Transformational Leadership and Employee Well-Being;
a Longitudinal Two-Study Investigation.

by

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Abstract

The present study examined the relationship between transformational leadership (using the Global Transformational Leadership Scale) and employee well-being (using the General Health Questionnaire – 12, and the Job-related Affective Well-being Scale) in 3 three-wave longitudinal analyses. In study 1, participants were 187 male (32%) and female (67%) employees of a small community college, between 20 and 65 years of age. Data were collected over five waves using experience sampling methodology and analyzed in two analyses using random coefficient modelling. I analyzed effects over 1 week, with measures taken on Monday, Wednesday and Friday, and over 2 weeks, with measures taken on three consecutive Fridays. Results show a strong cross-sectional relationship between leadership and well-being, and a strong autoregressive relationship between intercepts (i.e., initial values) and slopes (i.e., rates of change) of both leadership and well-being; however, there was no longitudinal effect between changes in leadership and changes in well-being. In Study 2, data were collected in three waves over 8 months, with 4 months between sampling. Participants were a stratified random sample of 1387 working adult men (50%) and women (50%) from across the province of Nova Scotia, Canada, ranging in age from 21 to 77 years. Analysis was conducted using a structural equation modelling approach to latent growth curve modelling. Results provide strong evidence for cross-sectional ($\beta = -.42$, P < .001) and longitudinal effects ($\beta = -.51$, P < .001) between transformational leadership and employee well-being.

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Introduction

The relationship between leadership and employee well-being is well-established in the empirical literature, with studies dating back almost a half century (e.g., Day & Hamblin, 1964). Recent reviews (e.g., Kelloway & Barling, 2010; Mullen & Kelloway, 2011) suggest that leadership behaviour is linked to many positive and negative outcomes, such as psychological well-being (e.g., Arnold, Turner, Barling, Kelloway, & McKee, 2007), lifestyle choices (Kelloway, Teed, & Prosser, 2008), alcohol use (Bamberger & Bacharach, 2006), employee stress (Arnold et al., 2007; Offermann & Hellmann, 1996), and workplace safety (Barling, Loughlin, & Kelloway, 2002; Kelloway, Mullen, & Francis, 2006; Mullen & Kelloway, 2009). Most studies have been cross-sectional, showing the relationship between leadership and myriad indicators of well-being, and while there have been some studies showing causal relationships, (i.e., Mullen & Kelloway, 2009; McKee & Kelloway, 2009; Zohar, 2002b), there remains a need for additional, well-developed longitudinal studies to demonstrate the causal relationship between leadership and well-being. That is the purpose of this set of studies.

In the current paper, I report on two studies that examined the relationship between employee perceptions of leadership style and employee self-reported well-being in a longitudinal framework. In the first study, I use a diary or experience sampling methodology to examine whether leadership affects well-being on a daily or weekly basis. In the second study I report on a larger longitudinal study that examines this relationship over an 8 month time frame. In both cases, the use of a true longitudinal

design (i.e., using three or more waves of data collection) allows the modeling of the form of the leadership well-being relationship.

Theoretical background

A significant amount of previous research has been focused on the well-being of people at work, and the importance of employee well-being for individual performance and organizational productivity. For example, empirical studies found strong relationships between employee well-being and increased productivity (Lowe, 2003), job performance and job satisfaction (Wright & Cropanzano, 2000). Heavy workloads are common in organizations and often necessary to accomplish goals; however, employee well-being can suffer as a result of heavy workloads, resulting in health problems such as exhaustion, burnout, negative attitudes (Bakker, Van Veldhoven, & Xanthopoulou, 2010), and ultimately, negative organizational outcomes (Bakker & Demerouti, 2007). Two theoretical models, the Job Demands-Control Model and the Job Demands-Resources Model, provide a basis on which to examine the effects of job demands on employee well-being and they provide clues that suggest leadership is an important factor in safeguarding the well-being of employees.

The job demands-control model. The demand-control model proposed that job strain is the result of an imbalance between high job demands (i.e., work load and time pressure) and low control over task completion (Karasek, 1979). Karasek (1979) postulated that jobs with high demands and low control (i.e., high-strain jobs) would result in job-related anxiety, health problems, physical exhaustion and job-dissatisfaction. However, not all high demand jobs result in job strain. For example, some very demanding jobs are associated with task enjoyment, learning and personal growth, as long

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as they are characterized by the combination of high job demands *and* high job control. Karasek (1979) suggested that when employees have sufficient decision making power, they will be inspired and motivated to apply their available skills and resources to effective problem solving, and they will not feel the same level of strain. While there is evidence to support the hypothesis that high demand and low control result in strain (Karasek, 1979), support for the "Buffer" hypothesis, which says control will moderate the negative effects of high job demands on well-being, is less compelling (e.g., De Jonge & Kompier, 1997). In fact, the job demand-control model is most commonly criticized for being too simplistic, and not able to fully explain the complex nature of job strain in the context of a complex work environment. Previous research has shown that job control may not be the only important factor related to coping with high job demands. For example, some studies found that colleague social support was another resource that increased the ability to cope with job demands (Johnson & Hall, 1988; Van der Doef & Maes, 1999), while others found that physical and emotional demands (e.g., Van Vegchel, De Jonge, Bakker, and Schaufeli, 2002) played an important role, in addition to workload and time pressure. It was this desire to explain the complexities of the work environment as it relates to job strain, that led to development of the job demands-resources (JDR) model (Bakker & Demerouti, 2007; Demerouti, Bakker, Nachreiner, & Schaufeli, 2001).

The job demands-resources model. The job demands-resources model is centered on the premise that, while all jobs may have their own specific factors associated with job-stress, all of those factors can be classified into two categories; that is, job demands and job resources (Demerouti et al., 2001).

Job demands and resources. Job *demands* refer to the physical, psychological, social and organizational aspects of work that require sustained effort (i.e., physical, cognitive or emotional effort), and which may be associated with physiological or psychological costs (e.g., stress, strain, exhaustion, or burnout; Demerouti et al., 2001). Some examples of common job demands are work load, time pressure, emotionally demanding client interactions, or shift schedules. Although some or all of these demands may not be negative, they could become stressors if they require high levels of sustained effort, without sufficient opportunities for recovery (Bakker & Demerouti, 2007). Job *resources* are the physical, psychological, social or organizational characteristics of the job that are functional in achieving work related goals, or that reduce job demands and the associated physical and mental costs, or that stimulate personal growth, learning and development (Bakker and Demerouti, 2007). Resources could be organizational issues such as pay, career opportunities, or job security. Other resources may be at the social level, such as organizational (social) climate, supervisor or colleague support, and finally, resources may be directly related to the job or task, such as role clarity, participative decision making, skill variety, task significance, autonomy, or performance feedback (Bakker & Demerouti, 2007).

Resources as motivators. Resources are important to counter balance job demands, but they are also important in and of themselves, for intrinsic and extrinsic motivation. Resources contribute to intrinsic motivation through fostering employee learning, development and growth (Bakker et al., 2010). Thus, resources fulfill basic human needs such as the need for autonomy, relatedness, and competence described by Deci and Ryan (1985). This is consistent with job characteristics theory (Hackman & Lawler, 1971;

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Hackman & Oldham, 1980), which proposed that five core job characteristics, including skill variety, task identity, task significance, autonomy, and feedback, were positively related to meaningfulness of the task, feelings of responsibility, and knowledge of results, which in turn were related to increased job satisfaction and performance. Clearly, the link between job resources and *intrinsic* motivation has been established in theory and empirical findings; however, there is also a link between job resources and *extrinsic* motivation. For example, job resources such as positive feedback from supportive colleagues or supervisors, pay, benefits, career opportunities, etc. are all extrinsic motivators of performance (Bakker & Demerouti, 2007; Bakker et al., 2010).

Interactions between job demands and resources; the buffering hypothesis. One of the key tenets of the JDR model is that job resources may buffer the effects of job demands on job strain, including burnout (Bakker, Demerouti, Taris, Schaufeli, & Schreurs, 2003). The model claims that multiple job resources can buffer the effects of several different job demands, depending on the prevalent characteristics of the job. So, whereas the demand-control model says that control over one's job (i.e., autonomy) will moderate the impact of work load on job stress, the JDR model states that there may be numerous potential interactions between different job demands and resources in predicting job strain.

There are several well understood moderators of the relationship between job demands and job strain. Social support is probably the most well known situational variable that may buffer the relationship between job demands and strain (e.g., Johnson & Hall, 1988); however, others may include the predictability of a stressor (i.e., role clarity and performance feedback), the extent to which the stressor is undesirable, or the extent

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to which the employee has control over the stressor (i.e., autonomy; Bakker & Demerouti, 2007). Indeed, resources may act as buffers for different reasons, depending on the nature of the demand and the resource. For example, a good relationship between an employee and their supervisor may have a very positive effect on the influence that job demands may have on job strain, because knowing that the leader is appreciative and supportive makes the demands more palatable. In fact, previous studies found that appreciation and support from a leader were related to employee coping (with job demands), performance, and health (Vaananen et al., 2003). At the same time, autonomy was also found to be related to employee health and well-being (Karasek, 1979). Finally, constructive feedback helped employees to work more effectively as well as to communicate better with their supervisor. Specific and accurate information exchange between employees and supervisors was related to better performance. Hackman and Oldman (1980) found that employees who were praised for good performance were motivated to maintain that performance and those who were provided with clear and positive communication, regarding needed improvements, were also motivated to perform well. A large body of research linking leadership to employee well-being provides evidence that leadership behaviours may be important job resources that could counter-balance the impact of job demands.

Leadership as a job resource. Leaders can control a great number of resources available to employees. They provide or affect social and psychological resources in the form of employee job satisfaction, confidence, and motivation through mechanisms such as organizational culture, leader and colleague supportiveness, training and development. They have an obvious effect on physical resources through their ability to provide the

facilities, equipment, and other things required to do the job. For example, leaders have a strong impact on the social setting in organizations, which facilitates the effective communication and the colleague and supervisor supportiveness that are known to be important job resources (Offermann & Hellmann, 1996). Previous research has found that lower levels of employee well-being are associated with supervisors who do not clearly communicate responsibilities, provide supportive feedback, or who exert unnecessary pressure on employees (Offermann & Hellmann, 1996; Sosik & Godshalk, 2000). Several studies also found a significant relationship between supervisor support and employee well-being (e.g., Offermann & Hellmann, 1996; Sosik & Godshalk, 2000).

Leadership and well-being

There has been a plethora of research looking at the effects of leadership on employee well-being. Recent reviews (e.g., Kelloway & Barling, 2010; Mullen & Kelloway, 2011; Skakon, Nielsen, Borg, & Guzman, 2010) indicate that leadership behaviour has been linked to many positive and negative outcomes, such as psychological well-being (e.g., Arnold, et al., 2007), lifestyle choices (Kelloway et al., 2008), alcohol use (Bamberger & Bacharach, 2006), employee stress (Arnold et al., 2007; Offermann & Hellmann, 1996), and workplace safety (Barling et al., 2002; Kelloway et al., 2006; Mullen & Kelloway, 2009). Many studies focused on the effects of different leadership styles (i.e., positive, passive or abusive) on well-being with much of the emphasis on the relationship between poor leadership and reduced levels of employee well-being (Kelloway & Barling, 2010; Kelloway, Sivanathan, Francis, & Barling, 2005).

Abusive leadership. There is a growing body of literature looking at the effects of abusive supervision on organizational performance and employee well-being (Hoobler &

Brass, 2006; Kelloway et al., 2005; Tepper, 2007; Tepper, Henle, Lambert, Giacalone, & Duffy, 2008). Abusive supervision is generally characterized by aggressive or punitive, but non-physical behaviour by leaders toward their employees (Kelloway, et al., 2005; Tepper, 2000); behaviours may include angry outbursts, threatening employees, withholding information, name-calling, and ridiculing in public (Keashly, Trott, & MacLean, 1994; Kelloway et al., 2005). Such behaviours have appeared in the literature under many different labels, such as harassment (Rospenda, 2002), emotional abuse (Keashly, 2001), bullying (Ferris, Zinko, Brouer, Buckley, & Harvey, 2007; Mathisen, Einarsen, & Mykletun, 2008), incivility (Caza & Cortina, 2007; Felblinger, 2008; Twale & De Luca, 2008), petty tyranny (Ashforth, 1994) and workplace aggression (e.g., Inness, LeBlanc, & Barling, 2008; Schat, Frone, Kelloway, Barling, & Hurrell, 2006). While some research found that abusive behaviour tends to come from bosses (e.g., Keashly, 2001; Keashly et al., 1994), others found that abusive behaviour is reported to be more common from members of the public than from supervisors (Pizzino, 2002). However, some researchers (Burton & Hoobler, 2006; Kelloway et al., 2005) have argued that the impact of abusive behaviour from supervisors is more serious because of the influence that supervisors have over subordinates.

Effects of abusive leadership. Abusive supervision, regardless of what it is called, has many negative effects on employee well-being (Tepper, 2007). A substantial number (i.e., 13%) of US workers have been affected by abusive supervision, resulting in reduced well-being and quality of life both at work and at home (Schat, Frone, & Kelloway, 2006). Abusive supervision was found to be associated with several indicators of decreased psychological well-being (Hobman, Restubog, Bordia, & Tang, 2009; Rogers

& Kelloway, 1997a; Schat & Kelloway, 2003; Tepper, 2007) such as decreased job satisfaction (Breaux, Perrewé, Hall, Frink, & Hochwarter, 2008; Caza & Cortina, 2007; Harris et al., 2007; Keashly et al., 1994; Tepper, 2000), lower self-esteem (Burton & Hoobler, 2006), increased problem drinking (Bamberger & Bacharach, 2006), increased stress (Ashforth, 1994; Breaux et al., 2008; Rogers & Kelloway, 1997a; Schat & Kelloway, 2003; Tepper, 2000; Tepper, Moss, Lockhart, & Carr, 2007), greater strain (Harvey, Stoner, Hochwarter & Kacmar, 2007), feelings of helplessness (Ashforth, 1997), and burnout (Grandey, Kern & Frone, 2007).

Abusive supervision was also associated with organizational performance indicators, such as decreased job performance (Ashforth, 1994; Caza & Cortina, 2007; Harris et al., 2007), organizational commitment (Ashforth, 1997; Tepper, 2000; Tepper, et al., 2008) organizational citizenship behaviours (Zellars, Tepper, & Duffy, 2002), self-efficacy (Duffy, Gangster, & Pagon, 2002), and increased intention to quit (Keashly et al., 1994; Rogers & Kelloway, 1997b; Tepper, 2000; Tepper et al., 2009), and organizational deviance (Mitchell & Ambrose, 2007; Tepper et al., 2008).

Passive Leadership. Passive leadership, also known as laissez-faire or passive management by exception, has been associated with decreased leader effectiveness (Hinkin & Schriesheim, 2008a), employee performance and cohesion (Bass, Avolio, Jung, & Berson, 2003), employee well-being (Kelloway et al., 2006; Skogstad, Einarsen, Torsheim, Aasland, & Hetland, 2007) and some have suggested it may be a root-cause of employee stress (Kelloway et al., 2005). Passive leadership is commonly described as having components of both laissez-faire, and management by exception (passive) styles described in the theory of transformational leadership (Kelloway, et al., 2005). Laissez-

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faire leaders tend to avoid leadership responsibilities and decision-making, they do not give feedback to their subordinates, and they make little or no effort to facilitate followers' needs satisfaction. Laissez-faire leaders do not actively promote their followers' professional development or growth. Leaders who practice passive management by exception tend to wait until there is a problem serious enough to demand attention before intervening with followers.

Effects of passive leadership. Research on the effects of passive leadership is much more limited than for transformational or abusive leadership; however, the available evidence suggests that passive leadership is normally ineffective (Kelloway et al., 2006; Kelloway et al., 2005). Some studies found relationships between passive leadership and decreased organizational productivity (Bycio, Hackett, & Allen, 1995; Howell & Avolio, 1993), decreased leader effectiveness, group cohesion and group performance (Bass et al., 2003).

Researchers also found that passive leadership is related to decreased employee well-being. For example, Zohar (2002a) found that both laissez-faire and passive management by exception styles contributed to increased accident rates. Kelloway et al. (2006) found that passive safety leadership was associated with increases in safety events and injuries. Skogstad et al. (2007) found that laissez-faire leadership resulted in workplace stressors, such as role conflict and role ambiguity, which led to bullying (i.e., among coworkers) and increased employee psychological distress. Offerman and Hellmann (1996) concluded that passive leadership is related to higher levels of employee stress, reduced leader effectiveness, employee morale and organizational commitment.

Poor versus positive leadership. While the empirical literature contains many studies looking at the relationship between leadership and well-being, much of that work has been focused on the negative effects of poor leadership on well-being (for a review, see Kelloway et al., 2005). Unfortunately, this large body of research does not necessarily tell us whether or not more positive leadership styles would in fact have a positive effect on well-being. There is a growing body of work focusing on the positive effect of good leadership on employee well-being (Arnold et al., 2007; Kelloway & Barling, 2010; Kelloway, Turner, Barling and Loughlin, 2012). Other studies have looked at the effects of a range of leadership behaviours (i.e., poor and positive leadership) on employee well-being. For example, Kelloway et al. (2012) looked at transformational leadership as well as poor leadership (i.e., passive laissez-faire leadership and active management by exception) as predictors of safety outcomes and found that transformational leadership had an equal and opposite effect on trust and well-being, compared to poor leadership. In another study, Kelloway et al. (2006) found that transformational leadership and passive leadership had opposite effects on safety climate, safety consciousness, and, ultimately, safety events and injuries. Transformational leadership is studied more than any other leadership theory (Barling, Christie & Hoption, 2010) and recent studies have found compelling evidence that transformational leadership is a very important predictor of employee well-being (e.g., Kelloway et al., 2012; Turner, Barling, & Zacharatos, 2002).

Transformational Leadership. The theory of transformational leadership, originated by Burns (1978) and developed to its current form by Bernard Bass (1985), purports that transformational leaders will develop followers to their fullest potential and they will motivate followers to act in support of the organization, rather than in self-

interest. Transformational leaders are able to accomplish these goals by helping followers to understand and internalize the importance of organizational goals, by influencing followers to transcend their own self-interest for the sake of the organization, and by getting followers to focus on higher-order needs.

The four principles or factors that constitute the model of transformational leadership are a) idealized influence, b) inspirational motivation, c) intellectual stimulation, and d) individualized consideration (Bass, 1985). Idealized influence (also known as charisma) refers to leaders' ability to gain the trust and respect of followers by demonstrating very high moral and ethical standards, and providing a clear vision and mission to followers. Inspirational motivation is characterized by leaders' communication of high expectations to followers, using symbols and emotional appeals to inspire increased commitment to group and organizational goals. Intellectual stimulation includes leaders' tendency to encourage creativity, innovation, and self-reflection in followers so they will challenge the beliefs and values of their leaders, the organization and themselves, in order to become better analysts and problem solvers. Individualized consideration describes leaders' supportive efforts to tailor their leadership style and actions to the individual needs, strengths and weaknesses of each follower to help them reach their own full potential and desired level of satisfaction. Transformational leadership is different than other styles of leadership because it is focused, not only on the performance of followers, but also on their personal needs, goals and ambitions (Northouse, 2001).

Effects of transformational leadership. According to theory, transformational leadership would be effective in any situation or culture. Indeed, meta-analyses have

found that transformational leadership is an equally valid predictor of many different outcome variables (e.g., follower job satisfaction, satisfaction with leader, motivation, leader performance and effectiveness, and organizational performance) across diverse settings and populations such as business professionals, college students, military personnel, and public sector employees (Judge & Piccolo, 2004). Transformational leadership is effective across different levels of authority, different industries, different locations and different cultures (Bass, 1997). Transformational leadership was related to organizational outcomes such as organizational commitment (Barling et al., 1996; Bycio et al., 1995; Walumbwa, Orwa, Wang, & Lawler, 2005), safety (Barling et al., 2002; Kelloway et al., 2006; Mullen & Kelloway, 2009, 2011; Mullen et al., 2011; Zohar, 2002b), team performance (Gunderson, Hellesoy, & Reader, 2012), and subordinate performance (Barling, Weber, & Kelloway, 1996; Bass et al., 2003; Dvir, Eden, Avolio, & Shamir, 2002; Howell & Avolio, 1993; Howell & Frost, 1989; Kirkpatrick & Locke, 1996).

