What it Means to Love One’s Job: Determining the Latent Structure, Longitudinal Stability and Correlates of a New Construct

By

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Abstract

The Love of Job (LOJ), as presented by Kelloway, Inness, Barling, Francis and Turner (2010), is a new framework for describing the intense positive emotions individuals can have towards their job. Based on Sternberg’s (1986) Triangular Theory of Love, LOJ is believed to be comprised of simultaneously high measures of passion for work, affective commitment to the organization, and intimate co-worker relationships. This hypothesis was tested using taxometric procedures that actually confirmed that the latent structure of LOJ is dimensional in nature. Structural equation modeling revealed that cross-sectional correlates of LOJ include positive work experiences such as challenge, control, closeness between co-workers and a positive work climate. A longitudinal reliability test over five years revealed a strong coefficient of stability ($r = .54$), even when accounting for job change. These results have important implications for future use of this construct.

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It’s advice heard by all new graduates upon their first venture into the world of work: “Find a job that you love!”, or “it’s not work when you love what you’re doing”. Indeed, even Freud is attributed to have said that “to work, and to love” are the cornerstones of mental health (Erickson, 1963), emphasizing two concepts that bring meaning to human lives. It is true that an intimate connection between work and mental health is consistent with previous scientific literature (Paul & Moser, 2009), which has striven to identify the antecedents of reduced stress, vocational success, mental health, well-being, and happiness at work (e.g. Begley & Czajka, 1993; Cassidy, 2000; Parker & Wall, 1998; Kelloway, Inness, Barling, Francis and Turner., 2010). Yet, it is only recently that the construct of “loving one’s job” has come under empirical scrutiny by researchers in organizational psychology, despite its pertinence and fundamental relation to positive outcomes in the workplace (Kelloway et al., 2010).

Through casual observation, one might imagine the vague concept of “loving one’s job” to represent pleasure at work, persistence, positive feelings when working, connectedness, and involvement. When assessed using more established constructs such as job involvement or job satisfaction, this informal and undefined notion of “loving one’s job” has been associated with previously-mentioned positive outcomes including well-being and happiness at work (Rabinowitz & Hall, 1977; Saal, 1978), in addition to higher parental and community involvement (Kirchmeyer, 1992), and organizational citizenship behaviours (Meyer, Stanley, Herscovitch, & Topolnytsky, 2002). Where
historical attempts at finding a causal link between performance and job satisfaction were largely indeterminate (Bowling, 2007). “loving one’s job”, loosely defined and measured as passion, tenacity, drive, and longing for one’s work, has successfully predicted both task performance and financial performance (Baum & Locke, 2004). In an effort to operationalize what it is to “love one’s job”, Kelloway et al. (2010) present a logical argument for its definition founded in theories of interpersonal love. Laying out what it means to love in the context of a job, Kelloway et al. (2010) come to the conclusion that individuals can and do love their job, and suggest that the intense positive feelings that can be had towards a job are a combination of passion, intimacy, and commitment. Specifically, they propose that Love of Job (LOJ) exists in individuals who simultaneously score “high” on measures of passion, intimacy, and commitment, such that it functions as a taxonic construct indicated by those three categories (Kelloway et al., 2010).

Initial analyses for LOJ have warranted additional research, testing, and validation for its development as a new construct in industrial/organizational psychology. The ideas put forward by Kelloway et al. (2010) represent exciting new research potential founded in positive psychology, whose premise is to redirect scientific energy towards the positive human experiences that allow individuals to flourish and improve their quality of life (Seligman & Csikszentmihalyi, 2000).

Purpose

Accordingly, the goal of this research is to begin operationalizing LOJ as presented by Kelloway et al. (2010). In doing so, two objectives were established. First,
as Kelloway et al. (2010) raise the possibility of LOJ’s latent structure being taxonic rather than dimensional, the empirical examination of this suggestion entails conducting a series of taxometric analyses. Second, an investigation of the correlates of LOJ (i.e. its hypothesized antecedents and outcomes) will be conducted using both cross-sectional and longitudinal data.

**Operationalizing the Love of Job**

What is love? The definition of love has eluded many a researcher; unsurprising, given that love means different things to different people (Berscheid, 2006; Sternberg, 1988; Rubin, 1988; Hendrick & Hendrick, 2006; Hatfield & Walster, 1978; Sternberg, 2006). Defining love has proven notoriously difficult since it spiked the interest of social scientists in the 1970s (Rubin, 1988). In a compelling argument, Rempel and Burris (2005) define love as a motivational state rather than love as an attitude, an emotion, or behaviour. In this sense, the goal of love is preservation and promotion of the other’s well-being.

Conceptualizing love over the years has not been an easy task. There is still no agreement about a single conceptualization, probably because the word “love” has many meanings (Berscheid, 2006). In defining love, many researchers have attempted to sort the meanings of “love” into taxonic classifications.

Sternberg (1986) proposed the Triangular Theory of Love, contending that all forms of love stem from three components that each manifests a different aspect of love. Intimacy, referring to feelings of closeness and connectedness, gives rise to the experience of warmth and eventually love in loving relationships, while commitment
LOVE OF JOB refers to the decision to maintain that love (Sternberg, 1997). In this respect, passion refers to sexual excitement, feelings of euphoria, and infatuation, which are largely motivational drives that influence loving relationships (Sternberg, 1997). From these components arise eight possible types of relationships loosely predicted by the model, depending on the aspects that are present in a given relationship. Where non-love is the absence of all three components, liking occurs when only intimacy is present without passion or commitment. Infatuated love results from passion existing without intimacy nor commitment, while empty love ensues from the decision to continue the loving relationship (commitment) despite a lack of passion and intimacy. Romantic love, on the other hand, arises from a combination of intimacy and passion, while companionate love lacks but the element of passion. Passion is present in combination with commitment in fatuous love, but in the absence of intimacy (Sternberg, 1997). True “consummate”, or complete love, Sternberg (1988) claims, exists when the three components are present in roughly equal proportions and reciprocated by the object of one’s attention.

Validation studies conducted on Sternberg’s (1986) Triangular Theory of Love have been generally supportive, showing three distinct factors (Sternberg, 1997), though the role of commitment has found to be less clear in leading to different types of love (Aron & Westbay, 1996; Fehr, 1988; Fehr & Russell, 1991). In defining love, commitment is sometimes seen as a problematic addition because it can be seen as referring to a quality of a loving relationship as opposed to an aspect of love itself (Rempel & Burris, 2005). Although commitment is an important element of a loving
relationship, it assumes, by definition, the existence of a relationship where none may exist (Rempel & Burris, 2005).

Kelloway et al. (2010) build on Sternberg’s (1986) Triangular Theory of Love, proposing a model for the Love Of Job (LOJ) comprised of “the experiences of passion for one’s work, affective commitment to the employing organization, and a sense of intimacy with the people at work” (p.114). Kelloway et al. (2010) incorporate theory from research on work passion, commitment to the organization, and intimacy in co-worker relations in constructing their theoretical model of love for one’s job.

**Passion for the Work**

To have passion is to have a strong inclination toward a cherished subject in which one invests time and energy (Vallerand et al., 2003). As the specific concept of passion has only recently become a focus of study in organizational psychology, there is much literature available on passionate love in close relationships (e.g. Hatfield & Walster, 1978), but only limited research on passion toward activities. Vallerand and his colleagues (Vallerand et al., 2003; Vallerand & Houlfort, 2003) have developed a Dualistic Model of Passion in which two types of passion regulate the internalization of motives for activities. The dualistic model proposes that individuals who have harmonious passion choose to engage in the activity that they like, whereas obsessive passion originates from intra- or interpersonal pressure, and pushes individuals to engage in activities that they may enjoy, but still feel compelled to engage in. Where harmonious passion promotes healthy adaptation, obsessive passion thwarts it (Vallerand et al., 2003).
The Dualistic Model of Passion is based in part on Self-Determination Theory (Deci & Ryan, 1985; Ryan & Deci, 2000), which posits that the three basic psychological needs of autonomy, competence, and relatedness motivate growth. Indeed, passion has a motivational component (i.e. Baum & Locke, 2004), and, as previously reported, is characterized by strong affect (Baumeister & Bratslavsky, 1999; Vallerand et al., 2003).

It is therefore not surprising that passion is associated with a high degree of investment in the activity, deliberate practice and mastery goals (Vallerand et al., 2007). In the workplace, employees who have the autonomy to direct their own work and find it challenging are more likely to be engaged (Kahn, 1990; Gibbons, 2006; Gibbons & Schutt, 2010). In turn, passion and engagement in a task are associated with well-being (Philippe, Vallerand & Lavigne, 2009; Vallerand et al., 2007) and performance (Harter, Schmidt, & Hayes, 2002).

Drawing from these various representations of passion at work, Kelloway et al. (2010) define passion as comprising of “high levels of engagement with, involvement in, and excitement stemming from the work itself” (p.117).

