mitra et al. (1992) meta-analyses, respectively, we wished to determine if the case was the same for the lateness–turnover relationship. In support of Hypothesis 3, the lateness–turnover correlation was −.100 in samples not included in Koslowsky et al. and was .137 in samples included in Koslowsky et al. Although this is a sizable difference, the number of samples in each category is quite small, so these estimates are susceptible to second-order sampling error.

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Table 3. Results of the meta-analytic path analyses.

	Meta-analytic correlations used in path analyses[a]			Fit indices for path models		Standardized pathways in path models		
	L–A	A–T	L–T	*CFI*	*SRMR*	L–A	A–T	L–T
Overall relationships	.256	.253	.011					
Spillover model ($N = 4995$)				—	—	.26	.25	.01
Progression of withdrawal model ($N = 4995$)				0.97	0.03	.26	.25	—
Moderator category correlations substituted into the progression of withdrawal model								
Overall relationships—only frequency absenteeism measures for the lateness–absenteeism relationship ($N = 4058$)	.414	.253	.011	0.96	0.04	.41	.25	—
Only samples included in previous meta-analyses ($N = 3451$)	.376	.331	.011	0.94	0.05	.38	.33	—
Only samples not included in previous meta-analyses ($N = 3992$)	.133	.212	.011	0.99	0.01	.13	.21	—
Manufacturing samples only ($N = 2427$)	.283	.371	.011	0.95	0.04	.28	.37	—
Healthcare samples only ($N = 782$)	.349	.157	.011	0.98	0.02	.35	.16	—
Finance and insurance samples only ($N = 2059$)	.195	.370	.011	0.98	0.03	.20	.37	—

L–A, lateness–absenteeism; A–T, absenteeism–turnover; L–T, lateness–turnover; *CFI*, comparative fit index; *SRMR*, standardized root mean square residual; the sample sizes used in each path analysis are the harmonic means of the sample sizes for the three meta-analytic correlations included in each path analysis.
[a]We used the overall lateness–turnover relationship in all path analyses because there were not enough lateness–turnover samples for meaningful moderator analyses.

Path analyses based on the meta-analytic findings

We carried out the path analyses testing viability of the competing models of the interrelationships between withdrawal behaviors (e.g., Johns, 2001) using the meta-analytic correlation matrices listed in Table 3. The positive meta-analytic lateness–absenteeism and absenteeism–turnover correlations are incompatible with the alternate forms, compensatory forms, and independent forms models (which hypothesize either negative or null relationships between the withdrawal behaviors) but are potentially compatible with the progression and spillover models. Therefore, we ran path analyses for the competing progression and spillover models using the overall meta-analytic estimates (i.e., the overall relationship correlation matrix in Table 3). The progression model posits that lateness leads to absenteeism, which leads to turnover, suggesting that the effect of lateness on turnover is indirect through absenteeism. Thus, support for the progression model is in the form of an indirect relationship between lateness and turnover via absenteeism (LeBreton, Wu, & Bing, 2009). The spillover model is a correlational model wherein all three withdrawal behaviors are allowed to intercorrelate, with no causal direction to the relationships. We list the results of the path analyses for these two competing models in Table 3 and in Figure 1. The spillover model is statistically saturated, and thus no fit indices can be calculated. However, because the progression model is more parsimonious (i.e., the key difference between the progression and spillover models is that the direct lateness-to-turnover path is removed in the progression model), one can make the case that it is a better fitting model as long as it fits adequately in absolute terms (i.e., nothing is lost by removing the lateness-to-turnover path).[4]

This is indeed the case as the progression model exhibited adequate fit ($CFI = 0.97$, $SRMR = 0.03$). Additionally, a Sobel test of the indirect effect of lateness on turnover (Sobel, 1982) suggested a significant indirect effect ($z = 14.54$, $p < .05$). Beyond statistical tests and fit indices, the spillover model is not tenable simply because it hypothesizes

[4]Because the progression model is nested within the spillover model, one could assess the relative fit of the two models by the difference in the minimum fit function chi-square ($\chi^2 = 24.01$, $df = 1$, $p < .05$). However, sample size greatly affected the chi-square difference, and our meta-analytic sample sizes were large. Thus, even negligible differences between models result in a statistically significant chi-square statistic in the present circumstance.