More recently, researchers have started to focus on health related outcomes (Kelloway & Barling, 2010; Kelloway et al., 2012; Mullen & Kelloway, 2011), finding relationships between transformational leadership and subordinates' job satisfaction (Bono, Foldes, Vinson, & Muros, 2007; Kuoppala, Lamminpaa, Liira, & Vainio, 2008; Walumbwa et al., 2005; Nielsen, Yarker, Randall, & Munir, 2009), stress (Bono et al., 2007; Lyons & Schneider, 2009; Offermann & Hellmann, 1996; Sosik & Godshalk, 2000), depression (Munir, Nielsen, & Cameiro, 2010), and overall well-being (Arnold et al., 2007; Gilbreath & Benson, 2004; Gilbreath, 2001; Kuoppala et al., 2008; Kelloway et

al., 2012; Nielson, Randall, Yarker & Brenner, 2008; Nielson, Yarker, Brenner, Randall, & Borg, 2008; Nielsen & Munir, 2009; Nielsen et al., 2009).

Transformational leadership as a job resource. The job demands-resources model suggests that well-being is improved if employees are provided with the resources necessary to deal with the demands of the job. It is clear that transformational leadership provides many meaningful resources as described in the job demands-resources literature. The hallmarks of transformational leadership are idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration. Leaders who display idealized influence are charismatic, behaving in ways that employees can identify with. They appeal to employees on an emotional level, displaying conviction and determination, which evokes positive emotions (a psychological resource) in their subordinates (Bono et al., 2007), often through instilling meaning and a sense of purpose (also psychological resources) (Arnold et al., 2007; Sparks & Schenk, 2001). Inspirational motivation is the second hallmark of a transformational leader, accomplished by communicating their vision to employees in a way that is appealing and inspiring, by being optimistic about achieving goals, and challenging employees to achieve high standards on meaningful tasks. Motivation is a resource that results in stronger performance and the inevitable rewards that follow. Many studies have found strong relationships between transformational leadership and performance (Barling et al., 1996; Bass et al., 2003; Dvir et al., 2002; Howell & Avolio, 1993; Howell & Frost, 1989; Kirkpatrick & Locke, 1996). Intellectual stimulation refers to a leaders' ability to challenge assumptions, and take risks, but more importantly, to stimulate creativity in followers by asking for their input on how to get things done. Finally, individualized

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consideration is evident when leaders pay attention to each employee's unique needs and concerns, and act as mentors and coaches to help them to succeed. These resources are all indicators of a healthy workplace, where transformational leaders play an important role (Kelloway & Day, 2005). Clearly, transformational leadership behaviours provide myriad resources to employees, so it stands to reason that a transformational leader will have a positive impact on employee well-being.

Based on the theory provided in the job demands-resources model (Demerouti et al., 2001), it makes sense to expect leadership behaviour in general, and transformational leadership in particular, to be related to employee well-being. Not surprisingly, the relationship between transformational leadership and employee well-being has already been demonstrated in the empirical literature (Kelloway et al., 2012). In the current research, I look at transformational leadership as an important resource that is related to employee well-being, and I will test one aspect of the Job Demands-Resources model that says job resources (i.e., leadership) predict outcomes (i.e., well-being) over time. *Therefore, I hypothesized that Transformational Leadership will be positively related to employee well-being (H1).*

Research designs

Cross-sectional research. The body of literature linking leadership and well-being is growing rapidly; however, most studies have employed cross-sectional designs. Cross sectional research is focused on between person differences; that is, the difference between people on some construct of interest (e.g., well-being). However, longitudinal research has the ability to analyze within person differences, or changes over time. In some cases, cross-sectional studies will use the between-person differences (e.g., strong

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versus weak leadership skills) as a proxy for within-person changes (e.g., improving leadership skills leads to improved well-being); however, this methodology is not a reliable way to capture within person effects. Even if significant relationships are found between variables, cross-sectional research cannot rule out alternative explanations such as common method variance (Lance, Dawson, Birkelbach, & Hoffman, 2010; Spector & Brannick, 2010). Cross-sectional studies provide a snapshot in time, but do not capture the dynamic nature and inter-relationships between variables (e.g., Chan, 1998). Cross-sectional designs normally cannot explain whether and how variables change over time and may result in drawing incorrect or inaccurate conclusions (Maxwell & Cole, 2007) and, perhaps most importantly, cross-sectional research cannot detect the causal relationships between variables, which is precisely what most organizational research is trying to do (Ployhart & Vandenberg, 2010).

Cook and Campbell (1979) stated that three criteria must be met to infer causation between variables. That is, there must be significant covariation between the predictor and the outcome, there must be a specific temporal order where the predictor must precede the outcome, and competing explanations must be excluded (e.g., effects of third variables). Longitudinal designs will always have the challenge of explaining third variable effects (e.g., Zapf, Dormann, & Frese, 1996); therefore, even with a longitudinal design, we cannot be sure of causality (Taris & Kompier, 2003). However; by establishing temporal order, in addition to having a priori expectations of relationships and evidence of significant covariation between predictors and criteria, we can strengthen our argument for the plausibility of causal relationships (Taris & Kompier, 2003; Kelloway & Francis, in press).

"Longitudinal" research in the literature. There have been an increasing number of "longitudinal" studies conducted over the past thirty years (Taris & Kompier, 2003); however, many studies claiming to be longitudinal designs were conducted with two-wave data. For example, Feldt, Kinnunen, and Maunao (2000) found that participants who experienced changes in leadership also experienced corresponding changes in well-being when sampled twice over a one-year period. Tafvelin, Armelius, and Westerberg (2011) found that the effect of leadership on well-being across two time periods was mediated by a positive climate for innovation. Nielsen et al., (2008) examined the effects of transformational leadership behaviours on well-being in a two-wave study over 18 months and found that leadership at time 1 predicted well-being at time 1 and time 2, and well-being at time 1 predicted well-being at time 2 and leadership at time 2. Nielsen and Munir (2009) measured transformational leadership and self-efficacy two times across an 18 month interval. They found a cross-sectional relationship between the two constructs, but they did not detect any longitudinal effects.

While these studies are commendable and considered by some as an improvement on purely cross-sectional designs (e.g., Rogosa, 1988; Taris & Kompier, 2003) they still do not satisfy all three criteria set out by Cook and Campbell (1979), and for the following reasons, the results of these studies may be misleading (Kelloway & Francis, in press; Taris & Kompier, 2003). For example, studies where changes were examined over two time periods do improve the ability for researchers to control for common method bias (Chan, 1998, Ployhart and Vandenberg, 2010); however, they still do not capture the dynamic nature of the variables, which may vary significantly over time. In addition, neither two wave, nor three (or more) wave designs can always control for third

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variable effects; however, true longitudinal studies do establish temporal order through three or more waves of observations, thereby increasing the ability to infer causal effects when significant longitudinal relationships are found (Kelloway & Francis, in press).

Improving longitudinal research designs. The majority of longitudinal studies to date have been two-wave designs, and one of their weaknesses relates to the concept of temporal order (Kelloway & Francis, in press). On the surface, it seems like temporal order is simply a matter of ensuring the predictor event occurs before the criterion event; however, in reality, most psychological phenomena are not tangible *events*, per se (Kelloway & Francis, in press). For example, if we measure leadership at time 1 and well-being at time 2, we will not learn much. The level of leadership at time 1 may be the same at time 2, and the level of well-being we measured at time 2 may have already existed at time 1 and, if so, we have no more information than what would have been detected in a fully cross-sectional design. In other words, we can comment on the static relationship but we cannot say whether changes in the predictor result in changes in the criterion (Kelloway & Francis, in press). A simple improvement is what Zapf et al. (1996) call the *incomplete* two-wave panel design (figure 1), where the outcome is measured at both time periods and then the effect of the predictor on the outcome at time 2 is tested with the stability of the outcome variable as a covariate. In other words well-being at time 2 would be predicted first by well-being and then by leadership at time 1 (Kelloway & Francis, in press). This model estimates the change in the outcome variable, but it does not estimate the change in the predictor or the relationship between changes in the predictor and the outcome.
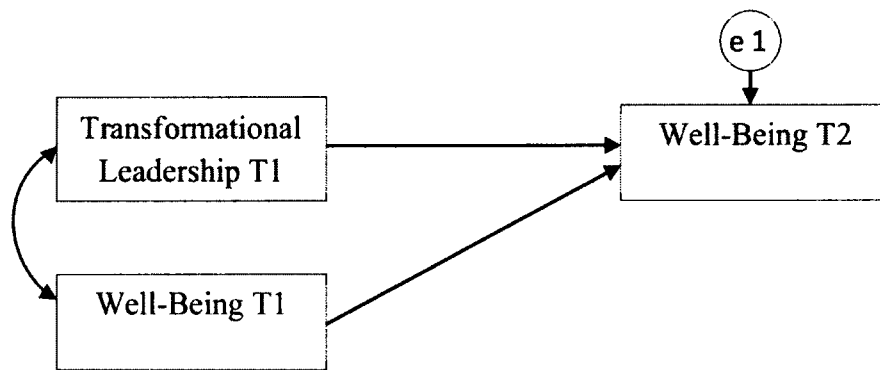
Figure 1. Incomplete two-wave panel design (Kelloway & Francis in press).

The obvious solution to the above mentioned problems are to measure predictors

and outcomes at both time periods. The *complete* two panel design (figure 2) is the most

widely used "longitudinal" research design (Kelloway & Francis, in press), enabling the

researcher to examine the predictors and outcomes in cross-lagged correlations, cross-

lagged regression analysis, or structural equation modelling (Kelloway & Francis, in

press). Cross-lagged correlation analysis is no longer supported in the literature (e.g.,

Zapf et al., 1996); however, regression analysis and structural equation modelling are

commonly applied. In a cross-lagged regression model, well-being at time 2 would be

regressed on well-being at time 1 (stability) and leadership (the predictor) at time 1.

Reverse causality would be established by regressing leadership at time 2 on leadership at

time 1 (stability) and well-being (as the predictor) at time 1. Similar analyses can be

conducted using structural equation modelling techniques (Kelloway, Gottlieb, &

Bartham, 1999), with the advantage of being able to consider measurement error,

correlated errors (Kelloway et al, 1999) and several causal relationships at the same time

(Zapf et al., 1996).
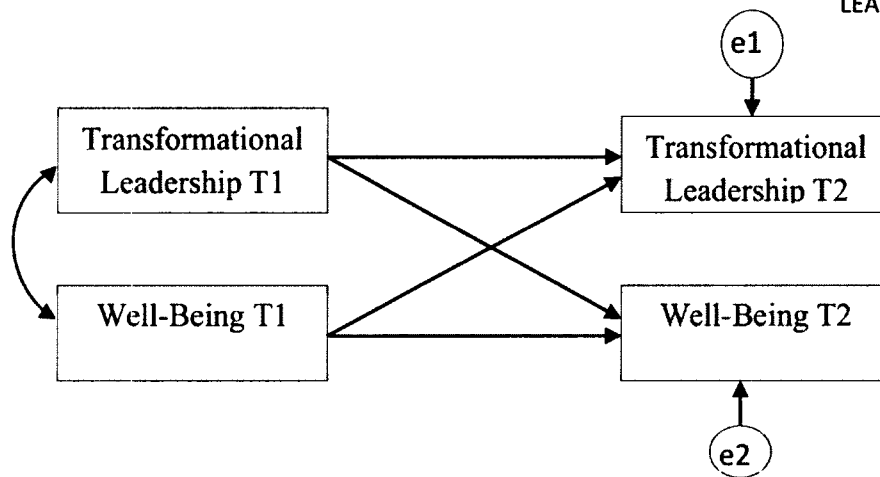
Figure 2. Complete two-wave panel design (Kelloway & Francis, in press).

The value of two-wave designs is dramatically limited for several reasons (Ployhart & Vandenberg, 2010). First, any detected change between time 1 and time 2 is by default linear, which assumes there are no other possibilities. The issue of assumed linearity is a glaring problem, since we know that many constructs tend to change in a curvilinear or non-linear fashion (Ployhart, Holtz, & Bliese, 2002; Rogosa, 1988). Second, two-wave designs confound true change and measurement error. For example, this could be a problem in cases where scores were suppressed at time 1 or inflated at time 2 (as a result of measurement error), resulting in the erroneous conclusion that there was a significant change (Ployhart & Vandenberg, 2010; Rogosa, Brandt, & Zimowsky, 1982; Singer & Willett, 2003). Additional observations serve to increase reliability and reduce error of measurement (Willett, 1989). It is clear that true longitudinal research requires repeated measurements of a variable of interest over *at least three* time periods in order to detect changes that may be linear, curvilinear, or non-linear (e.g., Kelloway & Francis, in press; Ployhart & Vandenberg, 2010; Ployhart et al., 2002) and to increase reliability of measurement (Willett, 1989); however, more (than three) repeated measures are better (Ployhart & Vandenberg, 2010).

True longitudinal research. The goal of longitudinal research is to describe changes in variables of interest over time and to explain the relationships between variables (e.g., Chan, 2011); that is, how change in one construct affects change in others. There are two aspects of variability that must be considered in longitudinal research; that is, intra-individual change, or the within person variability in constructs over time, and inter-individual change, or the differences between-persons in how they change over time (Ployhart et al., 2002). By looking at both intra- and inter-individual differences together, longitudinal analyses are able to capture the dynamic nature of constructs over time. Ployhart and Vandenberg (2010) discuss descriptive and explanatory research as two distinct and necessary aspects of longitudinal modelling. Descriptive longitudinal research is concerned with describing the amount and form (i.e., linear, curvilinear, non-linear) of change over time, whereas explanatory longitudinal research endeavours to identify the cause of change through analysis of relationships between variables over time (Ployhart & Vandenberg, 2010). Ployhart and Vandenberg (2010) stress that it is necessary to have a priori knowledge of what the change *trends* in variables *are* before one can attempt to *explain* them. This implies that there is a need for descriptive longitudinal studies to establish those trends before developing theories of causal effects and testing those theories.

Descriptive longitudinal analysis. The primary purpose of descriptive analysis is to develop theoretical models, which can be tested; that is, one must first conceptualize the *form* of change, and then develop a theoretical model for the *cause* of change (Ployhart & Vandenberg, 2010). For example in conceptualizing the form of change, we need to know if the change is typically linear or not, and if not linear, whether or not there are

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identifiable times when growth spikes (up or down) or flattens. These observations will lead us to decide how many observations will be required and at what time intervals, in order to detect the changes over time. Descriptive research will also enable us to develop hypotheses regarding *reasons* for observed changes, which will lead to building theoretical models that can be tested empirically. Research by Dormann and Zapf (2002) demonstrated the value of such an effort, when they conducted a multi-phase panel study and concluded that the strongest effects were found with a two-year time lag. However, like many research areas in occupational health psychology (Kelloway & Francis, in press), the literature on the relationship between leadership and well-being lacks this descriptive research, and to date there have not been any consistent recommendations regarding the many factors described above as they relate to leadership and well-being. The result is that there is currently no guidance on how to shape a study, in terms of the number of required observations or the appropriate latency time between them. In the absence of such guidance, researchers typically use limited previous research to rationalize their choice of time frames (e.g., Tafvelin et al., 2011), or they do not explain it at all (e.g., Nielsen et al., 2008), and it is likely that many studies are being designed based on strictly pragmatic considerations (Taris & Kompier, 2003; van Dierendonck, Haynes, Borrill, & Stride, 2004), such as by using convenience samples. Indeed this lack of a theoretical basis for longitudinal analysis of leadership and well-being is mentioned (albeit, often implicitly) in the discussion section of many studies where researchers offer the time frame as a "potential" explanation of the (poor) results, and an area worthy of future research (e.g., Tafvelin, et al., 2011; van Dierendonch et al., 2004).

Kelloway and Francis (in press) provide a summary of methods to conduct

descriptive longitudinal analyses in occupational health psychology research, including

application of the general linear model, application of time series analysis and modelling

growth curves. One of the least complicated and best understood methods is to apply the

general linear model, where a within-groups analysis of variance is used to see if the

variable of interest has changed over time. The second method presented by Kelloway

and Francis (in press) is to use time-series models (Rosel & Plewis, 2008) because of

their emphasis on description and forecasting. In the first order auto-regressive model

(i.e., Simplex, or Markov model; figure 3), each observation is hypothesized to be a

function of the observation immediately preceding it (Rosel & Plewis, 2008). Second and

higher order effects can be included after first order effects are accounted for and for K

observations over time, higher order effects up to K-1 can be tested (Kelloway & Francis,

in press). Using time series models, the researcher can constrain paths in various ways,

(e.g., to hypothesize a constant autoregressive effect), and they can model a moving

average, where each variable is hypothesized to be a function of the same variable and

error at the preceding time period.
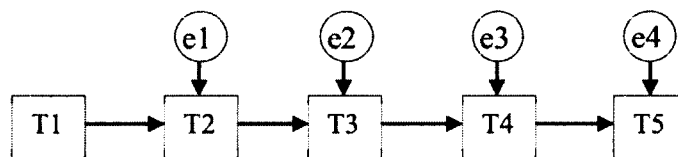
Figure 3. First order autoregressive model (Kelloway & Francis, in press).

Growth curve modelling. Growth curve modelling (McArdle, 1988; Ployhart &

Vandenberg, 2010) is another approach to descriptive longitudinal analysis when

modelling multiple observations over time. The primary focus of growth curve modelling

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is on within-person change over time; however, it is well-suited to analyze both within-
and between person variance. If everyone changed in a similar manner, the average
change over time would explain the growth curve for each person (Ployhart et al., 2002).
However, since we know people are not all the same and that each person is likely to
change differently, we need to analyze the between-person differences as well, to get a
full understanding of how and why people change over time. Two common approaches to
growth curve modelling are random coefficient modelling (i.e., regression analysis) or
structural equation modelling techniques (Ployhart et al., 2002).

Random coefficient modelling. Random coefficient modelling is commonly used to
model longitudinal data in social science research and provides many advantages over
general linear model options, such as analysis of variance or analysis of covariance
(Ployhart & Vandenberg, 2010). Random coefficient models are robust to violations of
the error assumptions that are inherent to the general linear model (Bliese & Ployhart,
2002; Ployhart et al., 2002), they can accommodate taking measurements on different
occasions (Singer & Willett, 2003), and estimates will be unbiased, as long as missing
data are random. Ployhart and colleagues (Bliese & Ployhart, 2002, Ployhart et al., 2002,
Ployhart & Vandenberg, 2010) provide many good descriptions and examples of the
random coefficient modelling approach to longitudinal data analysis.

Random coefficient growth models are an extension of random effects regression
models. Random effects regression is easiest to understand in terms of how data are
handled. In normal regression analysis all data are presented in one row for each
participant, and DVs are regressed onto IVs (table 1). When we have repeated measures,
variables that are measured at each time period would all be included on the same line

and we would not be able to analyze the effect of time. However, in random effects regression analysis, data are restructured so that each participant has a line of data for each time that measurements are taken (table 2), and separate regressions are run for each time period. We add a variable called time to look at the effect of time on each dependant variable and then we use the regression coefficients (intercepts and slopes) to summarize the shape of change across all time periods; i.e., between- and within-persons (Ployhart et al., 2002).

Table 1

Cross Sectional Data Set Example

Subject	Ldrshp1	Ldrshp2	Ldrshp3	W-B 1	W-B 2	W-B 3
1	20	40	60	30	50	70
2	15	25	35	10	20	30

Note. Ldrshp = Leadership; W-B = Well-being.

Table 2

Growth Curve Modelling Data Set Example

Subject	Leadership	Well-being	Time
1	20	30	0
1	40	50	1
1	60	70	2
2	15	10	0
2	25	20	1
2	35	30	2

Random coefficient models analyze longitudinal data at two levels. At level one, the growth parameters (i.e., within-person differences) are estimated. That is, the level one model analyzes different forms of *intra*-individual changes over time; for example,

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changes in each variable (such as leadership and well-being) for each participant (individually) across all time periods (Ployhart et al., 2002). The form and amount of change may be different for each person; therefore, each person will have a different intercept and slope parameter. In the level one model (Equation 1), leadership (and separately, well-being) (Y_{ti}; vector of repeated leadership measures) is a function of the intercept (b_{0i}; initial status), slope (b_{1i}; rate of change over time), time (X_{ti}; matrix of time as a function of the initial status and each of the other time frames) and error (e_{ti})

Level 1: $Y_{ti} = b_{0i} + b_{1i}(X_{ti}) + e_{ti}$

(1)

The second level of analysis (Equation 2) is focused on identifying predictors of the change parameters by estimating the *inter*-individual differences (i.e., between-persons) in change over time. So, the level 2 model says that the intercept (b_{0i}) is a function of both the fixed effect (π_{00}; average initial status for all individuals) and the random residual effect (r_{0i}; individual differences in initial status). The slope (b_{1i}) is comprised of a fixed effect (π_{10}; average rate of change for all individuals) and a random residual effect (r_{1i}; individual differences in rates of change).