**Organizational commitment**

Commitment in interpersonal love theory refers to a decision to maintain the relationship with the certain other (Sternberg, 1988). Like passion and intimacy, it represents an aspect of love and demands a certain degree of affect. The workplace literature is comprised of an abundance of research on organizational commitment, mostly stemming from the widely-accepted work of Allen and Meyer (1990). Specifically, Allen and Meyer (1990) proposed a three-component model that
characterizes the employee’s relationship with the organization and has implications for the employee’s decision to continue or discontinue membership in the organization. The three approaches to commitment include affective, continuance, and normative commitment to organizations. According to Allen and Meyer (1990; Meyer, Bobocel, Allen, 1991; Meyer, Allen & Smith, 1993; Meyer & Allen, 1997), employees who remain with the organization because of an emotional attachment to the organization have what is called “affective commitment”. In contrast, those who perceive that the costs of leaving the organization exceed the costs of staying have high continuance commitment, while normative commitment refers to the feeling of remaining with the organization because one feels that he/she “ought to do so” (Meyer & Allen, 1997).

Of the three types of organizational commitment proposed by Allen and Meyer (1990; Meyer, Allen, & Smith, 1993), affective commitment has the most favourable correlations with organization-relevant outcomes such as performance and organizational citizenship behaviours (OCBs) (Meyer, Stanley, Herscovitch, & Topolnytsky, 2002). Furthermore, a meta-analysis by Meyer, Stanley, Herscovitch and Topolnytsky (2002) found a correlation of $p = .53$ between affective commitment and job involvement, suggesting that they are correlated yet distinct constructs.

Cooper-Hakim and Viswesvaran (2005) propose that social exchange theory explains how the interactions between the employees and their organization shape positive attitudes. As this theory puts emphasis on the reciprocation of benefits and costs incurred from such interactions, it explains how work experiences that are supportive and are consistent with employee expectations are associated with higher affective

Because of the focus on affective involvement in defining affective commitment, which is a concept at the heart of interpersonal love, Kelloway et al.’s (2010) framework focuses explicitly on affective commitment rather than normative or continuance commitment in defining LOJ.

**Intimacy with Co-workers**

The feelings of closeness, connectedness and bondedness in loving relationships are what comprise intimacy in interpersonal love (Sternberg, 1988). Intimacy in relationships results in a desire to promote the welfare of the relative other, experience happiness, share possessions and resources, and reciprocate emotional support (Sternberg & Grajek, 1984). Comparably, positive relationships in the workplace are high-quality connections that provide emotional, esteem, informational or instrumental support (Dutton & Ragins, 2007). Despite the popular sentiment that positive workplace relationships are not meaningful to everyone, Cohen and Wills (1985) explain that gender differences may exist in the instrumentality of positive workplace relationships such that men derive satisfaction from companionship and instrumental task accomplishments while women derive satisfaction from sharing and talking about feelings. Nonetheless, positive workplace relationships are a relevant factor affecting work outcomes nonetheless (Dutton & Ragins, 2007; Rousseau, Salek, Aubé & Morin, 2009).

Evidence supporting a hypothesis that social support interacts with stressors to predict strain has been inconsistent (Beehr, 1995; Kahn & Byosiere, 1992). Perhaps due
to the unclear definitions of social support that have plagued early studies (Cohen & Wills, 1985), studies that show this trend are likely to have used measures of emotional and communication support that are too specific (Beehr, Jex, Stacy, and Murray, 2000).

In their model of LOJ, Kelloway et al. (2010) acknowledge that intimacy at work is reflected in trust as the foundation of positive and high-quality relationships in the workplace. This statement reflects previous findings by many organizational researchers stemming as early as the Hawthorne Electric Studies of 1939 (Roethlisberger & Dickson, 1939; e.g. Pratt & Dirks, 2007; Harvey, Kelloway, & Duncan-Leiper, 2003; Dirks, 1999), and is grounded in theory highlighting basic relatedness and belongingness needs at work (Baumeister & Leary, 2000; Locke & Taylor, 1990).

**Putting It All Together: Combining the Components**

The question of how the three dimensions should be combined in creating the LOJ construct is addressed by Kelloway et al. (2010), who suggest three possible approaches to operationalizing the construct: interactional, common factors, and, taxonic. Concerned with preserving the fundamental premise that the whole of LOJ is superior in its predictive ability than its individual components alone, the interactional approach of conceptualizing LOJ calls for a significant three-way interaction that is logically conceivable, but difficult to detect in a statistical analysis. A more conventional approach to combining a multidimensional construct is the common factors approach, by which a higher-order construct is created through the addition of all parts. Examples of common constructs combined in this manner include core self-evaluations (self-esteem, generalized self-efficacy, locus of control, and emotional stability) and psychological
capital (aka “PsyCap”, comprised of hope, optimism, resiliency, and self-efficacy) (Judge & Bono, 2001; Judge, Locke, Durham & Kluger, 1998; Luthans, Youssef & Avolio, 2006).

In the taxonic approach, individuals who love their jobs are defined as those who score high on measures of all three components, while those who demonstrate any other pattern of scores are said to represent individuals who do not love their jobs. According to Kelloway et al. (2010), a taxonic operationalization of LOJ would allow for the study of two groups: individuals who love their jobs, and individuals who do not. A taxonic definition of LOJ would provide for a conceptual definition that does not confound the contribution of the individual components with the higher-order construct, and is not statistically limited by constraints that exist in multiple regression (Dawson & Richter, 2006; Kelloway et al., 2010).

The Taxometric Method

Taxometry is a series of data-analytic techniques capable of revealing the latent structure of psychological constructs or phenomena (Ruscio, Haslam & Ruscio, 2006). Fundamentally, taxometrics allows observers to make distinctions in qualities or kinds through investigation of the variation that occurs between each subset of a population. It is based on the simple premise that not all differences are alike—for instance, the differences between sharp and dull objects are not the same as the differences between hot and cold objects (Ruscio et al., 2006). One of the forefathers of taxometrics in psychology, Paul Meehl, preferred the terminology used in biological classification instead of framing his work under the guise of types versus traits, qualitative versus
quantitative differences, or categories versus dimensions. Through his research and that of numerous others, taxometrics as an analytic approach has substantially increased in popularity since the early 1990s, and is now used to determine whether categories exist in psychological data sets (Haslam & Kim, 2002; Ruscio, Haslam, & Ruscio, 2006).

In contemporary clinical psychology especially, classification is used in diagnostic practice in order to determine whether an individual is afflicted with a particular mental disorder (Ruscio et al., 2006). A common analogy used to explain taxometrics is the conceptualization of a construct likened to a lamp with an ‘on’ and ‘off’ switch (Gordon, Holm-Denoma, Smith, Fink, & Joiner, 2007). When the construct, often a mental disorder in the psychological literature, is present in an individual, the light is turned ‘on’ so to speak and this state is distinguishable from the absence of light—the absence of the diagnosable construct.

In practice, LOJ could be “diagnosed” in an individual using a diagnostic algorithm found through taxometric analysis. In fact, despite the preponderance of studies investigating the latent structure of mental disorders compared to other characteristics, the use of taxometric methodologies to “diagnose” a certain condition, attitude, or identity, can also be found in the literature. For example, this approach was used by Gangestad, Bailey and Martin (2000) to classify sexual orientation and gender identity in a sample of 5 000 Australian residents in an effort to empirically investigate the famous 7-point Kinsey Scale (Kinsey, Pomeroy, & Martin, 1948).

**Taxons vs. dimensions.** Taxometric procedures aim to determine whether categories exist in data sets, represented by taxa. A taxon is a latent “category” with a
boundary that is nonarbitrary and reasonably enduring, and behaves quite distinctively in taxometric procedures. Boundaries imposed on continua by human classificatory decisions do not constitute taxa—those are dimensional constructs. In fact, MacCallum, Zhang, Preacher and Rucker (2002) would consider such splitting of a sample on a quantitative variable in order to define separate groups inappropriate, warning specifically against the dichotomization of such variables to represent underlying categories of individuals. According to them, negative consequences associated with this practice may include the occurrence of spurious significant main effects and running the risk of overlooking nonlinear effects (MacCallum, Zhang, Preacher & Rucker, 2002). Posing arbitrary boundaries on a variable may thus create problems in comparing and aggregating findings across studies, resulting in sample-specific conclusions (MacCallum et al., 2002).

Socio-economic status constitutes one such example of a human-imposed boundary on a continuum. In this case, low-income individuals are classified using a pragmatically useful and justified boundary, but still do not belong to a naturally occurring taxon. Although taxons may show continuous variation within a group, just as a Chihuahua varies in size from a Great Dane, the dimensional variation within the taxon is different from the distinction between the Chihuahua and a Siamese cat.

Dimensional structures, therefore, should be inferred using taxometric analysis. However, these constructs are better understood using factor analysis to fully delineate their latent structures. To continue with the example of the lamp as a classification system, where a power switch would represent a taxonic structure, a dimensional
structure can be likened to a lamp with a dimmer switch whereby light emissions can range from darkness to bright light (Gordon et al., 2007). Regardless of its dimensional or taxonic nature, taxometric analyses examine the relations among fallible indicators to provide “clues” about the latent structure of the construct and capitalize on the predictable differences in which indicators relate to each other when a taxonic boundary is absent or present (Ruscio et al., 2006).