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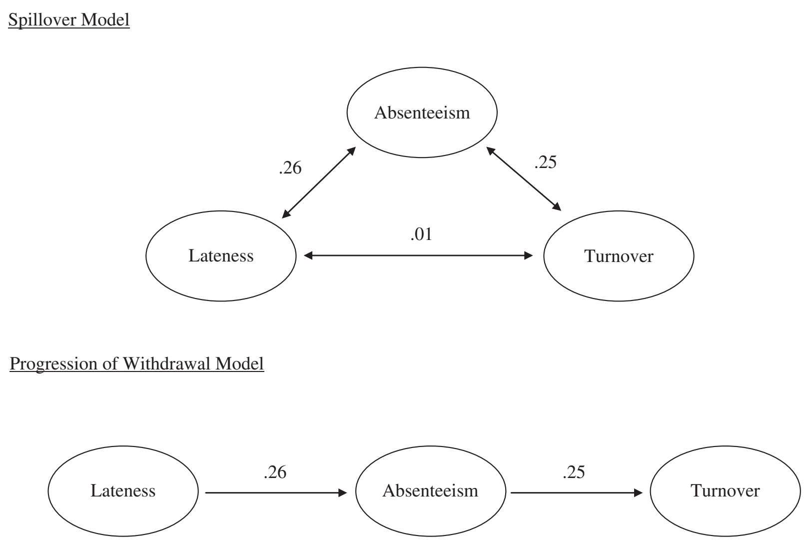

Figure 1. Path models representing the spillover and progression of withdrawal models, along with standardized path weights when the overall lateness–absenteeism, absenteeism–turnover, and lateness–turnover relationships are used

positive relationships between each of the withdrawal behaviors, which is at odds with the near-zero relationship between lateness and turnover. Given this near-zero relationship, lateness and turnover can only be indirectly related, as posited by the progression model, and as supported by the path analyses.

Further, we additionally carried out the path analyses substituting meta-analytic correlations from the significant moderator categories (e.g., substituting the corrected correlation of .414 between lateness and frequency measures of absenteeism for the overall lateness–absenteeism correlation of .256), to determine if path analysis results changed depending on the significant moderators (see bottom half of Table 3). Across all moderator categories, fit indices never changed by more than 0.03, with *CFI*s never falling below 0.94 and *SRMR*s never rising above 0.05. Therefore, the path analysis support for the progression model did not change depending on the significant moderators.

Discussion

Summary of findings

The main objective of this study was to determine the degree of support for a withdrawal construct that includes voluntary employee lateness, absenteeism, and turnover. A withdrawal construct perspective implies that each of the three withdrawal behaviors reflects a common construct, has common antecedents, and therefore should be strongly related to each other. Thus, this study meta-analyzed the relationships between these three withdrawal behaviors, more than doubling the total sample sizes of previous meta-analyses of these relationships. Contrary to previous meta-analyses documenting relatively strong correlations between the withdrawal behaviors (Koslowsky et al., 1997; Mitra et al., 1992), this meta-analysis found small-to-moderate mean correlations ranging from .01 to .26 between the withdrawal behaviors. If these three behaviors were each manifestations of a withdrawal construct, one would expect higher correlations between composite measures of these behaviors (e.g., number of absences over the course of weeks, months, or even years). Although the relationships between withdrawal behaviors were moderated by a number of variables (i.e., the lateness–absenteeism correlation was stronger when frequency measures of

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absence were used; the absenteeism–turnover relationship was stronger in certain industries and when unemployment rates were lower), in no instances did mean correlations within any moderator category reach what would typically be thought of as "strong correlations" (Cohen, 1992).

Further, this meta-analysis documented that the relationships between the withdrawal behaviors have each reduced considerably in magnitude since the previous meta-analyses by Koslowsky et al. (1997) and Mitra et al. (1992). The lateness–absenteeism correlation is .13 in samples not included in Koslowsky et al., as compared with a correlation of .38 in the studies included in Koslowsky et al. The absenteeism–turnover and lateness–turnover correlations similarly have reduced from .33 to .21 and from .14 to −.10, respectively, since previous meta-analyses. As suggested by Hypothesis 2, such reductions in the relationships between withdrawal behaviors are supportive of the idea that the employee–employer loyalty relationship has changed in recent years (Cooper, 1999; Sullivan, 1999), making employees more willing to withdraw from the organization because of sudden shocks (e.g., Harman et al., 2007), even if employees were previously relatively satisfied with their jobs or organizations. This decreased employee loyalty and increased willingness to precipitously withdraw from the organization is less compatible with an overall withdrawal construct that posits that relationships between the withdrawal behaviors are a function of prolonged and increasing dissatisfaction (e.g., Rosse & Hulin, 1985).