Level 2: Intercept; $b_{0i} = \pi_{00} + r_{0i}$ Slope; $b_{1i} = \pi_{10} + r_{1i}$

(2)

Structural equation modelling approach to growth curve modelling. Kelloway and Francis (in press) explain the structural equation modelling approach to growth curve modelling. Figure 4 presents a sample growth curve model where two latent variables representing the intercept and the slope are associated with three indicators (three

indicators is the minimum required). Additional latent variables could be added to test for different growth curves (e.g., quadratic, cubic, etc). Latent variables are characterized by means and variances. The means represent the mean starting score, or score at time 1 (for the intercept), and the average rate of change over each time period (for the slope). The variances represent the random coefficient; that is, the significant inter-individual difference (i.e., differences in initial scores across participants) and significant intra-individual differences (i.e., differences in mean rates of change across time frames). Intercepts are by definition a constant; therefore, all paths between intercepts and indicators are set to 1. The paths linking slopes to indicators must be set, depending on the hypothesized shape of change. For hypothesized linear growth curves, paths are set at equal intervals, in this case, 0, 1, and 2. Path values can be changed to hypothesize different growth trajectories if required (e.g., quadratic, cubic, etc.) For example, hypothesized quadratic change would require paths be set at the square of the linear curve values; i.e., 0, 1, 4, etc. Growth curve models can accommodate more than one order of change simultaneously (i.e., linear, quadratic, cubic, etc.) by adding additional latent variables in the model. Testing a latent growth model is like other structural equation models, that is, model fit assesses how well the hypothesized relationships, including the hypothesized growth parameters, fit the data.
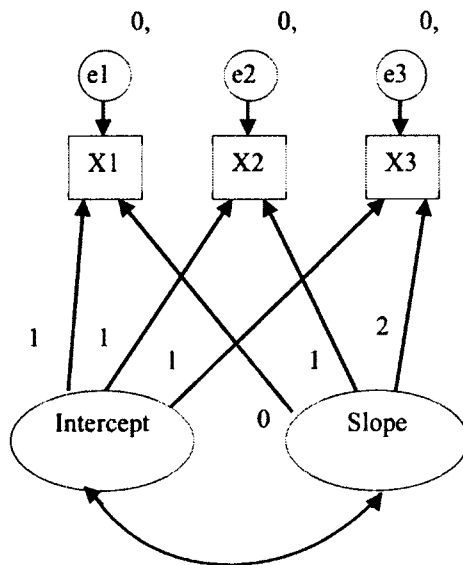
Figure 4. Latent growth curve model with two latent variables (Kelloway & Francis, in press).

Explanatory longitudinal analysis. Explanatory longitudinal research is focused on detecting the *causes* of change over time (Ployhart & Vandenberg, 2010), rather than just describing change that occurs. This is accomplished by incorporating predictor variables. Predictors do not have to be dynamic; rather they could be static or time invariant (Pitariu & Ployhart, 2010). An example would be predicting change in one construct (e.g., well-being) by some other stable characteristic, such as personality or cognitive ability. This could be done using a between and within groups analysis of variance, where a static predictor is hypothesized to predict change in a dependant variable over time. It can also be done in latent growth curve modelling, where the intercept (mean at time 1) is hypothesized to predict the slope (mean rate of change over time; see figure 5), and additional variables could be incorporated to predict both the intercept and slope. I will apply explanatory longitudinal analysis to investigate the relationship between starting values of the predictor and the criterion (i.e., intercepts), to the rates of change over time (i.e., slopes).
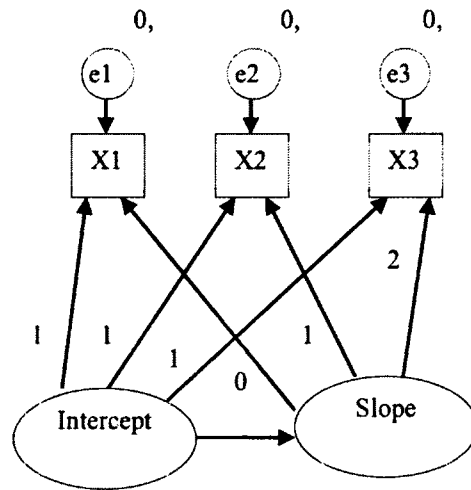
Figure 5. Latent growth curve model with intercept predicting the slope.

The methods described above will help to understand change in the predictor or the outcome variable, but they do not capture the full dynamic relationships inherent to longitudinal models (Kelloway & Francis, in press; Pitariu & Ployhart, 2010). One of the most powerful aspects of true longitudinal studies is the ability to capture the dynamic relationships *between* changing variables over time. Rosel and Plewis (2008) propose a variation of time-series modelling to study dynamic relationships where two parallel auto-regressive models are estimated, incorporating cross-lagged effects (figure 6). This is a flexible methodology where hypotheses could be tested for various time-lags, order effects, and parameter constraints. Kelloway and Francis (in press) suggest this model as a good alternative when theory does not provide ample specific guidance regarding hypothesized longitudinal relationships between predictors and outcomes.
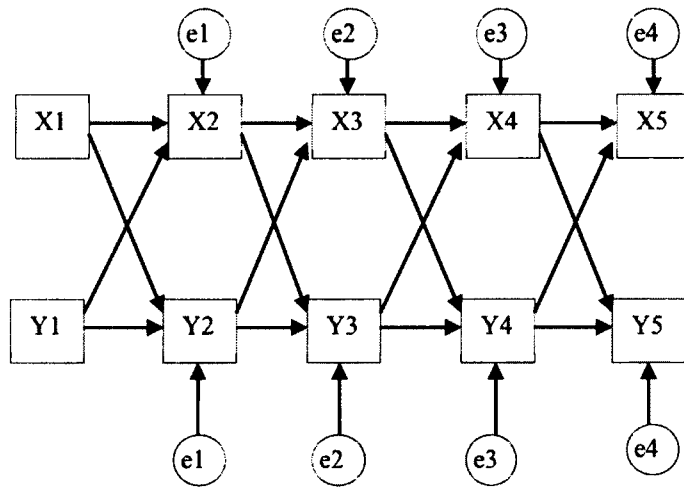
Figure 6. Two autoregressive models with cross-lagged effects (Kelloway & Francis, in press).

Latent growth curve models provide some additional distinct advantages when studying complex multivariate change models (Ployhart & Vandnenberg, 2010). For example, rather than assuming no measurement error, as is the case with GLM procedures, latent growth models account for error in the estimation approach (Ployhart and Vandenberg, 2010). In addition, latent intercepts (initial status) and slopes (rates of change) can be used as dependant, independent, mediating or moderating variables (Lance, Vandenberg, & Self, 2000), which is very helpful when testing the effect of change in one variable on change in another (Ployhart and Vandenberg, 2010). Cross-domain latent growth curve models are employed to test more complex relationships between multiple growth curves (McArdle and Hamagami, 1996). Using this technique, two or more growth curves can be estimated simultaneously, and one can be predicted from the other. For example, a model with one predictor and one outcome would be modeled such that growth curves are estimated for each variable (i.e., predictor and outcome), and directional paths are included from the slope of the predictor to the slope of the outcome to test the hypothesis that change in the predictor variable is associated

with change in the outcome variable (figure 7). Other relationships can also be tested such as whether or not the starting value of the predictor is related to rates of change in the predictor or the outcome by simply incorporating the appropriate paths. More complex models have been developed to incorporate growth curves for mediators (e.g., Pitariu & Ployhart, 2010). Such models are very similar to what was just described; however, an additional predictor is added (i.e., the mediator). In addition, paths are included to test hypothesized full or partial mediation of the relationship between the change in a predictor on the change in an outcome, by the change in the mediator. The *change* variables are represented by the slopes in each of three growth curves.
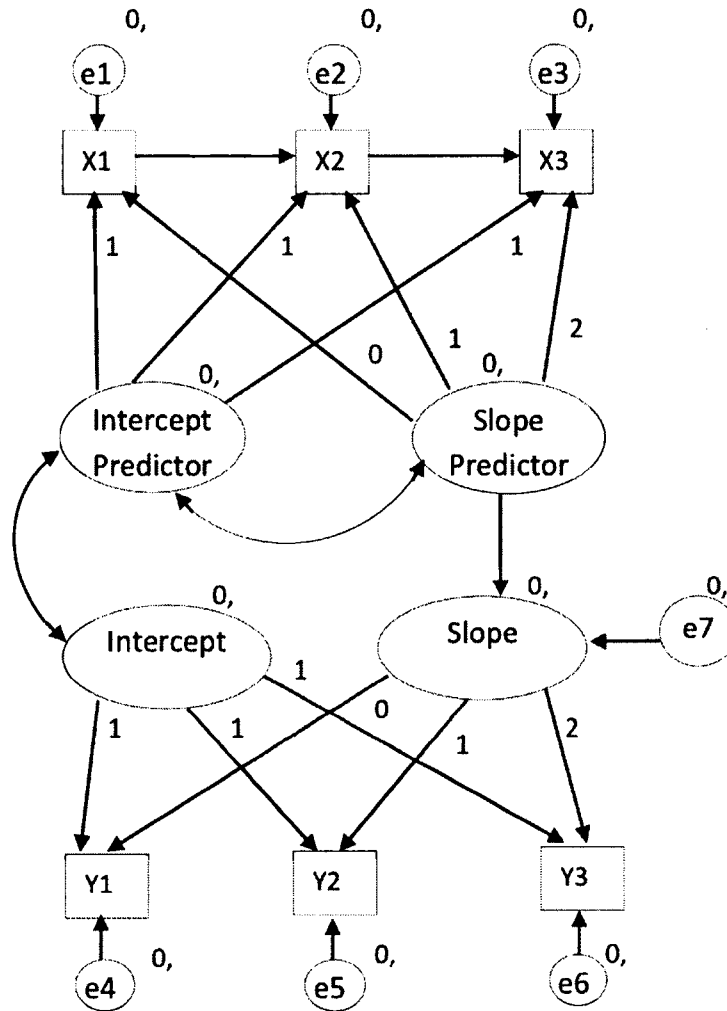
Figure 7. Two latent growth curves with change in one variable predicting change in the other.

True longitudinal studies in the literature. Very few researchers have looked at the relationship between leadership and various individual and organizational indicators in true longitudinal designs. Van Dierendonck et al. (2004) looked at leadership (using their own composite measure of supervisor leadership behaviour) and well-being (using the General Health Questionnaire – 12) across four time periods and found that leadership at time 1 predicted leadership at time 2, 3 and 4 and was correlated with well-being at time 1. Well-being at time 1 predicted well-being at time 2, 3 and 4; however, there were no longitudinal effects between leadership and well-being; that is, changes in leadership

were not significantly related to changes in well-being. Moyle (1998) examined the effect of manager support (using a six-item scale of social support; House, 1981) on employee well-being (using the General Health Questionnaire – 12) in a three-wave study over one year, finding that managerial support was related to mental health at each time period; however, changes in leader support were not associated with changes in well-being. These researchers have established the cross-sectional relationship between leadership and well-being and the auto-regressive nature of multiwave sampling; therefore, I expect to see the same relationships in this study.

I hypothesize (H2) that Transformational Leadership at time 1 (intercept) will be related to transformational leadership at later times, and that Well-being at time 1 (intercept) will be related to well-being at later times (H3).

I found only one study in the literature that detected a longitudinal relationship between leadership and well-being. Heck and Hallinger (2010) looked at the relationship between distributed leadership, school improvement capacity, and student performance in a three-wave study over four years. They found that changes in school improvement capacity were directly related to changes in student performance, and changes in distributed leadership were indirectly associated with changes in student performance over time, mediated by educational practices. In that study, distributed leadership referred to teacher perceptions of school leadership (in general), based on school improvement, school governance, and resource management (Heck & Hallinger, 2010). The empircal literature provides strong evidense that leadership is related to well-being, and Heck and Hallinger have shown that changes in leadership result in changes in individual outcomes; therefore, based on the limited empircal evidense:

I hypothesize that changes in leadership will result in changes in well-being (H4).

While Heck & Hallinger (2010) provide some evidense for a longitudinal effect of leadership on well-being; in general, the empirical evidense is mixed. In fact, none of the studies found in the literature looked at *transformational* leadership *behaviours* as the variable of interest when analyzing the relationship between leadership and employee well-being. I will bridge that gap by looking at at transformational leadership behaviours as the predictor variable.

Time periods associated with longitudinal effects. One of the questions in the empirical literature, regarding the longtudinal relationship between leadership and well-being, has been regarding the latency periods between data collection. The literature on longitudinal research in general contains few descriptive longitudinal studies; therefore, very little guidance is provided in terms of what is the appropriate latency period between sampling (Ployhart & Vandenberg, 2010). This is also true in the literature looking at leadership and well-being. I found no studies that looked at latency periods in longitudinal designs in any detail; however, some researchers have considered whether the time frame of the research is a factor in detecting longitudinal effects. For example, van Dierendonck et al. (2004) conducted a cross-lagged longitudinal study of the relationship between leadership and well-being over four time periods spanning 15 months, with surveys administered every five months. They investigated both the direction of the relationship and the associated time frame, concluding that the direction was reciprocal and in fact they did not find any direct longitudinal effects of leadership on well-being across any given time frame. As a result they could not determine the time frame associated with the relationship, concluding that it could be anywhere from a few

days to several months, based on the results of their study. The authors proposed that additional research is required looking for longitudinal effects, hypothesizing that analyses over shorter, rather than longer periods of time, with frequent samplings of behaviour (i.e., weekly) may be more fruitful. In their three-wave study, Heck and Hallinger (2010) looked at the relationship between distributed leadership and student performance over a four year period finding that changes in distributed leadership were indirectly associated with changes in student performance. Time periods for this study were selected based on the school year and in conjunction with aggressive educational reforms focused on two of the variables of interest (i.e., distributed leadership and school improvement) and not on any theoretical reasons. The authors did not provide any discussion regarding the impact or appropriateness of the time periods used in their study, nor did they comment on the issue of latency periods in longitudinal research designs. Overall, these longitudinal studies provided little guidance regarding appropriate time frames. Moyle (1998) conducted a three-wave study of the relationship between managerial support and employee well-being, collecting data over 18 months with approximately six months between samples. Similar to Heck and Hallinger (2010), Moyle (1998) conducted her study at a time coincident with planned changes to organizational management structures. She found that there were significant changes to well-being over time, but there was no significant relationship between changes in mental health and changes in managerial support; i.e., there was no significant longitudinal effect for leadership. Moyle (1998) did not discuss the issue of time frames or latency periods related to studying the longitudinal effects of leadership on well-being; however, as a result of the non-significant findings, it is clear that her study does not provide any

guiding information about the time frame required to detect longitudinal effects between leadership and well-being.

There have been some insights regarding latency periods provided by authors of two-wave studies. In their two-wave study of the relationship between leadership and well-being, Nielsen et al. (2008) collected data on two occasions across an 18-month latency period. They found a reciprocal relationship between leadership and well-being, consistent with other research; however, they also found an indirect relationship between leadership at time 1 and well-being at time 2 that was mediated by work characteristics. Feldt et al. (2000) also found effects of leadership on well-being over a one-year period.

The empirical research appears to provide very limited and inconsistent indications of what period of time is required to detect the longitudinal effects of leadership on employee well-being; clearly, this is a weakness in the extant literature. I will examine the relationship between leadership and well-being across three different time periods in an exploratory manner.

The present research.

The present set of two studies will look at the longitudinal relationship between leadership and well-being over three different time periods. Data collected over one week, two weeks and eight months will all be examined to try to identify what latency period is most likely to detect changes in leadership and well-being. While there has been some longitudinal research that looked at relationships between leadership and well-being (e.g., Feldt et al., 2000; Nielsen et al., 2008; van Dierendoncket al., 2004), overall, such studies are limited and in many cases the results were inconclusive. Most studies have to date been two-wave studies (e.g., Feldt, Kinnunen, and Maunao, 2000; Nielsen & Munir,

2009; Nielsen et al., 2008; Tafvelin et al., 2011), which cannot capture the dynamic

nature of changing variables over time (Ployhart & Vandenberg, 2010). Of the three true

longitudinal studies found in the literature (i.e., where data were collected over at least

three waves), only one of them found a longitudinal effect; however, none of them

examined transformational leadership behaviours as the leadership variable. In addition,

studies to date have not provided any clear guidance on what latency period between

observations is appropriate to capture changes in leadership and well-being. Finally, these

previous studies have not conducted growth curve modelling per se. In reality, they have

conducted repeated measures analyses using regression and structural equation modelling

approaches, but they have not taken advantage of the ability to use intercepts and slopes

as key variables of interest.

The present study aims to add to the literature by filling in some of these gaps. In

the present set of two studies, I looked at the relationship between transformational

leadership and well-being over one-week, two-week and eight-month time periods in 3

three-wave longitudinal analyses. My goal was to capture the dynamic nature of the

relationship between leadership and well-being, and to gain some new insight into what is

the most appropriate latency period for researching leadership and well-being over time.

In addition, the present set of studies looks at the relationship between transformational

leadership and employee well-being, using two variants of the techniques discussed

above, namely, mixed multi-level regression analysis (Shek & Ma, 2011) and latent

variable growth curve modelling (McArdle, 1988).

Measures of well-being. Researchers of the relationship between leadership and

well-being have measured well-being, based on a number of different conceptualizations,

such as safety incidents (Kelloway, Mullen and Francis, 2006; Mullen, Kelloway & Teed, 2011), stress (e.g., Bono, Foldes, Vinson, & Muros, 2007), Depression (e.g., Munir, Nielsen, & Cameiro, 2010), and mental health (Kelloway, Turner, Barling & Loughlin, 2012; Nielsen & Munir, 2009). Studies which conceptualized well-being as mental health, tended to use measures of contextual (i.e., job-related) affect, such as the Job-related Affective Well-being Scale (JAWS; Van Katwyk, et al., 2000) non-contextual affect such as the Positive and Negative Affectivity Scale (PANAS; Watson, Clark, & Tellegen, 1988), and many employed measures of general mental health using the General Health Questionnaire – 12 (GHQ-12). I was interested in mental health; therefore, I used the GHQ-12 and the JAWS in this set of studies. The GHQ-12 is a well-established measure of general mental health that has been used frequently in studies of employee well-being because of its strong psychometric properties and short length. In addition to the twelve item version of the GHQ-12, previous research found excellent psychometric properties for the four item anxiety depression scale (Kalliath, et al., 2004). I employed both the four item measure and the twelve item measure in the current set of studies. I chose the four item measure in study one because I wanted to keep the survey as short as possible in order to encourage repeated participation over short periods of time. For study two, I used archival data in which GHQ-12 data were available. The JAWS is a 30-item measure of job-related affect with two subscales, including Negative Emotion and Positive Emotion. There is also a 20-item version of the JAWS that includes subscales for High Pleasure - High Arousal, High Pleasure – Low Arousal, Low Pleasure - High Arousal, and Low Pleasure – Low Arousal, all with excellent psychometric properties. The Jaws has been used in work related well-being research, primarily because it is a measure of context

specific (i.e., job-related) affect as opposed to non-context specific affect. I used the five-item High Pleasure – High Arousal scale in study one only, to keep the survey short and to detect changes in well-being over very short time periods, which, may be too short to detect changes in general mental health.

Summary of hypotheses. I hypothesize that the same relationships found in the limited available empirical literature will be found in the present study; that is:

Hypothesis 1. Transformational leadership will be positively related to employee well-being.

Hypothesis 2. Transformational leadership at time 1 will be positively related to transformational leadership at later times (i.e., time 2, time 3).

Hypothesis 3. Employee well-being at time 1 will be positively related to well-being at later times.

Hypothesis 4. Changes in transformational leadership will be positively related to changes in well-being over time.

Exploratory research question. In addition to the four hypotheses above, the present study will examine three different time periods, in an attempt to identify the optimum time frame for detecting the dynamic relationship between transformational leadership and employee well-being.

Study 1

The purpose of study 1 was to investigate the relationship between transformational leadership and employee well-being in a three-wave longitudinal design, across short time periods (i.e., one or two weeks). Previous longitudinal studies of leadership and well-being have normally used relatively long time periods. For example, Heck and Hallinger (2010) looked at the effect of distributed leadership on school improvement over two 12-month latency periods; Nielsen et al. (2008) examined leadership and well-being over one 18-month time frame; Tafvelin et al. (2011) investigated transformational leadership and well-being across a one-year period and Nielsen and Munir (2009) looked at transformational leadership and affective well-being across an 18-month time period. Interestingly, only one of these studies found a significant longitudinal relationship between leadership and well-being (Heck & Hallinger, 2010). While none of the researchers provided any clear insights into what time frames would be most appropriate, their results suggest that shorter time periods would be more likely to detect longitudinal effects. The current study will attempt to investigate whether shorter time periods will be more successful at detecting longitudinal effects.