**Indicators of a latent construct.** The choice of indicators used in taxometric investigations have important bearings on the results of taxometric analyses (Bandalos, 2002; Bandalos, 2008; Hall, Snell & Foust, 1999). Using theory to define a set of indicators that will (a) assess all relevant facets of the target construct, and (b) not erroneously mislead interpretations in being too similar to one another, the taxometric method explores the relations among these indicators to make inferences about the latent structure of the construct. Gordon et al. (2007) present an example of the classification of biological sex in an effort to clarify the logic of taxometric procedures. In this example, plausible indicators for determining if being male is a taxon would include height, baldness, and voice pitch, as these characteristics occur more frequently in men. The patterns of correlation that exist among these indicators in the overall population are what emerge in taxometric analysis, such that indicators correlate equally if a construct is dimensional, but taxonic structures produce differences in correlation strength along the population distribution. On a further note, this particular example is a case where “biological sex” is a taxon (male or female), but the indicators (height, voice pitch, etc.) comprise dimensional variation.
Evaluating the results. Evaluating whether latent structures are dimensional or taxonic involves some subjective interpretations of curve fit, as well as the use of artificially-created comparison data (categorical and dimensional) with the same specifications as the data set that is being examined and an objective index of curve fit named the Comparison Curve Fit Index (CCFI). The CCFI is composed of Fit values, which consist of the root mean square residual (RMSR) of the values on the average curve for the research data (multiple curves may be produced in each analysis) and the averaged curve for either categorical or dimensional comparison data (Ruscio, 2007; Ruscio et al., 2006; Ruscio and Kaczetow, 2009). These Fit values are compared to one another and integrated into a single index, the CCFI.

CCFI values range between 0 and 1, where 1 represents the strongest possible support for a categorical structure and 0 represents the strongest possible support for a dimensional structure. Although the CCFI can be calculated automatically in R, a language and environment for statistical computing available online at www.r-project.org, the specific equations outlined by Ruscio (2011) can be seen in Figure 1.

Figure 1. Equation for Comparison Curve Fit Index (CCFI).

\[
\begin{align*}
(1) \quad \text{Fit}_{RMSR} & = \frac{\sum(y_R - y_C)^2}{N} \\
(2) \quad \text{Fit}_{RMSR} & = \frac{\sum \min(d_{ij})^2}{N} \\
(3) \quad \text{Fit}_{RMSR} & = \sqrt{\frac{(x_R - x_C)^2 + (y_R - y_C)^2}{(\text{Fit}_{RMSR-dim} + \text{Fit}_{RMSR-tac})}}
\end{align*}
\]

CCFI values in the range of .40 and .60 should be interpreted with caution, as the probability rate for valid inferences for values outside this range appears to be at least 90%, but decreases considerably as the CCFI approaches .50 (Ruscio & Walters, 2009; Ruscio, Walters, Marcus & Kaczetow, 2010). Monte Carlo studies exploring the utility
of the CCFI have demonstrated that the index performs very well across a wide range of data conditions, including sets with a low base rate (Ruscio & Kaczetow, 2009; Ruscio & Marcus, 2007).

**Data requirements for taxometrics.** In light of the fact that taxometric analysis is a relatively new approach to the analysis of categorical data, some preliminary work must be conducted in order to ensure that the data is adequate for this type of analysis. Taxometric procedures can only yield informative results if the data are appropriate in terms of the nature and construction of the sample and statistical characteristics of the data set (Ruscio, Haslam and Ruscio, 2006). Conventional guidelines on which the following considerations were based are derived from Monte Carlo studies on taxometric analyses that have been used to judge the adequacy of a data set (e.g. Beauchaine & Beauchaine, 2002; Meehl & Yonce, 1994, 1996). The following considerations outline the results of preliminary analyses that describe the characteristics of the dataset used further on.

**Sampling considerations.** Meehl and Yonce (1994, 1996) recommend that data sets submitted to taxometric analyses include a minimum of 300 cases. The current data set of n = 916 clearly surpasses the minimum recommended amount. The taxon base rate, i.e. the number of putative taxon members in a given sample, should be \( P = .10 \) at a minimum in samples of \( n = 300 \) (Meehl, 1995), but this guideline is flexible as the performance of taxometric procedures on samples with taxon base rates smaller than \( P = .10 \) has been rarely studied. As a crude estimate of the base rate of LOJ members in this sample, the percentage of participants with a z-score of 1 or more in all three subscales of
the LOJ measure (passion, commitment and intimacy) is 5.2%, or $P = .052$. Another estimate, consisting of the percentage of participants with a z-score of 1 or more in the sum of all LOJ items, yields a value of 17.2%. These estimates suggest that the actual number of LOJ members is very low and may make the distinction of two groups more difficult.

That being said, the sampling techniques for data collection were of very high standards, adding validity to the forthcoming taxometric analyses as the taxon base rate will not have been falsely influenced. When class membership is not known, taxometric analyses require that researchers first estimate the base rate of taxon members in their sample, and supply to the program this estimate. Otherwise, the program assigns cases to groups using an estimated base rate of $P = .50$ (Ruscio, 2011). In fact, having the program estimate the base rate using the data in question returns base rates ranging between $P = .44$ and $P = .57$ due to the assumption that both groups are equal in size.

Because taxometric analyses conducted with a supplied base rate of .05 are often inconclusive due to inadequate size of taxon group membership, it will be assumed that the base rate in this sample is between $P = .05$ and $P = .15$. As such, inconclusive results based on the assumption of $P = .05$ will entail a second analysis where $P = .15$ is assumed, though caution will be used in the interpretation of results in the case of the latter.

**Indicator considerations.** Widiger (2001) states that researchers must carefully consider the nature of a construct’s indicators as the validity of inferences drawn about the latent structure of that construct are dependent on how well it is represented by those
indicators. In addition, within-group correlations and the distributions of indicators have an impact on the procedures' ability to discover a latent taxonic structure.

Taxometric analyses involve no assumptions regarding normality or continuity of a construct's indicators, but deviations from normality can have an impact on estimates of taxonic model parameters. Therefore, it is important to test for normality of the indicators. In this data set, all indicators are normally distributed.

With regards to the within-group correlations of the indicators in question, Ruscio, Haslam, and Ruscio (2006) state that they should be correlated no more than $r = .30$ within groups. In addition, within-group correlations should be substantially smaller than full-sample correlations. In this data set, bivariate correlations between all three indicators in the full sample were significant and above $r = .40$. Passion and commitment yielded an $r = .76$ ($p < .01$) in the full sample that reduced to $r = .51$ ($p < .01$) in the "estimated" LOJ group, and all other correlations were non-significant. Although there are no universally acceptable limits for within-group correlations (Ruscio, Haslam and Ruscio, 2006), the high correlations between indicators in the full sample and in the non-taxon group could easily conceal a latent taxonic structure in this dataset, if it were to exist.

**The MAXSLOPE procedure.** The MAXSLOPE procedure involves a graphical analysis of the indicators of the target construct using a scatterplot that displays the relationship between two indicators (Ruscio, Haslam and Ruscio, 2006). Once the decision of how to assign the variables to serve as input and output indicators has been implemented, MAXSLOPE is a relatively simple procedure whereby one indicator is
placed on the y-axis of the scatter plot, and another is placed on the x-axis. This technique normally produces $2k$ number of curves, where $k$ is the number of indicators, although a variation to this approach is outlined below.

In a taxonic structure, two clouds of points become visible: taxon members in the upper right, and complement members in the lower left. Local regression curves are generated to estimate the slope within restricted regions, allowing for a curved regression function. The end result is an S-shaped curve for a taxonic data set, as outlined in Figure 2, and a straight line for a dimensional data set, which can be seen in Figure 3.

*Figure 2 (left).* Example of MAXSLOPE curve of categorical (taxonic) data. *Figure 3 (right).* Example of MAXSLOPE curve of dimensional data.

A recent paper by Ruscio and Walters (2009) discusses the uses of MAXSLOPE, suggesting that it is more useful as an adjunct to the MAMBAC technique when only two indicators are available for analysis. Since three plausible indicators are present in this sample, caution should be used in the interpretation of MAXSLOPE results, and Ruscio (2011) recommends conducting a MAXCOV procedure instead. However, the worth of
this straightforward technique is not lost when all graphs are considered simultaneously, and consequently analysis using this technique will proceed.

**MAXSLOPE implementation decisions.** Based on preliminary analyses of the data, it appears that the LOJ indicator variables (passion, commitment, and intimacy) are continuous, normally distributed, and seemingly dimensional themselves. Therefore, it is justified to assign a single variable to serve as the output indicator and combine all remaining variables into a single composite indicator by summing them. This composite will serve as the input variable, yielding three curves for the MAXSLOPE analysis: one per indicator (Ruscio, Haslam and Ruscio, 2006). The composite input variables include all the data in each analysis, allowing for a less biased interpretation of results, and provides a more reliable rank ordering of cases as it contains a larger range of values than any given input indicator.