It should be acknowledged that changes in employee loyalty over time cannot definitively account for the reductions in all of the withdrawal behavior intercorrelations (e.g., the reduction in the absenteeism–turnover correlation appeared to have more to do with changes over time in unemployment rates and concentration of primary studies in certain industries). Also, it is not clear whether this phenomenon generalizes outside of developed, post-industrial countries, as all but two of the studies in this meta-analysis were carried out in the USA, Canada, Israel, England, and Australia. For instance, it is likely that less developed and economically stable countries would not have experienced an increase in outsourcing in recent years, and large numbers of layoffs are probably always a concern in such countries. Thus, these factors probably would not have contributed to decreases in employee loyalty in such countries. Similarly, in relatively collectivist countries, the norms regarding withdrawing from the organization may differ from relatively individualistic countries. We encourage multicultural research investigating the degree to which the results of this meta-analysis generalize to developing or non-post-industrial countries. However, this does not change the fact that in the set of existing studies included in this meta-analysis, withdrawal intercorrelations have reduced. It is difficult to make the case that lateness, absenteeism, and turnover are manifestations of an overall withdrawal construct based on intercorrelations ranging from −.10 to .21 in recent research. In all, the results of this meta-analysis are not supportive of an aggregate withdrawal construct.

Another objective of this study was to test the viability of competing models of the relationships between withdrawal behaviors. The moderate positive lateness–absenteeism and absenteeism–turnover correlations, combined with the near-zero lateness–turnover correlation, are most supportive of an indirect effect of lateness on turnover through increased absenteeism, as postulated by the progression model. The meta-analytic path analyses supported this conclusion. This suggests that lateness is a predictor of absenteeism and absenteeism is a predictor of turnover. Although the lateness–absenteeism and absenteeism–turnover correlations were not high enough to support the idea of these behaviors all being manifestations of a single withdrawal construct, these correlations are still moderate, appreciable, and large enough to provide predictive utility. For instance, the correlation of .26 between lateness and absenteeism means that lateness is one of the strongest predictors of absenteeism and is at least as strong a predictor of absenteeism as job satisfaction (Hackett, 1989), organizational commitment (Farrell & Stamm, 1988), pay (Farrell & Stamm, 1988), and Big Five personality (Salgado, 2002). The correlation of .25 between absenteeism and turnover means that absenteeism is one of the strongest predictors of turnover and is at least as strong a predictor as frequently studied predictors such as tenure, job satisfaction, pay, distributive justice, alternative job opportunities, and job involvement (Griffeth et al., 2000). Especially given the high cost to organizations of absenteeism and turnover (Fitz-enz, 1997; Hale, 1998; Navarro & Bass, 2006; Sagie et al., 2002), identifying solid predictors of these behaviors is clearly of use to organizations. However, the criterion-related validities of lateness as a predictor of absenteeism and absenteeism as a predictor of turnover appear to have reduced in recent years, which calls into question how useful the progression model will continue to be in the future.

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Although the lateness–absenteeism and absenteeism–turnover relationships are appreciable, they are certainly not strong. When viewed from the perspective of the unfolding model of turnover (Harman et al., 2007), these relatively small correlations should not be surprising. The unfolding model outlines a number of different paths that employees can take to quitting. Only two of these paths (paths 4a and 4b; Harman et al.) involve accumulating dissatisfaction, which might be expected to result in the gradual process of increasing lateness leading to increasing absenteeism, which eventually leads to turnover. From this perspective, the progression model can be thought of as one possible path that employees can take to quitting. Given the many other possible paths employees can take, it is not surprising that lateness only moderately predicts absenteeism and absenteeism only moderately predicts turnover.

Theoretical and practical implications

One clear theoretical implication of this meta-analysis is the lack of support for the withdrawal construct perspective. If one thinks of lateness, absenteeism, and turnover as "multi-item scales" within an overall withdrawal construct measure, then inter-scale correlations ranging from approximately zero to .25 would suggest a lack of unidimensionality. Further, the correlations between withdrawal behaviors seem to be shrinking over time, suggesting a sort of disintegration of the withdrawal construct in recent years. The meta-analytic results are more supportive of the uniqueness perspective (e.g., Blau, 1998; Johns, 1998), which suggests that there is no benefit to aggregating withdrawal behaviors into an overall construct measure.