Most of the studies that looked at the effect of leadership on well-being currently found in the empirical literature have been two-wave studies (e.g., Feldt, Kinnunen, & Maunao, 2000; Nielsen & Munir, 2009; Nielsen et al., 2008; Tafvelin et al., 2011), which, technically are not appropriate to detect longitudinal relationships (e.g., Ployhart & Vandenberg, 2010). Of the very few studies that did employ longitudinal designs (e.g., Heck and Hallinger, 2010; van Dierendonck et al, 2004), none of them found any

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significant direct longitudinal effects. Therefore this study will employ true longitudinal designs in an attempt to detect the longitudinal effect of leadership on well-being.

Much of the research on leadership and well-being has been retrospective; that is these studies used surveys to sample behaviours that occurred sometime in the past (e.g., Kelloway et al, 2012; Nielsen et al., 2008; Nielsen et al., 2009). When conducting research on leadership and well-being, retrospective studies will result in a global assessment of leadership and a temporal assessment of well-being (i.e., based on some specific time frame). When asked to comment on perceptions of leadership and personal well-being during some specific time frame (in the past), participants would need to rely on their memory to recall leadership behaviours and their own feelings during the specified time-frame. Consequently, the more time that has passed since the specified time frame, the more likely it is that there will be inaccuracies in recall (Scollon, Kim-Prieto, & Diener, 2003). An approach that may help to avoid such inaccuracies is experience sampling methodology (Scollon et al., 2003). Experience sampling methodology refers to a method of data collection that captures data repeatedly over some specified time frame by people in their natural work setting. There are three distinct variations of experience sampling methodology, including, interval-contingent sampling, event-contingent sampling and signal-contingent sampling. Interval-contingent sampling is a data collection method whereby participants complete a self-report survey at designated intervals over a designated period of time (e.g., hourly, daily, weekly, etc.). Sometimes called "Diary Studies", this technique has been used to study many areas of psychology, including leadership (e.g., Bono et al., 2007; Harrison, 2009) and well-being (Bono et al., 2007; Longua, DeHart, Tennen, & Armeli, 2009). Mullen and Kelloway

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(2011) propose that experience sampling methodology may provide improvements on retrospective research, for testing relationships between leadership and well-being. Therefore, the current study employed experience sampling methodology to look at transformational leadership and employee well-being over one- and two-week periods in two separate analyses.

Method

Participants. For study 1, I recruited volunteer participants from a community college in the province of Prince Edward Island, Canada. Participants were 187 employees of the college who had been working there for anywhere from a few months up to 38 years (avg = 10 yrs). Participants were invited from across the college regardless of their job; however, they were not asked to identify what job they performed for reasons of confidentiality. Ages ranged from 20 to 65 years, with the average age being 45. Of those who identified their gender, there were 125 females (67%) and 59 males (32%). Participants' education levels ranged from having at least some high school (9%), to having completed college / undergraduate university studies (59%), or a graduate degree (32%).

Measures (Appendix A). *Transformational Leadership.* Transformational leadership was measured using an adapted version of the 7-item Global Transformational Leadership Scale (Carless, Wearing, & Mann, 2000). The adapted measure added two items to the original measure to avoid double-barrelled questions, resulting in a 9-item unitary measure ($\alpha T1$ = .96; $\alpha T2$ = .96; $\alpha T3$ = .97) of transformational leadership (Carless, Wearing, & Mann, 2000). Respondents were asked to reflect on recent interactions with supervisors (i.e., "Today, my supervisor ..."), and responses were rated

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on a Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). Higher scores represent higher levels of transformational leadership.

Well-Being. Well-being was measured using the General Health Questionnaire – 12 (Banks, et al., 1980) and the Job-related Affective Well-being Scale (Van Katwyk, Fox, Spector and Kelloway, 2000).

The General Health Questionnaire – 12. The General Health Questionnaire – 12 is a 12-item self-administered screening test that detects minor psychiatric disorders (Banks, et al., 1980). While intended as a unitary measure of general mental health, several studies have examined the factor structure of the General Health Questionnaire – 12, and argued for two-factor (e.g., Kalliath, O'Driscoll, & Brough, 2004) or three-factor (e.g., Worsley & Gribbin, 1977) models. Common to both the two- and three-factor solutions are scales labelled Anxiety-Depression and Social Dysfunction. The current study employed the General Health Questionnaire – 12 as a unitary measure, using only the four-item Anxiety-Depression scale ($\alpha T1 = .86$; $\alpha T2 = .80$; $\alpha T3 = .90$). Respondents were asked to rate how they felt on that day (i.e., "Today I feel...") and responses were measured on a 7-point likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Data were recoded so that higher scores on the General Health Questionnaire – 12 represent higher levels well-being.

Job-related Affective Well-being Scale. The Job-related Affective Well-being Scale is a 30-item test of context (i.e., job) specific affective well-being. The current study employed the Job-related Affective Well-being Scale as a unitary measure, using four items from the high pleasure / high arousal scale (Van Katwyk et al., 2000; $\alpha T1 = .94$; $\alpha T2 = .95$; $\alpha T3 = .96$). Respondents were asked to rate how they felt on that day (i.e.,

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"Today my job made me feel ... ecstatic, energetic, enthusiastic, excited") and responses were measured on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Higher scores on the Job-related Affective Well-being Scale represent more positive well-being.

Procedure. Surveys were administered at five time periods, via the Limesurvey server housed at Saint Mary's University. Participants were invited to participate via email on Monday, Wednesday and Friday of week 1, and then again on Friday of week 2, and Friday of week 3[1]. On each occasion they were provided with a link to take them directly to the survey. The first page of the survey contained the informed consent form and participants had to read the form and check an acceptance box, in order to proceed with the survey. By clicking the acceptance box, they were indicating they had read the details of the study and voluntarily conceded to participate. Participants had to read and check the informed consent acceptance before beginning each of the five surveys. When participants completed each survey, their names were entered into a draw for $200.00. Participants were informed by email when they won a draw and they were directed to contact the researcher's supervisor to arrange for payment of their prize.

There were a total of 187 participants who completed at least one survey for the study; 144 completed survey 1, 143 completed survey 2, 115 completed survey 3, 112 completed survey 4, and 103 completed survey 5. For survey 1, there were 100 females (69%) and 44 males (29%), ranging from 23 to 65 years of age. For survey 2 there were

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[1] Five waves of data were collected; however, data were analyzed in two, three-wave analyses. The first analysis looked at data collected over one week on Monday, Wednesday and Friday. The second analysis looked at data collected over two weeks on three consecutive Fridays. All employees were invited to participate each time, regardless of whether or not they participated in previous surveys.

99 females (69%) and 44 males (31%), between the ages of 20 and 65. For survey 3 there were 81 females (70%) and 34 males (29%) aged 23 to 65. For survey 4 there were 76 females (66%) and 36 males (31%) between the ages of 23 and 65. Finally, for survey 5 there were 70 females (66%) and 33 males (31%), aged 23 to 65.

Data Analyses

For study 1, data were analyzed in two separate sets of analyses. In the first set of analyses, three-wave data collected during Monday, Wednesday and Friday of week one were analyzed to investigate the longitudinal effects over a one-week period. In the second set of analyses, three-wave data collected on three consecutive Fridays were analyzed to investigate the longitudinal effects across a two-week time period.

Random coefficient models. To assess the longitudinal relationships between transformational leadership and two criterion variables (General Health Questionnaire – 12, and Job-related Affective Well-being Scale), I used the linear mixed models procedure in the Statistical Package for Social Sciences software. Linear mixed models are sometimes referred to as mixed-effects models, multilevel models, hierarchical linear models, or random-coefficient models. There are many advantages to using linear mixed models over ANOVA techniques. For example, linear mixed models can accommodate any data that are present and will not drop cases when some data are missing; unbalanced data is a common problem in longitudinal data where subjects may drop out, may not all respond at each time or may not all respond at the same times. Linear mixed models can consider multiple covariance structures for both random and fixed errors, and different covariance structures can be compared to determine the best fit. By including random effects, linear mixed models can help the researcher to answer questions about which

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subject-level predictors may explain random between-subject variance in growth curves. In addition to all of these advantages over ANOVA techniques, linear mixed models are less affected by smaller sample sizes than structural equation modelling techniques that will be applied in study 2.

In the first set of analyses six different models were tested, following guidelines provided by Shek and Ma (2011). The first model tested (Model 1) looked at the unconditional means model as a baseline to evaluate between subjects differences in the dependant variable (employee well-being), without looking at the effect of time. Next, the unconditional linear growth model (Model 2) was tested as a baseline growth model to examine individual growth rates over time, based on the assumption of a linear trend; that is, I was looking for inter-individual differences in growth trajectory changes in well-being over time. Next, I ran two nested models, first constraining the intercept and then constraining the slope variances to zero, to test for fixed effects.

The next model was a quadratic growth curve model (Model 3) to see if it was a better fit to the data than the linear model, followed by two nested models constraining the intercept and slope to test for random effects. The next model tested was the conditional growth model (model 4), adding transformational leadership as a predictor of changes in well-being. The final two models (models 5 and 6) examined the data to see which inter-individual error covariance structure was the best fit. The estimated variances of parameter estimates will normally be biased or inconsistent in repeated measures designs; therefore, identifying the covariance structure that best fits the data will improve predictions and inferences, particularly with random-effects models (Shek and Ma, 2011). For all model comparisons, the -2 log likelihood (2LL), Akaike Information Criterion

(AIC) and Bayesian Information Criterion (BIC) were used to determine the best model

fit, with a "smaller is better" criterion. Estimation was based on Maximum Likelihood

(ML). The dependant variable was employee well-being, and the independent variable

was transformational leadership.

All models described above were run twice to test the relationship between

transformational leadership and well-being, using two different criterion measures; that is,

mental health, measured by the General Health Questionnaire and job-related affect,

measured by the Job-related Affective Well-being Scale.

Results

Descriptive statistics and correlations for the first set of analyses are provided in

table 3. Gender and age were included as control variables in the final model. It is

noteworthy that both job-related affect and mental health appeared to vary in the same

direction as transformational leadership. That is, as transformational leadership increased,

job-related affect and mental health both appeared to increase (and vice versa; table 3).

Table 3

Study 1, Analysis 1, Descriptive Statistics and Correlations

	N	Mean	Sd	1	2	3	4	5	6	7	8	9
1. tfl1	145	5.52	1.22	1								
2. ghq1	145	6.00	1.10	.33**	1							
3. jaws1	145	4.63	1.32	.57**	.59 **	1						
4. tfl2	132	5.19	1.39	.74**	.31 **	.42 **	1					
5. ghq2	142	5.88	1.03	.25**	.70 **	.40 **	.30 **	1				
6. jaws2	139	4.59	1.36	.51**	.51 **	.74 **	.52 **	.37 **	1			
7. tfl3	100	5.26	1.39	.73**	.42 **	.50 **	.82 **	.27 *	.50 **	1		
8. ghq3	112	6.12	1.10	.46**	.73**	.50 **	.41 **	.68 **	.53 **	.50 **	1	
9. jaws3	109	4.65	1.41	.56**	.62 **	.75 **	.49 **	.40 **	.79 **	.52 **	.48 **	1

Notes. * p < .05 ** p < .01. Data were collected at three times across a one-week period. Time 1 = Monday; Time 2 = Wednesday; Time 3 = Friday. tfl1 = transformational leadership at time 1; tfl 2 = transformational leadership at time 2; tfl3 = transformational leadership at time 3. ghq1 = mental health at time 1; ghq 2 = mental health at time 2; ghq3 = mental health at time 3. jaws1 = job-related affect at time 1; jaws2 = job-related affect at time 2; jaws3 = job-related affect at time 3.

General Mental health

Model 1; unconditional means model. Table 4 provides a summary of Study 1 analyses. Model 1 is a fixed effects model that looks at variance in mental health across participants. The mean of the dependant variable (mental health) was 5.97 and it was significantly different from zero (p < .001). The intraclass correlation coefficient (ICC) was .824/(.824 + .350) = .70, suggesting that 70% of the variance in the variation in mental health could be explained by inter-individual differences. This strong ICC also suggests that the measure of mental health is very stable; therefore, growth curve modelling is the better analysis method to detect fixed effects, rather than using other methods such as ANOVA (Shek and & Ma, 2011). While a large proportion of the variance was explained by differences between-persons, a large amount also appears to be explained by within person variability (i.e., 30%), providing additional support for conducting longitudinal analyses to explain those differences.

Model 2; unconditional linear growth model. Examination of fixed effects found that the average starting point (intercept) was 5.88, p < .001; however, there was no significant change in mental health over time (β = .05, SE = .04, ns). Inspection of random effects reveals that the residual variance and the variance of the intercept were also both significant. Two additional nested models were examined, first holding the

intercept variance to zero and then holding the slope variance to zero; however, neither model provided an improved fit to the data, leaving the full model as the best fitting solution.

Model 3; unconditional quadratic growth model. An examination of fixed effects found that the intercept, linear and quadratic slopes were all significant. The initial status (grand mean at time 1) of mental health was 6.48 (β = 6.48, SE = .24, p < .001). The linear effect for time was -.68 (β = -.68, SE = .26, p = .01), indicating that mental health scores (on average) decreased over time. The quadratic effect was .18 (β = .18, SE = .07, p < .01), suggesting that there was a significant increase in the rate of (negative) growth over time (Heck, Thomas & Tabata, 2010). An inspection of random effects found that the variance of the intercept and residuals were both significant; however, random effects for slopes were not significant.

The quadratic trends model was a much better fit to the data than the linear model (χ^2 (1) = 1032.64 – 1025.03 = 7.61, p < .01); Δ AIC = 1044.64 – 1036.03 = 8.61; Δ BIC = 1068.58 – 1066.95 = 1.63); therefore, both linear and quadratic growth curve parameters were retained in subsequent analysis.

Two additional nested models were run, looking at quadratic trends, first holding the intercept variance to zero and then holding the slope variance to zero (i.e., to test fixed effects models); however, neither model provided an improved fit to the data; therefore, the full model was deemed to be the best fit.

Model 4; conditional growth model. In model 4, predictors were added to the model. Age and gender were added as control variables, and transformational leadership was added to test the effect of transformational leadership on well-being and changes in

well-being over time. The results suggest that after controlling for age and gender, transformational leadership was positively related to well-being initial status (β = .15, SE = .06, p < .01), and overall changes in mental health were explained by linear (β = -.69, SE = .28, p < .05) and quadratic (β = .18, SE = .07, p = .01) growth trajectories. However, transformational leadership was not a significant predictor of the linear or quadratic effects on mental health.

Models 5 and 6; covariance structures. To investigate which covariance structure is the best fit for the data in the current study, two models were run; first with an unstructured covariance matrix, and second, with a first-order auto-regressive matrix. The comparison of these two structures was chosen because the unstructured covariance matrix tends to be the best fit as a result of it being the least parsimonious structure, and the first order auto-regressive matrix is a logical matrix for repeated measures designs, as it assumes that each person's response is correlated to their previous response. Results indicate that the unstructured matrix was the better fit with Δ 2LL = 26.03, 13 df, p < .001 (993.85 – 967.82 = 26.03, 4 df, crit χ^2 = 10.83); ΔAIC = 18.03 (1011.85 – 993.82); and, ΔBIC = 2.32 (1047.19 – 1044.87).

Table 4

Longitudinal Effects of Transformational Leadership on Mental Health

	B	SE b	95% CI	p
Model 1; Unconditional Means Model				
Residual	.35	.03	.29 - .42	.000
Intercept	.82	.11	.64 - 1.07	.000

Model 2; Unconditional Linear Growth Model

Intercept	5.88	.11	5.67 - 6.09	.000
Time	.046	.04	-.03 - .12	ns

Model 3; Unconditional Quadratic Growth Model

Intercept	6.48	.24	6.01 - 9.56	.000
Time	-.68	.26	-1.20 - -.16	.010
Time*Time	.18	.07	.05 - .31	.006

Model 4; Unconditional Growth Model with transformational leadership as a predictor

Intercept	5.98	.43	5.13 - 6.83	.000
tfl	.15	.06	.04 - .26	.006
Time	-.69	.28	-1.24 - -.14	.015
Time * Time	.18	.07	.04 - .032	.010
Time * tfl	-.06	.29	-.64 - .52	.843
Time * Time * tfl	-.02	.07	-.12 - .17	.755

Model 5 and 6; Comparison of unstructured and first order autoregressive (AR1) covariance structures

	Unstructured/df	AR1/df	Δ df	p
-2LL	993.85/13	967.82/9	26.03/4	.001
AIC	1011.85	993.82	18.02	
BIC	1047.19	1044.87	2.32	

Affective well-being

Separate analyses were conducted looking at affective well-being measured by the Job-related Affective Well-Being Scale, as an alternative criterion; however, neither linear nor quadratic growth models showed any significant change over time. Therefore, no additional analyses were conducted and results are not reported.

Analysis 2

The results of the first analysis of study 1 were consistent with previous research where a strong cross-sectional relationship between transformational leadership and employee well-being exists, and longitudinal effects were not evident. Even though some researchers suggested sampling over short latency periods (e.g., Mullen & Kelloway, 2011; van Dierendonck et al., 2004), the current study did not find any longitudinal effects over a one-week time period. These results were not surprising, since guidance in the literature has been very mixed and all current investigations into latency periods of longitudinal research are somewhat exploratory. The second analysis of study 1 extends this exploration, by conducting three-wave longitudinal analysis over a two-week period, with seven day latency periods between measurements, using data collected from the same sample.

Linear mixed models. For part 2, data were analyzed exactly the same as for part one of study 1. Longitudinal relationships between transformational leadership and two criterion variables (general mental health and job-related affect) were tested using the linear mixed models procedure in the Statistical Package for Social Sciences software. Data were collected over a two week period on three consecutive Fridays. Three models were run, including the unconditional means model (Model 1), the unconditional linear growth model (Model 2) and the unconditional quadratic growth model (Model 3). Analyses were run separately with general mental health, measured by the General Health Questionnaire-12 and with job-related affect, measured by the Job-related Affective Well-being Scale as alternate indicators of employee well-being.

Results

Descriptive statistics and correlations are provided in table 5. Gender and age were included as control variables for all analyses.

General Mental health

Model 1; unconditional means model. This is a fixed effects model that looks at variance in mental health across participants. The mean of the dependant variable (general mental health) was 6.04 and it was significantly different from zero ($p < .001$). The intraclass correlation coefficient (ICC) was $.736/(.736 + .355) = .68$, suggesting that 68% of the variance in mental health scores could be explained by inter-individual differences. With such a stable general mental health variable, longitudinal analysis is more likely to detect fixed effects, than other techniques such as ANOVA (Shek and & Ma, 2011). While general mental health appears to be a very stable measure, a significant amount (i.e., 32%) of the variance appears to be explained by within-person differences over time; therefore, longitudinal analysis is the appropriate technique to explore reasons for that variability (Shek and & Ma, 2011).

Model 2: unconditional linear growth model. An examination of fixed effects revealed that the average intercept or initial level of mental health was 6.15, $p < .001$; however, the slope was not significant, suggesting that there was no significant linear change in mental health over time ($\beta = -.05$, SE = .05, ns). There were also significant random effects for the intercept and residuals, which may potentially be explained by predictor variables (Shek and & Ma, 2011). Two additional nested models were run, first holding the intercept variance to zero and then holding the slope variance to zero (i.e., to

test fixed effects models); however, neither model provided an improved fit to the data; therefore, the full model remained the best fitting model.

Model 3; unconditional quadratic growth model. Model 3 was run to examine whether a quadratic trend would be a better fit to the data. Fixed effects indicate a significant intercept but no significant slope. That is, the average starting point on general mental health was 5.85, $p < .001$; however, there was no significant quadratic trend over time ($\beta = -.09$, SE = .07, ns). Analysis of random effects similarly found significant variance in residuals and intercepts; however, there was no significant random effect for time. Additional nested models were run, first holding the intercept variance and then the slope variance to zero; however, neither model improved the fit to the data.

Table 5

Study 1, Analysis 2, Descriptive Statistics and Correlations

	N	Mean	Sd	1	2	3	4	5	6	7	8	9
1. tfl3	100	5.26	1.39	1								
2. ghq3	112	6.12	1.10	.50 **	1							
3. jaws3	109	4.65	1.41	.52 **	.48 **	1						
4. tfl4	103	5.20	1.37	.73 **	.32 **	.41 **	1					
5. ghq4	114	6.09	.96	.33 **	.67 **	.43 **	.24 *	1				
6. jaws4	114	4.63	1.37	.48 **	.32 **	.70 **	.52 **	.27 **	1			
7. tfl5	94	5.08	1.29	.70 **	.33 **	.42 **	.59 **	.16*	.36 **	1		
8. ghq5	106	5.96	1.04	.30 *	.64 **	.26 *	.19**	.67 **	.40 **	.14*	1	
9. jaws5	105	4.56	1.43	.45 **	.37 **	.61 **	.47 **	.22 *	.78 **	.40 **	.47 **	1

Notes. * $p < .05$ ** $p < .01$.