**The MAMBAC procedure.** The logic of the MAMBAC technique is that if two groups do exist in the data set, an optimal cut score that distinguishes them must also exist. Thus, like MAXSLOPE, MAMBAC uses two indicators on a graph to search for the optimal cut score.

The first step of the MAMBAC technique is to place a standardized composite of indicators (minus a chosen input indicator) on the x-axis. Next, arbitrary cut points for taxon membership at fixed standard deviation intervals are placed along the input indicator. Along the y-axis figure mean difference scores, calculated by subtracting the mean score of the output indicator for all cases falling below the arbitrary cut score from the mean score of all cases falling above the cut.
If an optimal cut score exists, thus lending support to a taxonic structure, mean differences should be largest around this score and decline as higher or lower scores are used (Ruscio, Haslam and Ruscio, 2006). Therefore, the resulting MAMBAC curve peaks in taxonic data sets, and appears bow-shaped in dimensional data sets.

**MAMBAC implementation decisions.** The same logic used to decide the composition of the input indicators in MAXSLOPE is used in MAMBAC. Thus, the only implementation decision to be made is regarding where the cut scores should be placed. As recommended by Meehl and Yonce (1996), the sample was divided along the standardized input indicator into cuts of .25 SD units. This allows for an interpretable curve that is clear and free of “noise”.

**The L-Mode procedure.** The L-Mode technique is quite different from the previous two in that no sliding cut is involved, and it stems from the idea that latent factors may not be solely continuous and can provide useful information about categorical variables (Thurstone, 1935; 1947). L-Mode is a factor-analytic procedure developed by Waller and Meehl (1998), which graphs the distribution of estimated factor scores of each case on a single latent factor. Using Bartlett’s (1937) method of factor score estimation, histograms of the indicators are produced with the expectation that composites of valid indicators should separate taxon members from non-members more validly than individual indicators. That is, it is expected that taxonic structures contain two groups (taxon members and taxon non-members) that can be differentiated using estimated factor scores, similar to those produced in regular factor analysis. When those estimated factor scores are graphed, taxonic structures should yield a bimodal distribution
(with each peak representing the mean factor score for each group), while dimensional data is normally distributed.

**L-Mode implementation decisions.** Because L-Mode automatically includes all indicators in a given analysis, there are fewer implementation decisions than there are for MAXSLOPE and MAMBAC. In this case there are three indicators, and as L-Mode’s minimum criteria for identifying factor loadings is three indicators, the factor scores were estimated based on a single factor with 3 indicators. No additional implementation decisions were warranted.

**The MAXCOV procedure.** Latent structure is tested in MAXCOV by examining the covariance between two indicators as a function of the taxon and complement base rates, and the validity of the two indicators. Meehl (1973, 1995) introduced the General Covariance Mixture Theorem, the algebraic identity that expresses the covariance between the indicators, outlined as follows: $\text{cov}(xy) = P\text{cov}_t(xy) + Q\text{cov}_c(xy) + PQD_xD_y$ where $\text{cov}_t(xy)$ is the covariance within the taxon, $\text{cov}_c(xy)$ is the covariance within the complement, and $D_x$ and $D_y$ represent the unstandardized mean differences between the taxon and complement on indicators $x$ and $y$. The taxon base rate $P$ and the complement base rate $Q$ weight each term.

Using a simplified version of this formula (as terms can be simplified under several assumptions; for example, if indicators do not covary within the taxon or complement groups, the first two terms can be dropped), and scatterplots that graph the covariance between indicators, latent structure is tested by examining the covariance of two indicators within a series of subsamples (Ruscio et al., 2006). Similarly to
MAXSLOPE, where regions that contain homogeneous subsamples of complement members yield flat local regression curves, the covariance between indicators should remain constant across subsamples in dimensional structures. Thus, MAXCOV curves in taxonic data sets yield peaks identifying the point at which the covariance is the largest (and the separation between taxon and complement members, the greatest, suggesting the location of an optimal cutting score), while dimensional data sets yield flatter curves that do not fluctuate very much (Ruscio et al., 2006).

**MAXCOV implementation decisions.** The first implementation decision involves the assignment of indicators into input-output roles, similarly to MAMBAC and MAXSLOPE. In this case, the same decision was taken for MAXCOV as for the previous two. The next decision involved the placement of cut scores. In this case, the same decision that was taken for MAMBAC was repeated. The final implementation decisions involve scaling of the graph axes and indicator corrections that are only applicable in the case of highly-skewed indicator distributions, which is not the case in this data.

The results of each taxometric procedure are gathered as evidence in a hypothesis-testing rather than exploratory approach, such that the null hypothesis predicts a dimensional structural model, and can only be rejected when there is some degree of consistency among all obtained results (Ruscio et al., 2006). Thus, the first objective of the current study is to examine the latent structure of the LOJ construct. In particular, the following hypothesis is tested:
Hypothesis A: LOJ will manifest a taxonic structure, composed of three indicators including work passion, affective commitment to the employing organization, and close positive relationships with co-workers.

Correlates of Love of Job: The Meaningful Experiences that Lead to LOJ

Regardless of the form, love undoubtedly conveys powerful messages of meaningfulness. As argued by Britt, Adler and Bartone (2001), individuals have a primary motive to seek meaning in events and life experiences. Meaning, as defined by the value of an experience judged in relation to a person’s own ideals or standards, is used to understand and interpret experiences (Frankl, 1969). It is necessary as a rationale for goals, values, or ideals, contributing to psychological well-being by allowing people to feel useful and fulfill themselves as human beings (Yalom, 1980; May, 2003; May, Gilson & Harter, 2004).

It is no surprise that individuals love objects that are meaningful to them, and that acting “out of love” gives meaning to life (Wolf, Koethe, Adams, Arpaly, & Haidt, 2010; Johnson, 2001). In the context of jobs, numerous models that describe the relationships between workplace variables and meaningfulness exist (e.g. Oldham & Hackman, 1976; Oldham & Hackman, 2010; Brief & Nord, 1990; Pratt & Ashforth, 2003; Arnold, Turner, Barling, Kelloway & McKee, 2007; Renn & Vandenberg, 1995). For Oldham and Hackman (1976), an individual will find work meaningful when it is perceived as important, valuable, and worthwhile. Their job characteristics model defines the relationships between task variety, identity and significance, feedback, and autonomy, leading to meaningfulness within jobs (Hackman & Oldham, 1980). Pratt and Ashworth
LOVE OF JOB

(2003) make a distinction between meaningfulness of work and meaningfulness at work in defining the roles and groups that individuals use to rationalize their identity and develop a sense of purpose. In these models, meaningful work is associated with internal work motivation (Hackman & Oldham, 1980), a sense of accomplishment and personal effectiveness, and even a meaning to life (Brief & Nord, 1990).

Pursuant to this argument, it is plausible that meaningful experiences at the job, organizational, and social level should lead to loving one’s job. In fact, in their review of the literature dealing with romantic love, Rempel and Burris (2005) suggest that “emotion-laden, personally meaningful experiences energize the love motive in its various forms” and are what lead to loving an object (p.299). Therefore, meaningful work experiences hypothesized to lead to Love of Job are described as follows:

**Challenge.** For work to be meaningful, employees must perceive a sense of challenge from the work experience (May, 2003; May, Gilson, & Harter, 2004). A job designed to call upon one’s skills, stimulate development and allow goal achievement will satisfy a human need for purpose (Baumeister, 1991), thus adding meaning to the work.

Finding meaning in work by harmonizing the employee’s attributes with his or her work environment is a perspective grounded in the interactionist theory of behaviour (Chatman, 1989; Muchinsky & Monahan, 1987). By redesigning a job and creating a fit between the incumbent’s skills and demands of the tasks, the experience of “flow” is likely to occur more often (Csikszentmihalyi, 2000). Flow is a mental state of operation in which a person is fully immersed in a feeling of energized focus, involvement, and
success in the process of the activity (Csikszentmihalyi, 2000). The hallmark of flow is a feeling of enjoyment while performing a task. An experiment by Keller and Bless (2008) demonstrated that the extent to which participants believed their skills were appropriately matched to the demands of a task predicted enjoyment and involvement. Similarly, a study by Fullagar and Kelloway (2009) found an association between increased skill variety in academic work and the experience of flow. Flow itself was correlated with positive mood. Thus, as an appropriate level of challenge in job demands is meaningful and internally motivating for individuals, it is hypothesized that challenge in the workplace will lead to LOJ.

_Hypothesis B: The experience of challenge on the job is associated with LOJ._

**Control.** According to Baumeister (1991), having a feeling of control and effectiveness renders an experience more meaningful. In the context of work, allowing individuals to exercise their skills and judgment, show creativity in problem solving or have a say in decisions that affect them would create such an experience (IRSST, 2008; 2010). Hackman and Oldham (1980) postulate that the experience of freedom, independence and discretion to organize one’s own work induces meaning in a job. According to them, the job characteristic of autonomy leads to a feeling of responsibility for achievement of the objectives.