Further, the withdrawal construct perspective typically entails that each of the withdrawal behaviors shares variance due to job dissatisfaction (Hulin, 1991; Rosse & Hulin, 1985; Rosse & Hulin, 1984). Although the withdrawal construct perspective was not supported in this meta-analysis, it is still possible that the small-to-moderate relationships between the withdrawal behaviors are a function of job dissatisfaction. This hypothesis can be tested by combining the withdrawal behavior intercorrelations from this meta-analysis with correlations between lateness and job satisfaction (−.11; Koslowsky et al., 1997), absenteeism and job satisfaction (−.17; Hackett, 1989), and turnover and job satisfaction (−.22; Griffeth et al., 2000) from other meta-analyses. If the relationships between the withdrawal behaviors are mostly a function of job satisfaction, then the correlations between withdrawal behaviors should reduce greatly when job satisfaction is partialled out. Using the aforementioned intercorrelations to partial satisfaction out of the lateness–absenteeism (bivariate meta-analytic correlation = .256, partial correlation = .240), absenteeism–turnover (bivariate correlation = .253, partial correlation = .222), and lateness–turnover (bivariate correlation = .011, partial correlation = −.013) correlations hardly had any effect. Given that job satisfaction does not explain the relationships between the withdrawal behaviors, it may be that a deviance model (Harrison & Martocchio, 1998), wherein lateness, absenteeism, and turnover share variance due to each behavior being a manifestation of organizational deviance (also known as counterproductive work behavior), is more appropriate. Regardless, this further suggests that a withdrawal construct perspective is not the most appropriate conceptualization.

However, the results of this meta-analysis do not necessarily rule out the possibility of a withdrawal construct; there are ways in which relatively small correlations between the behaviors could still be compatible with a withdrawal construct. For instance, Bollen and Lennox (1991) made a distinction between "effect indicators", where the observed indicators (lateness, absenteeism, and turnover) are caused by the latent construct (withdrawal), and "causal indicators", where the observed indicators cause the latent construct. Observed indicators should be highly intercorrelated if they are effect indicators of a single construct. Causal indicators of a single construct do not necessarily need to be highly intercorrelated. An example of causal indicators is race and sex as indicators of the construct "exposure to discrimination"; race and sex do not need to be intercorrelated to be indicators of this construct (Bollen & Lennox, 1991). If lateness, absenteeism, and turnover are causal indicators of the withdrawal construct, then the low intercorrelations in this meta-analysis between the indicators do not necessarily preclude the existence of a withdrawal construct. If this were the case, someone's standing on the "withdrawal construct" would just be the sum of their withdrawal behaviors or the degree to which they withdraw from the organization. Although this is certainly a possible conceptualization of a withdrawal construct, it does not reflect conceptualizations of the withdrawal

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construct that view each of the withdrawal behaviors as having common antecedents (e.g., satisfaction and commitment) and being manifestations of a higher order construct (e.g., Hulin, 1991; Rosse & Hulin, 1984, 1985).

Another way in which relatively small correlations between the withdrawal behaviors could still be compatible with a withdrawal construct is if the withdrawal construct were less like a latent construct and more akin to a Guttman scale. In this case, lateness would be the "least difficult item" in the withdrawal scale (as engaging in lateness would require the lowest standing on the withdrawal construct), whereas absenteeism and turnover would represent items of increasing difficulty. One would then only engage in withdrawal behaviors at or below one's standing on the withdrawal construct, which could make relationships between the behaviors small (e.g., one with relatively low standing on the withdrawal construct might only engage in lateness and not the other behaviors). This idea of a Guttman scale is most similar to the progression model. However, if this were the case, then someone who was chronically late, but never absent, would have lower standing on the Guttman withdrawal scale than someone who was absent once, but never late; as getting a more difficult item correct (i.e., engaging in absenteeism) in a Guttman scale implies that one would also get all of the less difficult items (i.e., engaging in lateness) correct as well. This Guttman scale conceptualization does not seem to be what those postulating a withdrawal construct perspective meant (e.g., Hanisch et al., 1998). Regardless, it is at least worth noting that there are ways in which low intercorrelations between withdrawal behaviors are compatible with a withdrawal construct.