Data were collected at three times across a two-week period on three consecutive Fridays. Time 3 = First Friday; Time 4 = Second Friday; Time 5 = Third Friday. tfl3 = transformational leadership at time 3; tfl 4 = transformational leadership at time 4; tfl5 = transformational leadership at time 5. ghq3 = mental health at time 3; ghq 4 = mental health at time 4; ghq5 = mental health at time 5. jaws3 = job-related affect at time 3; jaws4 = job-related affect at time 4; jaws5 = job-related affect at time 5.

Models 4 and 5; analysis of covariance structures. To investigate which

covariance structure is the best fit for the data in the current study, two models were run;

first with an unstructured covariance matrix, and second, with a first-order auto-

regressive matrix. The comparison of these two structures was chosen because the

unstructured covariance matrix tends to be the best fit as a result of it being the least

parsimonious structure, and the first order auto-regressive matrix is a logical matrix for

repeated measures designs, as it assumes that each person's response will be correlated

with their responses at other times. Results indicate that there was no significant

difference between the two covariance structures Δ -2LL = 7.58, 4df, ns (849.15 – 841.57

= 7.58; crit χ^2, p .05, = 9.49); ΔAIC = +.42 (859.15 – 859.57); and, ΔBIC = +15.65

(878.17 – 893.82). Since neither covariance matrix improved the model and since neither

the linear, nor the quadratic trends were significant, no further analyses were conducted

on the general mental health criterion.

Affective well-being

Separate analyses were conducted looking at job-related affect, measured by the

Job-related Affective Well-Being Scale as an alternative criterion; however, neither linear

nor quadratic growth models showed any significant change over time. Therefore, no

additional analyses were conducted and results are not reported.

Discussion (Study 1)

The results of study 1 support previous research that found a statistically

significant relationship between transformational leadership and employee well-being. In

the first analysis, measures were taken three times over a one-week time frame with two-

day latency periods between measurements (i.e., measures were taken on Monday,

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Wednesday, and Friday). Consistent with the first hypothesis, zero-order correlations

showed that leadership was correlated with well-being at all three times; however, the

relationship appears to be different depending on the measure that is used to represent

well-being. That is, mental health, measured by the General Health Questionnaire -12,

was only moderately related to transformational leadership (mean $r = .38$, $p < .01$), while

job-related affect, measured by the Job-related Affective Well-being Scale was more

strongly related to leadership at each sampling time period (mean $r = .54$, $p < .01$). These

findings are consistent with previous research which found correlations between

leadership and general mental health ranging from .09 to .29, and correlations between

leadership and job-related affective well-being ranging from .19 to .57 (e.g., Arnold, et

al., 2007; van Dierendonck et al, 2004). Linear Mixed Models analyses provided

additional evidence of the relationship between leadership and well-being that was

consistent with evidence found in the correlation tables. *Therefore hypothesis 1 was*

supported. The results of the second analysis were very similar to the first set of analyses.

Transformational Leadership and employee well-being, indicated by job-related affect or

general mental health were related across all time periods, providing strong support for

hypothesis 1.

    Hypotheses 2 and 3 were also supported. In addition to the cross-sectional

relationships found in this study, the relationships between study constructs over time

were found to be consistent with previous studies. Previous research consistently found

that leadership at time 1 was related to leadership at successive sampling periods and

well-being at time 1 was related to well-being at other times (e.g., Feldt et al, 2000;

Nielsen et al., 2008; van Dierendonck et al, 2004). In the current study, Transformational

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Leadership and both well-being measures were significantly correlated across all sampling times (table 1).

Hypothesis 4 could only be partially tested using random coefficient modelling. Random coefficient modelling can test the longitudinal growth of the dependant variable; the relationship between starting values (i.e., intercept) and the growth of the dependant variable; and, it can test the relationship between the predictor (transformational leadership) and the growth in the independent variable. In the first analysis, where measures were taken three times over one week on Monday, Wednesday and Friday, there were significant changes in well-being over time; however, there was no significant relationship between transformational leadership and changes in well-being. In the second analysis, where measures were taken over two weeks on three consecutive Fridays, no significant changes in well-being were detected. Therefore, *hypothesis 4 was not supported.*

These results are inconsistent and a bit puzzling. It is surprising that changes in well-being were detected over one week, but not over three weeks. Van Dierendonck et al. (2004) estimated that the time period associated with the ability to detect a relationship between leadership and well-being could be between a few days and several months and they suggested that the effect was probably best tested over shorter periods of time. The current study appears to provide evidence for and against their conclusion. Similarly, Sanchez and Viswesvaran (2002), found that changes in mental health may not be detectable over very short time periods, and again, this study provide both supporting and contradictory evidence of their results. One possible explanation for these results is related to the day of the week on which I collected data. I surveyed employees on five

occasions; that is, Monday, Wednesday and Friday of week one, and then on Friday for the two following weeks and I found significant changes in well-being across one week, but not across three consecutive Fridays. While I did not conduct analyses to look at differences in responses attributable to the day of the week, it is conceivable that employees feel higher levels of well being on each Friday, as they are thinking about the weekend off work. That would explain growth between Monday and Friday, but no growth across Fridays. Future research could look at this question by collecting data daily over several weeks and analyzing similarities and differences attributed to the day of the week and possible covariates, such as average daily workload, family activities, etc. There may also have been other mediating or moderating effects that were not analyzed; for example, social relationships may be a factor. It is conceivable that employees and supervisors at a small community college may sometimes be personal friends outside of the workplace. Social relationships between employees and supervisors may have an impact on the perceptions of leadership, expressed by employees in surveys. The number of supervisors per employee may be a factor. In this sample, there were only 45 supervisors, who supervised between 1 and 45 persons each. If there had been more supervisors, there may have been more variance in leadership scores and the potential for more noticeable effects. Researchers interested in conducting longitudinal studies should consider collecting data across several organizations to increase variability in leadership behaviour. In study two, this particular issue was mitigated by including participants from many different organizations.

Limitations of study 1. Several limitations of the current study warrant mentioning. The most significant and predictable problem with longitudinal research is

sample size, which is always affected by drop-out rates. In the current study, 187 participants started the study, which is a sufficient, but not a large sample size for multivariate analyses. The number of participants dropped to 112 in the final survey leaving the sample size at a minimally acceptable number (Breckler, 1990) and reducing the power of analyses significantly. A larger starting sample size may have resulted in a larger sample over three or more waves of data collection. Second, this was an applied study with data collected from a group of people who were all employed at the same organization; therefore, between persons variance in perceptions of leadership is likely to be limited. Third, in the present study data were collected across very short time periods (i.e., one-week, and two-week); therefore any changes in leadership would be somewhat random and unpredictable. Over such short time periods, any changes in leadership are unlikely to elicit changes in well-being quickly enough to be detected, contrary to what has been suggested in previous studies.

Notwithstanding the limitations noted above, the present study provided strong support for the cross-sectional relationship between leadership and well-being, consistent with previous studies. This study also demonstrated that the inter-relationships between leadership and well-being are stable across short time periods. Finally, the present study suggests that the relationship between changes in leadership and changes in well-being may not be easily detected in daily and weekly sampling models.

Study 2 looks at the relationship between transformational leadership and employee well-being over eight months, with sampling across 2 four-month latency periods, using a structural equation modelling approach to latent variable growth curve analysis.

Study 2

The results of study 1 were consistent with previous research, finding a strong cross-sectional relationship between transformational leadership and well-being but providing inconclusive evidence of a longitudinal effect (c.f., Feldt et al., 2000; Nielsen et al., 2008; van Dierendonck et al., 2004). That is, there were no significant longitudinal effects of changes in leadership on changes in well-being over time. While previous research did not provide compelling guidance regarding latency periods between sampling, there were indications that longitudinal effects could be detected over short time frames (e.g., van Dierendonck et al., 2004). However, study 1 did not find longitudinal effects over one- or two-week time frames; therefore, the present study aims to extend the literature by looking at leadership and well-being over a time frame that has not yet been studied. Previous studies focused on latency periods of 18 months (Nielsen & Munir, 2009; Nielsen et al., 2008), 12 months (e.g., Heck & Hallinger, 2010; Tafvelin et al., 2011), and 6 months (e.g., Moyle, 1998); however, only one of them found longitudinal effects (i.e., Heck & Hallinger, 2010). In the present study, I wanted to see if the longitudinal effects could be detected if sampling occurred over what could be considered a moderate time period; that is, over latency periods of four months. Therefore, study 2 examined the relationship between leadership and well-being over an eight-month time frame with sampling taken across 2 four-month latency periods.

That is, individual growth curve modelling helps us to analyze the differences between individuals at the first wave of analysis (i.e., intercepts), the difference in rates of change over time (i.e., slopes), and the relationship between the two (i.e., between intercepts and slopes). The ability to analyze growth parameters is what sets growth curve

modelling apart from normal structural equation modelling techniques that are typically used. One of the most important advantages of individual growth curve modelling is that it can evaluate causal relationships between predictors and changes in outcome variables over time. Predictors can be categorical, continuous, time variant (i.e., changes over time), or time invariant (i.e., do not change over time; Shek & Ma, 2011). Growth curve models also have an advantage over random coefficient models in that they can model error, rather than assuming error is equal. Finally, individual growth curve models are a powerful method of modelling repeated measures because they can accommodate the modelling of the most appropriate (i.e., best-fitting) covariance structure for the data. One of the drawbacks of structural equation modelling is the need for large samples; however, in Study 2 a very large stratified sample was available; therefore, this was not a concern.

For study 2, I conducted analysis with Latent Variable Growth Curve Modelling using a Structural Equation Modelling approach. Latent growth curves can be analyzed a number of ways, including with random coefficient modelling (see study 1). However, for study 2 I applied a structural equation modelling approach using AMOS. There are a number of conditions that must be met in order to use structural equation modelling (Byrne, 2010). First, the outcome variable must be continuous. Second, all individuals must be measured at the same times (even though the times do not have to be evenly spaced). Third, data must be collected from each individual on at least three occasions. Fourth, the sample size must be large enough to detect person-level effects; i.e., at least 200 at each time point (Byrne, 2010). Notwithstanding these restrictions, there are at least two noteworthy advantages to using structural equation modelling, rather than other methods for longitudinal analysis (Byrne, 2010). First, this technique is based on mean

and covariance structures; therefore, it is designed to distinguish group effects found in means from individual effects, found in covariances. Second, structural equation models can model both observed and unobserved (i.e., latent) variables. This allows for the estimation of measurement error as well as latent intercepts (starting values) and slopes (Rates of change).

Many recent studies examining longitudinal relationships between leadership and well-being have used structural equation models. For example, Moyle (1998) used a structural equation modelling approach using EQS. Moyle (1998) constructed a cross-lagged model with indicators of managerial support and employee well-being, measured at three time periods, with 6-month latency periods between samples. Van Dierendonck et al. (2004) conducted a four-wave (cross-lagged) panel model using LISREL 8.5, and did not find significant longitudinal effects. Tafvelin et al. (2011) conducted a two-wave study of leadership and well-being using structural equation modelling in AMOS, finding no direct effect of transformational leadership on well-being over time. Several other studies have conducted two-wave designs using a structural equation modelling approach with LISREL 8.7 (Nielsen et al., 2008; Nielsen & Munir, 2009) and did not find longitudinal effects between leadership and well-being. I will extend the literature by employing latent variable growth curve modelling, using a structural equation modelling approach, to three wave longitudinal analysis of the relationship between leadership and well-being. This type of analysis has not been used to test the relationship between leadership and well-being to date.

Method

Participants. In Study 2, I analyzed archival data taken from the Nova Scotia

Stress Survey (Kelloway & Francis, 2006). Two thousand participants were recruited for

this study; randomly selected, using random digit dialing, from the population of working

Nova Scotia residents from all regions of the province. The sample was stratified to

represent the population based on the year 2000 census provided by Statistics Canada.

Ages ranged from 21 years to 77 years old.

Surveys were sent via mail (1700) and email (300); people were invited to

complete the survey three times, evenly spaced over a one year period (i.e., once every

four months). Of the 2000 people invited to participate, 1387 completed the survey at

Time 1(T1), 1032 at Time 2 (T2), and 915 at Time 3 (T3). Of those participants who

completed the survey at T1, 702 (50.6%) identified themselves as female and 685

(49.4%) identified themselves as male. Time 2 participants were 490 (47.5%) males and

542 (52.5%) females. Time 3 participants were 435 (47.5%) males and 479 (52.3%)

females.

Measures (Appendix B)

Transformational leadership. Transformational leadership was measured using

an adapted version of the 7-item Global Transformational Leadership Scale (Carless,

Wearing, & Mann, 2000). The adapted measure added two items to the original scale to

avoid double-barrelled questions, resulting in a 9-item unitary measure ($\alpha T1 = .90$; $\alpha T2 = .92$; $\alpha T3 = .97$) of transformational leadership (Kelloway, Hess, Francis, Catano, &

Flemming, In-preparation). Responses are rated on a Likert scale ranging from 1

(Strongly Disagree) to 7 (Strongly Agree).

Mental health. Mental health was measured with the General Health Questionnaire – 12 (Banks et al., 1980). The General Health Questionnaire – 12 is a 12-item self-administered screening test that detects minor psychiatric disorders (Banks et al., 1980). While intended as a unitary measure of general mental health, several studies have examined the factor structure of the GHQ, and argued for two-factor (e.g., Kalliath et al., 2004) or three-factor (e.g., Worsley & Gribbin, 1977) models. Common to both the two- and three-factor solutions are scales labelled anxiety-depression and social dysfunction. The current study employed the General Health Questionnaire – 12 as a unitary measure, using all 12 items (αT1 = .89; αT2 = .90; αT3 = .89). Responses were measured on a 7-point Likert scale ranging from 1 (Not at all) to 7 (All of the time). Higher scores indicated lower levels of general mental health.

Analysis

Data were examined using a structural equation modelling approach to latent growth curve modelling (McArdle, 1988). Latent growth curve modelling is a method of describing and explaining changes in variables of interest, including main effects, interaction effects, multi-level effects, etc. Latent growth curve modelling can be accomplished using hierarchical (i.e., multi-level) modelling or structural equation modelling techniques. In its simplest application, latent growth curve modelling examines the intercepts (outcome scores at the start of the curve), and the slope of the curve, i.e., the mean rate of change of the outcome variable over time. Latent growth curve models estimate intercepts and slopes as latent variables. This is accomplished by estimating means (average intercept or slope across people) and variance (indicator of individual differences) of intercept and slope latent variables. If significant variances are detected in

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the intercept or the slope, further analysis is warranted to examine potential predictor variables. One of the more powerful applications of latent growth curve modelling is predicting intercepts and slopes of one growth curve by the intercepts and slopes of another growth curve; that is the aim of the current study. In the present study, growth curves were estimated separately for leadership and well-being across three time periods, and the relationship between growth curves was examined.

Latent growth curve models are comprised of two sub-models (Willett & Sayer, 1994). The level one model is similar to a within-person regression model that looks at individual change over time, observed in two single outcome variables. In the present study leadership and employee well-being were the variables of interest. The level two model can be thought of as a between-subjects design that looks at inter-individual differences with respect to the outcome variables. The first step in developing the current latent growth curve model was to determine the extent and direction in which individual scores on leadership and well-being change over time. A critical part of this stage is to properly specify and test the latent growth curve model, which requires a priori knowledge of the growth trajectory (i.e., linear, quadratic, etc.). If the trajectory is linear, two growth parameters will be specified; an intercept, which represents individual scores on outcome variables at Time 1, and a slope, which represents individuals' rates of change over the specified time period on the outcome variables of interest. In the present study, the intercepts represent employees' perceptions of their supervisors' leadership style and their self-reported personal well-being at Time 1. The slopes in this study represent the rate of change in leadership and well-being scores across the three time periods.

All analyses in the present study were conducted using the Statistical Package for

the Social Sciences (SPSS) version 15 and AMOS version 7 (Arbuckle, 2008). Goodness

of fit for the growth curve model was tested using the Chi Square, (Hu & Bentler, 1999),

Comparative Fit Index (CFI; Bentler, 1990) and the root mean square error of

approximation (RMSEA; Hu & Bentler, 1999). CFI values range from 0 to 1.0 and values

above .95 indicate good fit (Hu & Bentler, 1999). RMSEA values of .08 or lower suggest

a reasonably good fit, and values below .05 indicate close (i.e., very good) fit (Hu &

Bentler, 1999).

Multivariate latent growth curve model; measurement model. Also known as

an associative model, multivariate latent growth curve models have the ability to evaluate

whether or not development in one variable (e.g., well-being) is associated with

development in another variable (such as leadership) (Duncan & Duncan, 2004). The first

step was to specify and test the measurement model, focussing on the relationships

between observed variables and their underlying latent factors. For the present study, I

constructed a dual-domain model to look at the growth curves of transformational

leadership and well-being simultaneously (see figure 8).

The six rectangular boxes represent observed scores for transformational

leadership and well-being. The error terms (E1 – E6) connected to each observed variable

represent random measurement error for each scale at each time, and variances were left

to be freely estimated from the data. The variables enclosed in circles across the bottom

of the model represent the unobserved latent intercept and slope factors for each growth

curve. The intercepts represent the score on each variable at time 1, and since it remains

the same across the three time periods, the regression path between each variable and its

corresponding intercept is constrained to the same value, in this case 1. The intercepts

also contain information about the sample means and covariances, which were estimated

from the data. The slopes represent the growth trajectory of each variable, in this case

both assumed to be linear; therefore, the regression weights are set at 0, 1, and 2 for time

1, 2, and 3 respectively (Byrne & Crombie, 2003). Sample means and covariances were

also estimated for the slopes. In this multiple-domain model, intercepts and slopes were

all assumed to be correlated, and, therefore, were allowed to covary (Duncan & Duncan,

2004).
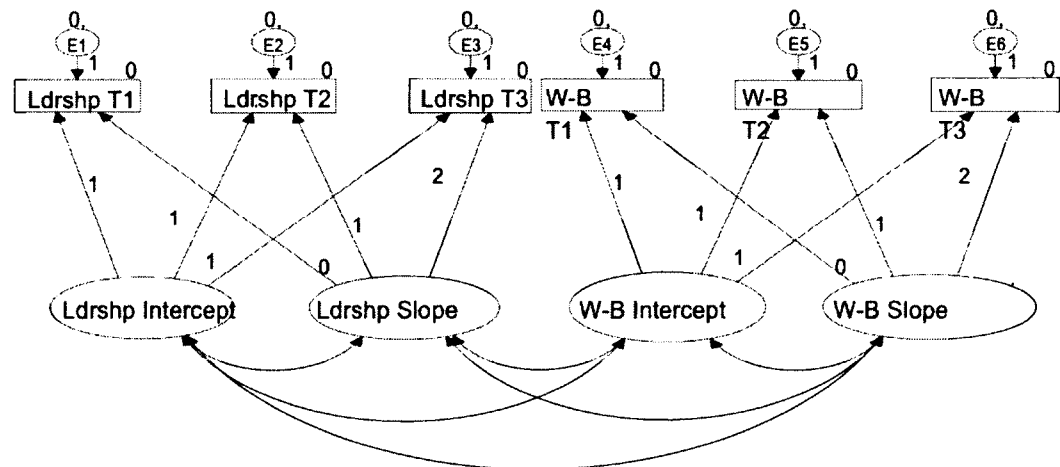
Figure 8. Multivariate three-wave linear growth curve (LGM) model of
transformational leadership and well-being; measurement model.
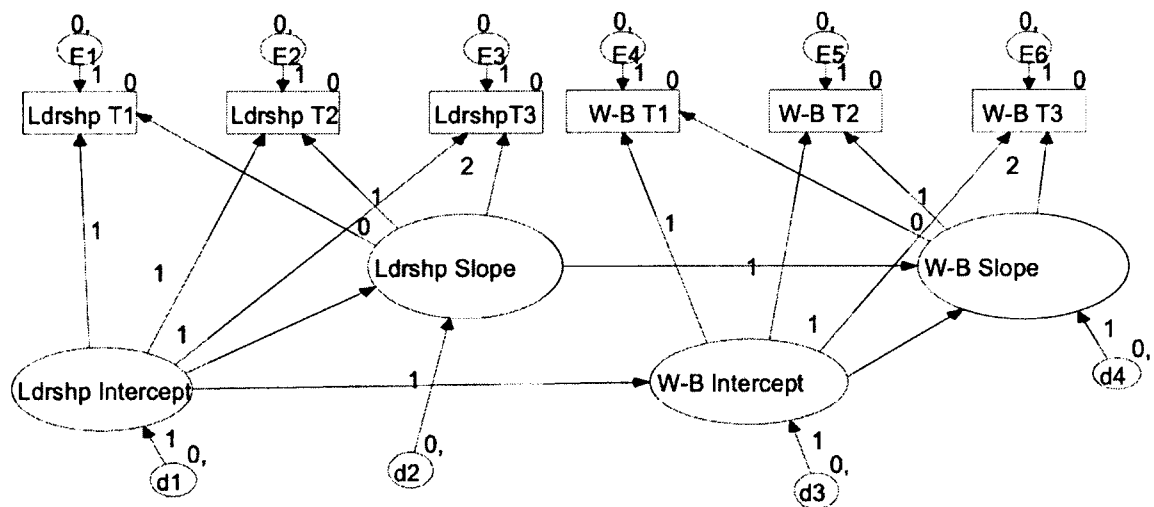
Figure 9. Multivariate three-wave LGM model predicting well-being from transformational leadership; structural model

Predictor model. To test whether or not leadership and well-being were related over time, I constructed a multivariate latent growth curve model with paths between latent factors (figure 9). Paths from intercept to slope of each variable tested whether initial levels predicted rates of change. To test the cross-sectional relationship between leadership and well-being, a path was added from Leadership Intercept to Well-being Intercept. The path from Leadership Slope to Well-being Slope tested the relationship between growth curves; i.e., the relationship between changes in transformational leadership and changes in well-being.