In addition, control has also been linked to higher job quality and low psychological strain. Karasek and Theorell (1990) describe how high decision latitude interacts with psychological job demands to affect perceived stress and coping mechanisms. It follows that the degree to which an employee has the freedom to
organize a work schedule and determine his or her own methods adds a sense of ownership and meaning to the job, ostensibly leading to increased LOJ.

*Hypothesis C: The experience of control over job processes and tasks is associated with LOJ.*

**Closeness.** The literature on relatedness needs has demonstrated that employees who experience rewarding interpersonal interactions with their co-workers derive more meaning from their job (Locke & Taylor, 1990; May, Gilson, & Harter, 2004). Developing trust in the workplace is essential to fostering the sense of belongingness, sense of social identity, and feelings of dignity that allow all members of an environment to cooperate with synergy (Baumeister and Leary, 2000; Aktouf, 1992). In fact, settings in which employees feel safe psychologically, feel that their co-workers are trustworthy, secure and predictable, and where interpersonal interactions promote dignity, a sense of value and appreciation are meaningful to individuals and reflect a basic human need to relate and belong (Kahn, 1990). Even theoreticians such as Aristotle, Weber and Marx recognized that human nature is undeniably social, and that restoring the meaning of work involves putting an end to estrangement from the human element of work (Aktouf, 1992).

*Hypothesis D: The experience of closeness between co-workers is associated with LOJ.*

**Climate.** In today’s modern workplace, a supportive work environment is vital to developing affective commitment to an organization (Meyer, Stanley, Herscovitch, & Topolnytsky, 2002). Based on the principles of social exchange theory, organizations
that wish to cultivate affective commitment in employees are urged to demonstrate their own commitment by providing employees with a safe, healthy and enabling workplace (Eisenberger, Huntington, Hutchison, & Sowa, 1986; Eisenberger, Stinglhamber, Vandenberghe, Sucharski, & Rhoades, 2002).

Fostering a supportive work climate involves the consideration of multiple workplace components that contribute to psychological well-being. The American Psychological Association, for example, defines psychologically healthy workplaces as safe, supportive, respectful and fair environments whereby the organization is instrumental in improving the quality of life of the employee (PHWP, 2011; Kelloway & Day, 2005). Their model focuses explicitly on employee recognition, health and safety, employee involvement and work-life balance in creating a positive work climate (PHWP, 2011). According to this model, recognition programs deemed to acknowledge employee efforts contribute to their sense of value and appreciation, helping to increase satisfaction, morale, and self-esteem (PHWP, 2011). Health and safety initiatives meant to prevent, assess, and treat potential health risks to employees also include the proper management of stress (PHWP, 2011). The involvement of employees in a fair and transparent decision-making process is a form of procedural justice that has been shown to predict organizational commitment and more positive relationships with supervisors (PHWP, 2011; Folger & Konovsky, 1989; McFarlin & Sweeney, 1992; Colquitt, Conlon, Wesson, Porter, & Yee Ng, 2001). Finally, organizations that effectively implement practices that help employees better manage the demands of work and family life are likely to notice
increases in job satisfaction and organizational commitment (Beauregard & Henry, 2009).

Thus, the following hypothesis is derived from the literature:

*Hypothesis E: Elements of a supportive work climate are associated with LOJ.*

**A Note on the Possibility of a Dispositional Source of LOJ**

An argument by Brief and Nord (1988) regarding the study of dispositional sources of job satisfaction spurred some discussion about the use of negative affect as a predictor of job satisfaction (Judge & Hulin, 1993; George, 1989). Subsequently, Levin and Stokes (1989) demonstrated that individuals with high negative affect report significantly lower job satisfaction than their low-negative affect counterparts, even when controlling for job characteristics. It was explained that these individuals have a tendency to experience aversive emotional states, thus affecting their perceptions of their job (Levin & Stokes, 1989). Due to the similarity between job satisfaction and LOJ, and the plausible negative relationship between LOJ and negative affect, negative affect will be included in this study as a predictor of LOJ.

**Summary and Hypotheses**

In summary, Sternberg’s (1988) construction of interpersonal love was the basis of the exploratory theory outlining the LOJ taxonomy. Testing the LOJ framework entails investigating the relationships between meaningful work experiences that may affect the components of LOJ. It is hypothesized that positive work experiences of adequate challenge and control in job tasks, closeness and trust in co-worker relationships, and a supportive work climate will be associated with increased LOJ.
These hypotheses are grounded in theory of personal meaning and the humanistic paradigm (Aktouf, 1992), addressing the human need for fulfilment, thriving, and a sense of purpose.

**Methodology**

**Sample**

Data for this project was collected from the same participants at two time points.

**Time 1.** The first wave of data collection occurred in 2006, when a survey of workplace stress and occupational health was sent out to 2000 employed persons in Nova Scotia. The target sample for the survey was male and female participants who have paid employment and work more than 30 hours a week. 916 responses were received from participants (52.3% female) for a response rate of 45.8%. Participants were full-time, part-time and seasonal employees in a large range of occupations, and the average hours worked per week was 40. Ages ranged from 22 to 77 (mean of 55.4, median of 49).

**Time 2.** The second wave of data collection occurred in March 2011. 728 invitations were sent out to participants from the first wave of data collection who had agreed to be contacted for participation in a future study. 168 responses were received for a response rate of 23.1%, although not all surveys were eligible for use due to some participants having retired or lost their employment over the past 5 years. The final sample size for Time 2 (and the longitudinal data set) totalled 124 participants (55.6% female). Participants were aged between 24 to 71 with a mean of 49, median of 50, and who worked an average of 39 hours a week.
A comparison of the two samples on demographic variables revealed differences in the mean education level and mean income of participants. Time 1 and time 2 sample demographics were otherwise equivalent. As for the participants from time 1 who did not participate in time 2, a MANOVA of all measured variables by whether or not participants responded in both waves revealed that no significant differences exist between groups.

**Procedure**

**Time 1.** In 2006, participants of the Nova Scotia Work Stress Survey were recruited by telephone, completed a mail-in or online survey, and received $15 in compensation for their participation in the survey. Sample characteristics are outlined above. The measured LOJ items included all three indicators (passion, intimacy and commitment) as part of a larger study examining a range of workplace variables, including job characteristics, job demands, work-family conflict, supervisor support, co-worker relationships, incivility and aggression, stress, strain, absenteeism, and demographics.

**Time 2.** In 2011, participants from the first wave who had agreed to be contacted at a later date (n = 728) received a mailed invitation to participate in an online survey. For this wave, participants were entered in a draw for one of two cash prizes of $500. Given the length of time between communications and accessibility to limited information about participants, huge attrition rates were expected, and observed. Sample characteristics are outlined above. Data collection spanned from February 15th to March 4th, 2011. LOJ items were included in this larger work study, which also included job
characteristics, demands, resources, workplace characteristics, supervisor support, experienced and enacted incivility, stress, strain, negative affect, and on-the-job work recovery items. Questionnaires were administered using an online surveying website sponsored by Saint Mary’s University, in Nova Scotia, Canada.

**Data analysis.** A confirmatory factor analysis (CFA) was conducted on the data using SPSS® AMOS analysis software. Item parcels were used instead of original items as indicators of each LOJ dimension in order to reduce the high number of degrees of freedom that would otherwise cause estimation problems. There is some controversy surrounding item parceling as, in some circumstances, uninformed use of parceling has resulted in better fitting solutions even when the parcel models were misspecified (Bandalos, 2002; Bandalos, 2008; Hall et al., 1999; Kim & Hagtvet, 2003). Further controversy surrounding item parceling has to do with the concern that no one approach is agreed upon within the scientific community (Sass & Smith, 2006). Despite the controversy, simulated and empirical testing has shown that item parceling does not result in increased parameter bias or better structural coefficient estimates as long as parcelled solutions are first analyzed for unidimensionality using a set of criteria other than factor loadings (Kim & Hagtvet, 2003; Alhija & Wisenbaker, 2006; Sass & Smith, 2006). By operationally defining unidimensionality in terms of a higher-order one-factor model, the following criteria emerge for multi-facet models: (a) one common factor underlies the parcels and items, (b) zero residual covariance remains among parcel composites after the common factor has been partialled out, (c) zero covariances remain among items after the parcel composite has been partialled out, (d) zero residual
covariances remain among parcel composites and items, and (e) zero residual covariances remain between any error variables and the latent common factor (Hagtvet, 1999; Kim, 2000; Kim & Hagtvet, 2003).

Accordingly, each indicator (passion, intimacy, and commitment) was analyzed for unidimensionality after being grouped into three parcels of one or two randomly-assigned items. In all instances, residual covariance was between 0 and 0.10. Following this procedure should result in negligible effects or parameter bias or bias in the estimation of factor correlations (Alhija & Wisenbaker, 2006; Sass & Smith, 2006; Kim & Hagtvet, 2003).