Whether each of the withdrawal behaviors can reasonably be grouped under a broad overall withdrawal construct or not, this meta-analysis provides evidence that the behaviors are related in a progressing fashion (even if some of these relationships are rather weak). This progression of withdrawal behaviors has practical implications for organizations concerned with employee withdrawal. The progression model suggests that relatively mild withdrawal behaviors, such as occasional lateness, are important predictors of more severe future withdrawal behaviors, such as frequent absenteeism or voluntary turnover. It also suggests that other conceptually related behaviors or attitudes that may be mild forms of employee withdrawal, such as intentionally reducing performance (Kanungo & Mendoca, 2002) or decreased job satisfaction or organizational commitment (Johns, 2001), might also be predictors of more extreme future withdrawal behaviors. Therefore, organizations concerned about employee withdrawal would do well to attend to relatively mild forms of withdrawal, as these are likely to be early warning signs of a progression toward more serious withdrawal behaviors. Organizational interventions aimed at controlling lateness should have an effect on levels of employee absenteeism, and interventions aimed at absenteeism should also have an effect on turnover; but the converses may not be true.

Additional issues and limitations

One potential issue with this study might be the relatively small number of samples included in the lateness–turnover meta-analysis ($k = 12$). One concern is that the small number of samples is a function of publication bias. To assess this, we carried out a funnel plot analysis. The results of this analysis (which are available upon request from the first author) did suggest that samples were missing from the lower left side of the funnel plot, which is an indicator of possible publication bias (i.e., smaller sample studies with lower correlations are less likely to be published). We then carried out Duval and Tweedie's (2000) trim and fill analysis to determine the number of missing studies and how much results would change if those studies were not missing. The trim and fill analysis suggested that two studies were missing and that replacing them would change the uncorrected lateness–turnover correlation from .005 to −.003. Thus, results remained essentially the same, regardless of publication bias, testifying to the robustness of the lateness–turnover meta-analytic correlation.

Another concern with the small number of lateness–turnover correlations is that this contributes to instability of estimates. Although additional samples are usually desirable, the lateness–turnover meta-analytic mean is not as unstable as one might think. It is instructive to ask how many additional lateness–turnover samples with different results would be required to change this correlation enough to alter study conclusions. For instance, study conclusions might be changed if, instead of being near-zero, the lateness–turnover correlation were at least moderate in size

DOI: 10.1002/job

(e.g., $r = .20$). It would require 46 additional samples, each with sample sizes of 208.25 (the mean sample size in this lateness–turnover meta-analysis) and lateness–turnover correlations of .25 to raise the lateness–turnover correlation to .20. Thus, it would require a fairly sizable number of new studies with different lateness–turnover results to substantially change the pattern of results in this meta-analysis.

An additional limitation of this study was its reliance on cross-sectional data. Specifically, the model that garnered the most support was the progression model, which is a longitudinal model, so having longitudinal data would have been ideal for testing this model. However, only cross-sectional data were available, and these cross-sectional data can be used to draw some inferences about the progression model. That is, the progression model suggests direct effects of lateness on absenteeism and absenteeism on turnover but an indirect effect of lateness on turnover. Therefore, support for the progression model is in the form of a stronger correlation between the proximal variables than between the distal variables. Such a pattern of correlation is not definitive evidence because it cannot account for the possibility of reverse causation (i.e., the pattern of stronger lateness–absenteeism and absenteeism–turnover correlations than lateness–turnover correlations is also compatible with absenteeism leading to lateness). Although the indirect lateness–turnover relationship is not definitive evidence in favor of the progression model, we believe it is one important piece of supporting evidence.

An additional potential issue in this meta-analysis is the inclusion of some samples that used combined measures of withdrawal (e.g., absenteeism measures that included both voluntary and involuntary absences). However, this did not affect study results, as the voluntariness of withdrawal measures did not moderate the relationship between withdrawal behaviors. So, whether this meta-analysis relied only on purely voluntary measures or measures that included some combination of voluntary and involuntary withdrawal, results did not change.

In all, the results of this meta-analysis did not support the withdrawal construct perspective but did support the idea of a progression model of the small-to-moderate relationships between withdrawal behaviors. The pattern of results is more supportive of conceptualizing the withdrawal behaviors as separate behavioral constructs that have small-to-moderate correlations with each other and perhaps even predict each other. If future researchers wish to continue to advance the idea of a withdrawal construct perspective, the low intercorrelations between the withdrawal behaviors will have to be reconciled.

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