Results

Descriptive statistics and correlations are presented in table 6. Mean scores were calculated for leadership and well-being across three time periods. It should be noted that mental health scores (i.e., on the General Health Questionnaire) are reverse scored; that is, lower scores reflect more positive well-being.

Measurement model

Goodness of fit statistics for the hypothesized measurement model (Figure 1) suggested an excellent fit to the data χ^2 (7, N = 712) = 14.07, p = .05 (CFI = .99, RMSEA = .038, PCLOSE = .73). Next we want to know the sample mean starting values and sample mean changes in leadership and well-being. Factor means represent the sample mean starting point and the sample mean change over time. Looking at the factor means (Table 7), it can be seen that all were significant except for the slope related to leadership. The mean starting score for leadership was 4.34 and the sample mean starting score was 2.92 for well-being. Scores on well-being decreased by an average of .04 (p < .01) over eight months; however, the overall mean increase in transformational leadership was less clear (mean = .03, ns).

Table 6

Descriptive Statistics and Correlations for Leadership and Well-Being Across Three Time Periods (n = 712)

	Mean	Sd	1	2	3	4	5
1. Leadership at Time 1	4.36	1.57					
2. Leadership at Time 2	4.33	1.56	.71				
3. Leadership at Time 3	4.41	1.51	.60	.71			
4. Well-being at Time 1	2.92	1.03	-.34	-.29	-.23		
5. Well-being at Time 2	2.89	1.03	-.28	-.31	-.25	.77	
6. Well-being at Time 3	2.84	1.02	-.23	-.26	-.30	.70	.75

All correlations are significant at p < .01.

Substantiation for conducting latent variable growth curve (predictive) analyses is based on a thorough evaluation of factor means, variances and covariances of the measured variables (i.e., the measurement model). It is the analysis of both individual and group-level factors that makes latent growth modelling unique (Duncan, Duncan &

Strycker, 2006). The first step is to analyze each repeated measure separately to determine whether they increase, decrease or remain unchanged over time. The next step is to determine from the univariate models whether there are sufficient inter-individual differences in intercepts and slopes to justify conducting a latent growth curve model. If intercept and slope factor variances are significantly different from zero, latent growth curve modelling is warranted. As described above, the analysis of factor means showed that the average change in well-being was significant over the three time periods; however, the average change in leadership was not significant. This is not surprising as leadership scores decreased between time 1 and time 2 and then increased between time 2 and time 3. More importantly, all factor variances (table 8) were significant, indicating the presence of significant inter-individual differences in initial status (intercepts) and in rates of change (slopes). The significant covariances (table 9) among factors suggest that leadership and well-being are indeed inter-related in a number of ways. Therefore, even though there does not appear to be a significant linear change in leadership over time, these results provide the required substantiation to investigate explanations for the variability in intercepts and growth trajectories through latent variable growth curve modelling (Duncan et al., 2006).

Table 7

Study 2, Measurement Model Means

	Mean	S.E.	P
Leadership Intercept	4.34	.058	***
Leadership Slope	.030	.026	.253
Well-being Intercept	2.92	.038	***
Well-being Slope	-.040	.015	.007

*** p < .001.

Table 8

Study 2, Measurement Model Variance

	Estimate	S.E.	P
Leadership Intercept	2.05	.15	***
Leadership Slope	.28	.05	***
Well-being Intercept	.89	.07	***
Well-being Slope	.07	.02	**

** P <.01, *** P < .001.

Factor covariance estimates in this model were all found to be significant (table 9). Significant covariance between intercepts and slopes within domains suggest that rates of change are related to initial levels; that is, for both Transformational Leadership and well-being, significant negative estimates suggest that higher initial scores are related to slower rates of change over time and this was more prevalent for leadership (mean = -.32) than for well-being (mean = -.08). The significant between-domain covariance estimates suggest that leadership and well-being are highly inter-related. Leadership and well-being were moderately correlated at time 1 (r = -.41, p < .05) suggesting, that stronger scores on Transformational Leadership were associated with more positive well-being. Rates of change were more strongly correlated (r = -.52, p < .05), indicating that, as the rate of change for leadership increased, the rate of change for well-being decreased. In addition, high scores on leadership at time 1 were associated with strong rates of change for well-being (r = .25, p < .05), and high scores on well-being at time 1 (i.e., more negative well-being) were related to a strong rate of change for leadership (r = .20, p < .05).

Table 9

Study 2, Measurement Model, Covariance

		Estimate	S.E.	P
Within-domain covariance				
Leadership Intercept	Leadership Slope	-.32	.07	***
Well-being Intercept	Well-being Slope	-.08	.03	**
Between-domain covariance				
Leadership Intercept	Well-being Intercept	-.56	.06	***
Leadership Intercept	Well-being Slope	.09	.02	***
Leadership Slope	Well-being Slope	-.07	.01	***
Leadership Slope	Well-being Intercept	.10	.03	***

*** p < .001, ** P < .01.

Predictor model

To further investigate the relationships between leadership behaviours of supervisors and employee well-being, paths were added between intercepts and slopes of the latent variables (figure 10). This model tested the hypotheses that leadership at time 1 (leadership intercept) predicts the rate of change of leadership over time (leadership slope) and employee well-being at time 1 (well-being intercept); well-being at time 1 (well-being intercept) predicts the rate of change in well-being over time (well-being slope); and, the rate of change of leadership (leadership slope) predicts the rate of change of employee well-being (well-being slope). Fit indices indicate that the model was a very good fit to the data, $\chi^2 (9) = 15.13$, p = .09 (CFI = .997, RMSEA = .031, PCLOSE = .871).

Figure 10 presents the final model. As expected the rate of change for each variable is predicted by the score reported at time 1. In addition, well-being scores reported at time 1 are predicted by leadership scores at time 1. Of greatest interest was whether or not changes in leadership would predict changes in well-being, and in fact, the growth trajectory of leadership was significantly related to the growth trajectory of well-being.
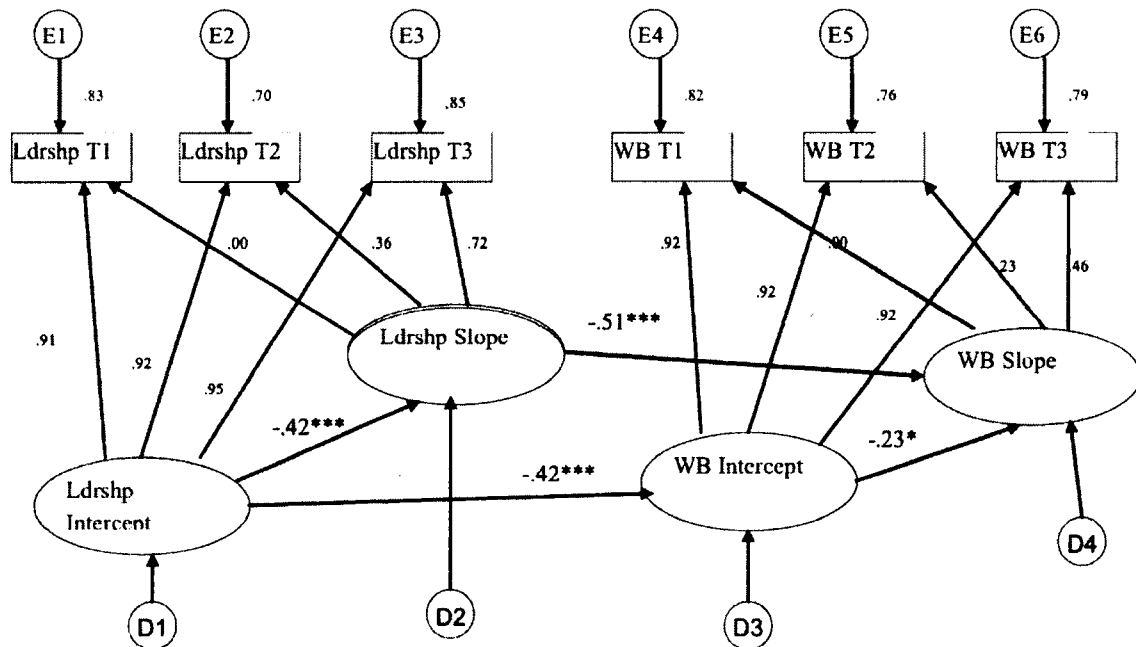

Figure 10. Study 3, predictor model - final model (standardized estimates).

Discussion (study 2)

The results of study 2 add to the extant literature in a number of ways. While the relationship between transformational leadership and well-being has been established in cross-sectional studies (e.g., Arnold et al., 2007; Bono et al., 2007; Sosik & Godshalk,

2000), very few studies have looked at these relationships in true longitudinal designs. Of the few longitudinal studies that were reviewed, most of them either limited observations to two time periods (e.g., Nielsen et al., 2008; Nielsen & Munir, 2009), which technically cannot detect longitudinal effects, or were multi-wave studies (i.e., more than two-wave) that did not find predictive relationships over time (e.g., Moyle, 1998; van Dierendonck et al., 2004). In addition, all studies to date have either employed a form of cross-lagged analysis or some version of structural equation modelling that did not include the modelling of latent growth parameters. The present study is the first to apply structural equation modelling techniques to latent growth curve modelling in a multi-wave study.

The current study provides strong evidence for the hypothesized relationship between transformational leadership and employee well-being, supporting all four hypotheses. The significant variance estimates for scores at time 1 and for growth trajectories in both leadership and well-being suggest that there were strong individual differences in those variables, and provided substantiation for further investigation of causality. *Therefore, hypotheses 1, 2, and 3 are all supported.* In addition, as expected, the significant path between the leadership slope and the well-being slope suggests that changes in leadership predict changes in well-being, providing support to my fourth hypothesis.

It is not surprising that changes in leadership are related to changes in well-being; however, it is surprising that faster rates of change in leadership are associated with slower rates of change in well-being. This seems odd at first glance; however, upon reflection it makes perfect sense. Previous research has shown that low levels of general mental health do not tend to improve quickly (Sanchez & Viswesvaran, 2002; see also

study 1); therefore, it is plausible that there is a lag effect where mental health improves after leadership has improved. In addition, it makes sense that if mental health is poor as a result of poor leadership, there may be a lack of trust between employees and supervisors that would cause employees to be skeptical when a leader suddenly appears to be changing their behaviour. In fact this supposition is supported by Kelloway et al. (2012), who found that trust in leadership fully mediates the relationship between transformational leadership and employee well-being. Future research should investigate trust as a covariate of the relationship between the changes in leadership and changes in well-being in longitudinal analyses.

These findings provide support for the Job Demands-Resources model, as expected. The Job Demands-Resources model proposes that resources act as a buffer between job demands and stress/strain outcomes. Higher levels of transformational leadership were associated with better well-being; therefore, if we accept that leadership is a resource for employees, then it appears as though good leadership may act a as buffer to the effects of job (and other) demands on well-being. By extension, it is implied that poor leadership is likely to be a risk factor to stress and strain. This is suggested in previous research where passive (e.g., Kelloway et al., 2006) and abusive (e.g., Schat, Frone, & Kelloway, 2006) leadership were related to decreased employee well-being. Future research should look at the effects of the full range of leadership (i.e., transformational, passive and abusive leadership) on employee well-being to test the hypothesis that leadership behaviour can be a buffer between job demands and stress or strain, or it can be a risk factor that exacerbates the problem.

General discussion

The implications of these two studies are important to both the science and practice of Industrial and Organizational (I/O) Psychology, extending what we know about the relationship between transformational leadership and employee well-being. The current study replicated what has been found in the empirical literature; that is, the cross sectional relationship between leadership and well-being and the autoregressive relationship between starting values and later values of both variables.

I extended the literature in several ways. First, I showed that higher initial levels of leadership are associated with slower rates of change in leadership, and lower initial levels of well-being are associated with slower rates of change in well-being. These findings are new to the literature, but not surprising. Based on the law of diminishing returns, or perhaps simple logic, it makes sense that leaders who demonstrate high levels of transformational leadership to start with, have less room for improvement and will likely improve more slowly than a leader who has much room to improve and is motivated (or trained) to do so. It also seems plausible that employees who are in poor general mental health to start with may be more likely to improve slowly, if at all; whereas, if they are experiencing moderate to higher levels of well-being to start with, perhaps they have the energy and positive attitude required to improve at a stronger rate. I also extended what we know about the relationship between transformational leadership and employee well-being by showing that there is a longitudinal relationship, whereby rates of change in transformational leadership are significantly inversely related to rates of change in general mental health. This is a significant finding in its own right, and it presents another important research question. That is, if well-being changes at a slower

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rate than leadership, we would expect the changes in well-being to follow; however, we do not know by how much. This finding also begs the question of why changes in well-being lag behind changes in leadership; I believe this may be related to trust. Future studies should compare the amount of change in leadership and well-being over time, paying attention to the lag effect, and incorporating trust as a covariate.

The present set of studies also provide some insights into an area of research that has not been well developed; that is, looking at the appropriate time frame for longitudinal studies of the relationship between leadership and well-being. Previous studies employed a somewhat random selection of time frames and latency periods in their research designs, ranging from 5 months between samples (i.e., van Dierendonck et al., 2004) to 4 years (Dormann & Zapf, 2002). There does not appear to have been any real theoretical basis for selecting time frames in previous studies, and in fact most appeared to be based on more pragmatic considerations such as alignment with a school year (e.g., Heck & Hallinger, 2010), a calendar year (e.g., Tafvelin et al., 2011) or using archival data. Researchers have recommended using short time periods as low as 1 week (e.g., Kelloway et al., 2006; Tafvelin et al., 2011; van Dierendonck et al., 2004), and longer time periods up to 2 years (e.g., Dormann & Zapf, 2002). I chose to look at three different time frames in an exploratory manner, employing one-week, two-week, and eight-month time periods with latency periods between measurements of two days, seven days and four months. The results suggest that longitudinal effects of leadership on well-being are more likely to be detected over a 4-month time period, than a 1-week or 2-week period; however, future research should take a more methodical approach to build a theory and model of the longitudinal relationship between leadership and well-being.

Some issues that should be considered are the individual and organizational factors (i.e., covariates) associated with changes in leadership and well-being, including factors that may affect the timelines for the study.

Another question arising from these studies is, relates to what is the most appropriate indicator/measure of well-being. In Study 1 I employed a short measure of anxiety-depression to represent general mental health and a measure of job-related affect to see where the greatest effect would be found over short periods of one and two weeks; however, neither score changed significantly over time. Other researchers have suggested that changes in well-being take time (e.g., Sanchez & Viswesvaran, 2002), and perhaps the short one- and two-week time frames were just not long enough to detect such changes. It is not clear why neither measure appeared to be affected by changes in leadership; however, this should be investigated in future research. For study 2, I used a measure of general mental health as an indicator of well-being, since the time frame being tested was over 8 months with 4-month latency periods between surveys. As expected well-being significantly improved over each 4 month period, suggesting that an overall measure of general mental health is sensitive enough to detect changes over 4 month periods. Future research should try to gather data over extended periods (i.e., several weeks) with frequent sampling (i.e., daily), using a battery of well-being measures found in the literature.

The current research also provides strong support for the use of true longitudinal analysis techniques with at least three-wave data, as opposed to two-wave, cross-lagged or traditional structural equation modelling techniques. While the random coefficient modelling approach did not result in significant longitudinal effects, it did provide a

robust description of the relationships between leadership and well-being that is not possible with other methods, particularly with a relatively small sample size. For example, several studies examined the cross-sectional and autoregressive relationship between measures of leadership (or outcomes of leadership) at time 1 and at later times in longitudinal studies; however, none of those studies looked at the relationship between starting values (intercepts) of leadership (or leadership outcomes), and the rates of change (slopes) in those variables over time. In study 2, I used structural equation modelling to analyze the relationships between intercepts and slopes and to analyze the relationship between changes in leadership and changes in well-being, resulting in the detection of significant longitudinal effects that have not been detected before. Structural equation modelling requires a larger sample size than regression analysis; therefore, it is often not possible to use that technique. However, it is one of the very few methods that can model the relationship between two changing variables over time, through latent intercepts and slopes. Therefore, researchers are encouraged to try to find ways of gatherring sufficient longitudinal data to use the structural equation modelling approach to latent variable growth curve analysis.

The previous research and the current studies together serve to illuminate the problem explained by Ployhart and Vandenberg (2010); that is, regarding the lack of theory building that has taken place in the area of longitudinal research (e.g., Ployhart & Vandenberg, 2010). True longitudinal research is primarily focused on describing and explaining changes in variables of interest over time (Kelloway & Francis, in press; Ployhart & Vandenberg, 2010). This implies a number of theoretical and technical issues in longitudinal research design (Kelloway & Francis, in press); for example, researchers

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must establish a priori expectations of change in variables. These "theories" should consider the expected direction (positive, negative, or no change), shape (non-linear, linear, curvilinear), timing and duration (when will change occur and how long will it persist), and causes of change (Ployhart & Vandenberg, 2010). Similar theories should be developed regarding the relationships between variables (Pitariu & Ployhart, 2010). Kelloway and Francis (in press) advocate for incorporating a conceptualization of change when developing theories in occupational health psychology, where currently little guidance is provided for planning longitudinal research. Theories should provide guidance on issues such as the number of observations, the timing between observations, the day of the week, or perhaps the time of the year that are appropriate to detect real relationships and changes over time (Ployhart & Vandenberg, 2010). When researchers do not understand the nature of change in the construct of interest, they may spend a great amount of time and effort taking measurements at times when change should not have been expected and in so doing, will have misleading results.

I agree with Kelloway and Francis (in press) who recommend that more descriptive studies of change are required to build a more thorough understanding of the nature and timing of change in variables of interest, such as leadership and well-being. There is a clear need for descriptive longitudinal studies of leadership and well-being to develop a theoretical model of the various factors that may be related to changes in leadership and changes in well-being. For example, we do not really know how long it should take to see changes in leadership or well-being; however, we do know quite a bit about the covariates of both leadership and well-being, so perhaps we just need to structure longitudinal studies incorporating what we already know. The results of the present set of studies

suggest that the longitudinal effects of leadership on well-being are more likely to be detected over an 8 month period than over one or two weeks; however, I do not know why. Perhaps the day of the week is an important factor when asking employees about their well-being or their supervisors' leadership style. Future studies should take a methodical approach to developing and testing theories on the timing associated with changes in leadership and well-being. The literature to date assumes that leadership styles change from time to time, but there is not much to tell us why that is or when it should occur. Without an understanding of why leadership styles may change, it is impossible to infer when to expect to see changes and what time frames may be associated with those changes. In the absence of such guiding theory, future research should focus on developing quasi-experiemental designs where leadership behaviour is manipulated, such as through provision of training to an experimental group, while collecting data over extended periods of time (i.e., several years) with frequent repeated measurements in a diary study format. Such a study would help to develop theoretical models which could then be tested in a rigorous and organized fashion.