**Taxometric analysis.** Next, using the methods outlined by Ruscio, Haslam and Ruscio (2006), a classification procedure was conducted on the 2006 cross-sectional data set to determine whether LOJ is a taxonic or a dimensional construct (n = 824). The suitability of the data, theoretical indicators and sample sizes was first assessed according to the recommendations of Ruscio et al. (2006), and the data were then analyzed using the MAXSLOPE, MAMBAC, L-Mode and MAXCOV techniques for determining whether the latent structure of LOJ is taxonic or dimensional. MAXSLOPE was conducted using SPSS software, MAMBAC and L-Mode were conducted using a combination of SPSS, MS Excel and R software for data analysis, and MAXCOV was conducted solely using R.

As the last step for the taxometrics analysis, the taxonic model was compared to the higher order, 1-component, 2-component, and 3-component factor-analytic models.
Correlates of LOJ. The proposed predictors of LOJ (challenge, control, closeness and climate) were included in a structural equation model, in accordance with the results of the taxometrics analysis, as predictors of LOJ at (a) time 1, for a cross-sectional analysis (n = 886), and (b) time 2 while accounting for the longitudinal effects of LOJ at time 1, for a much stronger test of causality (n = 124).

Longitudinal Stability of LOJ. The temporal stability of LOJ was tested with structural equation modelling (SEM) using SPSS® AMOS software. Two longitudinal stability analyses were conducted: one with a path drawn from LOJ at time 1 to LOJ at time 2, and a second with paths drawn between each indicator at time 1 and time 2, such that a coefficient of stability was produced to describe the relationships between all latent variables. Further analyses were then conducted to account for negative affect and for job change since time 1.

Measures

Except for the items measuring Love of Job, negative affect and job change, all variables originated from the Canadian Forces Occupational Stress Questionnaire (Kelloway & Barling, 1994). All variables were measured using a 7-pt Likert scale ranging from strongly disagree to strongly agree, unless otherwise noted, and are described as follows:

Love of Job scale. Using a 7-pt Likert scale ranging from strongly disagree to strongly agree, the Love of Job scale required participants to respond to such items as “My work is more than just a job to me, it’s a passion”, “We care deeply for each other at work”, and “I really feel as if my organization’s problems are my own” (Inness, Turner,
Barling & Kelloway, 2010). These items are meant to assess each of the three LOJ workplace-related indicators, including passion, commitment, and intimacy. Cronbach's alpha is $\alpha = .94$ for all LOJ items, $\alpha = .95$ for passion, $\alpha = .89$ for commitment, and $\alpha = .95$ for intimacy. See Appendix A for items.

**Measuring Challenge.** Items measuring skill use were included in the first wave of data collection. Skill use is a measure of whether the job demands the use of a worker's skills and abilities to their fullest potential (Kelloway & Barling, 1994). Skill use was comprised of three items, including “my job requires the use of many skills”, “my job allows me to use my skills and abilities”, and “my job allows me to learn new things”, with a Cronbach’s alpha of $\alpha = .85$. High values indicate high skill use.

**Measuring Control.** Control was appraised using items designed to measure control over decision-making, which is a stressor when workers have a lack of authority over the decisions that are made about their job (Kelloway & Barling, 1994). Control over decision-making was comprised of three items including “I have enough influence on my job”, “I have a say in how my work gets done”, and “I have the opportunity to make my own decisions”, with a Cronbach’s alpha of $\alpha = .86$.

**Measuring Climate.** As previously described, workplace climate can be measured using a variety of variables. The variables included at time 1 as indicators of climate were recognition and procedural justice, as represented by Kelloway and Barling (1994). Recognition was a three-item variable including “I usually hear if I’ve done a good job”, “nobody in authority appreciates my work (R)”, and “there is not enough recognition for good work in my organization (R)” with a Cronbach’s alpha of $\alpha = .81$. 
Procedural justice included five items, including “the procedures [used to make important decisions in my organization]”… (a) “are based on accurate information”, (b) “are applied consistently”, (c) “are free of bias”, and (d) “uphold ethical and moral standards”, as well as “I am able to express my views and feelings during those procedures”, with a Cronbach’s alpha of $\alpha = .90$.

**Measuring Closeness.** The co-worker relationship scale composed of 12 items similar to “my co-workers can be relied on if things get tough at work” yielded a Cronbach’s alpha of $\alpha = .93$ (Kelloway & Barling, 1994).

**Other variables.** Other variables were included in the survey as a means of validation and control. The Negative Affect subscale of the PANAS (Positive and Negative Affect Scale), a 10-item scale measuring the extent to which participants have felt upset, nervous, tense or vulnerable over the past four months (Watson, Clark & Tellegen, 1988), returned a Cronbach’s alpha of $\alpha = .94$. In addition, participants were asked whether they had changed jobs since the last administration of the survey in 2006 using a yes/no question and an open-ended text box for clarification. The open-ended answers were screened for any responses that did not constitute a job change (i.e. supervisor had transferred but participant remained in the same job).

In assessing longitudinal stability, it is necessary to use the same items at both time points (Crocker and Algina, 2006). Accordingly, work experience and LOJ items administered at time 2 were the same as those administered at time 1, although some items were only administered at one time and thus were only considered for cross-sectional analysis.
Results

Confirmatory factor analysis

A confirmatory factor analysis (CFA) was conducted in AMOS to determine whether a higher-order, 1-, 2- or 3-component model of LOJ is a more accurate representation of the data. Factor analysis is best suited to examine whether the indicators are indeed separate variables estimating a single latent construct, and is used to describe dimensional structures as opposed to taxonic ones.

3-Component model. To reduce the degrees of freedom that posed restrictions on the analysis in the full model, each indicator consisted of three parceled items, which in turn were comprised of one or two random measure items. For example, Commitment is normally observed using six items, but for this analysis was calculated using three groups of parceled items. Items were parceled by computing the mean of the group.

The data was a very good fit to the 3-component model, with an overall $\chi^2 (24) = 140.98, p = .000$, RMSEA = .074, CFI = .984, and NFI = .980. After removing cases with missing data, the final sample size was $n = 886$. See Figure 4 for the model.
Figure 4 Three-component Love of Job CFA model (unstandardized paths shown).

2-Component model. Given the high correlation \( r = .76 \) between passion and commitment in this sample, it is plausible to imagine an alternative model consisting of two factors: passion + commitment, and intimacy. However, the data did not fit the 2-component model better than the higher-order model as it produced a \( \Delta \chi^2 = 315.42 \). See Table 1 for fit statistics, and Figure 5 for the model.
Table 1: *Fit Indices for Love of Job Models.*

<table>
<thead>
<tr>
<th>Factor Structure</th>
<th>$\chi^2$</th>
<th>df</th>
<th>NFI</th>
<th>CFI</th>
<th>RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Three-factor model</td>
<td>140.98</td>
<td>24</td>
<td>.980</td>
<td>.984</td>
<td>.074</td>
</tr>
<tr>
<td>Two-factor model</td>
<td>456.40</td>
<td>26</td>
<td>.936</td>
<td>.940</td>
<td>.137</td>
</tr>
<tr>
<td>One-factor model</td>
<td>2330.51</td>
<td>27</td>
<td>.674</td>
<td>.676</td>
<td>.310</td>
</tr>
<tr>
<td>Higher-order model</td>
<td>194.92</td>
<td>32</td>
<td>.973</td>
<td>.977</td>
<td>.078</td>
</tr>
</tbody>
</table>

*Note: all $\chi^2$ values are significant at $p < .001$.*

**Figure 5.** Two-component Love of Job CFA model (unstandardized paths shown).

**Single component model.** The 1-component model produced for comparison consisted of one single latent variable (LOJ) estimated by nine groups of items that were
combined as previously described. The items were combined by indicator, with one or two items forming each group.

In contrast to the 3-factor model, the fit was not nearly as good for the single factor model as the $\Delta \chi^2 = 2189.53$. See Table 1 for fit statistics and Figure 6 for the model.

*Figure 6.* Two-component Love of Job CFA model (unstandardized paths shown).

**Higher-order model.** The higher-order LOJ model consisted of one latent variable being estimated by the three latent indicators of the 3-factor model. Each
indicator again consisted of three parceled items, which in turn were comprised of one or two random measure items.

Compared to the 3-factor model, the fit for the higher-order model was slightly worse, and produced a \( \Delta \chi^2 = 53.94 \). See Table 1 for fit indices and Figure 7 for the model.

*Figure 7.* Higher-order Love of Job CFA model (unstandardized paths shown).
Although the fit was slightly worse for the higher-order model compared to the 3-factor model, the theoretical grounds for its use as the primary model for analysis compensate for the small increase in $\chi^2$. Furthermore, the use of a higher-order model allows for estimating correlates with LOJ directly instead of with its three individual components. Therefore, the higher-order model was used in all subsequent analyses.

**Taxometric analyses**

In interpreting the results it is important to remember that the base rate of taxon members in this general population sample is very low, estimated at $P = .05$. Low base rates can easily conceal latent taxonic structures (Ruscio et al., 2006).