The present research was based on an assumption that transformational leadership is a valuable resource that has the potential to mitigate the effects of high job demands on employee well-being. My results appear to support that assumption; that is, transformational leadership was clearly related to employee well-being, suggesting that it mitigates the negative impact of high job demands on well-being. While these results provide some support for the job demands resources model, it is an incomplete test of the model, since I did not include measures of job demands as a part of this study. Future

studies should include measures of job demands to examine the effect of transformational leadership as a buffer between job demands and well-being outcomes.

Limitations

Like most studies, there are a few limitations that should be considered. In fact, all of the suggestions above, related to what is lacking in the theoretical understanding of leadership and well-being, are also limitations in this study. Because there was no clear guidance in the literature regarding time frames and latency periods, those were selected based on the very limited recommendations in the literature and may not have been ideal to detect changes in leadership or well-being. The biggest challenge in longitudinal analysis is survey participant drop out and this study faced that challenge as well. Starting with almost 200 participants in study 1, I ended up with less than 100 participants in my smallest group, which severely limited my ability to detect significant results. In order to minimize the chance of drop out, surveys were designed to be as short as possible; however, in doing so, short measures of general mental health and job-related affect were used, which may not be the best measures of those constructs. All data are from self report measures, which are always subject to a number of biases including perceptual errors. While self report measures of personal well-being are relatively reliable, the questions regarding perceptions of supervisor leadership behaviours and styles could be prone to more error and bias. Transformational Leadership was measured as a unitary construct in this study, based on recommendations from the literature (e.g., Bass, 1985; Judge & Piccolo, 2004); however, it would be interesting to see if the multiple dimensions of transformational leadership are better predictors of well-being than the overall measure. Indeed the present research focused only on Transformational

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Leadership; however, it is possible that poor leadership is the better predictor of well-being. Future studies should consider looking at the full range of leadership and its relationship with employee well-being. Sample sizes are always a challenge when conducting complex analyses. The sample size in Study 2 was very good and presents no concerns at all; however, in Study 1 the sample size is a significant limiting factor, with a very small (n = 94) number in the smallest group.

Conclusions and practical implications

    I believe the current set of studies make a sound contribution to the scientific literature, but, perhaps as importantly, I believe these findings have important significance to organizational leaders and practitioners. The present research demonstrates that transformational leadership behaviours result in employee well-being and all of the positive effects of a healthy workplace. Previous research found that some of the most commonly reported sources of work stress are heavy workload, role ambiguity, and lack of recognition for good work (Kelloway & Francis, 2006). All of the sources of stress listed above are related to (poor) leadership, or low levels of transformational leadership. It is common for organizations to spend a significant amount of money on stress management training and interventions for employees; however, this study suggests that employers may be better off investing in developing their leaders. If employers invest the time and money to provide current leaders with training and developmental opportunities to improve their Transformational Leadership style, it will pay off with employee well-being and a healthy workplace. That notwithstanding, the present research also shows that changes in well-being take time. Employers should not expect leadership training to result in immediate changes in well-being. Supervisors

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should not notice improvements to employee well-being until some time after their leadership behaviours improve; therefore, they should not be discouraged when they do not see immediate changes in employee well-being. In order to maximize the positive impact of transformational leadership, without noticing the lagging improvements to well-being, the best strategy may be to develop a culture of leadership excellence, where leaders are continually working on developing and improving transformational leadership behaviours.

I have shown that transformational leadership is related to employee well-being and that improvements to transformational leadership will result in improved well-being. Indeed, previous research showed that training in transformational leadership does in fact result in improved transformational leadership behaviours (e.g., Barling, Weber, & Kelloway, 1996). It is well known that proactive organizations invest heavily in leadership training, often without the means to quantify the return on investment. The current research provides a way to validate organizational efforts to develop leaders, simply by measuring transformational leadership and organizational outcomes, such as well being, individual and organizational performance, before and at several times after training to monitor improvements that may have been attributed to the training.

Clearly there is a need for additional longitudinal studies of the relationship between leadership and well-being. Future studies should examine leadership and well-being over longer periods of time, such as two or three years, using a diary study methodology to take frequent samples at regular intervals, such as monthly or even weekly. Leadership should be measured based on the full range of leadership styles to investigate which leadership styles are the best predictors of well-being and several well-

being measures should be administered, such as affect / mood, and general mental health, to see what measures are most likely to detect changes over the various time frames. In addition, longitudinal investigations of leadership and well-being should include a leadership training intervention, so that there is an a priori reason to expect changes in leadership over at least one time frame during the study. Finally, future research should use sound analytical techniques, such as random coefficient modelling or structural equation modelling when the data allow it.

The current research extends the empirical literature by demonstrating that there is a clear longitudinal effect of leadership on employee well-being. However, some of the results leave us with more questions than answers. Therefore, scientists and practioners are urged to take the lessons learned in this study and move the yardstick further by building on what we know about the relationship between transformational leadership and employee well-being.

References

Arbuckle, J. L. (2008). *AMOS 17 users guide*. Chicago: SPSS Inc.

Arnold, K. A., Turner, N., Barling, J., Kelloway, E. K., & McKee, M. C. (2007).

Transformational leadership and psychological well-being: The mediating role of

meaningful work. *Journal of Occupational Health Psychology, 12*(3), 193-203.

Ashforth, B. (1994). Petty tyranny in organizations. *Human Relations, 47*(7), 755-778.

Ashforth, B. E. (1997). Petty Tyranny in Organizations: A Preliminary Examination of

Antecedents and Consequences. *Canadian Journal of Administrative Sciences /*

Revue Canadienne des Sciences de l'Administration, 14(2), 126-140.

Bakker, A.B., & Demerouti, E. (2007). The job demands-resources model: state of the art.

Journal of Managerial Psychology, 22, 3, 309-328.

Bakker, A.B., Demerouti, E., Taris, T., Schuafeli, W.B., & Schreurs, P. (2003). A multi-

group analysis of the job demands-resource model in four homecare

organizations. International Journal of Stress Management. 10, 16-38.

Bakker, A.B., Van Veldhoven, M., & Xanthopoulou, D. (2010). Beyond the demand-

control model: thriving on high job demands and resources. *Journal of Personnel*

Psychology, 9, 1, 3-16.

Bamberger, P. A., & Bacharach, S. B. (2006). Abusive supervision and subordinate

problem drinking: Taking resistance, stress and subordinate personality into

account. *Human Relations, 59*(6), 723-752.

Barling, J., Christie, A., & Hoption, A. (2010). Leadership. In S. Zedeck et al (Ed.)

Handbook of Industrial And Organizational Psychology. Washington, DC:

American Psychological Association.

Banks, M. H., Clegg, C. W., Jackson, P. R., Kemp, N. J., Stafford, E. M., & Wall, T. D.

   (1980). The use of the General Health Questionnaire as an indicator of mental

   health in occupational studies. *Journal of Occupational Psychology, 53*(3), 187-

   194.

Barling, J., Loughlin, C., & Kelloway, E. K. (2002). Development and test of a model

   linking safety-specific transformational leadership and occupational safety.

   Journal of Applied Psychology, 87, 488.

Barling, J., Weber, T., & Kelloway, E. K. (1996). Effects of transformational leadership

   training on attitudinal and financial outcomes: A field experiment. *Journal of*

   Applied Psychology, 81(6), 827-832.

Bass, B., M., & Avolio, B., J. (1990). *Transformational leadership development: Manual*

   for the Multifactor Leadership Questionnaire. Palo Alto, CA: Consulting

   Psychologists Press.

Bass, B. M. (1985). *Leadership and Performance Beyond Expectations*. New York: Free

   Press.

Bass, B. M. (1997). Does the transactional-transformational leadership paradigm

   transcend organizational and national boundaries? *American Psychologist, 52*(2),

   130-139.

Bass, B. M., Avolio, B. J., Jung, D. I., & Berson, Y. (2003). Predicting unit performance

   by assessing transformational and transactional leadership. *Journal of Applied*

   Psychology, 88(2), 207-218.

Bentler, P. M. (1990). Comparative fit indices in structural models. *Psychological*

   Bulletin, 107, 238-246.

Bliese, P.D., & Ployhart, R.E., (2002). Growth modelling using random coefficient modelling: model building, testing, and illustrations. *Oragnizational Research Methods*, 5 (4), p362- 387.

Bono, J. E., Foldes, H. J., Vinson, G., & Muros, J. P. (2007). Workplace emotions: The role of supervision and leadership. *Journal of Applied Psychology, 92*(5), 1357-1367.

Breaux, D. M., Perrewé, P. L., Hall, A. T., Frink, D. D., & Hochwarter, W. A. (2008). Time to try a little tenderness? The detrimental effects of accountability when coupled with abusive supervision. *Journal of Leadership & Organizational Studies, 15*(2), 111-122.

Breckler, S.J. (1990). Applications of covariance structure modeling in psychology: Cause for concern? *Psychological Bulletin*, 107(2), 260-273.

Burns, J. M. (1978). *Leadership*. New York: Harper & Row.

Burton, J. P., & Hoobler, J. M. (2006). Subordinate Self-esteem and Abusive Supervision. *Journal of Managerial Issues, 18*(3), 340-355.

Bycio, P., Hackett, R. D., & Allen, J. S. (1995). Further assessments of Bass's (1985) conceptualization of transactional and transformational leadership. *Journal of Applied Psychology, 80*(4), 468-478.

Byrne, B.M. (2010) Structural equation modelling with AMOS: Basic concepts, applications and programming. New York: Routledge.

Byrne, B. M., & Crombie, G. (2003). Modeling and testing change: An introduction to the latent growth curve model. *Understanding Statistics, 2*(3), 177-203.

Byrne, B. M., Lam, W. W. T., & Fielding, R. (2008). Measuring patterns of change in personality assessments; An annotated application of latent growth curve modelling. *Journal of Personality Assessment, 90*(6), 536-546.

Carless, S. A., Wearing, A. J., & Mann, L. (2000). A Short Measure of Transformational Leadership. *Journal of Business and Psychology, 14*(3), 389-405.

Caza, B. B., & Cortina, L. M. (2007). From insult to injury: Explaining the impact of incivility. *Basic and Applied Social Psychology, 29*(4), 335-350.

Chan, D. (1998). The conceptualization and analysis of change over time: An integrative approach incorporating longitudinal mean and covariance structures analysis (LMACS) and multiple indicator latent growth modeling (MLGM). *Organizational Research Methods, 1,* 421-483.

Chan, D. (2011). Advances in analytical strategies. In S.Zedeck (Ed.) *APA Handbook of Industrial and Organizational Psychology: Volume 1 Developing and Building the Organization.* Washington, DC: APA Books.

Cook, T.D. & Campbell, D.T. (1979). *Quasi-experimentation: Design and analysis for field settings.* Boston: Houghton Mifflin

Day, R. C., & Hamblin, R. L. (1964). Some Effects of Close and Punitive Styles of Supervision. *The American Journal of Sociology, 69*(5), 499-510.

Deci, E.L., & Ryan, R.M., (1985). *Intrinsic motivation and self determination in human behaviour.* New York: Plenum Press.

De Jonge, J., & Kompier, M.A.J., (1997). A critical examination of the demand-control-support model from a work psychological perspective. *International Journal of Stress Managament, 4,* 235-258.

Demerouti, E., Bakker, A.B., Nachreiner, F., & Schaufeli, W.B. (2001). The job

demands-resources model of burnout. Journal of Applied Psychology, 86, 499-

512.

Den Hartog, D. N., Van Muijen, J. J., & Koopman, P. L. (1997). Transactional versus

transformational leadership: An analysis of the MLQ. *Journal of Occupational*

and Organizational Psychology, 70(1), 19-34.

Dormann, C., & Zapf, D. (2002). Social stressors at work, irritation and depressive

symptoms: accounting for unmeasured third variables in a multi-wave study.

Journal of Occupational and Organizational Psychology, 75, 33-58.

Duffy, M.K., Gangster, D., & Pagon, M. (2002). Social undermining in the workplace.

Academy of Management Journal, 45, 331 – 351.

Duncan, T. E., & Duncan, S. C. (2004). An introduction to latent growth curve modeling.

Behavior Therapy, 35(2), 333-363.

Duncan, T. E., Duncan, S. C., & Strycker, L.A. (2006) *An introduction to latent variable*

growth curve modelling; concepts, issues, and applications. London: Lawrence

Earlbaum Associates.

Dvir, T., Eden, D., Avolio, B. J., & Shamir, B. (2002). Impact of Transformational

Leadership on Follower Development and Performance: A Field Experiment. *The*

Academy of Management Journal, 45(4), 735-744.

Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information

maximum likelihood estimation for missing data in structural equation models.

Structural Equation Modeling, 8(3), 430-457.

Felblinger, D. M. (2008). Incivility and bullying in the workplace and nurses' shame responses. *Journal of Obstetric, Gynecologic, & Neonatal Nursing: Clinical Scholarship for the Care of Women, Childbearing Families, & Newborns, 37*(2), 234-242.

Feldt, T., Kinnunen, U., & Maunao, S. (2000). A mediational model of sense of coherence in the work context: A one-year follow-up study. *Journal of Organizational Behavior, 21*(4), 461-476.

Ferris, G. R., Zinko, R., Brouer, R. L., Buckley, M. R., & Harvey, M. G. (2007). Strategic bullying as a supplementary, balanced perspective on destructive leadership. *The Leadership Quarterly, 18*(3), 195-206.

Fried, Y., & Ferris, G.R., (1987). The validity of the job characteristics model: a review and meta-analysis. Personnel Psychology, 40, 287-322.

Gilbreath, B., & Benson, P. G. (2004). The contribution of supervisor behaviour to employee psychological well-being. *Work & Stress, 18*(3), 255-266.

Gilbreath, J. B. (2001). *Supervisor behavior and employee psychological well-being.* ProQuest Information & Learning, US.

Gold, M. S., & Bentler, P. M. (2000). Treatments of missing data: A Monte Carlo comparison of RBHDI, iterative stochastic regression imputation, and expectation-maximization. *Structural Equation Modeling, 7*(3), 319-355.

Grandey, A.A., Kern, J., & Frone, M. (2007). Verbal abuse from outdsiders versus insiders: Comparing frequency, impact on emotional exhaustion, and the role of emotional labour. *Journal of Occupational Health Psychology, 12,* 63 – 79.

Gunderson, G., Hellesoy, B.T., & Reader, S. (2012). Leading international project teams: The effectiveness of transformational leadership in dynamic work environments. *Journal of Leadership and Organizational Studies*, 19, (1) 46-57.

Hackman, J.R., & Lawler, E.E., (1971). Employee reactioins to job characteristics. *Journal of Applied Psychology*, 55, 259-286.

Hackman, J.R., & Oldham, G.R., (1980). *Work redesign*. Reading, MA: Addison-Wesley.

Harris, K. J., Kacmar, K. M., & Zivnuska, S. (2007). An investigation of abusive supervision as a predictor of performance and the meaning of work as a moderator of the relationship. *The Leadership Quarterly, 18*(3), 252-263.

Harrison, M. M. (2009). *Finding meaning in the every day: An in-depth investigation of meaningful work experiences*. ProQuest Information & Learning, US.

Harvey, P., Stoner, J., Hochwarter, W., Kacmar, C. (2007). Coping with abusive bosses: The neutralizing effects of ingratiation and positive affect on negative employee outcomes. *Leadership Quarterly, 18* (3), 264 – 273.

Heck, R.H., & Hallinger, P. (2010). Testing a longitudinal model of distributed leadership effects on school improvement. *The leadership quarterly*, 21, 867-885.

Heck, T.R., Thomas, S.L., & Tabata, L.N. (2010) *Multilevel and longitudinal modelling with SPSS*. New York: Routledge/Taylor and Francis Group.

Hinkin, T. R., & Schriesheim, C. A. (2008a). An examination of 'nonleadership': From laissez-faire leadership to leader reward omission and punishment omission. *Journal of Applied Psychology, 93*(6), 1234-1248.

Hinkin, T. R., & Schriesheim, C. A. (2008b). A theoretical and empirical examination of

the transactional and non-leadership dimensions of the Multifactor Leadership

Questionnaire (MLQ). *The Leadership Quarterly, 19*(5), 501-513.

Hobman, E. V., Restubog, S. L. D., Bordia, P., & Tang, R. L. (2009). Abusive

supervision in advising relationships: Investigating the role of social support.

Applied Psychology: An International Review, 58(2), 233-256.

Hoobler, J. M., Brass, D.J., (2006). Abusive Supervision and Family Undermining as

Displaced Aggression. *Journal of Applied Psychology*, 91 (5), 1125

House, J.S., (1981). *Work Stress and Social Support*, Reading, MA; Addison-Wesley.

Howell, J. M., & Avolio, B. J. (1993). Transformational leadership, transactional

leadership, locus of control, and support for innovation; Key predictors of

consolidated business-unit performance. *Journal of Applied Psychology, 78*(6),

891-902.

Howell, J. M., & Frost, P. J. (1989). A laboratory study of charismatic leadership.

Organizational Behavior and Human Decision Processes, 43(2), 243-269.

Hu, L.-t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure

analysis: Conventional criteria versus new alternatives. *Structural Equation

Modeling, 6*(1), 1-55.

Inness, M., LeBlanc, M. M., & Barling, J. (2008). Psychosocial predictors of supervisor-,

peer-, subordinate-, and service-provider-targeted aggression. *Journal of Applied

Psychology, 93*(6), 1401-1411.

Johnson, J.V., & Hall, E.M. (1988). Job strain, work place social support, and

　　cardiovascular disease: a cross-sectional study of a random sample of the Swedish

　　working population. *American Journal of Public Health*, 78, 1336-1342.

Judge, T. A., & Piccolo, R. F. (2004). Transformational and transactional leadership: A

　　meta-analytic test of their relative validity. *Journal of Applied Psychology, 89*,

　　755-768.

Kalliath, T. J., O'Driscoll, M. P., & Brough, P. (2004). A confirmatory factor analysis of

　　the General Health Questionnaire - 12. *Stress and Health: Journal of the*

　　International Society for the Investigation of Stress, 20(1), 11-20.

Karasek, R. A., Jr. (1979). Job demands, job decision latitude, and mental strain:

　　implications for job redesign. *Administrative Science Quarterly* 24 (2), 285-308.

Keashly, L. (2001). Interpersonal and systemic aspects of emotional abuse at work: The

　　target's perspective. *Violence and Victims, 16*(3), 233-268.

Keashly, L., Trott, V., & MacLean, L. M. (1994). Abusive behavior in the workplace: A

　　preliminary investigation. *Violence and Victims, 9*(4), 341-357.

Kelloway, E. K., Barling, J. (2010). Leadership development as an intervention in

　　occupational health psychology. *Work & Stress*, 24(3), 260-279.

Kelloway, E.K., & Day, A. (2005). Building healthy workplaces. What we know so far.

　　Canadian Journal of Behavioral Science, 34 (7), 223 – 235.

Kelloway, E. K., Hess, A., Francis, L., Catano, V., M., & Flemming, M. (In-Preparation).

　　Development of the Positive Wellbeing Scale.

Kelloway, E.K., & Francis, L. (2006, February). *Stress & Strain in Nova Scotian Organizations: Results of the Nova Scotia Work Stress Survey*. Presented at the Nova Scotia Psychologically Healthy Workplace Conference, Halifax, NS.

Kelloway, E.K., & Francis, L. (in press) Longitudinal research and data analysis. To appear in M. Wang, R. Sinclair, & L. Tetrick (Eds) *Research methods in occupational health psychology*: Taylor and Francis

Kelloway, E.K., Gottlieb, B.H., & Barham, L. (1999). The source, nature, and direction of work and family conflict: A longitudinal investigation. *Journal of Occupational Health Psychology, 4*, 337-346.

Kelloway, E. K., Mullen, J., & Francis, L. (2006). Divergent effects of transformational and passive leadership on employee safety. *Journal of Occupational Health Psychology, 11*(1), 76-86.

Kelloway, E. K., Sivanathan, N., Francis, L., & Barling, J. (2005). Poor Leadership. In J. Barling, E. K. Kelloway & M. Frone (Eds.), *Handbook of Workplace Stress* (pp. 89-112). Thousand Oaks: Sage Publications.

Kelloway, E. K., Teed, M., & Prosser, M. (2008). Leading to a healthy workplace. In A. Kinder, R. Hughes & C. L. Cooper (Eds.), *Employee well-being support: A workplace resource.* (pp. 25-38). Chichester: Wiley and sons.

Kelloway, E.K., Turner, N., Barling, J., & Loughlin, C. (2012). Transformational leadership and employee well-being: The mediating role of employee trust in leadership. *Work and Sress*, 26, (1), 39-55.