**MAXSLOPE results.** The MAXSLOPE procedure resulted in three very similar scatterplots that resembled one cloud of points with a straight line running through them, lacking the clear S-shaped curve that would have been suggestive of a taxonomy. Please refer to Figure 8, Figure 9, and Figure 10 for the curves in question. In a taxonic structure, the location of the steepest point of the curve is used to estimate the relative size of the complement and the cut-off point for best discriminating between taxon members and non-members (Ruscio, Haslam and Ruscio, 2006). However, the “curves” yielded in this analysis were clearly linear, such that the identification of the steepest point was impossible.
Figure 8. MAXSLOPE analysis using Passion as the output variable and Commitment + Intimacy as a composite input variable.

Figure 9. MAXSLOPE analysis using Commitment as the output variable and Passion + Intimacy as a composite input variable.

Figure 10. MAXSLOPE analysis using Intimacy as the output variable and Passion + Commitment as a composite input variable.
Figures 11a and 11b demonstrate the average MAXSLOPE curve obtained with this data compared to artificially-created comparison data with (a) categorical parameters and (b) dimensional parameters. A visual inspection of these graphs suggests that the data more closely matches the dimensional comparison data.

**Figures 11a and 11b**  MAXSLOPE average curve compared to an artificially-constructed categorical comparison dataset (left) and an artificially-constructed dimensional comparison dataset (right).

**MAMBAC results.** MAMBAC curves were produced by assigning variables to the input-output indicator roles in all possible pairwise configurations, and placing cuts between every point as described above. The MAMBAC analysis yielded concave, bow-shaped curves expected of dimensional structures. See Figure 12 for a depiction of the average curve, which is prototypical of MAMBAC curves for dimensional structures.
Figure 12  Average MAMBAC curve of mean difference scores using 50 cuts at .25 SD intervals (supplied $P = .05$).

The comparison curve fit index (CCFI) value of the analysis when the base rate of taxon members was specified at $P = .05$ is CCFI = .417. Although lower than .50 and thus suggestive of a dimensional structure, it is likely to have a significance value of over $p = .10$ (Ruscio, 2011). Therefore, it was deemed inconclusive, and a second analysis was conducted with an assumed base rate of $P = .15$. This analysis yielded a value of CCFI = .342, denoting moderately strong support for a dimensional structure. The comparison curves produced with specifications of $P = .15$ also showed a strong semblance to the dimensional data set (see Figures 13a and 13b).
Figures 13a and 13b. MAMBAC average curve compared to an artificially-constructed categorical comparison dataset (left) and an artificially-constructed dimensional comparison dataset (right).

L-Mode results. As the first step of L-Mode, a principal components factor analysis was conducted on a 1-factor model. Bartlett factor scores were saved and plotted in a histogram. Refer to Figure 14. The histogram of factor scores was clearly normally distributed, with relatively equal measures of central tendency (mean = 0, median = .06, mode = 1.5) and a standard deviation of SD = 1.03. According to Ruscio et al. (2006), the seemingly displaced mode may be "the product of the lumpiness of chance", as this issue is very common when L-Mode is performed on data sets with substantially different taxon and complement base rates such as this.
As especially small taxon base rates may yield small peaks to the far side of zero, such that the taxon mode can be overlooked, Ruscio (2011) recommends visually checking for the left and right modes and manually specifying a value that approximates a visible trough in the distribution. Therefore, the start value for the left mode was set at -1, and yielded the curve depicted in Figure 15. With these specifications, the CCFI = .288 strongly suggested a dimensional construct. Indeed, the comparison data also suggested a better fit with the dimensional curves (Figures 16a and 16b).
Figures 16a and 16b. L-Mode curve compared to artificially-constructed categorical and dimensional datasets (supplied $P=.05$).

Maxcov results. Maxcov curves were produced using composite indicators as previously described (see Figure 17). When $P = .05$ was assumed, the comparison curve fit index of $CCFI = .515$ was inconclusive. When $P = .15$ was assumed, the $CCFI = .359$ pointed to a dimensional construct. This conclusion was further supported by an averaged Maxcov curve that was more similar to a dimensional comparison curve than a categorical comparison curve (Figure 18).

Figure 17. Maxcov average curve, $P = .05$. 
Correlates of LOJ

Based on the results of the taxometric analyses, it was deemed that the dimensional construct of Love of Job can be analyzed using a 3-factor structure or as a higher-order structure. For the analysis of LOJ correlates, proposed work experiences were related to LOJ as a higher-order measure in order to determine the path associated with LOJ instead of each individual indicator. These path analyses were conducted using AMOS for SPSS. In addition, see Table 2 for bivariate correlations of all variables.
LOVE OF JOB

Table 2: Bivariate Correlation Table for All Variables

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<td>Recognition</td>
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<td>.299**</td>
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<td>.467**</td>
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<td>Intimacy (time 1)</td>
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<td>.758**</td>
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<td>.573**</td>
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<td>.291**</td>
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<td>.239**</td>
<td>.196*</td>
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<td>.009</td>
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<td>.564**</td>
<td>.440**</td>
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<td>.568**</td>
<td>.471**</td>
<td>.332**</td>
<td>-.241**</td>
<td>.075</td>
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<tr>
<td>LOJ sum (time 2)</td>
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<td>.481**</td>
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<td>-.182*</td>
<td>-.139</td>
<td>.542**</td>
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</tbody>
</table>

<sup>A</sup> A positive relationship represents a higher likelihood to change jobs. * Correlation significant at p < .05 (two-tailed). ** Correlation significant at p < .001 (two-tailed).
**Cross-sectional data.** The cross-sectional data revealed significant paths for all work experience items. For the experience of Challenge, skill use was significantly related to LOJ ($b = .552, p < .001$). See Figure 19 for the model.

*Figure 19* Cross-sectional analysis of the relationship between Love of Job and skill use (Challenge).
For Control, control over decision-making was significantly related to LOJ, $b = .573, p < .001$. See Figure 20 for the model.

Figure 20. Cross-sectional analysis of the relationship between Love of Job and control over decision-making (Control).

For the experience of Closeness, the variable of positive co-worker relationships was significantly related to LOJ, $b = 2.74, p < .001$. See Figure 21 for the model.
Climate encompassed two different items. The strongest path to the higher-order LOJ factor was produced by procedural justice, $b = .62, p < .001$, while recognition was also significant at $b = .60, p < .001$. See Figure 22 for the model.
Longitudinal Stability

The test-retest analysis of stability revealed significant paths between the individual components and their specific counterparts at time 1 and time 2. The path for passion stood at $b = .48, p < .001$, commitment had a path of $b = .55, p < .001$, and the path for intimacy was $b = .45, p < .001$. The fit for the model was determined as follows: $\chi^2 (124) = 292.56$, RMSEA = .105, CFI = .916, NFI = .864. See Figure 23 for the model.
Figure 23. Test-retest longitudinal analysis of the Love of Job components at Time 1 and Time 2.

For the higher-order, 1-factor model, LOJ at time 1 showed a stability of $b = .56$, $p < .001$ after 5 years. See Figure 24 for the model.

Figure 24. Test-retest longitudinal analysis of the higher-order Love of Job construct at Time 1 and Time 2.
Given the high likelihood of the existence of multiple variables that may have affected the longitudinal stability of LOJ over five years, further analyses were conducted. Specifically, the model was altered to account for (a) whether participations had changed jobs over the data collection period, and (b) negative affect.

When job change was included in the model, the relationship between LOJ at time 1 and time 2 increased by .02 ($b = .58, p < .001$), and job change was significantly negatively related to LOJ at time 2 ($b = -.47, p = .017$). See Figure 25 for the model.

Approximately half the participants ($n = 63, or 45.7\%$) indicated that they had changed jobs in the past 5 years.

Figure 25. Longitudinal analysis of the higher-order Love of Job construct, accounting for job change.

Interestingly, accounting for negative affect decreased the path between LOJ at time 1 and time 2 by .02, and showed a significant negative relationship with LOJ ($b = -.39, p < .001$). See Figure 26 for the model.
Figure 26. Longitudinal analysis of the higher-order Love of Job construct, accounting for negative affect.

Correlates of LOJ using Longitudinal data. In order to impose a more stringent test upon the positive work experiences proposed to lead to LOJ, the antecedents showing significant associations in the cross-sectional analysis at time 1 were included in the model of longitudinal stability as predictors of LOJ at time 2. In other words, in this model, the antecedents and LOJ at time 1 figured together (uncorrelated) and predicted LOJ at time 2. Based on the evidence of weakened correlations between the correlates and the sum of LOJ from time 1 to time 2 (see Table 2), it was not expected that time 1 correlates would significantly predict LOJ at time 2. In order to avoid redundancies, the model was conducted using all time 1 variables present at the same time.
The results of this analysis revealed that the significant path between LOJ at time 1 and LOJ at time 2 was increased by .02 ($b = .58, p < .001$). However, as expected, no significant paths between the antecedents at time 1 and LOJ at time 2 were observed. See Figure 27 for the model.

*Figure 27.* Longitudinal analysis of positive work experiences (Challenge, Control, Closeness and Climate) measured at Time 1 predicting Love of Job at Time 2.
**Discussion**

The present study has established that LOJ is a dimensional construct (as opposed to taxonic), and can be represented by a 3-factor structure or higher-order construct of three indicators. Cross-sectional correlates include items that represent Challenge, Control, Closeness and Climate in the workplace, but none of these experiences predict LOJ longitudinally. Over five years, the LOJ construct shows impressive stability even when a job change has occurred. Finally, the negative affect of some individuals may result in attenuated love for their job, as a moderate association of NA with LOJ suggests that a significant proportion of variance in LOJ could be due to individual differences in affectivity.