Kirkpatrick, S. A., & Locke, E. A. (1996). Direct and indirect effects of three core charismatic leadership components on performance and attitudes. *Journal of Applied Psychology, 81,* 36-51.

Kuoppala, J., Lamminpaa, A., Liira, J., & Vainio, H. (2008). Leadership, job well-being, and health effects - A systematic review and a meta-analysis. *Journal of Occupational & Environmental Medicine, 50*(8), 904-915.

Lance, C.E., Vandenberg, R.J., & Self, R.M. (2000). Latent growth models of individual change: The case of newcomer adjustment. *Organizational Behaviour and Human Decision Processes*, 83, 107-140.

Lance, C.E., Dawson, B., Birkelbach, B., & Hoffman, B.J. (2010). Method effects, measurement error, and substantive conclusions. *Organizational Research Methods, 13,* 435-455.

Longua, J., DeHart, T., Tennen, H., & Armeli, S. (2009). Personality moderates the interaction between positive and negative daily events predicting negative affect and stress. *Journal of Research in Personality, 43*(4), 547-555.

Lowe, G.S. (2003). Healthy workplaces and productivity: a discussion paper. *Paper prepared for the Economic Analysis and Evaluation Division, Health Canada.*

Lyons, J. B., & Schneider, T. R. (2009). The effects of leadership style on stress outcomes. *The Leadership Quarterly, 20*(5), 737-748.

Mathisen, G. E., Einarsen, S. 1., & Mykletun, R. (2008). The occurrences and correlates of bullying and harassment in the restaurant sector. *Scandinavian Journal of Psychology, 49*(1), 59-68.

Maxwell, S.E. & Cole, D.A. (2007). Bias in the cross-sectional analysis of longitudinal mediation. *Psychological Methods, 12,* 23-44.

McArdle, J. J. (1988). Dynamic but structural equation modeling of repeated measures data. In J. R. Nesselroade & R. B. Cattell (Eds.), *Handbook of multivariate experimental psychology (2nd ed.).* (pp. 561-614). New York, NY US: Plenum Press.

McArdle, J.J. (2001). A latent difference score approach to longitudinal dynamic structural analysis. In R. Cudeck, S. DuToit and D.Sorbom (Eds.), *Structural equation modeling: present and future* (pp. 341-380). Lincolnwood, IL: Scientific Software International.

McArdle, J.J. & Hamagami., F. (1996). Multilevel models from a multiple group structural equation perspective. In G. Marcoulides & R. Schumaker (Eds.). *Advanced Structural Equation Modeling Techniques* (89-124). Hillsdale, NJ: Lawrence Erlbaum.

McKee, M., & Kelloway, E.K., (2009). *Leading to wellbeing.* Paper presented at the annual meeting of the European Academy of Work and Organizational Psychology, Santiago de Compostella, Spain.

Mitchell, M. S., & Ambrose, M. L. (2007). Abusive supervision and workplace deviance and the moderating effects of negative reciprocity beliefs. *Journal of Applied Psychology, 92*(4), 1159-1168.

Moyle, P. (1998) Longitudinal influences of managerial support on employee well-being. Work and Stress: *An International Journal of Work, Health and Organizations.* 12(1) 29-49.

Mullen, J., & Kelloway, E. K. (2009). Safety leadership: A longitudinal study of the effects of transformational leadership on safety outcomes. *Journal of Occupational & Organizational Psychology, 82*(2), 253-272.

Mullen, J., & Kelloway, E. K. (2011). Occupational health and safety leadership. In J. Campbell-Quick & L. Tetrick (Eds.), *Handbook of Occupational Health Psychology 2nd edition*. Washington, DC: APA Books.

Mullen, J., Kelloway, E.K., & Teed, M. (2011). Inconsistent style of leadership as a predictor of safety behaviour. *Work & Stress*, 25(1), 41-54.

Munir, F., Nielsen, K., & Cameiro, I.G. (2010). Transformational leadership and depressive symptoms: A prospective study. *Journal of Affective Disorders*, 120(1-3), 235-239.

Muthen, B. O. (2001). Second-generation structural equation modeling with a combination of categorical and continuous latent variables: New opportunities for latent class-latent growth modeling. In L. Collins and A. Sayer (Eds*). New methods for the analysis of change* (pp 291-322) Washington, DC: APA.

Muthen, B.O. (2004). Latent variable analysis: Growth mixture modeling and related techniques for longitudinal data. In D. Kaplan (Ed*). Handbook of quantitative methodology for the social sciences* (pp. 345-368). Thousand Oaks: SAGE.

Nielsen, K., & Munir, F. (2009). How do transformational leaders influence followers' affective well-being? Exploring the mediating role of self-efficacy. *Work & Stress*, 23(4), 313-329.

Nielsen, K., Randall, R., Yarker, J., & Brenner, S.-O. (2008). The effects of transformational leadership on followers' perceived work characteristics and psychological well-being: A longitudinal study. *Work & Stress, 22*(1), 16-32.

Nielsen, K., Yarkers, J., Brenner, S., Randall, R., & Borg, V. (2008). The importance of transformational leadership style for the well-being of employees working with older people. *Journal of Advanced Nursing, 63*, 465-475.

Nielsen, K., Yarker, J., Randall, R., & Munir, F. (2009).The mediating effects of team and self-efficacy on the relationship between transformational leadership, and job satisfaction and psychological well-being in healthcare professionals: A cross-sectional questionnaire survey. *International Journal of Nursing Studies*, 46 (9), 1236-1244.

Northouse, P. G. (2001). *Leadership Theory and Practice*. London: Sage Publications Inc.

Offermann, L. R., & Hellmann, P. S. (1996). Leadership behavior and subordinate stress: A 360' view. *Journal of Occupational Health Psychology,* 1(4), 382-390.

Painter, J. (2011). ***Designing multilevel models using SPSS 11.5 Mixed Model.*** Chapel Hill, NC: Jordan Institute for Families. Retrieved, http://www.unc.edu/~painter/SPSSMixed/SPSSMixedModels.PDF 2011.

Pitariu, A.H. & Ployhart, R.E. (2010). Explaining change: Theorizing and testing dynamic mediated longitudinal relationships. *Journal of Management, 36*, 405-429.

Pizzino, A. (2002). Dealing with violence in the workplace; the experience of Canadian unions. In M. Gill, B. Fisher & V. Bowie (Eds.), *Violence at work; causes, patterns and prevention* (pp. 165-179). Cullompton, Emgland: Willan.

Ployhart, R.E., Holtz, B.C., & Bliese, P.D. (2002). Logintudinal data analysis: Applications of random coefficient modeling to leadership research. *The leadership quarterly*, 13, 455-486.

Ployhart, R.E. & Vandenberg, R.K. (2010). Longitudinal research: The theory, design, and analysis of change. *Journal of Management, 36,* 94-120.

Reichard, R.J., Riggio, R.E., Guerin, D.W., Oliver, P.H., Gottfried, A.W., & Gottfried, A.E. (2011). A longitudinal analysis of relationships between adolescent personality and intelligence with adult leader emergence and transformational leadership. *The Leadership Quarterly*, 22(3), 471-481.

Rogers, K.-A., & Kelloway, E. K. (1997a). Violence at work: Personal and organizational outcomes. *Journal of Occupational Health Psychology, 2*(1), 63-71.

Rogers, K. A., & Kelloway, E. K. (1997b). Violence at work: Personal and organizational outcomes. *Journal of Occupational Health Psychology, 2,* 63-71.

Rogosa, D. (1988). Myths about longitudinal research. In K.W. Schaie, R.T. Campbell, & M.E. Rawlings SC (Eds), *Methodological issues in aging research.* New York: Springer.

Rogosa, D., Brandt, D., & Zimowsky, M. (1982). A growth curve approach to measurement of change. *Psychological Bulletin*, 92, 726-748.

Rosel, J. & Plewis, I. (2008). Longitudinal data analysis with structural equations. *Methodology, 4,* 37-50.

Rospenda, K. (2002). Workplace harassment, services utilization, and drinking outcomes. *Journal of Occupational Health Psychology, 7*(2), 141-155.

Sanchez, J.I., & Viswesvaran, C. (2002). The effects of temporal separation on the relations between self-reported work stressors and strains. *Organizational Research Methods, 5*(2), 173-183. Retrieved April 29, 2012, from ABI/INFORM Global. (Document ID: 112537089).

Schat, A. C. H., Frone, M. R., & Kelloway, E. K. (2006). Prevalence of Workplace Aggression in the U.S. Workforce: Findings From a National Study. In E. K. Kelloway, J. Barling & J. J. Hurrell, Jr. (Eds.), *Handbook of workplace violence.* (pp. 47-89). Thousand Oaks, CA US: Sage Publications, Inc.

Schat, A. C. H., Frone, M. R., Kelloway, E. K., Barling, J., & Hurrell, J. J., Jr. (2006). Prevalence of Workplace Aggression in the U.S. Workforce: Findings From a National Study *Handbook of workplace violence.* (pp. 47-89). Thousand Oaks, CA US: Sage Publications, Inc.

Schat, A. C. H., & Kelloway, E. K. (2003). Reducing the adverse consequences of workplace aggression and violence: The buffering effects of organizational support. *Journal of Occupational Health Psychology, 8*(2), 110-122.

Scollon, C. N., Kim-Prieto, C., & Diener, E. (2003). Experience Sampling: Promises and pitfalls, strengths and weaknesses. *Journal of Happiness Studies, 4*(1), 5-34.

Shek, D.T.L., & Ma, C.M.S. (2011). Longitudinal data analysis using Linear Mixed Models in SPSS; Concepts, procedures and illustrations. *The Scientific World Journal.* 11, 42-76.

Singer, J.D. & Willett, J.B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence.* New York: Oxford University Press.

Skakon, J., Nielsen, K., Borg, V., & Guzman, J. (2010). Are leaders well-being, behaviours and style associated with the affective well-being of their employees? A systematic review of three decades of research. *Work and Stress*, 24 (2) 107-139.

Skogstad, A., Einarsen, S. l., Torsheim, T. r., Aasland, M. S., & Hetland, H. (2007). The destructiveness of laissez-faire leadership behavior. *Journal of Occupational Health Psychology, 12*(1), 80-92.

Sosik, J. J., & Godshalk, V. M. (2000). Leadership styles, mentoring functions received, and job-related stress: A conceptual model and preliminary study. *Journal of Organizational Behavior, 21*(4), 365-390.

Sparks, J.R., Schenk, J.A. (2001). Explaining the effects of transformational leadership: An investigation of the effects of higher-order motives in multilevel marketing organizations. *Journal of Organizational Behavior, 22*, 849 – 869.

Spector, P.E. & Brannick, M.T. (2010). Common method issues: An introduction to the feature topic in Organizational Research Methods. *Organizational Research Methods, 13,* 403- 406.

Taris, T., & Kompier, M., (2003). Challenges in longitudinal designs in occupational health psychology. *Scandinavian Journal of Work and Environmental Health,* 29,(1) 1-4.

Tafvelin, S., Armelius, K., & Westerberg, K. (2011). Toward understanding the direct and indirect effects of transformational leadership on well-being: A longitudinal study. *Journal of Leadership & Organizational Studies*, 18(4), 480-492.

Tepper, B. J. (2000). Consequences of Abusive Supervision. *The Academy of Management Journal, 43*(2), 178-190.

Tepper, B.J. (2001). Health consequences of organizational injustice: Tests of main effects and interactive effects. *Organizational Behaviour and Human Decision Processes, 86,* 197 – 215.

Tepper, B. J. (2007). Abusive supervision in work organizations: Review synthesis, and research agenda. *Journal of Management, 33*(3), 261-289.

Tepper, B. J., Carr, J. C., Breaux, D. M., Geider, S., Hu, C., & Hua, W. (2009). Abusive supervision, intentions to quit, and employees' workplace deviance: A power/dependence analysis. *Organizational Behavior and Human Decision Processes, 109*(2), 156-167.

Tepper, B.J., Henle, C.A., Lambert, L.S., Giacalone, R.A., & Duffy, M.K. (2008) Abusive supervision and subordinates oreganization deviance. *Journal of Applied Psychology*, 93 (4) 721-732.

Tepper, B. J., Moss, S. E., Lockhart, D. E., & Carr, J. C. (2007). Abusive supervision, upward maintenance communication, and subordinates' psychological distress. *Academy of Management Journal, 50*(5), 1169-1180.

Turner, N., Barling, J., & Zacharatos, A., (2002). Positive psychology at work. In C.R. Snyder & S.J. Lopez (Eds.) *The handbook of positive psychology*, (pp. 715-728), NY: Oxford University Press.

Twale, D. J., & De Luca, B. M. (2008). *Faculty incivility: The rise of the academic bully culture and what to do about it*. San Francisco, CA US: Jossey-Bass.

Vaananen, A., Toppinen-Tanner, S., Kalimo, R., Mutanen, P., Vahtera, J., & Peiro, J.M. (2003). Job characteristics, physical and psychological symptoms, and social support as antecedents of sickness absence among young men and women in the private industrial sector. *Social Science and Medicine*, 57, 807-824.

Van der Doef, M., & Maes, S. (1999). The job demand-control (support) model and sychological well-being: a review of twenty years of empirical research. *Work and Stress*, 13, 87-114.

van Dierendonck, D., Haynes, C., Borrill, C., & Stride, C. (2004). Leadership Behavior and Subordinate Well-Being. *Journal of Occupational Health Psychology, 9*(2), 165-175.

Van Katwyk, P.T., Fox, S., Spector, P.E., and Kelloway, E.K. (2000). Using the Job-related Affective Well-being Scale (JAWS) to investigate affective responses to work stressors. *Journal of Occupational Health Psychology*, 5 (2), 219-230.

Van Vegchel, N., De Jonge, J., Bakker, A.B., & Schaufeli, W.B. (2002). Testing global and specific indicators of rewards in the effort-reward imbalance model : does it make any difference? *Eurpoean Journal of Work and Organizational Psychology*, 11, 403-421.

Walumbwa, F. O., Orwa, B., Wang, P., & Lawler, J. J. (2005). Transformational Leadership, Organizational Commitment, and Job Satisfaction: A Comparative Study of Kenyan and U.S. Financial Firms. *Human Resource Development Quarterly, 16*(2), 235-256.

Warr, P. (1987). *Work, unemployment and mental health.* Oxford, England: Oxford University Press.

Watson, D., Clark, L. & Tellegen, A. (1988) Development and validation of brief measures of positive and negative affect; the PANAS scales. *Journal of Personality and Social Psychology*, 54, 1063-1070.

West, B. T. (2009) Analyzing longitudinal data with the linear mixed models procedure in SPSS. *Evaluation and The Health Professions*, 32, 3, 207-228.

Wilhelm, P. & Schoebi, D. (2007). Assessing mood in daily life; structural validity, sensitivity to change, and reliability of a short-scale to measure three basic dimensions of mood. *European Journal of Psychological Assessment*, 23, 258-267.

Willett, J.B., (1989). Some results on reliability for the longitudinal measurement of change: Implications for the design of studies of individual growth. *Educational and psychological measurement*, 49, 587-602.

Willett, J. B., & Sayer, A. G. (1994). Using covariance structure analysis to detect correlates and predictors of individual change over time. *Psychological Bulletin, 116*(2), 363-381.

Worsley, A., & Gribbin, C. C. (1977). A factor analytic study of the twelve item general health questionnaire. *Australian and New Zealand Journal of Psychiatry, 11*(4), 269-272.

Wright, T.A., & Cropanzano, R. (2000). Psychological well-being and job satisfaction as predictors of job performance. *Journal of Occupational Health Psychology*, 51, 84-94.

Zapf, D., Dormann, C. & Frese, M. (1996). Longitudinal studies in organizational stress research: A review of the literature with reference to methodological issues. *Journal of Occupational Health Psychology, 1,* 145-169.

Zellars, K. L., Tepper, B. J., & Duffy, M. K. (2002). Abusive supervision and subordinates' organizational citizenship behavior. *Journal of Applied Psychology, 87*(6), 1068-1076.

Zohar, D. (2002a). The effects of leadership dimensions, safety climate, and assigned priorities on minor injuries in work groups. *Journal of Organizational Behavior, 23*(1), 75-92.

Zohar, D. (2002b). Modifying supervisory practices to improve subunit safety: A leadership-based intervention model. *Journal of Applied Psychology, 87*(1), 156-163.

Appendix A

Leadership

The following statements are various actions that can be exhibited by a supervisor. Thinking of your immediate supervisor's behaviour *at work today, or when you saw him/her most recently*, please rate the extent to which you agree with each statement.

1 = Strongly Disagree; 2 = Disagree; 3 = Slightly Disagree; 4 = Neither Disagree/Agree; 5 = Slightly Agree; 6 = Agree; 7 = Strongly Agree.

Transformational Leadership							
Today, my supervisor...							
1 ... communicates a clear and positive vision of the future	1	2	3	4	5	6	7
2 ... treats staff as individuals and encourages their development	1	2	3	4	5	6	7
3 ... gives encouragement and recognition to staff	1	2	3	4	5	6	7
4 ... fosters trust, involvement, and cooperation among team members	1	2	3	4	5	6	7
5 ... encourages thinking about problems in new ways	1	2	3	4	5	6	7
6 ... is clear about his/her values	1	2	3	4	5	6	7
7 ... practices what he/she preaches	1	2	3	4	5	6	7
8 ... instills pride and respect in others	1	2	3	4	5	6	7
9 ... inspires me by being highly competent	1	2	3	4	5	6	7

Employee Well-being

Please read the following statements and use the scale to circle the response that best applies to you, *today*.

1 = Strongly Disagree; 2 = Disagree; 3 = Slightly Disagree; 4 = Neither Disagree/Agree; 5 = Slightly Agree; 6 = Agree; 7 = Strongly Agree.

General Health Questionnaire – 12 (GHQ-12); Anxiety-depression scale

Today, I feel ...

1	... like I cannot overcome my difficulties.	1	2	3	4	5	6	7
2	... unhappy and/or depressed.	1	2	3	4	5	6	7
3	... like I am losing confidence in myself.	1	2	3	4	5	6	7
4	... like a worthless person.	1	2	3	4	5	6	7

Job-related Affective Well-being scale; High pleasure / High Arousal scale

Today, my job made me feel ...

1	... ecstatic	1	2	3	4	5	6	7
2	... energetic	1	2	3	4	5	6	7
3	... enthusiastic	1	2	3	4	5	6	7
4	... excited	1	2	3	4	5	6	7

Appendix B

Leadership

The following statements are various actions that can be exhibited by a supervisor. Thinking of your immediate supervisor's behaviour at work, please rate the extent to which you agree with each statement.

1 = Strongly Disagree; 2 = Disagree; 3 = Slightly Disagree; 4 = Neither Disagree/Agree; 5 = Slightly Agree; 6 = Agree; 7 = Strongly Agree.

Transformational Leadership							
My supervisor…							
1 … communicates a clear and positive vision of the future	1	2	3	4	5	6	7
2 … treats staff as individuals and encourages their development	1	2	3	4	5	6	7
3 … gives encouragement and recognition to staff	1	2	3	4	5	6	7
4 … fosters trust, involvement, and cooperation among team members	1	2	3	4	5	6	7
5 … encourages thinking about problems in new ways	1	2	3	4	5	6	7
6 … is clear about his/her values	1	2	3	4	5	6	7
7 … practices what he/she preaches	1	2	3	4	5	6	7
8 … instills pride and respect in others	1	2	3	4	5	6	7
9 … inspires me by being highly competent	1	2	3	4	5	6	7

Employee Well-being

Please read the following statements and use the scale to circle the response that best applies to you.

1 = Not at all; 2 = Rarely; 3 = Once in a while; 4 = Some of the time; 5 = Fairly often; 6 = Often; 7 = All of the time.

General Health Questionnaire – 12 (GHQ-12)							
How often in last four months have you…							
1 … been able to concentrate on whatever you were doing?	1	2	3	4	5	6	7
2 … lost sleep from worry?	1	2	3	4	5	6	7
3 … felt you were playing a useful part in things?	1	2	3	4	5	6	7
4 … felt capable about making decisions about things?	1	2	3	4	5	6	7
5 … felt that you couldn't overcome your difficulties?	1	2	3	4	5	6	7
6 … been able to enjoy normal day to day activities?	1	2	3	4	5	6	7
7 … been able to face up to your problems?	1	2	3	4	5	6	7
8 … been feeling unhappy and/or depressed?	1	2	3	4	5	6	7
9 … been losing confidence in yourself?	1	2	3	4	5	6	7
10 … been thinking of yourself as a worthless person?	1	2	3	4	5	6	7
11 … felt under strain?	1	2	3	4	5	6	7
12 … been feeling happy, all things considered?	1	2	3	4	5	6	7

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