The results of the taxometric analyses conducted on this data are highly suggestive of a dimensional construct. However, the caveats to this conclusion include the apparently very low taxon base rate of the data, which may conceal a taxonic structure if it were to exist, and the high correlations between indicators. In order for the inferences of the taxometric analysis to be valid, the items that form the indicators must have the ability to distinguish the putative groups with sufficient validity and be sensitive enough to determine where a taxonic boundary exists (Ruscio et al., 2006). Although the LOJ measure items were empirically derived in their development, a validation study could be conducted in order to justify the assumption that each indicator set provides good content and discriminant validity in relation to the construct.

In the interest of triangulation, these same taxometric analyses could be repeated using an equal proportion of individuals who self-identify as taxon members, and general
population individuals. This would increase the base rate of taxon members in the group, and allow for additional interpretations. In fact, as sample composition can substantially impact the results of taxometric analyses, many researchers have argued for the practice of ensuring that a minimum number of putative taxon members are present in the sample by relying on selected populations (e.g. Franklin, Strong, & Greene, 2002; Slade & Andrews, 2007). However, Ruscio, Haslam and Ruscio (2006) warn that the inferences drawn from taxometric analyses in special populations (i.e. clinical samples where the incidence of taxon members is artificially high) are not as valid as those drawn from general population samples.

That being said, the evidence garnered by the previously described taxometric and factor analyses demonstrates that LOJ is a dimensional construct measured by three indicators. Hypothesis A was thus shown to be false. Therefore, it is suitable for LOJ items to be included in path analyses as a 3-factor latent variable, or as one observed variable calculated by obtaining the sum of all LOJ items. The rationale for the latter method is similar to the logic of L-Mode. Composite variables contain more variance than single indicators, and thus capture a larger proportion of extreme cases than would a single indicator. With all items combined, information about the relations between the indicators is also captured without compromising the structure of the construct, as it was deemed to be dimensional.

The purpose of collecting data over five years was to establish the longitudinal stability of LOJ, and to conduct some preliminary investigations on possible antecedents. Evaluating the magnitude of a stability estimate involves consideration of the elapsed
According to Crocker and Algina (2006), test-retest reliability estimates for personality, interest, or attitude measures (which generally range from low .70s to .90s) are often lower than estimates for aptitude tests. In comparison, the Love of Job instrument is an assessment of a motivational state (Rempel and Burris, 2005), which should arguably produce lower coefficients of stability than those for aptitude tests. A five year time period is long enough to allow effects of memory to fade, but in today’s fast-paced and dynamic workplace, personnel transfers or job characteristic modifications are likely to have occurred. Nonetheless, the coefficients of stability reported for the LOJ indicators are quite high for a test-retest period of 5 years, implying that LOJ is a relatively stable construct.

The additional analyses that accounted for job change and negative affect revealed very interesting results. The fact that job change did produce significant changes in LOJ after the change had occurred suggests that changing jobs may lead to a decrease in passion for the work done, commitment to the organization, and intimacy with co-workers. It would be interesting to conduct more research on whether this decrease in LOJ stabilizes after some time in the new job, and if so, when it happens.

That negative affect, a stable personality trait, was significantly related to loving one’s job suggests that LOJ may have a dispositional source. The extent to which low-NA individuals are predisposed to loving their jobs (or high-NA individuals are predisposed to not loving their jobs), as evidenced by the negative relationship between
NA and LOJ of $b = -.39$, appears to be comparable to correlations between NA and job satisfaction ($r = -.33$) reported in a meta-analysis by Connolly and Viswesvaran (2000).

Hypotheses B through E, which posited that specific work experiences would be associated with LOJ, were all shown to be true for the cross-sectional analysis, but false when considering the longitudinal analysis. The fact that the cross-sectional analysis revealed significant results but the more stringent longitudinal model did not hold may point to several issues. First, it is possible that the work experiences included in the model simply do not predict LOJ as well as would be expected according to theory. However, it is more plausible that the likely possibility of numerous extraneous influences on work experiences over five years has introduced confounds in the SEM analysis. Furthermore, as the items are required to be the same at each point of data collection, a severe limitation exists in this study in that the included items may not have perfectly reflected the work experiences presumed to lead to LOJ. For example, the broadly-described work experience of “closeness” was assessed using items that measure co-worker relationships, but not trust, which would have more accurately represented the experience of “closeness”. Finally, the relatively small sample size of the longitudinal data set ($n = 124$) would have had major implications for the power of the analysis.

Therefore, there is evidence of association between positive work experiences and loving one’s job at the same point in time. Specifically, measures significantly related to LOJ include skill use, autonomy, control over decision-making, positive co-worker relationships, procedural justice, and recognition.
Limitations

The limitations of this study, including the low base rate of LOJ group members and the pre-determined survey items, were regularly discussed as they arose. In addition to these, the longitudinal analysis is severely limited in its response rate. Although this was expected, recontacting participants six years after the initial study resulted in only 168 responses (141 of which were useable, due to retirements), and 93 returned envelopes (due to moving), for a final usable sample size consisting of only 18.8% of the previous sample. Also, the power of a longitudinal analysis using a sample size of n = 124 is likely to be very low.

Sample demographics for the longitudinal data set were relatively equal in most aspects, including gender, age, employment status, hours worked per week, management status, and union membership. However, a one-way ANOVA revealed group differences in the time 1 and time 2 samples for education level and income. As a regression analysis revealed that income level is very slightly, but significantly, related to LOJ ($b = .16, R^2 = .014, F (2, 860) = 5.96, p = .014$), this may be evidence of systematic bias present in the longitudinal dataset.

Implications and Future Research

For many a worker, loving their job is a goal that may seem unattainable. Indeed, the low estimate of a 5% base rate of job-lovers portends grim chances for achievement if that is in fact the objective. Yet is it really enough to strive for job satisfaction when it is possible to strive for engagement, fulfillment, and interpersonal harmony in one’s workplace? The contemporary literature on affective experiences inside and outside
organizational settings suggests that there are wide-ranging consequences of positive emotions in the workplace (Brief & Weiss, 2002). For instance, performance-relevant outcomes are pervasive, including judgment (Robbins & DeNisi 1994), self-efficacy (Saavedra & Earley, 1991), helping behavior (Isen & Baron, 1991; George, 1990; George, 1991; George, 1995; George & Bettenhausen 1990; Isen, 1987), and creative problem-solving (Isen, Daubman, & Nowicki, 1987; Estrada, Isen, & Young, 1997; Oldham & Cummings, 1996). The study of the relationships between LOJ and the preceding variables is a still-unexplored venue for new research.

Although the appropriate analyses for obtaining the coefficient of stability of the LOJ construct were conducted and discussed, something remains to be said about the very nature of love. As Sternberg so eloquently put it, "love is a story" (1998, 2006); a test-retest procedure of Love of Job over 5 years, although technically adequate according to psychometric principles (Crocker and Algina, 2006), fails to fully capture the roller coaster-like fluctuations and transitions that so embody the essence of love stories. It may be interesting and more informative to pursue studying the effects of LOJ over time by means of a daily diary study in order to discover the "story" behind loving one’s job.

In an early article about the future of I/O psychology at the time, Walter V. Bingham wrote that “[t]he purpose of industrial psychology is, as we all know, two-fold. It aims to increase the satisfactions of those who work, while helping them to accomplish more”. (Bingham, 1940, p.1). The continued investigation of Love of Job is in line with the realization of this objective, with the intention of providing organizational researchers
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with a perspective that encompasses the intense positive emotions that arise from loving one’s job (Kelloway et al., 2010). Additional validation of its predictors would allow this construct to achieve its potential of becoming a useful framework for creating motivated, productive employees.
References


LOVE OF JOB


May, D. R. (2003). *Fostering the human spirit at work: Toward an understanding of the influences on employees' experienced meaningfulness at work*. Unpublished manuscript. For more information, see May, Gilson, & Harter (2004).

LOVE OF JOB


Appendix A: Love of Job Scale Items

(Inness, Turner, Barling & Kelloway, 2010)

1. My work is more than just a job to me, it’s a passion.
2. I adore what I do at work.
3. My job keeps my interest engaged like no other task.
4. I wish my friends found their work as personally fulfilling as I find mine.
5. I am so happy that I do the job that I do.
6. I love the organization for which I work.
7. I would do almost anything just to do what I currently do in this organization.
8. I would be very happy to spend the rest of my career at this organization.
9. I enjoy discussing my organization with people outside of it.
10. I really feel as if my organization’s problems are my own.
11. My organization has a great deal of personal meaning to me.
12. We care deeply for each other at work.
13. I love the people I work with.
14. I feel very close to the people at work.
15. We value each other greatly in our worklife.
16. I would feel a deep sense of loss if I could no longer work with my coworkers/clients.
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